MMDetection

Release 2.25.1

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GET STARTED

CHAPTER

ONE

PREREQUISITES

In this section we demonstrate how to prepare an environment with PyTorch.

FGVCLib works on Linux, Windows and macOS. It requires Python 3.7+, CUDA 10.0+ and PyTorch 1.5+.

Note: If you are experienced with PyTorch and have already installed it, just skip this part and jump to the *next section*. Otherwise, you can follow these steps for the preparation.

Step 0. Download and install Anaconda from the official website.

Step 1. Create a conda environment and activate it.

```
conda create --name openmmlab python=3.7 -y
conda activate pytorch
```

Step 2. Install PyTorch following official instructions, e.g.

On GPU platforms:

```
conda install pytorch torchvision -c pytorch
```

On CPU platforms:

```
conda install pytorch torchvision cpuonly -c pytorch
```

CHAPTER

TWO

INSTALLATION

We recommend that users follow our best practices to install FGVCLib However, the whole process is highly customizable. See Customize Installation section for more information.

2.1 Best Practices

Step 0. Install FGVCLib.

Please install it from source:

```
git clone https://github.com/dongliangchang/Fine-grained-Visual-Analysis-Library.git
```

CHAPTER

THREE

BENCHMARK AND MODEL ZOO

3.1 Mirror sites

We only use aliyun to maintain the model zoo since MMDetection V2.0. The model zoo of V1.x has been deprecated.

3.2 Common settings

- All models were trained on `coco_2017_train`, and tested on the `coco_2017_val`.
- We use distributed training.
- All pytorch-style pretrained backbones on ImageNet are from PyTorch model zoo, caffe-style pretrained backbones are converted from the newly released model from detectron2.
- For fair comparison with other codebases, we report the GPU memory as the maximum value of `torch.cuda.max_memory_allocated()` for all 8 GPUs. Note that this value is usually less than what `nvidia-smi` shows.
- We report the inference time as the total time of network forwarding and post-processing, excluding the data loading time. Results are obtained with the script benchmark.py which computes the average time on 2000 images.

3.3 ImageNet Pretrained Models

It is common to initialize from backbone models pre-trained on ImageNet classification task. All pre-trained model links can be found at open_mmlab. According to `img_norm_cfg` and source of weight, we can divide all the ImageNet pre-trained model weights into some cases:

- TorchVision: Corresponding to torchvision weight, including ResNet50, ResNet101. The `img_norm_cfg` is `dict(mean=[123.675, 116.28, 103.53], std=[58.395, 57.12, 57.375], to_rgb=True)`.
- Pycls: Corresponding to pycls weight, including RegNetX. The `img_norm_cfg` is `dict( mean=[103.530, 116.280, 123.675], std=[57.375, 57.12, 58.395], to_rgb=False)`.
- MSRA styles: Corresponding to MSRA weights, including ResNet50_Caffe and ResNet101_Caffe. The `img_norm_cfg` is `dict( mean=[103.530, 116.280, 123.675], std=[1.0, 1.0, 1.0], to_rgb=False)`.
- Caffe2 styles: Currently only contains ResNext101_32x8d. The `img_norm_cfg` is `dict(mean=[103.530, 116.280, 123.675], std=[57.375, 57.120, 58.395], to_rgb=False)`.

- Other styles: E.g SSD which corresponds to `img_norm_cfg` is `dict(mean=[123.675, 116.28, 103.53], std=[1, 1, 1], to_rgb=True)` and YOLOv3 which corresponds to `img_norm_cfg` is `dict(mean=[0, 0, 0], std=[255., 255., 255.], to_rgb=True)`.

The detailed table of the commonly used backbone models in MMDetection is listed below :

3.4 Baselines

3.4.1 RPN

Please refer to RPN for details.

3.4.2 Faster R-CNN

Please refer to Faster R-CNN for details.

3.4.3 Mask R-CNN

Please refer to Mask R-CNN for details.

3.4.4 Fast R-CNN (with pre-computed proposals)

Please refer to Fast R-CNN for details.

3.4.5 RetinaNet

Please refer to RetinaNet for details.

3.4.6 Cascade R-CNN and Cascade Mask R-CNN

Please refer to Cascade R-CNN for details.

3.4.7 Hybrid Task Cascade (HTC)

Please refer to HTC for details.

3.4.8 SSD

Please refer to SSD for details.

3.4.9 Group Normalization (GN)

Please refer to Group Normalization for details.

3.4.10 Weight Standardization

Please refer to Weight Standardization for details.

3.4.11 Deformable Convolution v2

Please refer to Deformable Convolutional Networks for details.

3.4.12 CARAFE: Content-Aware ReAssembly of FEatures

Please refer to CARAFE for details.

3.4.13 Instaboost

Please refer to Instaboost for details.

3.4.14 Libra R-CNN

Please refer to Libra R-CNN for details.

3.4.15 Guided Anchoring

Please refer to Guided Anchoring for details.

3.4.16 FCOS

Please refer to FCOS for details.

3.4.17 FoveaBox

Please refer to FoveaBox for details.

3.4.18 RepPoints

Please refer to RepPoints for details.

3.4.19 FreeAnchor

Please refer to FreeAnchor for details.

3.4.20 Grid R-CNN (plus)

Please refer to Grid R-CNN for details.

3.4.21 GHM

Please refer to GHM for details.

3.4.22 GCNet

Please refer to GCNet for details.

3.4.23 HRNet

Please refer to HRNet for details.

3.4.24 Mask Scoring R-CNN

Please refer to Mask Scoring R-CNN for details.

3.4.25 Train from Scratch

Please refer to Rethinking ImageNet Pre-training for details.

3.4.26 NAS-FPN

Please refer to NAS-FPN for details.

3.4.27 ATSS

Please refer to ATSS for details.

3.4.28 FSAF

Please refer to FSAF for details.

3.4.29 RegNetX

Please refer to RegNet for details.

3.4.30 Res2Net

Please refer to Res2Net for details.

3.4.31 GRoIE

Please refer to GRoIE for details.

3.4.32 Dynamic R-CNN

Please refer to Dynamic R-CNN for details.

3.4.33 PointRend

Please refer to PointRend for details.

3.4.34 DetectoRS

Please refer to DetectoRS for details.

3.4.35 Generalized Focal Loss

Please refer to Generalized Focal Loss for details.

3.4.36 CornerNet

Please refer to CornerNet for details.

3.4.37 YOLOv3

Please refer to YOLOv3 for details.

3.4.38 PAA

Please refer to PAA for details.

3.4.39 SABL

Please refer to SABL for details.

3.4.40 CentripetalNet

Please refer to CentripetalNet for details.

3.4.41 ResNeSt

Please refer to ResNeSt for details.

3.4.42 DETR

Please refer to DETR for details.

3.4.43 Deformable DETR

Please refer to Deformable DETR for details.

3.4.44 AutoAssign

Please refer to AutoAssign for details.

3.4.45 YOLOF

Please refer to YOLOF for details.

3.4.46 Seesaw Loss

Please refer to Seesaw Loss for details.

3.4.47 CenterNet

Please refer to CenterNet for details.

3.4.48 YOLOX

Please refer to YOLOX for details.

3.4.49 PVT

Please refer to PVT for details.

3.4.50 SOLO

Please refer to SOLO for details.

3.4.51 QueryInst

Please refer to QueryInst for details.

3.4.52 PanopticFPN

Please refer to PanopticFPN for details.

3.4.53 MaskFormer

Please refer to MaskFormer for details.

3.4.54 DyHead

Please refer to DyHead for details.

3.4.55 Mask2Former

Please refer to Mask2Former for details.

3.4.56 Efficientnet

Please refer to Efficientnet for details.

3.4.57 Other datasets

We also benchmark some methods on PASCAL VOC, Cityscapes, OpenImages and WIDER FACE.

3.4.58 Pre-trained Models

We also train Faster R-CNN and Mask R-CNN using ResNet-50 and RegNetX-3.2G with multi-scale training and longer schedules. These models serve as strong pre-trained models for downstream tasks for convenience.

3.5 Speed benchmark

3.5.1 Training Speed benchmark

We provide analyze_logs.py to get average time of iteration in training. You can find examples in Log Analysis.

We compare the training speed of Mask R-CNN with some other popular frameworks (The data is copied from detectron2). For mmdetection, we benchmark with mask_rcnn_r50_caffe_fpn_poly_1x_coco_v1.py, which should have the same setting with mask_rcnn_R_50_FPN_noaug_1x.yaml of detectron2. We also provide the checkpoint and training log for reference. The throughput is computed as the average throughput in iterations 100-500 to skip GPU warmup time.

3.5.2 Inference Speed Benchmark

We provide benchmark.py to benchmark the inference latency. The script benchmarkes the model with 2000 images and calculates the average time ignoring first 5 times. You can change the output log interval (defaults: 50) by setting `LOG-INTERVAL`.

```
python tools/benchmark.py ${CONFIG} ${CHECKPOINT} [--log-interval $[LOG-INTERVAL]] [--
↪fuse-conv-bn]
```

The latency of all models in our model zoo is benchmarked without setting `fuse-conv-bn`, you can get a lower latency by setting it.

3.6 Comparison with Detectron2

We compare mmdetection with Detectron2 in terms of speed and performance. We use the commit id 185c27e(30/4/2020) of detectron. For fair comparison, we install and run both frameworks on the same machine.

3.6.1 Hardware

- 8 NVIDIA Tesla V100 (32G) GPUs
- Intel(R) Xeon(R) Gold 6148 CPU @ 2.40GHz

3.6.2 Software environment

- Python 3.7
- PyTorch 1.4
- CUDA 10.1
- CUDNN 7.6.03
- NCCL 2.4.08

3.6.3 Performance

3.6.4 Training Speed

The training speed is measure with s/iter. The lower, the better.

3.6.5 Inference Speed

The inference speed is measured with fps (img/s) on a single GPU, the higher, the better. To be consistent with Detectron2, we report the pure inference speed (without the time of data loading). For Mask R-CNN, we exclude the time of RLE encoding in post-processing. We also include the officially reported speed in the parentheses, which is slightly higher than the results tested on our server due to differences of hardwares.

3.6.6 Training memory

CHAPTER

FOUR

1: INFERENCE AND TRAIN WITH EXISTING MODELS AND STANDARD DATASETS

MMDetection provides hundreds of existing and existing detection models in Model Zoo), and supports multiple standard datasets, including Pascal VOC, COCO, CityScapes, LVIS, etc. This note will show how to perform common tasks on these existing models and standard datasets, including:

- Use existing models to inference on given images.
- Test existing models on standard datasets.
- Train predefined models on standard datasets.

4.1 Inference with existing models

By inference, we mean using trained models to detect objects on images. In MMDetection, a model is defined by a configuration file and existing model parameters are save in a checkpoint file.

To start with, we recommend Faster RCNN with this configuration file and this checkpoint file. It is recommended to download the checkpoint file to `checkpoints` directory.

4.1.1 High-level APIs for inference

MMDetection provide high-level Python APIs for inference on images. Here is an example of building the model and inference on given images or videos.

```
from mmdet.apis import init_detector, inference_detector
import mmcv

# Specify the path to model config and checkpoint file
config_file = 'configs/faster_rcnn/faster_rcnn_r50_fpn_1x_coco.py'
checkpoint_file = 'checkpoints/faster_rcnn_r50_fpn_1x_coco_20200130-047c8118.pth'

# build the model from a config file and a checkpoint file
model = init_detector(config_file, checkpoint_file, device='cuda:0')

# test a single image and show the results
img = 'test.jpg'  # or img = mmcv.imread(img), which will only load it once
result = inference_detector(model, img)
# visualize the results in a new window
model.show_result(img, result)
```

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```
# or save the visualization results to image files
model.show_result(img, result, out_file='result.jpg')

# test a video and show the results
video = mmcv.VideoReader('video.mp4')
for frame in video:
    result = inference_detector(model, frame)
    model.show_result(frame, result, wait_time=1)
```

A notebook demo can be found in demo/inference_demo.ipynb.

Note: `inference_detector` only supports single-image inference for now.

4.1.2 Asynchronous interface - supported for Python 3.7+

For Python 3.7+, MMDetection also supports async interfaces. By utilizing CUDA streams, it allows not to block CPU on GPU bound inference code and enables better CPU/GPU utilization for single-threaded application. Inference can be done concurrently either between different input data samples or between different models of some inference pipeline.

See `tests/async_benchmark.py` to compare the speed of synchronous and asynchronous interfaces.

```
import asyncio
import torch
from mmdet.apis import init_detector, async_inference_detector
from mmdet.utils.contextmanagers import concurrent

async def main():
    config_file = 'configs/faster_rcnn/faster_rcnn_r50_fpn_1x_coco.py'
    checkpoint_file = 'checkpoints/faster_rcnn_r50_fpn_1x_coco_20200130-047c8118.pth'
    device = 'cuda:0'
    model = init_detector(config_file, checkpoint=checkpoint_file, device=device)

    # queue is used for concurrent inference of multiple images
    streamqueue = asyncio.Queue()
    # queue size defines concurrency level
    streamqueue_size = 3

    for _ in range(streamqueue_size):
        streamqueue.put_nowait(torch.cuda.Stream(device=device))

    # test a single image and show the results
    img = 'test.jpg'  # or img = mmcv.imread(img), which will only load it once

    async with concurrent(streamqueue):
        result = await async_inference_detector(model, img)

    # visualize the results in a new window
    model.show_result(img, result)
    # or save the visualization results to image files
    model.show_result(img, result, out_file='result.jpg')
```

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```
asyncio.run(main())
```

4.1.3 Demos

We also provide three demo scripts, implemented with high-level APIs and supporting functionality codes. Source codes are available here.

Image demo

This script performs inference on a single image.

```
python demo/image_demo.py \
    ${IMAGE_FILE} \
    ${CONFIG_FILE} \
    ${CHECKPOINT_FILE} \
    [--device ${GPU_ID}] \
    [--score-thr ${SCORE_THR}]
```

Examples:

```
python demo/image_demo.py demo/demo.jpg \
    configs/faster_rcnn/faster_rcnn_r50_fpn_1x_coco.py \
    checkpoints/faster_rcnn_r50_fpn_1x_coco_20200130-047c8118.pth \
    --device cpu
```

Webcam demo

This is a live demo from a webcam.

```
python demo/webcam_demo.py \
    ${CONFIG_FILE} \
    ${CHECKPOINT_FILE} \
    [--device ${GPU_ID}] \
    [--camera-id ${CAMERA-ID}] \
    [--score-thr ${SCORE_THR}]
```

Examples:

```
python demo/webcam_demo.py \
    configs/faster_rcnn/faster_rcnn_r50_fpn_1x_coco.py \
    checkpoints/faster_rcnn_r50_fpn_1x_coco_20200130-047c8118.pth
```

Video demo

This script performs inference on a video.

```
python demo/video_demo.py \
    ${VIDEO_FILE} \
    ${CONFIG_FILE} \
    ${CHECKPOINT_FILE} \
    [--device ${GPU_ID}] \
    [--score-thr ${SCORE_THR}] \
    [--out ${OUT_FILE}] \
    [--show] \
    [--wait-time ${WAIT_TIME}]
```

Examples:

```
python demo/video_demo.py demo/demo.mp4 \
    configs/faster_rcnn/faster_rcnn_r50_fpn_1x_coco.py \
    checkpoints/faster_rcnn_r50_fpn_1x_coco_20200130-047c8118.pth \
    --out result.mp4
```

Video demo with GPU acceleration

This script performs inference on a video with GPU acceleration.

```
python demo/video_gpuaccel_demo.py \
    ${VIDEO_FILE} \
    ${CONFIG_FILE} \
    ${CHECKPOINT_FILE} \
    [--device ${GPU_ID}] \
    [--score-thr ${SCORE_THR}] \
    [--nvdecode] \
    [--out ${OUT_FILE}] \
    [--show] \
    [--wait-time ${WAIT_TIME}]
```

Examples:

```
python demo/video_gpuaccel_demo.py demo/demo.mp4 \
    configs/faster_rcnn/faster_rcnn_r50_fpn_1x_coco.py \
    checkpoints/faster_rcnn_r50_fpn_1x_coco_20200130-047c8118.pth \
    --nvdecode --out result.mp4
```

4.2 Test existing models on standard datasets

To evaluate a model's accuracy, one usually tests the model on some standard datasets. MMDetection supports multiple public datasets including COCO, Pascal VOC, CityScapes, and more. This section will show how to test existing models on supported datasets.

4.2.1 Prepare datasets

Public datasets like Pascal VOC or mirror and COCO are available from official websites or mirrors. Note: In the detection task, Pascal VOC 2012 is an extension of Pascal VOC 2007 without overlap, and we usually use them together. It is recommended to download and extract the dataset somewhere outside the project directory and symlink the dataset root to `$MMDETECTION/data` as below. If your folder structure is different, you may need to change the corresponding paths in config files.

We provide a script to download datasets such as COCO , you can run `python tools/misc/download_dataset.py --dataset-name coco2017` to download COCO dataset.

For more usage please refer to dataset-download

```
mmdetection
├── mmdet
├── tools
├── configs
├── data
│   ├── coco
│   │   ├── annotations
│   │   ├── train2017
│   │   ├── val2017
│   │   ├── test2017
│   ├── cityscapes
│   │   ├── annotations
│   │   ├── leftImg8bit
│   │   │   ├── train
│   │   │   ├── val
│   │   ├── gtFine
│   │   │   ├── train
│   │   │   ├── val
│   ├── VOCdevkit
│   │   ├── VOC2007
│   │   ├── VOC2012
```

Some models require additional COCO-stuff datasets, such as HTC, DetectoRS and SCNet, you can download and unzip then move to the coco folder. The directory should be like this.

```
mmdetection
├── data
│   ├── coco
│   │   ├── annotations
│   │   ├── train2017
│   │   ├── val2017
│   │   ├── test2017
│   │   ├── stuffthingmaps
```

Panoptic segmentation models like PanopticFPN require additional COCO Panoptic datasets, you can download and unzip then move to the coco annotation folder. The directory should be like this.

```
mmdetection
├── data
│   ├── coco
│   │   ├── annotations
│   │   │   ├── panoptic_train2017.json
│   │   │   ├── panoptic_train2017
│   │   │   ├── panoptic_val2017.json
│   │   │   ├── panoptic_val2017
│   │   ├── train2017
│   │   ├── val2017
│   │   ├── test2017
```

The cityscapes annotations need to be converted into the coco format using `tools/dataset_converters/cityscapes.py`:

```
pip install cityscapesscripts

python tools/dataset_converters/cityscapes.py \
    ./data/cityscapes \
    --nproc 8 \
    --out-dir ./data/cityscapes/annotations
```

TODO: CHANGE TO THE NEW PATH

4.2.2 Test existing models

We provide testing scripts for evaluating an existing model on the whole dataset (COCO, PASCAL VOC, Cityscapes, etc.). The following testing environments are supported:

- single GPU
- CPU
- single node multiple GPUs
- multiple nodes

Choose the proper script to perform testing depending on the testing environment.

```
# single-gpu testing
python tools/test.py \
    ${CONFIG_FILE} \
    ${CHECKPOINT_FILE} \
    [--out ${RESULT_FILE}] \
    [--eval ${EVAL_METRICS}] \
    [--show]

# CPU: disable GPUs and run single-gpu testing script
export CUDA_VISIBLE_DEVICES=-1
python tools/test.py \
    ${CONFIG_FILE} \
    ${CHECKPOINT_FILE} \
```

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```
    [--out ${RESULT_FILE}] \
    [--eval ${EVAL_METRICS}] \
    [--show]

# multi-gpu testing
bash tools/dist_test.sh \
    ${CONFIG_FILE} \
    ${CHECKPOINT_FILE} \
    ${GPU_NUM} \
    [--out ${RESULT_FILE}] \
    [--eval ${EVAL_METRICS}]
```

`tools/dist_test.sh` also supports multi-node testing, but relies on PyTorch's launch utility.

Optional arguments:

- `RESULT_FILE`: Filename of the output results in pickle format. If not specified, the results will not be saved to a file.
- `EVAL_METRICS`: Items to be evaluated on the results. Allowed values depend on the dataset, e.g., `proposal_fast`, `proposal`, `bbox`, `segm` are available for COCO, `mAP`, `recall` for PASCAL VOC. Cityscapes could be evaluated by `cityscapes` as well as all COCO metrics.
- `--show`: If specified, detection results will be plotted on the images and shown in a new window. It is only applicable to single GPU testing and used for debugging and visualization. Please make sure that GUI is available in your environment. Otherwise, you may encounter an error like `cannot connect to X server`.
- `--show-dir`: If specified, detection results will be plotted on the images and saved to the specified directory. It is only applicable to single GPU testing and used for debugging and visualization. You do NOT need a GUI available in your environment for using this option.
- `--show-score-thr`: If specified, detections with scores below this threshold will be removed.
- `--cfg-options`: if specified, the key-value pair optional cfg will be merged into config file
- `--eval-options`: if specified, the key-value pair optional eval cfg will be kwargs for dataset.evaluate() function, it's only for evaluation

4.2.3 Examples

Assuming that you have already downloaded the checkpoints to the directory `checkpoints/`.

1. Test Faster R-CNN and visualize the results. Press any key for the next image. Config and checkpoint files are available here.

```
python tools/test.py \
    configs/faster_rcnn/faster_rcnn_r50_fpn_1x_coco.py \
    checkpoints/faster_rcnn_r50_fpn_1x_coco_20200130-047c8118.pth \
    --show
```

2. Test Faster R-CNN and save the painted images for future visualization. Config and checkpoint files are available here.

```
python tools/test.py \
    configs/faster_rcnn/faster_rcnn_r50_fpn_1x_coco.py \
```

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```
    checkpoints/faster_rcnn_r50_fpn_1x_coco_20200130-047c8118.pth \
    --show-dir faster_rcnn_r50_fpn_1x_results
```

3. Test Faster R-CNN on PASCAL VOC (without saving the test results) and evaluate the mAP. Config and checkpoint files are available here.

```
python tools/test.py \
    configs/pascal_voc/faster_rcnn_r50_fpn_1x_voc.py \
    checkpoints/faster_rcnn_r50_fpn_1x_voc0712_20200624-c9895d40.pth \
    --eval mAP
```

4. Test Mask R-CNN with 8 GPUs, and evaluate the bbox and mask AP. Config and checkpoint files are available here.

```
./tools/dist_test.sh \
    configs/mask_rcnn_r50_fpn_1x_coco.py \
    checkpoints/mask_rcnn_r50_fpn_1x_coco_20200205-d4b0c5d6.pth \
    8 \
    --out results.pkl \
    --eval bbox segm
```

5. Test Mask R-CNN with 8 GPUs, and evaluate the **classwise** bbox and mask AP. Config and checkpoint files are available here.

```
./tools/dist_test.sh \
    configs/mask_rcnn/mask_rcnn_r50_fpn_1x_coco.py \
    checkpoints/mask_rcnn_r50_fpn_1x_coco_20200205-d4b0c5d6.pth \
    8 \
    --out results.pkl \
    --eval bbox segm \
    --options "classwise=True"
```

6. Test Mask R-CNN on COCO test-dev with 8 GPUs, and generate JSON files for submitting to the official evaluation server. Config and checkpoint files are available here.

```
./tools/dist_test.sh \
    configs/mask_rcnn/mask_rcnn_r50_fpn_1x_coco.py \
    checkpoints/mask_rcnn_r50_fpn_1x_coco_20200205-d4b0c5d6.pth \
    8 \
    --format-only \
    --options "jsonfile_prefix=./mask_rcnn_test-dev_results"
```

   This command generates two JSON files `mask_rcnn_test-dev_results.bbox.json` and `mask_rcnn_test-dev_results.segm.json`.

7. Test Mask R-CNN on Cityscapes test with 8 GPUs, and generate txt and png files for submitting to the official evaluation server. Config and checkpoint files are available here.

```
./tools/dist_test.sh \
    configs/cityscapes/mask_rcnn_r50_fpn_1x_cityscapes.py \
    checkpoints/mask_rcnn_r50_fpn_1x_cityscapes_20200227-afe51d5a.pth \
    8 \
    --format-only \
    --options "txtfile_prefix=./mask_rcnn_cityscapes_test_results"
```

The generated png and txt would be under `./mask_rcnn_cityscapes_test_results` directory.

4.2.4 Test without Ground Truth Annotations

MMDetection supports to test models without ground-truth annotations using `CocoDataset`. If your dataset format is not in COCO format, please convert them to COCO format. For example, if your dataset format is VOC, you can directly convert it to COCO format by the script in tools. If your dataset format is Cityscapes, you can directly convert it to COCO format by the script in tools. The rest of the formats can be converted using this script.

```
python tools/dataset_converters/images2coco.py \
    ${IMG_PATH} \
    ${CLASSES} \
    ${OUT} \
    [--exclude-extensions]
```

arguments

- `IMG_PATH`: The root path of images.
- `CLASSES`: The text file with a list of categories.
- `OUT`: The output annotation json file name. The save dir is in the same directory as `IMG_PATH`.
- `exclude-extensions`: The suffix of images to be excluded, such as 'png' and 'bmp'.

After the conversion is complete, you can use the following command to test

```
# single-gpu testing
python tools/test.py \
    ${CONFIG_FILE} \
    ${CHECKPOINT_FILE} \
    --format-only \
    --options ${JSONFILE_PREFIX} \
    [--show]

# CPU: disable GPUs and run single-gpu testing script
export CUDA_VISIBLE_DEVICES=-1
python tools/test.py \
    ${CONFIG_FILE} \
    ${CHECKPOINT_FILE} \
    [--out ${RESULT_FILE}] \
    [--eval ${EVAL_METRICS}] \
    [--show]

# multi-gpu testing
bash tools/dist_test.sh \
    ${CONFIG_FILE} \
    ${CHECKPOINT_FILE} \
    ${GPU_NUM} \
    --format-only \
    --options ${JSONFILE_PREFIX} \
    [--show]
```

Assuming that the checkpoints in the model zoo have been downloaded to the directory `checkpoints/`, we can test Mask R-CNN on COCO test-dev with 8 GPUs, and generate JSON files using the following command.

```
./tools/dist_test.sh \
    configs/mask_rcnn/mask_rcnn_r50_fpn_1x_coco.py \
    checkpoints/mask_rcnn_r50_fpn_1x_coco_20200205-d4b0c5d6.pth \
    8 \
    -format-only \
    --options "jsonfile_prefix=./mask_rcnn_test-dev_results"
```

This command generates two JSON files `mask_rcnn_test-dev_results.bbox.json` and `mask_rcnn_test-dev_results.segm.json`.

4.2.5 Batch Inference

MMDetection supports inference with a single image or batched images in test mode. By default, we use single-image inference and you can use batch inference by modifying `samples_per_gpu` in the config of test data. You can do that either by modifying the config as below.

```
data = dict(train=dict(...), val=dict(...), test=dict(samples_per_gpu=2, ...))
```

Or you can set it through `--cfg-options` as `--cfg-options data.test.samples_per_gpu=2`

4.2.6 Deprecated ImageToTensor

In test mode, `ImageToTensor` pipeline is deprecated, it's replaced by `DefaultFormatBundle` that recommended to manually replace it in the test data pipeline in your config file. examples:

```
# use ImageToTensor (deprecated)
pipelines = [
   dict(type='LoadImageFromFile'),
   dict(
       type='MultiScaleFlipAug',
       img_scale=(1333, 800),
       flip=False,
       transforms=[
           dict(type='Resize', keep_ratio=True),
           dict(type='RandomFlip'),
           dict(type='Normalize', mean=[0, 0, 0], std=[1, 1, 1]),
           dict(type='Pad', size_divisor=32),
           dict(type='ImageToTensor', keys=['img']),
           dict(type='Collect', keys=['img']),
       ])
   ]

# manually replace ImageToTensor to DefaultFormatBundle (recommended)
pipelines = [
   dict(type='LoadImageFromFile'),
   dict(
       type='MultiScaleFlipAug',
       img_scale=(1333, 800),
       flip=False,
       transforms=[
           dict(type='Resize', keep_ratio=True),
```

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```
            dict(type='RandomFlip'),
            dict(type='Normalize', mean=[0, 0, 0], std=[1, 1, 1]),
            dict(type='Pad', size_divisor=32),
            dict(type='DefaultFormatBundle'),
            dict(type='Collect', keys=['img']),
        ])
    ]
```

4.3 Train predefined models on standard datasets

MMDetection also provides out-of-the-box tools for training detection models. This section will show how to train *predefined* models (under configs) on standard datasets i.e. COCO.

4.3.1 Prepare datasets

Training requires preparing datasets too. See section *Prepare datasets* above for details.

Note: Currently, the config files under `configs/cityscapes` use COCO pretrained weights to initialize. You could download the existing models in advance if the network connection is unavailable or slow. Otherwise, it would cause errors at the beginning of training.

4.3.2 Learning rate automatically scale

Important: The default learning rate in config files is for 8 GPUs and 2 sample per gpu (batch size = 8 * 2 = 16). And it had been set to `auto_scale_lr.base_batch_size` in `config/_base_/default_runtime.py`. Learning rate will be automatically scaled base on this value when the batch size is `16`. Meanwhile, in order not to affect other codebase which based on mmdet, the flag `auto_scale_lr.enable` is set to `False` by default.

If you want to enable this feature, you need to add argument `--auto-scale-lr`. And you need to check the config name which you want to use before you process the command, because the config name indicates the default batch size. By default, it is `8 x 2 = 16 batch size`, like `faster_rcnn_r50_caffe_fpn_90k_coco.py` or `pisa_faster_rcnn_x101_32x4d_fpn_1x_coco.py`. In other cases, you will see the config file name have `_NxM_` in dictating, like `cornernet_hourglass104_mstest_32x3_210e_coco.py` which batch size is `32 x 3 = 96`, or `scnet_x101_64x4d_fpn_8x1_20e_coco.py` which batch size is `8 x 1 = 8`.

Please remember to check the bottom of the specific config file you want to use, it will have `auto_scale_lr.base_batch_size` if the batch size is not 16. If you can't find those values, check the config file which in `_base_=[xxx]` and you will find it. Please do not modify its values if you want to automatically scale the LR.

Learning rate automatically scale basic usage is as follows.

```
python tools/train.py \
    ${CONFIG_FILE} \
    --auto-scale-lr \
    [optional arguments]
```

If you enabled this feature, the learning rate will be automatically scaled according to the number of GPUs of the machine and the batch size of training. See linear scaling rule for details. For example, If there are 4 GPUs and 2 pictures on each GPU, `lr = 0.01`, then if there are 16 GPUs and 4 pictures on each GPU, it will automatically scale to `lr = 0.08`.

If you don't want to use it, you need to calculate the learning rate according to the linear scaling rule manually then change `optimizer.lr` in specific config file.

4.3.3 Training on a single GPU

We provide `tools/train.py` to launch training jobs on a single GPU. The basic usage is as follows.

```
python tools/train.py \
    ${CONFIG_FILE} \
    [optional arguments]
```

During training, log files and checkpoints will be saved to the working directory, which is specified by `work_dir` in the config file or via CLI argument `--work-dir`.

By default, the model is evaluated on the validation set every epoch, the evaluation interval can be specified in the config file as shown below.

```
# evaluate the model every 12 epoch.
evaluation = dict(interval=12)
```

This tool accepts several optional arguments, including:

- `--no-validate` (**not suggested**): Disable evaluation during training.
- `--work-dir ${WORK_DIR}`: Override the working directory.
- `--resume-from ${CHECKPOINT_FILE}`: Resume from a previous checkpoint file.
- `--options 'Key=value'`: Overrides other settings in the used config.

Note:

Difference between `resume-from` and `load-from`:

`resume-from` loads both the model weights and optimizer status, and the epoch is also inherited from the specified checkpoint. It is usually used for resuming the training process that is interrupted accidentally. `load-from` only loads the model weights and the training epoch starts from 0. It is usually used for finetuning.

4.3.4 Training on CPU

The process of training on the CPU is consistent with single GPU training. We just need to disable GPUs before the training process.

```
export CUDA_VISIBLE_DEVICES=-1
```

And then run the script above.

Note:

We do not recommend users to use CPU for training because it is too slow. We support this feature to allow users to debug on machines without GPU for convenience.

4.3.5 Training on multiple GPUs

We provide `tools/dist_train.sh` to launch training on multiple GPUs. The basic usage is as follows.

```
bash ./tools/dist_train.sh \
    ${CONFIG_FILE} \
    ${GPU_NUM} \
    [optional arguments]
```

Optional arguments remain the same as stated above.

Launch multiple jobs simultaneously

If you would like to launch multiple jobs on a single machine, e.g., 2 jobs of 4-GPU training on a machine with 8 GPUs, you need to specify different ports (29500 by default) for each job to avoid communication conflict.

If you use `dist_train.sh` to launch training jobs, you can set the port in commands.

```
CUDA_VISIBLE_DEVICES=0,1,2,3 PORT=29500 ./tools/dist_train.sh ${CONFIG_FILE} 4
CUDA_VISIBLE_DEVICES=4,5,6,7 PORT=29501 ./tools/dist_train.sh ${CONFIG_FILE} 4
```

4.3.6 Train with multiple machines

If you launch with multiple machines simply connected with ethernet, you can simply run following commands:

On the first machine:

```
NNODES=2 NODE_RANK=0 PORT=$MASTER_PORT MASTER_ADDR=$MASTER_ADDR sh tools/dist_train.sh
↪$CONFIG $GPUS
```

On the second machine:

```
NNODES=2 NODE_RANK=1 PORT=$MASTER_PORT MASTER_ADDR=$MASTER_ADDR sh tools/dist_train.sh
↪$CONFIG $GPUS
```

Usually it is slow if you do not have high speed networking like InfiniBand.

4.3.7 Manage jobs with Slurm

Slurm is a good job scheduling system for computing clusters. On a cluster managed by Slurm, you can use `slurm_train.sh` to spawn training jobs. It supports both single-node and multi-node training.

The basic usage is as follows.

```
[GPUS=${GPUS}] ./tools/slurm_train.sh ${PARTITION} ${JOB_NAME} ${CONFIG_FILE} ${WORK_DIR}
```

Below is an example of using 16 GPUs to train Mask R-CNN on a Slurm partition named *dev*, and set the work-dir to some shared file systems.

```
GPUS=16 ./tools/slurm_train.sh dev mask_r50_1x configs/mask_rcnn_r50_fpn_1x_coco.py /nfs/
↪xxxx/mask_rcnn_r50_fpn_1x
```

You can check the source code to review full arguments and environment variables.

When using Slurm, the port option need to be set in one of the following ways:

1. Set the port through `--options`. This is more recommended since it does not change the original configs.

```
CUDA_VISIBLE_DEVICES=0,1,2,3 GPUS=4 ./tools/slurm_train.sh ${PARTITION} ${JOB_NAME}␣
↪config1.py ${WORK_DIR} --options 'dist_params.port=29500'
CUDA_VISIBLE_DEVICES=4,5,6,7 GPUS=4 ./tools/slurm_train.sh ${PARTITION} ${JOB_NAME}␣
↪config2.py ${WORK_DIR} --options 'dist_params.port=29501'
```

2. Modify the config files to set different communication ports.

   In `config1.py`, set

```
dist_params = dict(backend='nccl', port=29500)
```

   In `config2.py`, set

```
dist_params = dict(backend='nccl', port=29501)
```

   Then you can launch two jobs with `config1.py` and `config2.py`.

```
CUDA_VISIBLE_DEVICES=0,1,2,3 GPUS=4 ./tools/slurm_train.sh ${PARTITION} ${JOB_NAME}␣
↪config1.py ${WORK_DIR}
CUDA_VISIBLE_DEVICES=4,5,6,7 GPUS=4 ./tools/slurm_train.sh ${PARTITION} ${JOB_NAME}␣
↪config2.py ${WORK_DIR}
```

CHAPTER

FIVE

2: TRAIN WITH CUSTOMIZED DATASETS

In this note, you will know how to inference, test, and train predefined models with customized datasets. We use the balloon dataset as an example to describe the whole process.

The basic steps are as below:

1. Prepare the customized dataset
2. Prepare a config
3. Train, test, inference models on the customized dataset.

5.1 Prepare the customized dataset

There are three ways to support a new dataset in MMDetection:

1. reorganize the dataset into COCO format.
2. reorganize the dataset into a middle format.
3. implement a new dataset.

Usually we recommend to use the first two methods which are usually easier than the third.

In this note, we give an example for converting the data into COCO format.

Note: MMDetection only supports evaluating mask AP of dataset in COCO format for now. So for instance segmentation task users should convert the data into coco format.

5.1.1 COCO annotation format

The necessary keys of COCO format for instance segmentation is as below, for the complete details, please refer here.

```
{
    "images": [image],
    "annotations": [annotation],
    "categories": [category]
}


image = {
    "id": int,
    "width": int,
    "height": int,
```

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```
    "file_name": str,
}

annotation = {
    "id": int,
    "image_id": int,
    "category_id": int,
    "segmentation": RLE or [polygon],
    "area": float,
    "bbox": [x,y,width,height],
    "iscrowd": 0 or 1,
}

categories = [{
    "id": int,
    "name": str,
    "supercategory": str,
}]
```

Assume we use the balloon dataset. After downloading the data, we need to implement a function to convert the annotation format into the COCO format. Then we can use implemented COCODataset to load the data and perform training and evaluation.

If you take a look at the dataset, you will find the dataset format is as below:

```
{'base64_img_data': '',
 'file_attributes': {},
 'filename': '34020010494_e5cb88e1c4_k.jpg',
 'fileref': '',
 'regions': {'0': {'region_attributes': {},
   'shape_attributes': {'all_points_x': [1020,
     1000,
     994,
     1003,
     1023,
     1050,
     1089,
     1134,
     1190,
     1265,
     1321,
     1361,
     1403,
     1428,
     1442,
     1445,
     1441,
     1427,
     1400,
     1361,
     1316,
     1269,
     1228,
```

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```
    1198,
    1207,
    1210,
    1190,
    1177,
    1172,
    1174,
    1170,
    1153,
    1127,
    1104,
    1061,
    1032,
    1020],
   'all_points_y': [963,
    899,
    841,
    787,
    738,
    700,
    663,
    638,
    621,
    619,
    643,
    672,
    720,
    765,
    800,
    860,
    896,
    942,
    990,
    1035,
    1079,
    1112,
    1129,
    1134,
    1144,
    1153,
    1166,
    1166,
    1150,
    1136,
    1129,
    1122,
    1112,
    1084,
    1037,
    989,
    963],
   'name': 'polygon'}}},
```

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```
 'size': 1115004}
```

The annotation is a JSON file where each key indicates an image's all annotations. The code to convert the balloon dataset into coco format is as below.

```
import os.path as osp
import mmcv

def convert_balloon_to_coco(ann_file, out_file, image_prefix):
    data_infos = mmcv.load(ann_file)

    annotations = []
    images = []
    obj_count = 0
    for idx, v in enumerate(mmcv.track_iter_progress(data_infos.values())):
        filename = v['filename']
        img_path = osp.join(image_prefix, filename)
        height, width = mmcv.imread(img_path).shape[:2]

        images.append(dict(
            id=idx,
            file_name=filename,
            height=height,
            width=width))

        bboxes = []
        labels = []
        masks = []
        for _, obj in v['regions'].items():
            assert not obj['region_attributes']
            obj = obj['shape_attributes']
            px = obj['all_points_x']
            py = obj['all_points_y']
            poly = [(x + 0.5, y + 0.5) for x, y in zip(px, py)]
            poly = [p for x in poly for p in x]

            x_min, y_min, x_max, y_max = (
                min(px), min(py), max(px), max(py))


            data_anno = dict(
                image_id=idx,
                id=obj_count,
                category_id=0,
                bbox=[x_min, y_min, x_max - x_min, y_max - y_min],
                area=(x_max - x_min) * (y_max - y_min),
                segmentation=[poly],
                iscrowd=0)
            annotations.append(data_anno)
            obj_count += 1

    coco_format_json = dict(
```

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```
        images=images,
        annotations=annotations,
        categories=[{'id':0, 'name': 'balloon'}])
    mmcv.dump(coco_format_json, out_file)
```

Using the function above, users can successfully convert the annotation file into json format, then we can use `CocoDataset` to train and evaluate the model.

5.2 Prepare a config

The second step is to prepare a config thus the dataset could be successfully loaded. Assume that we want to use Mask R-CNN with FPN, the config to train the detector on balloon dataset is as below. Assume the config is under directory `configs/balloon/` and named as `mask_rcnn_r50_caffe_fpn_mstrain-poly_1x_balloon.py`, the config is as below.

```
# The new config inherits a base config to highlight the necessary modification
_base_ = 'mask_rcnn/mask_rcnn_r50_caffe_fpn_mstrain-poly_1x_coco.py'

# We also need to change the num_classes in head to match the dataset's annotation
model = dict(
    roi_head=dict(
        bbox_head=dict(num_classes=1),
        mask_head=dict(num_classes=1)))

# Modify dataset related settings
dataset_type = 'COCODataset'
classes = ('balloon',)
data = dict(
    train=dict(
        img_prefix='balloon/train/',
        classes=classes,
        ann_file='balloon/train/annotation_coco.json'),
    val=dict(
        img_prefix='balloon/val/',
        classes=classes,
        ann_file='balloon/val/annotation_coco.json'),
    test=dict(
        img_prefix='balloon/val/',
        classes=classes,
        ann_file='balloon/val/annotation_coco.json'))

# We can use the pre-trained Mask RCNN model to obtain higher performance
load_from = 'checkpoints/mask_rcnn_r50_caffe_fpn_mstrain-poly_3x_coco_bbox_mAP-0.408__
↪segm_mAP-0.37_20200504_163245-42aa3d00.pth'
```

This checkpoint file can be downloaded here

5.3 Train a new model

To train a model with the new config, you can simply run

```
python tools/train.py configs/balloon/mask_rcnn_r50_caffe_fpn_mstrain-poly_1x_balloon.py
```

For more detailed usages, please refer to the *Case 1*.

5.4 Test and inference

To test the trained model, you can simply run

```
python tools/test.py configs/balloon/mask_rcnn_r50_caffe_fpn_mstrain-poly_1x_balloon.py␣
↪work_dirs/mask_rcnn_r50_caffe_fpn_mstrain-poly_1x_balloon/latest.pth --eval bbox segm
```

For more detailed usages, please refer to the *Case 1*.

CHAPTER

SIX

3: TRAIN WITH CUSTOMIZED MODELS AND STANDARD DATASETS

In this note, you will know how to train, test and inference your own customized models under standard datasets. We use the cityscapes dataset to train a customized Cascade Mask R-CNN R50 model as an example to demonstrate the whole process, which using `AugFPN` to replace the default `FPN` as neck, and add `Rotate` or `Translate` as training-time auto augmentation.

The basic steps are as below:

1. Prepare the standard dataset
2. Prepare your own customized model
3. Prepare a config
4. Train, test, and inference models on the standard dataset.

6.1 Prepare the standard dataset

In this note, as we use the standard cityscapes dataset as an example.

It is recommended to symlink the dataset root to `$MMDETECTION/data`. If your folder structure is different, you may need to change the corresponding paths in config files.

```
mmdetection
├── mmdet
├── tools
├── configs
├── data
│   ├── coco
│   │   ├── annotations
│   │   ├── train2017
│   │   ├── val2017
│   │   ├── test2017
│   ├── cityscapes
│   │   ├── annotations
│   │   ├── leftImg8bit
│   │   │   ├── train
│   │   │   ├── val
│   │   ├── gtFine
│   │   │   ├── train
│   │   │   ├── val
│   ├── VOCdevkit
│   │   ├── VOC2007
```

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```
│   │   ├── VOC2012
```

Or you can set your dataset root through

```
export MMDET_DATASETS=$data_root
```

We will replace dataset root with `$MMDET_DATASETS`, so you don't have to modify the corresponding path in config files.

The cityscapes annotations have to be converted into the coco format using `tools/dataset_converters/cityscapes.py`:

```
pip install cityscapesscripts
python tools/dataset_converters/cityscapes.py ./data/cityscapes --nproc 8 --out-dir ./
↪data/cityscapes/annotations
```

Currently the config files in `cityscapes` use COCO pre-trained weights to initialize. You could download the pre-trained models in advance if network is unavailable or slow, otherwise it would cause errors at the beginning of training.

6.2 Prepare your own customized model

The second step is to use your own module or training setting. Assume that we want to implement a new neck called `AugFPN` to replace with the default `FPN` under the existing detector Cascade Mask R-CNN R50. The following implements`AugFPN` under MMDetection.

6.2.1 1. Define a new neck (e.g. AugFPN)

Firstly create a new file `mmdet/models/necks/augfpn.py`.

```
from ..builder import NECKS

@NECKS.register_module()
class AugFPN(nn.Module):

    def __init__(self,
                 in_channels,
                 out_channels,
                 num_outs,
                 start_level=0,
                 end_level=-1,
                 add_extra_convs=False):
        pass

    def forward(self, inputs):
        # implementation is ignored
        pass
```

6.2.2 2. Import the module

You can either add the following line to `mmdet/models/necks/__init__.py`,

```
from .augfpn import AugFPN
```

or alternatively add

```
custom_imports = dict(
    imports=['mmdet.models.necks.augfpn.py'],
    allow_failed_imports=False)
```

to the config file and avoid modifying the original code.

6.2.3 3. Modify the config file

```
neck=dict(
    type='AugFPN',
    in_channels=[256, 512, 1024, 2048],
    out_channels=256,
    num_outs=5)
```

For more detailed usages about customize your own models (e.g. implement a new backbone, head, loss, etc) and runtime training settings (e.g. define a new optimizer, use gradient clip, customize training schedules and hooks, etc), please refer to the guideline *Customize Models* and *Customize Runtime Settings* respectively.

6.3 Prepare a config

The third step is to prepare a config for your own training setting. Assume that we want to add `AugFPN` and `Rotate` or `Translate` augmentation to existing Cascade Mask R-CNN R50 to train the cityscapes dataset, and assume the config is under directory `configs/cityscapes/` and named as `cascade_mask_rcnn_r50_augfpn_autoaug_10e_cityscapes.py`, the config is as below.

```
# The new config inherits the base configs to highlight the necessary modification
_base_ = [
    '../_base_/models/cascade_mask_rcnn_r50_fpn.py',
    '../_base_/datasets/cityscapes_instance.py', '../_base_/default_runtime.py'
]

model = dict(
    # set None to avoid loading ImageNet pretrained backbone,
    # instead here we set `load_from` to load from COCO pretrained detectors.
    backbone=dict(init_cfg=None),
    # replace neck from defaultly `FPN` to our new implemented module `AugFPN`
    neck=dict(
        type='AugFPN',
        in_channels=[256, 512, 1024, 2048],
        out_channels=256,
        num_outs=5),
    # We also need to change the num_classes in head from 80 to 8, to match the
    # cityscapes dataset's annotation. This modification involves `bbox_head` and `mask_
↪head`.
```

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```
    roi_head=dict(
        bbox_head=[
            dict(
                type='Shared2FCBBoxHead',
                in_channels=256,
                fc_out_channels=1024,
                roi_feat_size=7,
                # change the number of classes from defaultly COCO to cityscapes
                num_classes=8,
                bbox_coder=dict(
                    type='DeltaXYWHBBoxCoder',
                    target_means=[0., 0., 0., 0.],
                    target_stds=[0.1, 0.1, 0.2, 0.2]),
                reg_class_agnostic=True,
                loss_cls=dict(
                    type='CrossEntropyLoss',
                    use_sigmoid=False,
                    loss_weight=1.0),
                loss_bbox=dict(type='SmoothL1Loss', beta=1.0,
                               loss_weight=1.0)),
            dict(
                type='Shared2FCBBoxHead',
                in_channels=256,
                fc_out_channels=1024,
                roi_feat_size=7,
                # change the number of classes from defaultly COCO to cityscapes
                num_classes=8,
                bbox_coder=dict(
                    type='DeltaXYWHBBoxCoder',
                    target_means=[0., 0., 0., 0.],
                    target_stds=[0.05, 0.05, 0.1, 0.1]),
                reg_class_agnostic=True,
                loss_cls=dict(
                    type='CrossEntropyLoss',
                    use_sigmoid=False,
                    loss_weight=1.0),
                loss_bbox=dict(type='SmoothL1Loss', beta=1.0,
                               loss_weight=1.0)),
            dict(
                type='Shared2FCBBoxHead',
                in_channels=256,
                fc_out_channels=1024,
                roi_feat_size=7,
                # change the number of classes from defaultly COCO to cityscapes
                num_classes=8,
                bbox_coder=dict(
                    type='DeltaXYWHBBoxCoder',
                    target_means=[0., 0., 0., 0.],
                    target_stds=[0.033, 0.033, 0.067, 0.067]),
                reg_class_agnostic=True,
                loss_cls=dict(
                    type='CrossEntropyLoss',
```

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```
                    use_sigmoid=False,
                    loss_weight=1.0),
                loss_bbox=dict(type='SmoothL1Loss', beta=1.0, loss_weight=1.0))
        ],
        mask_head=dict(
            type='FCNMaskHead',
            num_convs=4,
            in_channels=256,
            conv_out_channels=256,
            # change the number of classes from defaultly COCO to cityscapes
            num_classes=8,
            loss_mask=dict(
                type='CrossEntropyLoss', use_mask=True, loss_weight=1.0))))

# over-write `train_pipeline` for new added `AutoAugment` training setting
img_norm_cfg = dict(
    mean=[123.675, 116.28, 103.53], std=[58.395, 57.12, 57.375], to_rgb=True)
train_pipeline = [
    dict(type='LoadImageFromFile'),
    dict(type='LoadAnnotations', with_bbox=True, with_mask=True),
    dict(
        type='AutoAugment',
        policies=[
            [dict(
                 type='Rotate',
                 level=5,
                 img_fill_val=(124, 116, 104),
                 prob=0.5,
                 scale=1)
            ],
            [dict(type='Rotate', level=7, img_fill_val=(124, 116, 104)),
             dict(
                 type='Translate',
                 level=5,
                 prob=0.5,
                 img_fill_val=(124, 116, 104))
            ],
        ]),
    dict(
        type='Resize', img_scale=[(2048, 800), (2048, 1024)], keep_ratio=True),
    dict(type='RandomFlip', flip_ratio=0.5),
    dict(type='Normalize', **img_norm_cfg),
    dict(type='Pad', size_divisor=32),
    dict(type='DefaultFormatBundle'),
    dict(type='Collect', keys=['img', 'gt_bboxes', 'gt_labels', 'gt_masks']),
]

# set batch_size per gpu, and set new training pipeline
data = dict(
    samples_per_gpu=1,
    workers_per_gpu=3,
    # over-write `pipeline` with new training pipeline setting
```

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```
    train=dict(dataset=dict(pipeline=train_pipeline)))

# Set optimizer
optimizer = dict(type='SGD', lr=0.01, momentum=0.9, weight_decay=0.0001)
optimizer_config = dict(grad_clip=None)
# Set customized learning policy
lr_config = dict(
    policy='step',
    warmup='linear',
    warmup_iters=500,
    warmup_ratio=0.001,
    step=[8])
runner = dict(type='EpochBasedRunner', max_epochs=10)

# We can use the COCO pretrained Cascade Mask R-CNN R50 model for more stable␣
↪performance initialization
load_from = 'https://download.openmmlab.com/mmdetection/v2.0/cascade_rcnn/cascade_mask_
↪rcnn_r50_fpn_1x_coco/cascade_mask_rcnn_r50_fpn_1x_coco_20200203-9d4dcb24.pth'
```

6.4 Train a new model

To train a model with the new config, you can simply run

```
python tools/train.py configs/cityscapes/cascade_mask_rcnn_r50_augfpn_autoaug_10e_
↪cityscapes.py
```

For more detailed usages, please refer to the *Case 1*.

6.5 Test and inference

To test the trained model, you can simply run

```
python tools/test.py configs/cityscapes/cascade_mask_rcnn_r50_augfpn_autoaug_10e_
↪cityscapes.py work_dirs/cascade_mask_rcnn_r50_augfpn_autoaug_10e_cityscapes.py/latest.
↪pth --eval bbox segm
```

For more detailed usages, please refer to the *Case 1*.

CHAPTER

SEVEN

TUTORIAL 1: LEARN ABOUT CONFIGS

We incorporate modular and inheritance design into our config system, which is convenient to conduct various experiments. If you wish to inspect the config file, you may run `python tools/misc/print_config.py /PATH/TO/CONFIG` to see the complete config.

7.1 Modify config through script arguments

When submitting jobs using "tools/train.py" or "tools/test.py", you may specify `--cfg-options` to in-place modify the config.

- Update config keys of dict chains.

  The config options can be specified following the order of the dict keys in the original config. For example, `--cfg-options model.backbone.norm_eval=False` changes the all BN modules in model backbones to `train` mode.

- Update keys inside a list of configs.

  Some config dicts are composed as a list in your config. For example, the training pipeline `data.train.pipeline` is normally a list e.g. `[dict(type='LoadImageFromFile'), ...]`. If you want to change `'LoadImageFromFile'` to `'LoadImageFromWebcam'` in the pipeline, you may specify `--cfg-options data.train.pipeline.0.type=LoadImageFromWebcam`.

- Update values of list/tuples.

  If the value to be updated is a list or a tuple. For example, the config file normally sets `workflow=[('train', 1)]`. If you want to change this key, you may specify `--cfg-options workflow="[(train,1),(val,1)]"`. Note that the quotation mark " is necessary to support list/tuple data types, and that **NO** white space is allowed inside the quotation marks in the specified value.

7.2 Config File Structure

There are 4 basic component types under `config/_base_`, dataset, model, schedule, default_runtime. Many methods could be easily constructed with one of each like Faster R-CNN, Mask R-CNN, Cascade R-CNN, RPN, SSD. The configs that are composed by components from `_base_` are called *primitive*.

For all configs under the same folder, it is recommended to have only **one** *primitive* config. All other configs should inherit from the *primitive* config. In this way, the maximum of inheritance level is 3.

For easy understanding, we recommend contributors to inherit from existing methods. For example, if some modification is made base on Faster R-CNN, user may first inherit the basic Faster R-CNN structure by specifying `_base_ = ../faster_rcnn/faster_rcnn_r50_fpn_1x_coco.py`, then modify the necessary fields in the config files.

If you are building an entirely new method that does not share the structure with any of the existing methods, you may create a folder `xxx_rcnn` under `configs`,

Please refer to mmcv for detailed documentation.

7.3 Config Name Style

We follow the below style to name config files. Contributors are advised to follow the same style.

```
{model}_[model setting]_{backbone}_{neck}_[norm setting]_[misc]_[gpu x batch_per_gpu]_
↪{schedule}_{dataset}
```

`{xxx}` is required field and `[yyy]` is optional.

- `{model}`: model type like `faster_rcnn`, `mask_rcnn`, etc.
- `[model setting]`: specific setting for some model, like `without_semantic` for `htc`, `moment` for `reppoints`, etc.
- `{backbone}`: backbone type like `r50` (ResNet-50), `x101` (ResNeXt-101).
- `{neck}`: neck type like `fpn`, `pafpn`, `nasfpn`, `c4`.
- `[norm_setting]`: `bn` (Batch Normalization) is used unless specified, other norm layer type could be `gn` (Group Normalization), `syncbn` (Synchronized Batch Normalization). `gn-head`/`gn-neck` indicates GN is applied in head/neck only, while `gn-all` means GN is applied in the entire model, e.g. backbone, neck, head.
- `[misc]`: miscellaneous setting/plugins of model, e.g. `dconv`, `gcb`, `attention`, `albu`, `mstrain`.
- `[gpu x batch_per_gpu]`: GPUs and samples per GPU, `8x2` is used by default.
- `{schedule}`: training schedule, options are `1x`, `2x`, `20e`, etc. `1x` and `2x` means 12 epochs and 24 epochs respectively. `20e` is adopted in cascade models, which denotes 20 epochs. For `1x`/`2x`, initial learning rate decays by a factor of 10 at the 8/16th and 11/22th epochs. For `20e`, initial learning rate decays by a factor of 10 at the 16th and 19th epochs.
- `{dataset}`: dataset like `coco`, `cityscapes`, `voc_0712`, `wider_face`.

7.4 Deprecated train_cfg/test_cfg

The `train_cfg` and `test_cfg` are deprecated in config file, please specify them in the model config. The original config structure is as below.

```
# deprecated
model = dict(
    type=...,
    ...
)
train_cfg=dict(...)
test_cfg=dict(...)
```

The migration example is as below.

```
# recommended
model = dict(
   type=...,
   ...
   train_cfg=dict(...),
   test_cfg=dict(...),
)
```

7.5 An Example of Mask R-CNN

To help the users have a basic idea of a complete config and the modules in a modern detection system, we make brief comments on the config of Mask R-CNN using ResNet50 and FPN as the following. For more detailed usage and the corresponding alternative for each modules, please refer to the API documentation.

```
model = dict(
    type='MaskRCNN',  # The name of detector
    backbone=dict(  # The config of backbone
        type='ResNet',  # The type of the backbone, refer to https://github.com/open-
↪mmlab/mmdetection/blob/master/mmdet/models/backbones/resnet.py#L308 for more details.
        depth=50,  # The depth of backbone, usually it is 50 or 101 for ResNet and␣
↪ResNext backbones.
        num_stages=4,  # Number of stages of the backbone.
        out_indices=(0, 1, 2, 3),  # The index of output feature maps produced in each␣
↪stages
        frozen_stages=1,  # The weights in the first 1 stage are frozen
        norm_cfg=dict(  # The config of normalization layers.
            type='BN',  # Type of norm layer, usually it is BN or GN
            requires_grad=True),  # Whether to train the gamma and beta in BN
        norm_eval=True,  # Whether to freeze the statistics in BN
        style='pytorch' # The style of backbone, 'pytorch' means that stride 2 layers␣
↪are in 3x3 conv, 'caffe' means stride 2 layers are in 1x1 convs.
            init_cfg=dict(type='Pretrained', checkpoint='torchvision://resnet50')),  #␣
↪The ImageNet pretrained backbone to be loaded
    neck=dict(
        type='FPN',  # The neck of detector is FPN. We also support 'NASFPN', 'PAFPN',␣
↪etc. Refer to https://github.com/open-mmlab/mmdetection/blob/master/mmdet/models/necks/
↪fpn.py#L10 for more details.
        in_channels=[256, 512, 1024, 2048],  # The input channels, this is consistent␣
↪with the output channels of backbone
        out_channels=256,  # The output channels of each level of the pyramid feature map
        num_outs=5),  # The number of output scales
    rpn_head=dict(
        type='RPNHead',  # The type of RPN head is 'RPNHead', we also support 'GARPNHead
↪', etc. Refer to https://github.com/open-mmlab/mmdetection/blob/master/mmdet/models/
↪dense_heads/rpn_head.py#L12 for more details.
        in_channels=256,  # The input channels of each input feature map, this is␣
↪consistent with the output channels of neck
        feat_channels=256,  # Feature channels of convolutional layers in the head.
        anchor_generator=dict(  # The config of anchor generator
            type='AnchorGenerator',  # Most of methods use AnchorGenerator, SSD␣
↪Detectors uses `SSDAnchorGenerator`. Refer to https://github.com/open-mmlab/
↪mmdetection/blob/master/mmdet/core/anchor/anchor_generator.py#L10 for more details
```

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```
            scales=[8],  # Basic scale of the anchor, the area of the anchor in one␣
↪position of a feature map will be scale * base_sizes
            ratios=[0.5, 1.0, 2.0],  # The ratio between height and width.
            strides=[4, 8, 16, 32, 64]),  # The strides of the anchor generator. This is␣
↪consistent with the FPN feature strides. The strides will be taken as base_sizes if␣
↪base_sizes is not set.
        bbox_coder=dict(  # Config of box coder to encode and decode the boxes during␣
↪training and testing
            type='DeltaXYWHBBoxCoder',  # Type of box coder. 'DeltaXYWHBBoxCoder' is␣
↪applied for most of methods. Refer to https://github.com/open-mmlab/mmdetection/blob/
↪master/mmdet/core/bbox/coder/delta_xywh_bbox_coder.py#L9 for more details.
            target_means=[0.0, 0.0, 0.0, 0.0],  # The target means used to encode and␣
↪decode boxes
            target_stds=[1.0, 1.0, 1.0, 1.0]),  # The standard variance used to encode␣
↪and decode boxes
        loss_cls=dict(  # Config of loss function for the classification branch
            type='CrossEntropyLoss',  # Type of loss for classification branch, we also␣
↪support FocalLoss etc.
            use_sigmoid=True,  # RPN usually perform two-class classification, so it␣
↪usually uses sigmoid function.
            loss_weight=1.0),  # Loss weight of the classification branch.
        loss_bbox=dict(  # Config of loss function for the regression branch.
            type='L1Loss',  # Type of loss, we also support many IoU Losses and smooth␣
↪L1-loss, etc. Refer to https://github.com/open-mmlab/mmdetection/blob/master/mmdet/
↪models/losses/smooth_l1_loss.py#L56 for implementation.
            loss_weight=1.0)),  # Loss weight of the regression branch.
    roi_head=dict(  # RoIHead encapsulates the second stage of two-stage/cascade␣
↪detectors.
        type='StandardRoIHead',  # Type of the RoI head. Refer to https://github.com/
↪open-mmlab/mmdetection/blob/master/mmdet/models/roi_heads/standard_roi_head.py#L10 for␣
↪implementation.
        bbox_roi_extractor=dict(  # RoI feature extractor for bbox regression.
            type='SingleRoIExtractor',  # Type of the RoI feature extractor, most of␣
↪methods uses SingleRoIExtractor. Refer to https://github.com/open-mmlab/mmdetection/
↪blob/master/mmdet/models/roi_heads/roi_extractors/single_level.py#L10 for details.
            roi_layer=dict(  # Config of RoI Layer
                type='RoIAlign',  # Type of RoI Layer, DeformRoIPoolingPack and␣
↪ModulatedDeformRoIPoolingPack are also supported. Refer to https://github.com/open-
↪mmlab/mmdetection/blob/master/mmdet/ops/roi_align/roi_align.py#L79 for details.
                output_size=7,  # The output size of feature maps.
                sampling_ratio=0),  # Sampling ratio when extracting the RoI features. 0␣
↪means adaptive ratio.
            out_channels=256,  # output channels of the extracted feature.
            featmap_strides=[4, 8, 16, 32]),  # Strides of multi-scale feature maps. It␣
↪should be consistent to the architecture of the backbone.
        bbox_head=dict(  # Config of box head in the RoIHead.
            type='Shared2FCBBoxHead',  # Type of the bbox head, Refer to https://github.
↪com/open-mmlab/mmdetection/blob/master/mmdet/models/roi_heads/bbox_heads/convfc_bbox_
↪head.py#L177 for implementation details.
            in_channels=256,  # Input channels for bbox head. This is consistent with␣
↪the out_channels in roi_extractor
            fc_out_channels=1024,  # Output feature channels of FC layers.
```

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```
            roi_feat_size=7,  # Size of RoI features
            num_classes=80,  # Number of classes for classification
            bbox_coder=dict(  # Box coder used in the second stage.
                type='DeltaXYWHBBoxCoder',  # Type of box coder. 'DeltaXYWHBBoxCoder' is␣
↪applied for most of methods.
                target_means=[0.0, 0.0, 0.0, 0.0],  # Means used to encode and decode box
                target_stds=[0.1, 0.1, 0.2, 0.2]),  # Standard variance for encoding and␣
↪decoding. It is smaller since the boxes are more accurate. [0.1, 0.1, 0.2, 0.2] is a␣
↪conventional setting.
            reg_class_agnostic=False,  # Whether the regression is class agnostic.
            loss_cls=dict(  # Config of loss function for the classification branch
                type='CrossEntropyLoss',  # Type of loss for classification branch, we␣
↪also support FocalLoss etc.
                use_sigmoid=False,  # Whether to use sigmoid.
                loss_weight=1.0),  # Loss weight of the classification branch.
            loss_bbox=dict(  # Config of loss function for the regression branch.
                type='L1Loss',  # Type of loss, we also support many IoU Losses and␣
↪smooth L1-loss, etc.
                loss_weight=1.0)),  # Loss weight of the regression branch.
        mask_roi_extractor=dict(  # RoI feature extractor for mask generation.
            type='SingleRoIExtractor',  # Type of the RoI feature extractor, most of␣
↪methods uses SingleRoIExtractor.
            roi_layer=dict(  # Config of RoI Layer that extracts features for instance␣
↪segmentation
                type='RoIAlign',  # Type of RoI Layer, DeformRoIPoolingPack and␣
↪ModulatedDeformRoIPoolingPack are also supported
                output_size=14,  # The output size of feature maps.
                sampling_ratio=0),  # Sampling ratio when extracting the RoI features.
            out_channels=256,  # Output channels of the extracted feature.
            featmap_strides=[4, 8, 16, 32]),  # Strides of multi-scale feature maps.
        mask_head=dict(  # Mask prediction head
            type='FCNMaskHead',  # Type of mask head, refer to https://github.com/open-
↪mmlab/mmdetection/blob/master/mmdet/models/roi_heads/mask_heads/fcn_mask_head.py#L21␣
↪for implementation details.
            num_convs=4,  # Number of convolutional layers in mask head.
            in_channels=256,  # Input channels, should be consistent with the output␣
↪channels of mask roi extractor.
            conv_out_channels=256,  # Output channels of the convolutional layer.
            num_classes=80,  # Number of class to be segmented.
            loss_mask=dict(  # Config of loss function for the mask branch.
                type='CrossEntropyLoss',  # Type of loss used for segmentation
                use_mask=True,  # Whether to only train the mask in the correct class.
                loss_weight=1.0))))  # Loss weight of mask branch.
    train_cfg = dict(  # Config of training hyperparameters for rpn and rcnn
        rpn=dict(  # Training config of rpn
            assigner=dict(  # Config of assigner
                type='MaxIoUAssigner',  # Type of assigner, MaxIoUAssigner is used for␣
↪many common detectors. Refer to https://github.com/open-mmlab/mmdetection/blob/master/
↪mmdet/core/bbox/assigners/max_iou_assigner.py#L10 for more details.
                pos_iou_thr=0.7,  # IoU >= threshold 0.7 will be taken as positive␣
↪samples
                neg_iou_thr=0.3,  # IoU < threshold 0.3 will be taken as negative samples
```

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```
                min_pos_iou=0.3,  # The minimal IoU threshold to take boxes as positive␣
↪samples
                match_low_quality=True,  # Whether to match the boxes under low quality␣
↪(see API doc for more details).
                ignore_iof_thr=-1),  # IoF threshold for ignoring bboxes
            sampler=dict(  # Config of positive/negative sampler
                type='RandomSampler',  # Type of sampler, PseudoSampler and other␣
↪samplers are also supported. Refer to https://github.com/open-mmlab/mmdetection/blob/
↪master/mmdet/core/bbox/samplers/random_sampler.py#L8 for implementation details.
                num=256,  # Number of samples
                pos_fraction=0.5,  # The ratio of positive samples in the total samples.
                neg_pos_ub=-1,  # The upper bound of negative samples based on the␣
↪number of positive samples.
                add_gt_as_proposals=False),  # Whether add GT as proposals after␣
↪sampling.
            allowed_border=-1,  # The border allowed after padding for valid anchors.
            pos_weight=-1,  # The weight of positive samples during training.
            debug=False),  # Whether to set the debug mode
        rpn_proposal=dict(  # The config to generate proposals during training
            nms_across_levels=False,  # Whether to do NMS for boxes across levels. Only␣
↪work in `GARPNHead`, naive rpn does not support do nms cross levels.
            nms_pre=2000,  # The number of boxes before NMS
            nms_post=1000,  # The number of boxes to be kept by NMS, Only work in␣
↪`GARPNHead`.
            max_per_img=1000,  # The number of boxes to be kept after NMS.
            nms=dict( # Config of NMS
                type='nms',  # Type of NMS
                iou_threshold=0.7 # NMS threshold
                ),
            min_bbox_size=0),  # The allowed minimal box size
        rcnn=dict(  # The config for the roi heads.
            assigner=dict(  # Config of assigner for second stage, this is different for␣
↪that in rpn
                type='MaxIoUAssigner',  # Type of assigner, MaxIoUAssigner is used for␣
↪all roi_heads for now. Refer to https://github.com/open-mmlab/mmdetection/blob/master/
↪mmdet/core/bbox/assigners/max_iou_assigner.py#L10 for more details.
                pos_iou_thr=0.5,  # IoU >= threshold 0.5 will be taken as positive␣
↪samples
                neg_iou_thr=0.5,  # IoU < threshold 0.5 will be taken as negative samples
                min_pos_iou=0.5,  # The minimal IoU threshold to take boxes as positive␣
↪samples
                match_low_quality=False,  # Whether to match the boxes under low quality␣
↪(see API doc for more details).
                ignore_iof_thr=-1),  # IoF threshold for ignoring bboxes
            sampler=dict(
                type='RandomSampler',  # Type of sampler, PseudoSampler and other␣
↪samplers are also supported. Refer to https://github.com/open-mmlab/mmdetection/blob/
↪master/mmdet/core/bbox/samplers/random_sampler.py#L8 for implementation details.
                num=512,  # Number of samples
                pos_fraction=0.25,  # The ratio of positive samples in the total samples.
                neg_pos_ub=-1,  # The upper bound of negative samples based on the␣
↪number of positive samples.
```

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```
                add_gt_as_proposals=True
            ),  # Whether add GT as proposals after sampling.
            mask_size=28,  # Size of mask
            pos_weight=-1,  # The weight of positive samples during training.
            debug=False))  # Whether to set the debug mode
    test_cfg = dict(  # Config for testing hyperparameters for rpn and rcnn
        rpn=dict(  # The config to generate proposals during testing
            nms_across_levels=False,  # Whether to do NMS for boxes across levels. Only␣
↪work in `GARPNHead`, naive rpn does not support do nms cross levels.
            nms_pre=1000,  # The number of boxes before NMS
            nms_post=1000,  # The number of boxes to be kept by NMS, Only work in␣
↪`GARPNHead`.
            max_per_img=1000,  # The number of boxes to be kept after NMS.
            nms=dict( # Config of NMS
                type='nms',  #Type of NMS
                iou_threshold=0.7 # NMS threshold
                ),
            min_bbox_size=0),  # The allowed minimal box size
        rcnn=dict(  # The config for the roi heads.
            score_thr=0.05,  # Threshold to filter out boxes
            nms=dict(  # Config of NMS in the second stage
                type='nms',  # Type of NMS
                iou_thr=0.5),  # NMS threshold
            max_per_img=100,  # Max number of detections of each image
            mask_thr_binary=0.5))  # Threshold of mask prediction
dataset_type = 'CocoDataset'  # Dataset type, this will be used to define the dataset
data_root = 'data/coco/'  # Root path of data
img_norm_cfg = dict(  # Image normalization config to normalize the input images
    mean=[123.675, 116.28, 103.53],  # Mean values used to pre-training the pre-trained␣
↪backbone models
    std=[58.395, 57.12, 57.375],  # Standard variance used to pre-training the pre-
↪trained backbone models
    to_rgb=True
)  # The channel orders of image used to pre-training the pre-trained backbone models
train_pipeline = [  # Training pipeline
    dict(type='LoadImageFromFile'),  # First pipeline to load images from file path
    dict(
        type='LoadAnnotations',  # Second pipeline to load annotations for current image
        with_bbox=True,  # Whether to use bounding box, True for detection
        with_mask=True,  # Whether to use instance mask, True for instance segmentation
        poly2mask=False),  # Whether to convert the polygon mask to instance mask, set␣
↪False for acceleration and to save memory
    dict(
        type='Resize',  # Augmentation pipeline that resize the images and their␣
↪annotations
        img_scale=(1333, 800),  # The largest scale of image
        keep_ratio=True
    ),  # whether to keep the ratio between height and width.
    dict(
        type='RandomFlip',  # Augmentation pipeline that flip the images and their␣
↪annotations
        flip_ratio=0.5),  # The ratio or probability to flip
```

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```
    dict(
        type='Normalize',  # Augmentation pipeline that normalize the input images
        mean=[123.675, 116.28, 103.53],  # These keys are the same of img_norm_cfg since␣
↪the
        std=[58.395, 57.12, 57.375],  # keys of img_norm_cfg are used here as arguments
        to_rgb=True),
    dict(
        type='Pad',  # Padding config
        size_divisor=32),  # The number the padded images should be divisible
    dict(type='DefaultFormatBundle'),  # Default format bundle to gather data in the␣
↪pipeline
    dict(
        type='Collect',  # Pipeline that decides which keys in the data should be passed␣
↪to the detector
        keys=['img', 'gt_bboxes', 'gt_labels', 'gt_masks'])
]
test_pipeline = [
    dict(type='LoadImageFromFile'),  # First pipeline to load images from file path
    dict(
        type='MultiScaleFlipAug',  # An encapsulation that encapsulates the testing␣
↪augmentations
        img_scale=(1333, 800),  # Decides the largest scale for testing, used for the␣
↪Resize pipeline
        flip=False,  # Whether to flip images during testing
        transforms=[
            dict(type='Resize',  # Use resize augmentation
                 keep_ratio=True),  # Whether to keep the ratio between height and width,
↪ the img_scale set here will be suppressed by the img_scale set above.
            dict(type='RandomFlip'),  # Thought RandomFlip is added in pipeline, it is␣
↪not used because flip=False
            dict(
                type='Normalize',  # Normalization config, the values are from img_norm_
↪cfg
                mean=[123.675, 116.28, 103.53],
                std=[58.395, 57.12, 57.375],
                to_rgb=True),
            dict(
                type='Pad',  # Padding config to pad images divisible by 32.
                size_divisor=32),
            dict(
                type='ImageToTensor',  # convert image to tensor
                keys=['img']),
            dict(
                type='Collect',  # Collect pipeline that collect necessary keys for␣
↪testing.
                keys=['img'])
        ])
]
data = dict(
    samples_per_gpu=2,  # Batch size of a single GPU
    workers_per_gpu=2,  # Worker to pre-fetch data for each single GPU
    train=dict(  # Train dataset config
```

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```
        type='CocoDataset',  # Type of dataset, refer to https://github.com/open-mmlab/
↪mmdetection/blob/master/mmdet/datasets/coco.py#L19 for details.
        ann_file='data/coco/annotations/instances_train2017.json',  # Path of annotation␣
↪file
        img_prefix='data/coco/train2017/',  # Prefix of image path
        pipeline=[  # pipeline, this is passed by the train_pipeline created before.
            dict(type='LoadImageFromFile'),
            dict(
                type='LoadAnnotations',
                with_bbox=True,
                with_mask=True,
                poly2mask=False),
            dict(type='Resize', img_scale=(1333, 800), keep_ratio=True),
            dict(type='RandomFlip', flip_ratio=0.5),
            dict(
                type='Normalize',
                mean=[123.675, 116.28, 103.53],
                std=[58.395, 57.12, 57.375],
                to_rgb=True),
            dict(type='Pad', size_divisor=32),
            dict(type='DefaultFormatBundle'),
            dict(
                type='Collect',
                keys=['img', 'gt_bboxes', 'gt_labels', 'gt_masks'])
        ]),
    val=dict(  # Validation dataset config
        type='CocoDataset',
        ann_file='data/coco/annotations/instances_val2017.json',
        img_prefix='data/coco/val2017/',
        pipeline=[  # Pipeline is passed by test_pipeline created before
            dict(type='LoadImageFromFile'),
            dict(
                type='MultiScaleFlipAug',
                img_scale=(1333, 800),
                flip=False,
                transforms=[
                    dict(type='Resize', keep_ratio=True),
                    dict(type='RandomFlip'),
                    dict(
                        type='Normalize',
                        mean=[123.675, 116.28, 103.53],
                        std=[58.395, 57.12, 57.375],
                        to_rgb=True),
                    dict(type='Pad', size_divisor=32),
                    dict(type='ImageToTensor', keys=['img']),
                    dict(type='Collect', keys=['img'])
                ])
        ]),
    test=dict(  # Test dataset config, modify the ann_file for test-dev/test submission
        type='CocoDataset',
        ann_file='data/coco/annotations/instances_val2017.json',
        img_prefix='data/coco/val2017/',
```

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```
        pipeline=[  # Pipeline is passed by test_pipeline created before
            dict(type='LoadImageFromFile'),
            dict(
                type='MultiScaleFlipAug',
                img_scale=(1333, 800),
                flip=False,
                transforms=[
                    dict(type='Resize', keep_ratio=True),
                    dict(type='RandomFlip'),
                    dict(
                        type='Normalize',
                        mean=[123.675, 116.28, 103.53],
                        std=[58.395, 57.12, 57.375],
                        to_rgb=True),
                    dict(type='Pad', size_divisor=32),
                    dict(type='ImageToTensor', keys=['img']),
                    dict(type='Collect', keys=['img'])
                ])
        ],
        samples_per_gpu=2  # Batch size of a single GPU used in testing
        ))
evaluation = dict(  # The config to build the evaluation hook, refer to https://github.
↪com/open-mmlab/mmdetection/blob/master/mmdet/core/evaluation/eval_hooks.py#L7 for more␣
↪details.
    interval=1,  # Evaluation interval
    metric=['bbox', 'segm'])  # Metrics used during evaluation
optimizer = dict(  # Config used to build optimizer, support all the optimizers in␣
↪PyTorch whose arguments are also the same as those in PyTorch
    type='SGD',  # Type of optimizers, refer to https://github.com/open-mmlab/
↪mmdetection/blob/master/mmdet/core/optimizer/default_constructor.py#L13 for more␣
↪details
    lr=0.02,  # Learning rate of optimizers, see detail usages of the parameters in the␣
↪documentation of PyTorch
    momentum=0.9,  # Momentum
    weight_decay=0.0001)  # Weight decay of SGD
optimizer_config = dict(  # Config used to build the optimizer hook, refer to https://
↪github.com/open-mmlab/mmcv/blob/master/mmcv/runner/hooks/optimizer.py#L8 for␣
↪implementation details.
    grad_clip=None)  # Most of the methods do not use gradient clip
lr_config = dict(  # Learning rate scheduler config used to register LrUpdater hook
    policy='step',  # The policy of scheduler, also support CosineAnnealing, Cyclic, etc.
↪ Refer to details of supported LrUpdater from https://github.com/open-mmlab/mmcv/blob/
↪master/mmcv/runner/hooks/lr_updater.py#L9.
    warmup='linear',  # The warmup policy, also support `exp` and `constant`.
    warmup_iters=500,  # The number of iterations for warmup
    warmup_ratio=
    0.001,  # The ratio of the starting learning rate used for warmup
    step=[8, 11])  # Steps to decay the learning rate
runner = dict(
    type='EpochBasedRunner', # Type of runner to use (i.e. IterBasedRunner or␣
↪EpochBasedRunner)
    max_epochs=12) # Runner that runs the workflow in total max_epochs. For␣
↪IterBasedRunner use `max_iters`
```

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```
checkpoint_config = dict(  # Config to set the checkpoint hook, Refer to https://github.
↪com/open-mmlab/mmcv/blob/master/mmcv/runner/hooks/checkpoint.py for implementation.
    interval=1)  # The save interval is 1
log_config = dict(  # config to register logger hook
    interval=50,  # Interval to print the log
    hooks=[
        # dict(type='TensorboardLoggerHook')  # The Tensorboard logger is also supported
        dict(type='TextLoggerHook')
    ])  # The logger used to record the training process.
dist_params = dict(backend='nccl')  # Parameters to setup distributed training, the port␣
↪can also be set.
log_level = 'INFO'  # The level of logging.
load_from = None  # load models as a pre-trained model from a given path. This will not␣
↪resume training.
resume_from = None  # Resume checkpoints from a given path, the training will be resumed␣
↪from the epoch when the checkpoint's is saved.
workflow = [('train', 1)]  # Workflow for runner. [('train', 1)] means there is only one␣
↪workflow and the workflow named 'train' is executed once. The workflow trains the␣
↪model by 12 epochs according to the total_epochs.
work_dir = 'work_dir'  # Directory to save the model checkpoints and logs for the␣
↪current experiments.
```

7.6 FAQ

7.6.1 Ignore some fields in the base configs

Sometimes, you may set `_delete_=True` to ignore some of fields in base configs. You may refer to mmcv for simple illustration.

In MMDetection, for example, to change the backbone of Mask R-CNN with the following config.

```
model = dict(
    type='MaskRCNN',
    pretrained='torchvision://resnet50',
    backbone=dict(
        type='ResNet',
        depth=50,
        num_stages=4,
        out_indices=(0, 1, 2, 3),
        frozen_stages=1,
        norm_cfg=dict(type='BN', requires_grad=True),
        norm_eval=True,
        style='pytorch'),
    neck=dict(...),
    rpn_head=dict(...),
    roi_head=dict(...))
```

`ResNet` and `HRNet` use different keywords to construct.

```
_base_ = '../mask_rcnn/mask_rcnn_r50_fpn_1x_coco.py'
model = dict(
    pretrained='open-mmlab://msra/hrnetv2_w32',
    backbone=dict(
        _delete_=True,
        type='HRNet',
        extra=dict(
            stage1=dict(
                num_modules=1,
                num_branches=1,
                block='BOTTLENECK',
                num_blocks=(4, ),
                num_channels=(64, )),
            stage2=dict(
                num_modules=1,
                num_branches=2,
                block='BASIC',
                num_blocks=(4, 4),
                num_channels=(32, 64)),
            stage3=dict(
                num_modules=4,
                num_branches=3,
                block='BASIC',
                num_blocks=(4, 4, 4),
                num_channels=(32, 64, 128)),
            stage4=dict(
                num_modules=3,
                num_branches=4,
                block='BASIC',
                num_blocks=(4, 4, 4, 4),
                num_channels=(32, 64, 128, 256)))),
    neck=dict(...))
```

The `_delete_=True` would replace all old keys in `backbone` field with new keys.

7.6.2 Use intermediate variables in configs

Some intermediate variables are used in the configs files, like `train_pipeline/test_pipeline` in datasets. It's worth noting that when modifying intermediate variables in the children configs, user need to pass the intermediate variables into corresponding fields again. For example, we would like to use multi scale strategy to train a Mask R-CNN. `train_pipeline/test_pipeline` are intermediate variable we would like modify.

```
_base_ = './mask_rcnn_r50_fpn_1x_coco.py'
img_norm_cfg = dict(
    mean=[123.675, 116.28, 103.53], std=[58.395, 57.12, 57.375], to_rgb=True)
train_pipeline = [
    dict(type='LoadImageFromFile'),
    dict(type='LoadAnnotations', with_bbox=True, with_mask=True),
    dict(
        type='Resize',
        img_scale=[(1333, 640), (1333, 672), (1333, 704), (1333, 736),
                   (1333, 768), (1333, 800)],
```

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```
        multiscale_mode="value",
        keep_ratio=True),
    dict(type='RandomFlip', flip_ratio=0.5),
    dict(type='Normalize', **img_norm_cfg),
    dict(type='Pad', size_divisor=32),
    dict(type='DefaultFormatBundle'),
    dict(type='Collect', keys=['img', 'gt_bboxes', 'gt_labels', 'gt_masks']),
]
test_pipeline = [
    dict(type='LoadImageFromFile'),
    dict(
        type='MultiScaleFlipAug',
        img_scale=(1333, 800),
        flip=False,
        transforms=[
            dict(type='Resize', keep_ratio=True),
            dict(type='RandomFlip'),
            dict(type='Normalize', **img_norm_cfg),
            dict(type='Pad', size_divisor=32),
            dict(type='ImageToTensor', keys=['img']),
            dict(type='Collect', keys=['img']),
        ])
]
data = dict(
    train=dict(pipeline=train_pipeline),
    val=dict(pipeline=test_pipeline),
    test=dict(pipeline=test_pipeline))
```

We first define the new `train_pipeline/test_pipeline` and pass them into `data`.

Similarly, if we would like to switch from `SyncBN` to `BN` or `MMSyncBN`, we need to substitute every `norm_cfg` in the config.

```
_base_ = './mask_rcnn_r50_fpn_1x_coco.py'
norm_cfg = dict(type='BN', requires_grad=True)
model = dict(
    backbone=dict(norm_cfg=norm_cfg),
    neck=dict(norm_cfg=norm_cfg),
    ...)
```

CHAPTER

EIGHT

TUTORIAL 2: CUSTOMIZE DATASETS

8.1 Support new data format

To support a new data format, you can either convert them to existing formats (COCO format or PASCAL format) or directly convert them to the middle format. You could also choose to convert them offline (before training by a script) or online (implement a new dataset and do the conversion at training). In MMDetection, we recommend to convert the data into COCO formats and do the conversion offline, thus you only need to modify the config's data annotation paths and classes after the conversion of your data.

8.1.1 Reorganize new data formats to existing format

The simplest way is to convert your dataset to existing dataset formats (COCO or PASCAL VOC).

The annotation json files in COCO format has the following necessary keys:

```
'images': [
    {
        'file_name': 'COCO_val2014_000000001268.jpg',
        'height': 427,
        'width': 640,
        'id': 1268
    },
    ...
],

'annotations': [
    {
        'segmentation': [[192.81,
            247.09,
            ...
            219.03,
            249.06]],  # if you have mask labels
        'area': 1035.749,
        'iscrowd': 0,
        'image_id': 1268,
        'bbox': [192.81, 224.8, 74.73, 33.43],
        'category_id': 16,
        'id': 42986
    },
    ...
```

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```
],

'categories': [
    {'id': 0, 'name': 'car'},
 ]
```

There are three necessary keys in the json file:

- `images`: contains a list of images with their information like `file_name`, `height`, `width`, and `id`.
- `annotations`: contains the list of instance annotations.
- `categories`: contains the list of categories names and their ID.

After the data pre-processing, there are two steps for users to train the customized new dataset with existing format (e.g. COCO format):

1. Modify the config file for using the customized dataset.
2. Check the annotations of the customized dataset.

Here we give an example to show the above two steps, which uses a customized dataset of 5 classes with COCO format to train an existing Cascade Mask R-CNN R50-FPN detector.

1. Modify the config file for using the customized dataset

There are two aspects involved in the modification of config file:

1. The `data` field. Specifically, you need to explicitly add the `classes` fields in `data.train`, `data.val` and `data.test`.
2. The `num_classes` field in the `model` part. Explicitly over-write all the `num_classes` from default value (e.g. 80 in COCO) to your classes number.

In `configs/my_custom_config.py`:

```
# the new config inherits the base configs to highlight the necessary modification
_base_ = './cascade_mask_rcnn_r50_fpn_1x_coco.py'

# 1. dataset settings
dataset_type = 'CocoDataset'
classes = ('a', 'b', 'c', 'd', 'e')
data = dict(
    samples_per_gpu=2,
    workers_per_gpu=2,
    train=dict(
        type=dataset_type,
        # explicitly add your class names to the field `classes`
        classes=classes,
        ann_file='path/to/your/train/annotation_data',
        img_prefix='path/to/your/train/image_data'),
    val=dict(
        type=dataset_type,
        # explicitly add your class names to the field `classes`
        classes=classes,
```

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```
        ann_file='path/to/your/val/annotation_data',
        img_prefix='path/to/your/val/image_data'),
    test=dict(
        type=dataset_type,
        # explicitly add your class names to the field `classes`
        classes=classes,
        ann_file='path/to/your/test/annotation_data',
        img_prefix='path/to/your/test/image_data'))

# 2. model settings

# explicitly over-write all the `num_classes` field from default 80 to 5.
model = dict(
    roi_head=dict(
        bbox_head=[
            dict(
                type='Shared2FCBBoxHead',
                # explicitly over-write all the `num_classes` field from default 80 to 5.
                num_classes=5),
            dict(
                type='Shared2FCBBoxHead',
                # explicitly over-write all the `num_classes` field from default 80 to 5.
                num_classes=5),
            dict(
                type='Shared2FCBBoxHead',
                # explicitly over-write all the `num_classes` field from default 80 to 5.
                num_classes=5)],
    # explicitly over-write all the `num_classes` field from default 80 to 5.
    mask_head=dict(num_classes=5)))
```

2. Check the annotations of the customized dataset

Assuming your customized dataset is COCO format, make sure you have the correct annotations in the customized dataset:

1. The length for `categories` field in annotations should exactly equal the tuple length of `classes` fields in your config, meaning the number of classes (e.g. 5 in this example).
2. The `classes` fields in your config file should have exactly the same elements and the same order with the `name` in `categories` of annotations. MMDetection automatically maps the uncontinuous `id` in `categories` to the continuous label indices, so the string order of `name` in `categories` field affects the order of label indices. Meanwhile, the string order of `classes` in config affects the label text during visualization of predicted bounding boxes.
3. The `category_id` in `annotations` field should be valid, i.e., all values in `category_id` should belong to `id` in `categories`.

Here is a valid example of annotations:

```
'annotations': [
    {
        'segmentation': [[192.81,
```

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```
            247.09,
            ...
            219.03,
            249.06]],  # if you have mask labels
        'area': 1035.749,
        'iscrowd': 0,
        'image_id': 1268,
        'bbox': [192.81, 224.8, 74.73, 33.43],
        'category_id': 16,
        'id': 42986
    },
    ...
],

# MMDetection automatically maps the uncontinuous `id` to the continuous label indices.
'categories': [
    {'id': 1, 'name': 'a'}, {'id': 3, 'name': 'b'}, {'id': 4, 'name': 'c'}, {'id': 16,
↪'name': 'd'}, {'id': 17, 'name': 'e'},
 ]
```

We use this way to support CityScapes dataset. The script is in cityscapes.py and we also provide the finetuning configs.

Note

1. For instance segmentation datasets, **MMDetection only supports evaluating mask AP of dataset in COCO format for now**.
2. It is recommended to convert the data offline before training, thus you can still use `CocoDataset` and only need to modify the path of annotations and the training classes.

8.1.2 Reorganize new data format to middle format

It is also fine if you do not want to convert the annotation format to COCO or PASCAL format. Actually, we define a simple annotation format and all existing datasets are processed to be compatible with it, either online or offline.

The annotation of a dataset is a list of dict, each dict corresponds to an image. There are 3 field `filename` (relative path), `width`, `height` for testing, and an additional field `ann` for training. `ann` is also a dict containing at least 2 fields: `bboxes` and `labels`, both of which are numpy arrays. Some datasets may provide annotations like crowd/difficult/ignored bboxes, we use `bboxes_ignore` and `labels_ignore` to cover them.

Here is an example.

```
[
    {
        'filename': 'a.jpg',
        'width': 1280,
        'height': 720,
        'ann': {
            'bboxes': <np.ndarray, float32> (n, 4),
            'labels': <np.ndarray, int64> (n, ),
            'bboxes_ignore': <np.ndarray, float32> (k, 4),
            'labels_ignore': <np.ndarray, int64> (k, ) (optional field)
        }
```

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```
    },
    ...
]
```

There are two ways to work with custom datasets.

- online conversion

  You can write a new Dataset class inherited from `CustomDataset`, and overwrite two methods `load_annotations(self, ann_file)` and `get_ann_info(self, idx)`, like CocoDataset and VOCDataset.

- offline conversion

  You can convert the annotation format to the expected format above and save it to a pickle or json file, like pascal_voc.py. Then you can simply use `CustomDataset`.

8.1.3 An example of customized dataset

Assume the annotation is in a new format in text files. The bounding boxes annotations are stored in text file `annotation.txt` as the following

```
#
000001.jpg
1280 720
2
10 20 40 60 1
20 40 50 60 2
#
000002.jpg
1280 720
3
50 20 40 60 2
20 40 30 45 2
30 40 50 60 3
```

We can create a new dataset in `mmdet/datasets/my_dataset.py` to load the data.

```
import mmcv
import numpy as np

from .builder import DATASETS
from .custom import CustomDataset


@DATASETS.register_module()
class MyDataset(CustomDataset):

    CLASSES = ('person', 'bicycle', 'car', 'motorcycle')

    def load_annotations(self, ann_file):
        ann_list = mmcv.list_from_file(ann_file)
```

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```
        data_infos = []
        for i, ann_line in enumerate(ann_list):
            if ann_line != '#':
                continue

            img_shape = ann_list[i + 2].split(' ')
            width = int(img_shape[0])
            height = int(img_shape[1])
            bbox_number = int(ann_list[i + 3])

            anns = ann_line.split(' ')
            bboxes = []
            labels = []
            for anns in ann_list[i + 4:i + 4 + bbox_number]:
                bboxes.append([float(ann) for ann in anns[:4]])
                labels.append(int(anns[4]))

            data_infos.append(
                dict(
                    filename=ann_list[i + 1],
                    width=width,
                    height=height,
                    ann=dict(
                        bboxes=np.array(bboxes).astype(np.float32),
                        labels=np.array(labels).astype(np.int64))
                ))

        return data_infos

    def get_ann_info(self, idx):
        return self.data_infos[idx]['ann']
```

Then in the config, to use `MyDataset` you can modify the config as the following

```
dataset_A_train = dict(
    type='MyDataset',
    ann_file = 'image_list.txt',
    pipeline=train_pipeline
)
```

8.2 Customize datasets by dataset wrappers

MMDetection also supports many dataset wrappers to mix the dataset or modify the dataset distribution for training. Currently it supports to three dataset wrappers as below:

- `RepeatDataset`: simply repeat the whole dataset.
- `ClassBalancedDataset`: repeat dataset in a class balanced manner.
- `ConcatDataset`: concat datasets.

8.2.1 Repeat dataset

We use `RepeatDataset` as wrapper to repeat the dataset. For example, suppose the original dataset is `Dataset_A`, to repeat it, the config looks like the following

```
dataset_A_train = dict(
        type='RepeatDataset',
        times=N,
        dataset=dict(  # This is the original config of Dataset_A
            type='Dataset_A',
            ...
            pipeline=train_pipeline
        )
    )
```

8.2.2 Class balanced dataset

We use `ClassBalancedDataset` as wrapper to repeat the dataset based on category frequency. The dataset to repeat needs to instantiate function `self.get_cat_ids(idx)` to support `ClassBalancedDataset`. For example, to repeat `Dataset_A` with `oversample_thr=1e-3`, the config looks like the following

```
dataset_A_train = dict(
        type='ClassBalancedDataset',
        oversample_thr=1e-3,
        dataset=dict(  # This is the original config of Dataset_A
            type='Dataset_A',
            ...
            pipeline=train_pipeline
        )
    )
```

You may refer to source code for details.

8.2.3 Concatenate dataset

There are three ways to concatenate the dataset.

1. If the datasets you want to concatenate are in the same type with different annotation files, you can concatenate the dataset configs like the following.

   ```
   dataset_A_train = dict(
       type='Dataset_A',
       ann_file = ['anno_file_1', 'anno_file_2'],
       pipeline=train_pipeline
   )
   ```

   If the concatenated dataset is used for test or evaluation, this manner supports to evaluate each dataset separately. To test the concatenated datasets as a whole, you can set `separate_eval=False` as below.

   ```
   dataset_A_train = dict(
       type='Dataset_A',
       ann_file = ['anno_file_1', 'anno_file_2'],
   ```

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```
    separate_eval=False,
    pipeline=train_pipeline
)
```

2. In case the dataset you want to concatenate is different, you can concatenate the dataset configs like the following.

```
dataset_A_train = dict()
dataset_B_train = dict()

data = dict(
    imgs_per_gpu=2,
    workers_per_gpu=2,
    train = [
        dataset_A_train,
        dataset_B_train
    ],
    val = dataset_A_val,
    test = dataset_A_test
    )
```

   If the concatenated dataset is used for test or evaluation, this manner also supports to evaluate each dataset separately.

3. We also support to define `ConcatDataset` explicitly as the following.

```
dataset_A_val = dict()
dataset_B_val = dict()

data = dict(
    imgs_per_gpu=2,
    workers_per_gpu=2,
    train=dataset_A_train,
    val=dict(
        type='ConcatDataset',
        datasets=[dataset_A_val, dataset_B_val],
        separate_eval=False))
```

   This manner allows users to evaluate all the datasets as a single one by setting `separate_eval=False`.

Note:

1. The option `separate_eval=False` assumes the datasets use `self.data_infos` during evaluation. Therefore, COCO datasets do not support this behavior since COCO datasets do not fully rely on `self.data_infos` for evaluation. Combining different types of datasets and evaluating them as a whole is not tested thus is not suggested.
2. Evaluating `ClassBalancedDataset` and `RepeatDataset` is not supported thus evaluating concatenated datasets of these types is also not supported.

A more complex example that repeats `Dataset_A` and `Dataset_B` by N and M times, respectively, and then concatenates the repeated datasets is as the following.

```
dataset_A_train = dict(
    type='RepeatDataset',
    times=N,
```

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```
    dataset=dict(
        type='Dataset_A',
        ...
        pipeline=train_pipeline
    )
)
dataset_A_val = dict(
    ...
    pipeline=test_pipeline
)
dataset_A_test = dict(
    ...
    pipeline=test_pipeline
)
dataset_B_train = dict(
    type='RepeatDataset',
    times=M,
    dataset=dict(
        type='Dataset_B',
        ...
        pipeline=train_pipeline
    )
)
data = dict(
    imgs_per_gpu=2,
    workers_per_gpu=2,
    train = [
        dataset_A_train,
        dataset_B_train
    ],
    val = dataset_A_val,
    test = dataset_A_test
)
```

8.3 Modify Dataset Classes

With existing dataset types, we can modify the class names of them to train subset of the annotations. For example, if you want to train only three classes of the current dataset, you can modify the classes of dataset. The dataset will filter out the ground truth boxes of other classes automatically.

```
classes = ('person', 'bicycle', 'car')
data = dict(
    train=dict(classes=classes),
    val=dict(classes=classes),
    test=dict(classes=classes))
```

MMDetection V2.0 also supports to read the classes from a file, which is common in real applications. For example, assume the `classes.txt` contains the name of classes as the following.

```
person
bicycle
car
```

Users can set the classes as a file path, the dataset will load it and convert it to a list automatically.

```
classes = 'path/to/classes.txt'
data = dict(
    train=dict(classes=classes),
    val=dict(classes=classes),
    test=dict(classes=classes))
```

Note:

- Before MMDetection v2.5.0, the dataset will filter out the empty GT images automatically if the classes are set and there is no way to disable that through config. This is an undesirable behavior and introduces confusion because if the classes are not set, the dataset only filter the empty GT images when `filter_empty_gt=True` and `test_mode=False`. After MMDetection v2.5.0, we decouple the image filtering process and the classes modification, i.e., the dataset will only filter empty GT images when `filter_empty_gt=True` and `test_mode=False`, no matter whether the classes are set. Thus, setting the classes only influences the annotations of classes used for training and users could decide whether to filter empty GT images by themselves.
- Since the middle format only has box labels and does not contain the class names, when using `CustomDataset`, users cannot filter out the empty GT images through configs but only do this offline.
- Please remember to modify the `num_classes` in the head when specifying `classes` in dataset. We implemented NumClassCheckHook to check whether the numbers are consistent since v2.9.0(after PR#4508).
- The features for setting dataset classes and dataset filtering will be refactored to be more user-friendly in the future (depends on the progress).

8.4 COCO Panoptic Dataset

Now we support COCO Panoptic Dataset, the format of panoptic annotations is different from COCO format. Both the foreground and the background will exist in the annotation file. The annotation json files in COCO Panoptic format has the following necessary keys:

```
'images': [
    {
        'file_name': '000000001268.jpg',
        'height': 427,
        'width': 640,
        'id': 1268
    },
    ...
]

'annotations': [
    {
        'filename': '000000001268.jpg',
        'image_id': 1268,
        'segments_info': [
            {
```

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```
                'id':8345037,  # One-to-one correspondence with the id in the annotation␣
↪map.
                'category_id': 51,
                'iscrowd': 0,
                'bbox': (x1, y1, w, h),  # The bbox of the background is the outer␣
↪rectangle of its mask.
                'area': 24315
            },
            ...
        ]
    },
    ...
]

'categories': [  # including both foreground categories and background categories
    {'id': 0, 'name': 'person'},
    ...
 ]
```

Moreover, the `seg_prefix` must be set to the path of the panoptic annotation images.

```
data = dict(
    type='CocoPanopticDataset',
    train=dict(
        seg_prefix = 'path/to/your/train/panoptic/image_annotation_data'
    ),
    val=dict(
        seg_prefix = 'path/to/your/train/panoptic/image_annotation_data'
    )
)
```

CHAPTER

NINE

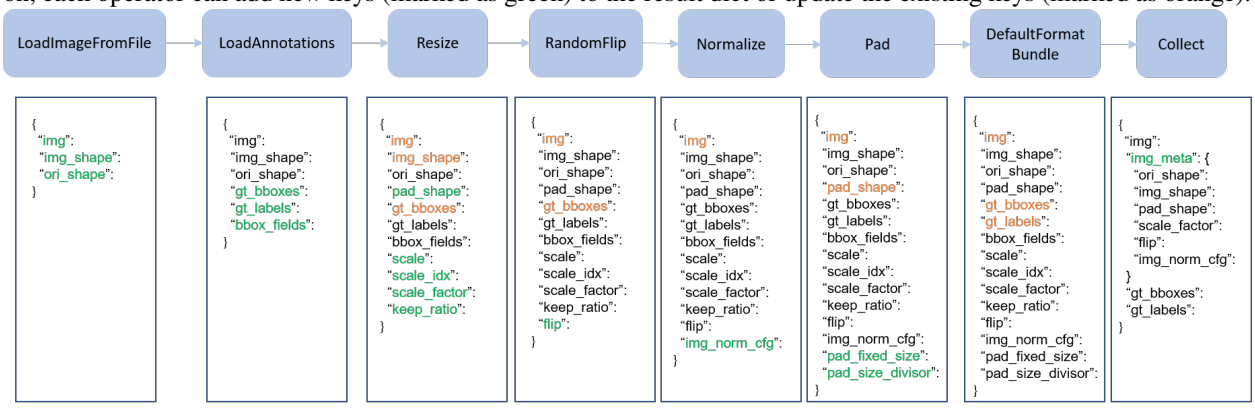
TUTORIAL 3: CUSTOMIZE DATA PIPELINES

9.1 Design of Data pipelines

Following typical conventions, we use `Dataset` and `DataLoader` for data loading with multiple workers. `Dataset` returns a dict of data items corresponding the arguments of models' forward method. Since the data in object detection may not be the same size (image size, gt bbox size, etc.), we introduce a new `DataContainer` type in MMCV to help collect and distribute data of different size. See here for more details.

The data preparation pipeline and the dataset is decomposed. Usually a dataset defines how to process the annotations and a data pipeline defines all the steps to prepare a data dict. A pipeline consists of a sequence of operations. Each operation takes a dict as input and also output a dict for the next transform.

We present a classical pipeline in the following figure. The blue blocks are pipeline operations. With the pipeline going on, each operator can add new keys (marked as green) to the result dict or update the existing keys (marked as orange).



The operations are categorized into data loading, pre-processing, formatting and test-time augmentation.

Here is a pipeline example for Faster R-CNN.

```
img_norm_cfg = dict(
    mean=[123.675, 116.28, 103.53], std=[58.395, 57.12, 57.375], to_rgb=True)
train_pipeline = [
    dict(type='LoadImageFromFile'),
    dict(type='LoadAnnotations', with_bbox=True),
    dict(type='Resize', img_scale=(1333, 800), keep_ratio=True),
    dict(type='RandomFlip', flip_ratio=0.5),
    dict(type='Normalize', **img_norm_cfg),
    dict(type='Pad', size_divisor=32),
    dict(type='DefaultFormatBundle'),
    dict(type='Collect', keys=['img', 'gt_bboxes', 'gt_labels']),
```

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```
]
test_pipeline = [
    dict(type='LoadImageFromFile'),
    dict(
        type='MultiScaleFlipAug',
        img_scale=(1333, 800),
        flip=False,
        transforms=[
            dict(type='Resize', keep_ratio=True),
            dict(type='RandomFlip'),
            dict(type='Normalize', **img_norm_cfg),
            dict(type='Pad', size_divisor=32),
            dict(type='ImageToTensor', keys=['img']),
            dict(type='Collect', keys=['img']),
        ])
]
```

For each operation, we list the related dict fields that are added/updated/removed.

9.1.1 Data loading

`LoadImageFromFile`

- add: img, img_shape, ori_shape

`LoadAnnotations`

- add: gt_bboxes, gt_bboxes_ignore, gt_labels, gt_masks, gt_semantic_seg, bbox_fields, mask_fields

`LoadProposals`

- add: proposals

9.1.2 Pre-processing

`Resize`

- add: scale, scale_idx, pad_shape, scale_factor, keep_ratio
- update: img, img_shape, *bbox_fields, *mask_fields, *seg_fields

`RandomFlip`

- add: flip
- update: img, *bbox_fields, *mask_fields, *seg_fields

`Pad`

- add: pad_fixed_size, pad_size_divisor
- update: img, pad_shape, *mask_fields, *seg_fields

`RandomCrop`

- update: img, pad_shape, gt_bboxes, gt_labels, gt_masks, *bbox_fields

`Normalize`

- add: img_norm_cfg
- update: img

`SegRescale`

- update: gt_semantic_seg

`PhotoMetricDistortion`

- update: img

`Expand`

- update: img, gt_bboxes

`MinIoURandomCrop`

- update: img, gt_bboxes, gt_labels

`Corrupt`

- update: img

9.1.3 Formatting

`ToTensor`

- update: specified by `keys`.

`ImageToTensor`

- update: specified by `keys`.

`Transpose`

- update: specified by `keys`.

`ToDataContainer`

- update: specified by `fields`.

`DefaultFormatBundle`

- update: img, proposals, gt_bboxes, gt_bboxes_ignore, gt_labels, gt_masks, gt_semantic_seg

`Collect`

- add: img_meta (the keys of img_meta is specified by `meta_keys`)
- remove: all other keys except for those specified by `keys`

9.1.4 Test time augmentation

`MultiScaleFlipAug`

9.2 Extend and use custom pipelines

1. Write a new pipeline in a file, e.g., in `my_pipeline.py`. It takes a dict as input and returns a dict.

```
import random
from mmdet.datasets import PIPELINES


@PIPELINES.register_module()
class MyTransform:
    """Add your transform

    Args:
        p (float): Probability of shifts. Default 0.5.
    """

    def __init__(self, p=0.5):
        self.p = p

    def __call__(self, results):
        if random.random() > self.p:
            results['dummy'] = True
        return results
```

2. Import and use the pipeline in your config file. Make sure the import is relative to where your train script is located.

```
custom_imports = dict(imports=['path.to.my_pipeline'], allow_failed_imports=False)

img_norm_cfg = dict(
    mean=[123.675, 116.28, 103.53], std=[58.395, 57.12, 57.375], to_rgb=True)
train_pipeline = [
    dict(type='LoadImageFromFile'),
    dict(type='LoadAnnotations', with_bbox=True),
    dict(type='Resize', img_scale=(1333, 800), keep_ratio=True),
    dict(type='RandomFlip', flip_ratio=0.5),
    dict(type='Normalize', **img_norm_cfg),
    dict(type='Pad', size_divisor=32),
    dict(type='MyTransform', p=0.2),
    dict(type='DefaultFormatBundle'),
    dict(type='Collect', keys=['img', 'gt_bboxes', 'gt_labels']),
]
```

3. Visualize the output of your augmentation pipeline

   To visualize the output of your augmentation pipeline, `tools/misc/browse_dataset.py` can help the user to browse a detection dataset (both images and bounding box annotations) visually, or save the image to a designated directory. More detials can refer to *useful_tools*

CHAPTER

TEN

TUTORIAL 4: CUSTOMIZE MODELS

We basically categorize model components into 5 types.

- backbone: usually an FCN network to extract feature maps, e.g., ResNet, MobileNet.
- neck: the component between backbones and heads, e.g., FPN, PAFPN.
- head: the component for specific tasks, e.g., bbox prediction and mask prediction.
- roi extractor: the part for extracting RoI features from feature maps, e.g., RoI Align.
- loss: the component in head for calculating losses, e.g., FocalLoss, L1Loss, and GHMLoss.

10.1 Develop new components

10.1.1 Add a new backbone

Here we show how to develop new components with an example of MobileNet.

1. Define a new backbone (e.g. MobileNet)

Create a new file `mmdet/models/backbones/mobilenet.py`.

```
import torch.nn as nn

from ..builder import BACKBONES


@BACKBONES.register_module()
class MobileNet(nn.Module):

    def __init__(self, arg1, arg2):
        pass

    def forward(self, x):  # should return a tuple
        pass
```

2. Import the module

You can either add the following line to `mmdet/models/backbones/__init__.py`

```
from .mobilenet import MobileNet
```

or alternatively add

```
custom_imports = dict(
    imports=['mmdet.models.backbones.mobilenet'],
    allow_failed_imports=False)
```

to the config file to avoid modifying the original code.

3. Use the backbone in your config file

```
model = dict(
    ...
    backbone=dict(
        type='MobileNet',
        arg1=xxx,
        arg2=xxx),
    ...
```

10.1.2 Add new necks

1. Define a neck (e.g. PAFPN)

Create a new file `mmdet/models/necks/pafpn.py`.

```
from ..builder import NECKS

@NECKS.register_module()
class PAFPN(nn.Module):

    def __init__(self,
                 in_channels,
                 out_channels,
                 num_outs,
                 start_level=0,
                 end_level=-1,
                 add_extra_convs=False):
        pass

    def forward(self, inputs):
        # implementation is ignored
        pass
```

2. Import the module

You can either add the following line to `mmdet/models/necks/__init__.py`,

```
from .pafpn import PAFPN
```

or alternatively add

```
custom_imports = dict(
    imports=['mmdet.models.necks.pafpn.py'],
    allow_failed_imports=False)
```

to the config file and avoid modifying the original code.

3. Modify the config file

```
neck=dict(
    type='PAFPN',
    in_channels=[256, 512, 1024, 2048],
    out_channels=256,
    num_outs=5)
```

10.1.3 Add new heads

Here we show how to develop a new head with the example of Double Head R-CNN as the following.

First, add a new bbox head in `mmdet/models/roi_heads/bbox_heads/double_bbox_head.py`. Double Head R-CNN implements a new bbox head for object detection. To implement a bbox head, basically we need to implement three functions of the new module as the following.

```
from mmdet.models.builder import HEADS
from .bbox_head import BBoxHead

@HEADS.register_module()
class DoubleConvFCBBoxHead(BBoxHead):
    r"""Bbox head used in Double-Head R-CNN

                                    /-> cls
                  /-> shared convs ->
                                    \-> reg
    roi features
                                    /-> cls
                  \-> shared fc    ->
                                    \-> reg
    """  # noqa: W605

    def __init__(self,
                 num_convs=0,
                 num_fcs=0,
                 conv_out_channels=1024,
                 fc_out_channels=1024,
                 conv_cfg=None,
```

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```
                 norm_cfg=dict(type='BN'),
                 **kwargs):
        kwargs.setdefault('with_avg_pool', True)
        super(DoubleConvFCBBoxHead, self).__init__(**kwargs)


    def forward(self, x_cls, x_reg):
```

Second, implement a new RoI Head if it is necessary. We plan to inherit the new `DoubleHeadRoIHead` from `StandardRoIHead`. We can find that a `StandardRoIHead` already implements the following functions.

```
import torch

from mmdet.core import bbox2result, bbox2roi, build_assigner, build_sampler
from ..builder import HEADS, build_head, build_roi_extractor
from .base_roi_head import BaseRoIHead
from .test_mixins import BBoxTestMixin, MaskTestMixin


@HEADS.register_module()
class StandardRoIHead(BaseRoIHead, BBoxTestMixin, MaskTestMixin):
    """Simplest base roi head including one bbox head and one mask head.
    """

    def init_assigner_sampler(self):

    def init_bbox_head(self, bbox_roi_extractor, bbox_head):

    def init_mask_head(self, mask_roi_extractor, mask_head):


    def forward_dummy(self, x, proposals):


    def forward_train(self,
                      x,
                      img_metas,
                      proposal_list,
                      gt_bboxes,
                      gt_labels,
                      gt_bboxes_ignore=None,
                      gt_masks=None):

    def _bbox_forward(self, x, rois):

    def _bbox_forward_train(self, x, sampling_results, gt_bboxes, gt_labels,
                            img_metas):

    def _mask_forward_train(self, x, sampling_results, bbox_feats, gt_masks,
                            img_metas):
```

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```
    def _mask_forward(self, x, rois=None, pos_inds=None, bbox_feats=None):


    def simple_test(self,
                    x,
                    proposal_list,
                    img_metas,
                    proposals=None,
                    rescale=False):
        """Test without augmentation."""
```

Double Head's modification is mainly in the bbox_forward logic, and it inherits other logics from the StandardRoIHead. In the mmdet/models/roi_heads/double_roi_head.py, we implement the new RoI Head as the following:

```
from ..builder import HEADS
from .standard_roi_head import StandardRoIHead


@HEADS.register_module()
class DoubleHeadRoIHead(StandardRoIHead):
    """RoI head for Double Head RCNN

    https://arxiv.org/abs/1904.06493
    """

    def __init__(self, reg_roi_scale_factor, **kwargs):
        super(DoubleHeadRoIHead, self).__init__(**kwargs)
        self.reg_roi_scale_factor = reg_roi_scale_factor

    def _bbox_forward(self, x, rois):
        bbox_cls_feats = self.bbox_roi_extractor(
            x[:self.bbox_roi_extractor.num_inputs], rois)
        bbox_reg_feats = self.bbox_roi_extractor(
            x[:self.bbox_roi_extractor.num_inputs],
            rois,
            roi_scale_factor=self.reg_roi_scale_factor)
        if self.with_shared_head:
            bbox_cls_feats = self.shared_head(bbox_cls_feats)
            bbox_reg_feats = self.shared_head(bbox_reg_feats)
        cls_score, bbox_pred = self.bbox_head(bbox_cls_feats, bbox_reg_feats)

        bbox_results = dict(
            cls_score=cls_score,
            bbox_pred=bbox_pred,
            bbox_feats=bbox_cls_feats)
        return bbox_results
```

Last, the users need to add the module in mmdet/models/bbox_heads/__init__.py and mmdet/models/roi_heads/__init__.py thus the corresponding registry could find and load them.

Alternatively, the users can add

```
custom_imports=dict(
    imports=['mmdet.models.roi_heads.double_roi_head', 'mmdet.models.bbox_heads.double_
↪bbox_head'])
```

to the config file and achieve the same goal.

The config file of Double Head R-CNN is as the following

```
_base_ = '../faster_rcnn/faster_rcnn_r50_fpn_1x_coco.py'
model = dict(
    roi_head=dict(
        type='DoubleHeadRoIHead',
        reg_roi_scale_factor=1.3,
        bbox_head=dict(
            _delete_=True,
            type='DoubleConvFCBBoxHead',
            num_convs=4,
            num_fcs=2,
            in_channels=256,
            conv_out_channels=1024,
            fc_out_channels=1024,
            roi_feat_size=7,
            num_classes=80,
            bbox_coder=dict(
                type='DeltaXYWHBBoxCoder',
                target_means=[0., 0., 0., 0.],
                target_stds=[0.1, 0.1, 0.2, 0.2]),
            reg_class_agnostic=False,
            loss_cls=dict(
                type='CrossEntropyLoss', use_sigmoid=False, loss_weight=2.0),
            loss_bbox=dict(type='SmoothL1Loss', beta=1.0, loss_weight=2.0))))
```

Since MMDetection 2.0, the config system supports to inherit configs such that the users can focus on the modification. The Double Head R-CNN mainly uses a new DoubleHeadRoIHead and a new `DoubleConvFCBBoxHead`, the arguments are set according to the `__init__` function of each module.

10.1.4 Add new loss

Assume you want to add a new loss as `MyLoss`, for bounding box regression. To add a new loss function, the users need implement it in `mmdet/models/losses/my_loss.py`. The decorator `weighted_loss` enable the loss to be weighted for each element.

```
import torch
import torch.nn as nn

from ..builder import LOSSES
from .utils import weighted_loss

@weighted_loss
def my_loss(pred, target):
    assert pred.size() == target.size() and target.numel() > 0
    loss = torch.abs(pred - target)
```

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```
    return loss

@LOSSES.register_module()
class MyLoss(nn.Module):

    def __init__(self, reduction='mean', loss_weight=1.0):
        super(MyLoss, self).__init__()
        self.reduction = reduction
        self.loss_weight = loss_weight

    def forward(self,
                pred,
                target,
                weight=None,
                avg_factor=None,
                reduction_override=None):
        assert reduction_override in (None, 'none', 'mean', 'sum')
        reduction = (
            reduction_override if reduction_override else self.reduction)
        loss_bbox = self.loss_weight * my_loss(
            pred, target, weight, reduction=reduction, avg_factor=avg_factor)
        return loss_bbox
```

Then the users need to add it in the `mmdet/models/losses/__init__.py`.

```
from .my_loss import MyLoss, my_loss
```

Alternatively, you can add

```
custom_imports=dict(
    imports=['mmdet.models.losses.my_loss'])
```

to the config file and achieve the same goal.

To use it, modify the `loss_xxx` field. Since MyLoss is for regression, you need to modify the `loss_bbox` field in the head.

```
loss_bbox=dict(type='MyLoss', loss_weight=1.0))
```

CHAPTER

ELEVEN

TUTORIAL 5: CUSTOMIZE RUNTIME SETTINGS

11.1 Customize optimization settings

11.1.1 Customize optimizer supported by Pytorch

We already support to use all the optimizers implemented by PyTorch, and the only modification is to change the `optimizer` field of config files. For example, if you want to use `ADAM` (note that the performance could drop a lot), the modification could be as the following.

```
optimizer = dict(type='Adam', lr=0.0003, weight_decay=0.0001)
```

To modify the learning rate of the model, the users only need to modify the `lr` in the config of optimizer. The users can directly set arguments following the API doc of PyTorch.

11.1.2 Customize self-implemented optimizer

1. Define a new optimizer

A customized optimizer could be defined as following.

Assume you want to add a optimizer named `MyOptimizer`, which has arguments `a`, `b`, and `c`. You need to create a new directory named `mmdet/core/optimizer`. And then implement the new optimizer in a file, e.g., in `mmdet/core/optimizer/my_optimizer.py`:

```
from .registry import OPTIMIZERS
from torch.optim import Optimizer


@OPTIMIZERS.register_module()
class MyOptimizer(Optimizer):

    def __init__(self, a, b, c)
```

2. Add the optimizer to registry

To find the above module defined above, this module should be imported into the main namespace at first. There are two options to achieve it.

- Modify `mmdet/core/optimizer/__init__.py` to import it.

  The newly defined module should be imported in `mmdet/core/optimizer/__init__.py` so that the registry will find the new module and add it:

```
from .my_optimizer import MyOptimizer
```

- Use `custom_imports` in the config to manually import it

```
custom_imports = dict(imports=['mmdet.core.optimizer.my_optimizer'], allow_failed_
↪imports=False)
```

The module `mmdet.core.optimizer.my_optimizer` will be imported at the beginning of the program and the class `MyOptimizer` is then automatically registered. Note that only the package containing the class `MyOptimizer` should be imported. `mmdet.core.optimizer.my_optimizer.MyOptimizer` **cannot** be imported directly.

Actually users can use a totally different file directory structure using this importing method, as long as the module root can be located in `PYTHONPATH`.

3. Specify the optimizer in the config file

Then you can use `MyOptimizer` in `optimizer` field of config files. In the configs, the optimizers are defined by the field `optimizer` like the following:

```
optimizer = dict(type='SGD', lr=0.02, momentum=0.9, weight_decay=0.0001)
```

To use your own optimizer, the field can be changed to

```
optimizer = dict(type='MyOptimizer', a=a_value, b=b_value, c=c_value)
```

11.1.3 Customize optimizer constructor

Some models may have some parameter-specific settings for optimization, e.g. weight decay for BatchNorm layers. The users can do those fine-grained parameter tuning through customizing optimizer constructor.

```
from mmcv.utils import build_from_cfg

from mmcv.runner.optimizer import OPTIMIZER_BUILDERS, OPTIMIZERS
from mmdet.utils import get_root_logger
from .my_optimizer import MyOptimizer


@OPTIMIZER_BUILDERS.register_module()
class MyOptimizerConstructor(object):

    def __init__(self, optimizer_cfg, paramwise_cfg=None):

    def __call__(self, model):

```

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```
        return my_optimizer
```

The default optimizer constructor is implemented here, which could also serve as a template for new optimizer constructor.

11.1.4 Additional settings

Tricks not implemented by the optimizer should be implemented through optimizer constructor (e.g., set parameter-wise learning rates) or hooks. We list some common settings that could stabilize the training or accelerate the training. Feel free to create PR, issue for more settings.

- **Use gradient clip to stabilize training**: Some models need gradient clip to clip the gradients to stabilize the training process. An example is as below:

```
optimizer_config = dict(
    _delete_=True, grad_clip=dict(max_norm=35, norm_type=2))
```

  If your config inherits the base config which already sets the `optimizer_config`, you might need `_delete_=True` to override the unnecessary settings. See the config documentation for more details.

- **Use momentum schedule to accelerate model convergence**: We support momentum scheduler to modify model's momentum according to learning rate, which could make the model converge in a faster way. Momentum scheduler is usually used with LR scheduler, for example, the following config is used in 3D detection to accelerate convergence. For more details, please refer to the implementation of CyclicLrUpdater and CyclicMomentumUpdater.

```
lr_config = dict(
    policy='cyclic',
    target_ratio=(10, 1e-4),
    cyclic_times=1,
    step_ratio_up=0.4,
)
momentum_config = dict(
    policy='cyclic',
    target_ratio=(0.85 / 0.95, 1),
    cyclic_times=1,
    step_ratio_up=0.4,
)
```

11.2 Customize training schedules

By default we use step learning rate with 1x schedule, this calls `StepLRHook` in MMCV. We support many other learning rate schedule here, such as `CosineAnnealing` and `Poly` schedule. Here are some examples

- Poly schedule:

```
lr_config = dict(policy='poly', power=0.9, min_lr=1e-4, by_epoch=False)
```

- ConsineAnnealing schedule:

```
lr_config = dict(
    policy='CosineAnnealing',
    warmup='linear',
    warmup_iters=1000,
    warmup_ratio=1.0 / 10,
    min_lr_ratio=1e-5)
```

11.3 Customize workflow

Workflow is a list of (phase, epochs) to specify the running order and epochs. By default it is set to be

```
workflow = [('train', 1)]
```

which means running 1 epoch for training. Sometimes user may want to check some metrics (e.g. loss, accuracy) about the model on the validate set. In such case, we can set the workflow as

```
[('train', 1), ('val', 1)]
```

so that 1 epoch for training and 1 epoch for validation will be run iteratively.

Note:

1. The parameters of model will not be updated during val epoch.
2. Keyword `total_epochs` in the config only controls the number of training epochs and will not affect the validation workflow.
3. Workflows `[('train', 1), ('val', 1)]` and `[('train', 1)]` will not change the behavior of `EvalHook` because `EvalHook` is called by `after_train_epoch` and validation workflow only affect hooks that are called through `after_val_epoch`. Therefore, the only difference between `[('train', 1), ('val', 1)]` and `[('train', 1)]` is that the runner will calculate losses on validation set after each training epoch.

11.4 Customize hooks

11.4.1 Customize self-implemented hooks

1. Implement a new hook

There are some occasions when the users might need to implement a new hook. MMDetection supports customized hooks in training (#3395) since v2.3.0. Thus the users could implement a hook directly in mmdet or their mmdet-based codebases and use the hook by only modifying the config in training. Before v2.3.0, the users need to modify the code to get the hook registered before training starts. Here we give an example of creating a new hook in mmdet and using it in training.

```
from mmcv.runner import HOOKS, Hook


@HOOKS.register_module()
class MyHook(Hook):

    def __init__(self, a, b):
```

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```
        pass

    def before_run(self, runner):
        pass

    def after_run(self, runner):
        pass

    def before_epoch(self, runner):
        pass

    def after_epoch(self, runner):
        pass

    def before_iter(self, runner):
        pass

    def after_iter(self, runner):
        pass
```

Depending on the functionality of the hook, the users need to specify what the hook will do at each stage of the training in `before_run`, `after_run`, `before_epoch`, `after_epoch`, `before_iter`, and `after_iter`.

2. Register the new hook

Then we need to make `MyHook` imported. Assuming the file is in `mmdet/core/utils/my_hook.py` there are two ways to do that:

- Modify `mmdet/core/utils/__init__.py` to import it.

  The newly defined module should be imported in `mmdet/core/utils/__init__.py` so that the registry will find the new module and add it:

```
from .my_hook import MyHook
```

- Use `custom_imports` in the config to manually import it

```
custom_imports = dict(imports=['mmdet.core.utils.my_hook'], allow_failed_imports=False)
```

3. Modify the config

```
custom_hooks = [
    dict(type='MyHook', a=a_value, b=b_value)
]
```

You can also set the priority of the hook by adding key `priority` to `'NORMAL'` or `'HIGHEST'` as below

```
custom_hooks = [
    dict(type='MyHook', a=a_value, b=b_value, priority='NORMAL')
]
```

By default the hook's priority is set as `NORMAL` during registration.

11.4.2 Use hooks implemented in MMCV

If the hook is already implemented in MMCV, you can directly modify the config to use the hook as below

4. Example: `NumClassCheckHook`

We implement a customized hook named NumClassCheckHook to check whether the `num_classes` in head matches the length of `CLASSES` in `dataset`.

We set it in default_runtime.py.

```
custom_hooks = [dict(type='NumClassCheckHook')]
```

11.4.3 Modify default runtime hooks

There are some common hooks that are not registered through `custom_hooks`, they are

- log_config
- checkpoint_config
- evaluation
- lr_config
- optimizer_config
- momentum_config

In those hooks, only the logger hook has the `VERY_LOW` priority, others' priority are `NORMAL`. The above-mentioned tutorials already covers how to modify `optimizer_config`, `momentum_config`, and `lr_config`. Here we reveals how what we can do with `log_config`, `checkpoint_config`, and `evaluation`.

Checkpoint config

The MMCV runner will use `checkpoint_config` to initialize `CheckpointHook`.

```
checkpoint_config = dict(interval=1)
```

The users could set `max_keep_ckpts` to only save only small number of checkpoints or decide whether to store state dict of optimizer by `save_optimizer`. More details of the arguments are here

Log config

The `log_config` wraps multiple logger hooks and enables to set intervals. Now MMCV supports `WandbLoggerHook`, `MlflowLoggerHook`, and `TensorboardLoggerHook`. The detail usages can be found in the doc.

```
log_config = dict(
    interval=50,
    hooks=[
        dict(type='TextLoggerHook'),
        dict(type='TensorboardLoggerHook')
    ])
```

Evaluation config

The config of `evaluation` will be used to initialize the `EvalHook`. Except the key `interval`, other arguments such as `metric` will be passed to the `dataset.evaluate()`

```
evaluation = dict(interval=1, metric='bbox')
```

CHAPTER

TWELVE

TUTORIAL 6: CUSTOMIZE LOSSES

MMDetection provides users with different loss functions. But the default configuration may be not applicable for different datasets or models, so users may want to modify a specific loss to adapt the new situation.

This tutorial first elaborate the computation pipeline of losses, then give some instructions about how to modify each step. The modification can be categorized as tweaking and weighting.

12.1 Computation pipeline of a loss

Given the input prediction and target, as well as the weights, a loss function maps the input tensor to the final loss scalar. The mapping can be divided into five steps:

1. Set the sampling method to sample positive and negative samples.
2. Get **element-wise** or **sample-wise** loss by the loss kernel function.
3. Weighting the loss with a weight tensor **element-wisely**.
4. Reduce the loss tensor to a **scalar**.
5. Weighting the loss with a **scalar**.

12.2 Set sampling method (step 1)

For some loss functions, sampling strategies are needed to avoid imbalance between positive and negative samples.

For example, when using `CrossEntropyLoss` in RPN head, we need to set `RandomSampler` in `train_cfg`

```
train_cfg=dict(
    rpn=dict(
        sampler=dict(
            type='RandomSampler',
            num=256,
            pos_fraction=0.5,
            neg_pos_ub=-1,
            add_gt_as_proposals=False))
```

For some other losses which have positive and negative sample balance mechanism such as Focal Loss, GHMC, and QualityFocalLoss, the sampler is no more necessary.

12.3 Tweaking loss

Tweaking a loss is more related with step 2, 4, 5, and most modifications can be specified in the config. Here we take Focal Loss (FL) as an example. The following code sniper are the construction method and config of FL respectively, they are actually one to one correspondence.

```
@LOSSES.register_module()
class FocalLoss(nn.Module):

    def __init__(self,
                 use_sigmoid=True,
                 gamma=2.0,
                 alpha=0.25,
                 reduction='mean',
                 loss_weight=1.0):
```

```
loss_cls=dict(
    type='FocalLoss',
    use_sigmoid=True,
    gamma=2.0,
    alpha=0.25,
    loss_weight=1.0)
```

12.3.1 Tweaking hyper-parameters (step 2)

`gamma` and `beta` are two hyper-parameters in the Focal Loss. Say if we want to change the value of `gamma` to be 1.5 and `alpha` to be 0.5, then we can specify them in the config as follows:

```
loss_cls=dict(
    type='FocalLoss',
    use_sigmoid=True,
    gamma=1.5,
    alpha=0.5,
    loss_weight=1.0)
```

12.3.2 Tweaking the way of reduction (step 3)

The default way of reduction is `mean` for FL. Say if we want to change the reduction from `mean` to `sum`, we can specify it in the config as follows:

```
loss_cls=dict(
    type='FocalLoss',
    use_sigmoid=True,
    gamma=2.0,
    alpha=0.25,
    loss_weight=1.0,
    reduction='sum')
```

12.3.3 Tweaking loss weight (step 5)

The loss weight here is a scalar which controls the weight of different losses in multi-task learning, e.g. classification loss and regression loss. Say if we want to change to loss weight of classification loss to be 0.5, we can specify it in the config as follows:

```
loss_cls=dict(
    type='FocalLoss',
    use_sigmoid=True,
    gamma=2.0,
    alpha=0.25,
    loss_weight=0.5)
```

12.4 Weighting loss (step 3)

Weighting loss means we re-weight the loss element-wisely. To be more specific, we multiply the loss tensor with a weight tensor which has the same shape. As a result, different entries of the loss can be scaled differently, and so called element-wisely. The loss weight varies across different models and highly context related, but overall there are two kinds of loss weights, `label_weights` for classification loss and `bbox_weights` for bbox regression loss. You can find them in the `get_target` method of the corresponding head. Here we take ATSSHead as an example, which inherit AnchorHead but overwrite its `get_targets` method which yields different `label_weights` and `bbox_weights`.

```
class ATSSHead(AnchorHead):

    ...

    def get_targets(self,
                    anchor_list,
                    valid_flag_list,
                    gt_bboxes_list,
                    img_metas,
                    gt_bboxes_ignore_list=None,
                    gt_labels_list=None,
                    label_channels=1,
                    unmap_outputs=True):
```

CHAPTER

THIRTEEN

TUTORIAL 7: FINETUNING MODELS

Detectors pre-trained on the COCO dataset can serve as a good pre-trained model for other datasets, e.g., CityScapes and KITTI Dataset. This tutorial provides instruction for users to use the models provided in the *Model Zoo* for other datasets to obtain better performance.

There are two steps to finetune a model on a new dataset.

- Add support for the new dataset following *Tutorial 2: Customize Datasets*.
- Modify the configs as will be discussed in this tutorial.

Take the finetuning process on Cityscapes Dataset as an example, the users need to modify five parts in the config.

13.1 Inherit base configs

To release the burden and reduce bugs in writing the whole configs, MMDetection V2.0 support inheriting configs from multiple existing configs. To finetune a Mask RCNN model, the new config needs to inherit `_base_/models/mask_rcnn_r50_fpn.py` to build the basic structure of the model. To use the Cityscapes Dataset, the new config can also simply inherit `_base_/datasets/cityscapes_instance.py`. For runtime settings such as training schedules, the new config needs to inherit `_base_/default_runtime.py`. This configs are in the `configs` directory and the users can also choose to write the whole contents rather than use inheritance.

```
_base_ = [
    '../_base_/models/mask_rcnn_r50_fpn.py',
    '../_base_/datasets/cityscapes_instance.py', '../_base_/default_runtime.py'
]
```

13.2 Modify head

Then the new config needs to modify the head according to the class numbers of the new datasets. By only changing `num_classes` in the roi_head, the weights of the pre-trained models are mostly reused except the final prediction head.

```
model = dict(
    pretrained=None,
    roi_head=dict(
        bbox_head=dict(
            type='Shared2FCBBoxHead',
            in_channels=256,
            fc_out_channels=1024,
            roi_feat_size=7,
```

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```
            num_classes=8,
            bbox_coder=dict(
                type='DeltaXYWHBBoxCoder',
                target_means=[0., 0., 0., 0.],
                target_stds=[0.1, 0.1, 0.2, 0.2]),
            reg_class_agnostic=False,
            loss_cls=dict(
                type='CrossEntropyLoss', use_sigmoid=False, loss_weight=1.0),
            loss_bbox=dict(type='SmoothL1Loss', beta=1.0, loss_weight=1.0)),
        mask_head=dict(
            type='FCNMaskHead',
            num_convs=4,
            in_channels=256,
            conv_out_channels=256,
            num_classes=8,
            loss_mask=dict(
                type='CrossEntropyLoss', use_mask=True, loss_weight=1.0))))
```

13.3 Modify dataset

The users may also need to prepare the dataset and write the configs about dataset. MMDetection V2.0 already support VOC, WIDER FACE, COCO and Cityscapes Dataset.

13.4 Modify training schedule

The finetuning hyperparameters vary from the default schedule. It usually requires smaller learning rate and less training epochs

```
# optimizer
# lr is set for a batch size of 8
optimizer = dict(type='SGD', lr=0.01, momentum=0.9, weight_decay=0.0001)
optimizer_config = dict(grad_clip=None)
# learning policy
lr_config = dict(
    policy='step',
    warmup='linear',
    warmup_iters=500,
    warmup_ratio=0.001,
    step=[7])
# the max_epochs and step in lr_config need specifically tuned for the customized dataset
runner = dict(max_epochs=8)
log_config = dict(interval=100)
```

13.5 Use pre-trained model

To use the pre-trained model, the new config add the link of pre-trained models in the `load_from`. The users might need to download the model weights before training to avoid the download time during training.

```
load_from = 'https://download.openmmlab.com/mmdetection/v2.0/mask_rcnn/mask_rcnn_r50_
↪caffe_fpn_mstrain-poly_3x_coco/mask_rcnn_r50_caffe_fpn_mstrain-poly_3x_coco_bbox_mAP-0.
↪408__segm_mAP-0.37_20200504_163245-42aa3d00.pth'  # noqa
```

CHAPTER

FOURTEEN

TUTORIAL 8: PYTORCH TO ONNX (EXPERIMENTAL)

14.1 Try the new MMDeploy to deploy your model

14.2 How to convert models from Pytorch to ONNX

14.2.1 Prerequisite

1. Install the prerequisites following *get_started.md/Prepare environment*.
2. Build custom operators for ONNX Runtime and install MMCV manually following How to build custom operators for ONNX Runtime
3. Install MMdetection manually following steps 2-3 in *get_started.md/Install MMdetection*.

14.2.2 Usage

```
python tools/deployment/pytorch2onnx.py \
    ${CONFIG_FILE} \
    ${CHECKPOINT_FILE} \
    --output-file ${OUTPUT_FILE} \
    --input-img ${INPUT_IMAGE_PATH} \
    --shape ${IMAGE_SHAPE} \
    --test-img ${TEST_IMAGE_PATH} \
    --opset-version ${OPSET_VERSION} \
    --cfg-options ${CFG_OPTIONS}
    --dynamic-export \
    --show \
    --verify \
    --simplify \
```

14.2.3 Description of all arguments

- `config` : The path of a model config file.
- `checkpoint` : The path of a model checkpoint file.
- `--output-file`: The path of output ONNX model. If not specified, it will be set to `tmp.onnx`.
- `--input-img`: The path of an input image for tracing and conversion. By default, it will be set to `tests/data/color.jpg`.
- `--shape`: The height and width of input tensor to the model. If not specified, it will be set to `800 1216`.
- `--test-img` : The path of an image to verify the exported ONNX model. By default, it will be set to `None`, meaning it will use `--input-img` for verification.
- `--opset-version` : The opset version of ONNX. If not specified, it will be set to `11`.
- `--dynamic-export`: Determines whether to export ONNX model with dynamic input and output shapes. If not specified, it will be set to `False`.
- `--show`: Determines whether to print the architecture of the exported model and whether to show detection outputs when `--verify` is set to `True`. If not specified, it will be set to `False`.
- `--verify`: Determines whether to verify the correctness of an exported model. If not specified, it will be set to `False`.
- `--simplify`: Determines whether to simplify the exported ONNX model. If not specified, it will be set to `False`.
- `--cfg-options`: Override some settings in the used config file, the key-value pair in `xxx=yyy` format will be merged into config file.
- `--skip-postprocess`: Determines whether export model without post process. If not specified, it will be set to `False`. Notice: This is an experimental option. Only work for some single stage models. Users need to implement the post-process by themselves. We do not guarantee the correctness of the exported model.

Example:

```
python tools/deployment/pytorch2onnx.py \
    configs/yolo/yolov3_d53_mstrain-608_273e_coco.py \
    checkpoints/yolo/yolov3_d53_mstrain-608_273e_coco.pth \
```

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```
    --output-file checkpoints/yolo/yolov3_d53_mstrain-608_273e_coco.onnx \
    --input-img demo/demo.jpg \
    --test-img tests/data/color.jpg \
    --shape 608 608 \
    --show \
    --verify \
    --dynamic-export \
    --cfg-options \
      model.test_cfg.deploy_nms_pre=-1 \
```

14.3 How to evaluate the exported models

We prepare a tool `tools/deplopyment/test.py` to evaluate ONNX models with ONNXRuntime and TensorRT.

14.3.1 Prerequisite

- Install onnx and onnxruntime (CPU version)

```
pip install onnx onnxruntime==1.5.1
```

- If you want to run the model on GPU, please remove the CPU version before using the GPU version.

```
pip uninstall onnxruntime
pip install onnxruntime-gpu
```

  Note: onnxruntime-gpu is version-dependent on CUDA and CUDNN, please ensure that your environment meets the requirements.

- Build custom operators for ONNX Runtime following How to build custom operators for ONNX Runtime
- Install TensorRT by referring to How to build TensorRT plugins in MMCV (optional)

14.3.2 Usage

```
python tools/deployment/test.py \
    ${CONFIG_FILE} \
    ${MODEL_FILE} \
    --out ${OUTPUT_FILE} \
    --backend ${BACKEND} \
    --format-only ${FORMAT_ONLY} \
    --eval ${EVALUATION_METRICS} \
    --show-dir ${SHOW_DIRECTORY} \
    ----show-score-thr ${SHOW_SCORE_THRESHOLD} \
    ----cfg-options ${CFG_OPTIONS} \
    ----eval-options ${EVALUATION_OPTIONS} \
```

14.3.3 Description of all arguments

- `config`: The path of a model config file.
- `model`: The path of an input model file.
- `--out`: The path of output result file in pickle format.
- `--backend`: Backend for input model to run and should be `onnxruntime` or `tensorrt`.
- `--format-only` : Format the output results without perform evaluation. It is useful when you want to format the result to a specific format and submit it to the test server. If not specified, it will be set to `False`.
- `--eval`: Evaluation metrics, which depends on the dataset, e.g., "bbox", "segm", "proposal" for COCO, and "mAP", "recall" for PASCAL VOC.
- `--show-dir`: Directory where painted images will be saved
- `--show-score-thr`: Score threshold. Default is set to `0.3`.
- `--cfg-options`: Override some settings in the used config file, the key-value pair in `xxx=yyy` format will be merged into config file.
- `--eval-options`: Custom options for evaluation, the key-value pair in `xxx=yyy` format will be kwargs for `dataset.evaluate()` function

Notes:

- If the deployed backend platform is TensorRT, please add environment variables before running the file:

```
export ONNX_BACKEND=MMCVTensorRT
```

- If you want to use the `--dynamic-export` parameter in the TensorRT backend to export ONNX, please remove the `--simplify` parameter, and vice versa.

14.3.4 Results and Models

Notes:

- All ONNX models are evaluated with dynamic shape on coco dataset and images are preprocessed according to the original config file. Note that CornerNet is evaluated without test-time flip, since currently only single-scale evaluation is supported with ONNX Runtime.
- Mask AP of Mask R-CNN drops by 1% for ONNXRuntime. The main reason is that the predicted masks are directly interpolated to original image in PyTorch, while they are at first interpolated to the preprocessed input image of the model and then to original image in other backend.

14.4 List of supported models exportable to ONNX

The table below lists the models that are guaranteed to be exportable to ONNX and runnable in ONNX Runtime.

Notes:

- Minimum required version of MMCV is `1.3.5`
- *All models above are tested with Pytorch==1.6.0 and onnxruntime==1.5.1*, except for CornerNet. For more details about the torch version when exporting CornerNet to ONNX, which involves `mmcv::cummax`, please refer to the Known Issues in mmcv.

- Though supported, it is *not recommended* to use batch inference in onnxruntime for `DETR`, because there is huge performance gap between ONNX and torch model (e.g. 33.5 vs 39.9 mAP on COCO for onnxruntime and torch respectively, with a batch size 2). The main reason for the gap is that these is non-negligible effect on the predicted regressions during batch inference for ONNX, since the predicted coordinates is normalized by `img_shape` (without padding) and should be converted to absolute format, but `img_shape` is not dynamically traceable thus the padded `img_shape_for_onnx` is used.
- Currently only single-scale evaluation is supported with ONNX Runtime, also `mmcv::SoftNonMaxSuppression` is only supported for single image by now.

14.5 The Parameters of Non-Maximum Suppression in ONNX Export

In the process of exporting the ONNX model, we set some parameters for the NMS op to control the number of output bounding boxes. The following will introduce the parameter setting of the NMS op in the supported models. You can set these parameters through `--cfg-options`.

- `nms_pre`: The number of boxes before NMS. The default setting is `1000`.
- `deploy_nms_pre`: The number of boxes before NMS when exporting to ONNX model. The default setting is `0`.
- `max_per_img`: The number of boxes to be kept after NMS. The default setting is `100`.
- `max_output_boxes_per_class`: Maximum number of output boxes per class of NMS. The default setting is `200`.

14.6 Reminders

- When the input model has custom op such as `RoIAlign` and if you want to verify the exported ONNX model, you may have to build `mmcv` with ONNXRuntime from source.
- `mmcv.onnx.simplify` feature is based on onnx-simplifier. If you want to try it, please refer to onnx in `mmcv` and onnxruntime op in `mmcv` for more information.
- If you meet any problem with the listed models above, please create an issue and it would be taken care of soon. For models not included in the list, please try to dig a little deeper and debug a little bit more and hopefully solve them by yourself.
- Because this feature is experimental and may change fast, please always try with the latest `mmcv` and `mmdetecion`.

14.7 FAQs

- None

CHAPTER

FIFTEEN

TUTORIAL 9: ONNX TO TENSORRT (EXPERIMENTAL)

15.1 Try the new MMDeploy to deploy your model

15.2 How to convert models from ONNX to TensorRT

15.2.1 Prerequisite

1. Please refer to get_started.md for installation of MMCV and MMDetection from source.
2. Please refer to ONNXRuntime in mmcv and TensorRT plugin in mmcv to install `mmcv-full` with ONNXRuntime custom ops and TensorRT plugins.
3. Use our tool pytorch2onnx to convert the model from PyTorch to ONNX.

15.2.2 Usage

```
python tools/deployment/onnx2tensorrt.py \
    ${CONFIG} \
    ${MODEL} \
    --trt-file ${TRT_FILE} \
    --input-img ${INPUT_IMAGE_PATH} \
    --shape ${INPUT_IMAGE_SHAPE} \
    --min-shape ${MIN_IMAGE_SHAPE} \
    --max-shape ${MAX_IMAGE_SHAPE} \
    --workspace-size {WORKSPACE_SIZE} \
```

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```
    --show \
    --verify \
```

Description of all arguments:

- `config` : The path of a model config file.
- `model` : The path of an ONNX model file.
- `--trt-file`: The Path of output TensorRT engine file. If not specified, it will be set to `tmp.trt`.
- `--input-img` : The path of an input image for tracing and conversion. By default, it will be set to `demo/demo.jpg`.
- `--shape`: The height and width of model input. If not specified, it will be set to `400 600`.
- `--min-shape`: The minimum height and width of model input. If not specified, it will be set to the same as `--shape`.
- `--max-shape`: The maximum height and width of model input. If not specified, it will be set to the same as `--shape`.
- `--workspace-size` : The required GPU workspace size in GiB to build TensorRT engine. If not specified, it will be set to 1 GiB.
- `--show`: Determines whether to show the outputs of the model. If not specified, it will be set to `False`.
- `--verify`: Determines whether to verify the correctness of models between ONNXRuntime and TensorRT. If not specified, it will be set to `False`.
- `--verbose`: Determines whether to print logging messages. It's useful for debugging. If not specified, it will be set to `False`.

Example:

```
python tools/deployment/onnx2tensorrt.py \
    configs/retinanet/retinanet_r50_fpn_1x_coco.py \
    checkpoints/retinanet_r50_fpn_1x_coco.onnx \
    --trt-file checkpoints/retinanet_r50_fpn_1x_coco.trt \
    --input-img demo/demo.jpg \
    --shape 400 600 \
    --show \
    --verify \
```

15.3 How to evaluate the exported models

We prepare a tool `tools/deplopyment/test.py` to evaluate TensorRT models.

Please refer to following links for more information.

- *how-to-evaluate-the-exported-models*
- *results-and-models*

15.4 List of supported models convertible to TensorRT

The table below lists the models that are guaranteed to be convertible to TensorRT.

Notes:

- *All models above are tested with Pytorch==1.6.0, onnx==1.7.0 and TensorRT-7.2.1.6.Ubuntu-16.04.x86_64-gnu.cuda-10.2.cudnn8.0*

15.5 Reminders

- If you meet any problem with the listed models above, please create an issue and it would be taken care of soon. For models not included in the list, we may not provide much help here due to the limited resources. Please try to dig a little deeper and debug by yourself.
- Because this feature is experimental and may change fast, please always try with the latest `mmcv` and `mmdetecion`.

15.6 FAQs

- None

CHAPTER

SIXTEEN

TUTORIAL 10: WEIGHT INITIALIZATION

During training, a proper initialization strategy is beneficial to speeding up the training or obtaining a higher performance. MMCV provide some commonly used methods for initializing modules like `nn.Conv2d`. Model initialization in MMdetection mainly uses `init_cfg`. Users can initialize models with following two steps:

1. Define `init_cfg` for a model or its components in `model_cfg`, but `init_cfg` of children components have higher priority and will override `init_cfg` of parents modules.
2. Build model as usual, but call `model.init_weights()` method explicitly, and model parameters will be initialized as configuration.

The high-level workflow of initialization in MMdetection is :

model_cfg(init_cfg) -> build_from_cfg -> model -> init_weight() -> initialize(self, self.init_cfg) -> children's init_weight()

16.1 Description

It is dict or list[dict], and contains the following keys and values:

- `type` (str), containing the initializer name in `INTIALIZERS`, and followed by arguments of the initializer.
- `layer` (str or list[str]), containing the names of basiclayers in Pytorch or MMCV with learnable parameters that will be initialized, e.g. `'Conv2d'`,`'DeformConv2d'`.
- `override` (dict or list[dict]), containing the sub-modules that not inherit from BaseModule and whose initialization configuration is different from other layers' which are in `'layer'` key. Initializer defined in `type` will work for all layers defined in `layer`, so if sub-modules are not derived Classes of `BaseModule` but can be initialized as same ways of layers in `layer`, it does not need to use `override`. `override` contains:
  - `type` followed by arguments of initializer;
  - `name` to indicate sub-module which will be initialized.

16.2 Initialize parameters

Inherit a new model from `mmcv.runner.BaseModule` or `mmdet.models` Here we show an example of FooModel.

```
import torch.nn as nn
from mmcv.runner import BaseModule

class FooModel(BaseModule)
        def __init__(self,
```

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```
                arg1,
                arg2,
                init_cfg=None):
            super(FooModel, self).__init__(init_cfg)
                ...
```

- Initialize model by using `init_cfg` directly in code

```
import torch.nn as nn
from mmcv.runner import BaseModule
# or directly inherit mmdet models

class FooModel(BaseModule)
        def __init__(self,
                arg1,
                arg2,
                init_cfg=XXX):
                super(FooModel, self).__init__(init_cfg)
            ...
```

- Initialize model by using `init_cfg` directly in `mmcv.Sequential` or `mmcv.ModuleList` code

```
from mmcv.runner import BaseModule, ModuleList

class FooModel(BaseModule)
        def __init__(self,
                    arg1,
                    arg2,
                    init_cfg=None):
                super(FooModel, self).__init__(init_cfg)
            ...
            self.conv1 = ModuleList(init_cfg=XXX)
```

- Initialize model by using `init_cfg` in config file

```
model = dict(
        ...
        model = dict(
            type='FooModel',
            arg1=XXX,
            arg2=XXX,
            init_cfg=XXX),
        ...
```

16.3 Usage of init_cfg

1. Initialize model by `layer` key

   If we only define `layer`, it just initialize the layer in `layer` key.

   NOTE: Value of `layer` key is the class name with attributes weights and bias of Pytorch, (so such as `MultiheadAttention layer` is not supported).

- Define `layer` key for initializing module with same configuration.

```
init_cfg = dict(type='Constant', layer=['Conv1d', 'Conv2d', 'Linear'], val=1)
# initialize whole module with same configuration
```

- Define `layer` key for initializing layer with different configurations.

```
init_cfg = [dict(type='Constant', layer='Conv1d', val=1),
            dict(type='Constant', layer='Conv2d', val=2),
            dict(type='Constant', layer='Linear', val=3)]
# nn.Conv1d will be initialized with dict(type='Constant', val=1)
# nn.Conv2d will be initialized with dict(type='Constant', val=2)
# nn.Linear will be initialized with dict(type='Constant', val=3)
```

2. Initialize model by `override` key

- When initializing some specific part with its attribute name, we can use `override` key, and the value in `override` will ignore the value in init_cfg.

```
# layers
# self.feat = nn.Conv1d(3, 1, 3)
# self.reg = nn.Conv2d(3, 3, 3)
# self.cls = nn.Linear(1,2)

init_cfg = dict(type='Constant',
                layer=['Conv1d','Conv2d'], val=1, bias=2,
                override=dict(type='Constant', name='reg', val=3, bias=4))
# self.feat and self.cls will be initialized with         dict(type='Constant', val=1,
↪ bias=2)
# The module called 'reg' will be initialized with dict(type='Constant', val=3, bias=4)
```

- If `layer` is None in init_cfg, only sub-module with the name in override will be initialized, and type and other args in override can be omitted.

```
# layers
# self.feat = nn.Conv1d(3, 1, 3)
# self.reg = nn.Conv2d(3, 3, 3)
# self.cls = nn.Linear(1,2)

init_cfg = dict(type='Constant', val=1, bias=2,         override=dict(name='reg'))

# self.feat and self.cls will be initialized by Pytorch
# The module called 'reg' will be initialized with dict(type='Constant', val=1, bias=2)
```

- If we don't define `layer` key or `override` key, it will not initialize anything.
- Invalid usage

```
# It is invalid that override don't have name key
init_cfg = dict(type='Constant', layer=['Conv1d','Conv2d'], val=1, bias=2,
                    override=dict(type='Constant', val=3, bias=4))

# It is also invalid that override has name and other args except type
init_cfg = dict(type='Constant', layer=['Conv1d','Conv2d'], val=1, bias=2,
                override=dict(name='reg', val=3, bias=4))
```

3. Initialize model with the pretrained model

```
init_cfg = dict(type='Pretrained',
            checkpoint='torchvision://resnet50')
```

More details can refer to the documentation in MMCV and MMCV PR #780

CHAPTER

SEVENTEEN

TUTORIAL 11: HOW TO XXX

This tutorial collects answers to any `How to xxx with MMDetection`. Feel free to update this doc if you meet new questions about `How to` and find the answers!

17.1 Use backbone network through MMClassification

The model registry in MMDet, MMCls, MMSeg all inherit from the root registry in MMCV. This allows these repositories to directly use the modules already implemented by each other. Therefore, users can use backbone networks from MMClassification in MMDetection without implementing a network that already exists in MMClassification.

17.1.1 Use backbone network implemented in MMClassification

Suppose you want to use `MobileNetV3-small` as the backbone network of `RetinaNet`, the example config is as the following.

```
_base_ = [
    '../_base_/models/retinanet_r50_fpn.py',
    '../_base_/datasets/coco_detection.py',
    '../_base_/schedules/schedule_1x.py', '../_base_/default_runtime.py'
]
# please install mmcls>=0.20.0
# import mmcls.models to trigger register_module in mmcls
custom_imports = dict(imports=['mmcls.models'], allow_failed_imports=False)
pretrained = 'https://download.openmmlab.com/mmclassification/v0/mobilenet_v3/convert/
↪mobilenet_v3_small-8427ecf0.pth'
model = dict(
    backbone=dict(
        _delete_=True, # Delete the backbone field in _base_
        type='mmcls.MobileNetV3', # Using MobileNetV3 from mmcls
        arch='small',
        out_indices=(3, 8, 11), # Modify out_indices
        init_cfg=dict(
            type='Pretrained',
            checkpoint=pretrained,
            prefix='backbone.')), # The pre-trained weights of backbone network in MMCls␣
↪have prefix='backbone.'. The prefix in the keys will be removed so that these weights␣
↪can be normally loaded.
    # Modify in_channels
    neck=dict(in_channels=[24, 48, 96], start_level=0))
```

17.1.2 Use backbone network in TIMM through MMClassification

MMClassification also provides a wrapper for the PyTorch Image Models (timm) backbone network, users can directly use the backbone network in timm through MMClassification. Suppose you want to use EfficientNet-B1 as the backbone network of RetinaNet, the example config is as the following.

```
# https://github.com/open-mmlab/mmdetection/blob/master/configs/timm_example/retinanet_
↪timm_efficientnet_b1_fpn_1x_coco.py

_base_ = [
    '../_base_/models/retinanet_r50_fpn.py',
    '../_base_/datasets/coco_detection.py',
    '../_base_/schedules/schedule_1x.py', '../_base_/default_runtime.py'
]

# please install mmcls>=0.20.0
# import mmcls.models to trigger register_module in mmcls
custom_imports = dict(imports=['mmcls.models'], allow_failed_imports=False)
model = dict(
    backbone=dict(
        _delete_=True, # Delete the backbone field in _base_
        type='mmcls.TIMMBackbone', # Using timm from mmcls
        model_name='efficientnet_b1',
        features_only=True,
        pretrained=True,
        out_indices=(1, 2, 3, 4)), # Modify out_indices
    neck=dict(in_channels=[24, 40, 112, 320])) # Modify in_channels

optimizer = dict(type='SGD', lr=0.01, momentum=0.9, weight_decay=0.0001)
```

`type='mmcls.TIMMBackbone'` means use the `TIMMBackbone` class from MMClassification in MMDetection, and the model used is `EfficientNet-B1`, where `mmcls` means the MMClassification repo and `TIMMBackbone` means the TIMMBackbone wrapper implemented in MMClassification.

For the principle of the Hierarchy Registry, please refer to the MMCV document. For how to use other backbones in MMClassification, you can refer to the MMClassification document.

17.2 Use Mosaic augmentation

If you want to use `Mosaic` in training, please make sure that you use `MultiImageMixDataset` at the same time. Taking the 'Faster R-CNN' algorithm as an example, you should modify the values of `train_pipeline` and `train_dataset` in the config as below:

```
# Open configs/faster_rcnn/faster_rcnn_r50_fpn_1x_coco.py directly and add the following␣
↪fields
data_root = 'data/coco/'
dataset_type = 'CocoDataset'
img_scale=(1333, 800)
img_norm_cfg = dict(
    mean=[123.675, 116.28, 103.53], std=[58.395, 57.12, 57.375], to_rgb=True)

train_pipeline = [
```

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```
    dict(type='Mosaic', img_scale=img_scale, pad_val=114.0),
    dict(
        type='RandomAffine',
        scaling_ratio_range=(0.1, 2),
        border=(-img_scale[0] // 2, -img_scale[1] // 2)), # The image will be enlarged␣
↪by 4 times after Mosaic processing,so we use affine transformation to restore the␣
↪image size.
    dict(type='RandomFlip', flip_ratio=0.5),
    dict(type='Normalize', **img_norm_cfg),
    dict(type='Pad', size_divisor=32),
    dict(type='DefaultFormatBundle'),
    dict(type='Collect', keys=['img', 'gt_bboxes', 'gt_labels'])
]

train_dataset = dict(
    _delete_ = True, # remove unnecessary Settings
    type='MultiImageMixDataset',
    dataset=dict(
        type=dataset_type,
        ann_file=data_root + 'annotations/instances_train2017.json',
        img_prefix=data_root + 'train2017/',
        pipeline=[
            dict(type='LoadImageFromFile'),
            dict(type='LoadAnnotations', with_bbox=True)
        ],
        filter_empty_gt=False,
    ),
    pipeline=train_pipeline
    )

data = dict(
    train=train_dataset
    )
```

17.3 Unfreeze backbone network after freezing the backbone in the config

If you have freezed the backbone network in the config and want to unfreeze it after some epoches, you can write a hook function to do it. Taking the Faster R-CNN with the resnet backbone as an example, you can freeze one stage of the backbone network and add a `custom_hooks` in the config as below:

```
_base_ = [
    '../_base_/models/faster_rcnn_r50_fpn.py',
    '../_base_/datasets/coco_detection.py',
    '../_base_/schedules/schedule_1x.py', '../_base_/default_runtime.py'
]
model = dict(
    # freeze one stage of the backbone network.
    backbone=dict(frozen_stages=1),
```

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```
)
custom_hooks = [dict(type="UnfreezeBackboneEpochBasedHook", unfreeze_epoch=1)]
```

Meanwhile write the hook class UnfreezeBackboneEpochBasedHook in mmdet/core/hook/unfreeze_backbone_epoch_based_hook.py

```
from mmcv.parallel import is_module_wrapper
from mmcv.runner.hooks import HOOKS, Hook


@HOOKS.register_module()
class UnfreezeBackboneEpochBasedHook(Hook):
    """Unfreeze backbone network Hook.

    Args:
        unfreeze_epoch (int): The epoch unfreezing the backbone network.
    """

    def __init__(self, unfreeze_epoch=1):
        self.unfreeze_epoch = unfreeze_epoch

    def before_train_epoch(self, runner):
        # Unfreeze the backbone network.
        # Only valid for resnet.
        if runner.epoch == self.unfreeze_epoch:
            model = runner.model
            if is_module_wrapper(model):
                model = model.module
            backbone = model.backbone
            if backbone.frozen_stages >= 0:
                if backbone.deep_stem:
                    backbone.stem.train()
                    for param in backbone.stem.parameters():
                        param.requires_grad = True
                else:
                    backbone.norm1.train()
                    for m in [backbone.conv1, backbone.norm1]:
                        for param in m.parameters():
                            param.requires_grad = True

            for i in range(1, backbone.frozen_stages + 1):
                m = getattr(backbone, f'layer{i}')
                m.train()
                for param in m.parameters():
                    param.requires_grad = True
```

17.4 Get the channels of a new backbone

If you want to get the channels of a new backbone, you can build this backbone alone and input a pseudo image to get each stage output.

Take `ResNet` as an example:

```
from mmdet.models import ResNet
import torch
self = ResNet(depth=18)
self.eval()
inputs = torch.rand(1, 3, 32, 32)
level_outputs = self.forward(inputs)
for level_out in level_outputs:
    print(tuple(level_out.shape))
```

Output of the above script is as below:

```
(1, 64, 8, 8)
(1, 128, 4, 4)
(1, 256, 2, 2)
(1, 512, 1, 1)
```

Users can get the channels of the new backbone by Replacing the `ResNet(depth=18)` in this script with their customized backbone.

CHAPTER

EIGHTEEN

TUTORIAL 12: TEST RESULTS SUBMISSION

18.1 Panoptic segmentation test results submission

The following sections introduce how to produce the prediction results of panoptic segmentation models on the COCO test-dev set and submit the predictions to COCO evaluation server.

18.1.1 Prerequisites

- Download COCO test dataset images, testing image info, and panoptic train/val annotations, then unzip them, put 'test2017' to `data/coco/`, put json files and annotation files to `data/coco/annotations/`.

```
# suppose data/coco/ does not exist
mkdir -pv data/coco/

# download test2017
wget -P data/coco/ http://images.cocodataset.org/zips/test2017.zip
wget -P data/coco/ http://images.cocodataset.org/annotations/image_info_test2017.zip
wget -P data/coco/ http://images.cocodataset.org/annotations/panoptic_annotations_
↪trainval2017.zip

# unzip them
unzip data/coco/test2017.zip -d data/coco/
unzip data/coco/image_info_test2017.zip -d data/coco/
unzip data/coco/panoptic_annotations_trainval2017.zip -d data/coco/

# remove zip files (optional)
rm -rf data/coco/test2017.zip data/coco/image_info_test2017.zip data/coco/panoptic_
↪annotations_trainval2017.zip
```

- Run the following code to update category information in testing image info. Since the attribute `isthing` is missing in category information of 'image_info_test-dev2017.json', we need to update it with the category information in 'panoptic_val2017.json'.

```
python tools/misc/gen_coco_panoptic_test_info.py data/coco/annotations
```

After completing the above preparations, your directory structure of `data` should be like this:

```
data
`-- coco
    |-- annotations
```

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```
    |   |-- image_info_test-dev2017.json
    |   |-- image_info_test2017.json
    |   |-- panoptic_image_info_test-dev2017.json
    |   |-- panoptic_train2017.json
    |   |-- panoptic_train2017.zip
    |   |-- panoptic_val2017.json
    |   `-- panoptic_val2017.zip
    `-- test2017
```

18.1.2 Inference on coco test-dev

The commands to perform inference on test2017 are as below:

```
# test with single gpu
CUDA_VISIBLE_DEVICES=0 python tools/test.py \
    ${CONFIG_FILE} \
    ${CHECKPOINT_FILE} \
    --format-only \
    --cfg-options data.test.ann_file=data/coco/annotations/panoptic_image_info_test-
↪dev2017.json data.test.img_prefix=data/coco/test2017 \
    --eval-options jsonfile_prefix=${WORK_DIR}/results

# test with four gpus
CUDA_VISIBLE_DEVICES=0,1,3,4 bash tools/dist_test.sh \
    ${CONFIG_FILE} \
    ${CHECKPOINT_FILE} \
    4 \ # four gpus
    --format-only \
    --cfg-options data.test.ann_file=data/coco/annotations/panoptic_image_info_test-
↪dev2017.json data.test.img_prefix=data/coco/test2017 \
    --eval-options jsonfile_prefix=${WORK_DIR}/results

# test with slurm
GPUS=8 tools/slurm_test.sh \
    ${Partition} \
    ${JOB_NAME} \
    ${CONFIG_FILE} \
    ${CHECKPOINT_FILE} \
    --format-only \
    --cfg-options data.test.ann_file=data/coco/annotations/panoptic_image_info_test-
↪dev2017.json data.test.img_prefix=data/coco/test2017 \
    --eval-options jsonfile_prefix=${WORK_DIR}/results
```

Example

Suppose we perform inference on `test2017` using pretrained MaskFormer with ResNet-50 backbone.

```
# test with single gpu
CUDA_VISIBLE_DEVICES=0 python tools/test.py \
    configs/maskformer/maskformer_r50_mstrain_16x1_75e_coco.py \
    checkpoints/maskformer_r50_mstrain_16x1_75e_coco_20220221_141956-bc2699cb.pth \
```

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```
    --format-only \
    --cfg-options data.test.ann_file=data/coco/annotations/panoptic_image_info_test-
↪dev2017.json data.test.img_prefix=data/coco/test2017 \
    --eval-options jsonfile_prefix=work_dirs/maskformer/results
```

18.1.3 Rename files and zip results

After inference, the panoptic segmentation results (a json file and a directory where the masks are stored) will be in `WORK_DIR`. We should rename them according to the naming convention described on COCO's Website. Finally, we need to compress the json and the directory where the masks are stored into a zip file, and rename the zip file according to the naming convention. Note that the zip file should **directly** contains the above two files.

The commands to rename files and zip results:

```
# In WORK_DIR, we have panoptic segmentation results: 'panoptic' and 'results.panoptic.json
↪'.
cd ${WORK_DIR}

# replace '[algorithm_name]' with the name of algorithm you used.
mv ./panoptic ./panoptic_test-dev2017_[algorithm_name]_results
mv ./results.panoptic.json ./panoptic_test-dev2017_[algorithm_name]_results.json
zip panoptic_test-dev2017_[algorithm_name]_results.zip -ur panoptic_test-dev2017_
↪[algorithm_name]_results panoptic_test-dev2017_[algorithm_name]_results.json
```

CHAPTER

NINETEEN

TUTORIAL 13: USEFUL HOOKS

MMDetection and MMCV provide users with various useful hooks including log hooks, evaluation hooks, NumClassCheckHook, etc. This tutorial introduces the functionalities and usages of hooks implemented in MMDetection. For using hooks in MMCV, please read the API documentation in MMCV.

19.1 CheckInvalidLossHook

19.2 EvalHook and DistEvalHook

19.3 ExpMomentumEMAHook and LinearMomentumEMAHook

19.4 NumClassCheckHook

19.5 MemoryProfilerHook

Memory profiler hook records memory information including virtual memory, swap memory, and the memory of the current process. This hook helps grasp the memory usage of the system and discover potential memory leak bugs. To use this hook, users should install `memory_profiler` and `psutil` by `pip install memory_profiler psutil` first.

19.5.1 Usage

To use this hook, users should add the following code to the config file.

```
custom_hooks = [
    dict(type='MemoryProfilerHook', interval=50)
]
```

19.5.2 Result

During training, you can see the messages in the log recorded by `MemoryProfilerHook` as below. The system has 250 GB (246360 MB + 9407 MB) of memory and 8 GB (5740 MB + 2452 MB) of swap memory in total. Currently 9407 MB (4.4%) of memory and 5740 MB (29.9%) of swap memory were consumed. And the current training process consumed 5434 MB of memory.

```
2022-04-21 08:49:56,881 - mmdet - INFO - Memory information available_memory: 246360 MB,␣
↪used_memory: 9407 MB, memory_utilization: 4.4 %, available_swap_memory: 5740 MB, used_
↪swap_memory: 2452 MB, swap_memory_utilization: 29.9 %, current_process_memory: 5434 MB
```

19.6 SetEpochInfoHook

19.7 SyncNormHook

19.8 SyncRandomSizeHook

19.9 YOLOXLrUpdaterHook

19.10 YOLOXModeSwitchHook

19.11 How to implement a custom hook

In general, there are 10 points where hooks can be inserted from the beginning to the end of model training. The users can implement custom hooks and insert them at different points in the process of training to do what they want.

- global points: `before_run`, `after_run`
- points in training: `before_train_epoch`, `before_train_iter`, `after_train_iter`, `after_train_epoch`
- points in validation: `before_val_epoch`, `before_val_iter`, `after_val_iter`, `after_val_epoch`

For example, users can implement a hook to check loss and terminate training when loss goes NaN. To achieve that, there are three steps to go:

1. Implement a new hook that inherits the `Hook` class in MMCV, and implement `after_train_iter` method which checks whether loss goes NaN after every `n` training iterations.
2. The implemented hook should be registered in `HOOKS` by `@HOOKS.register_module()` as shown in the code below.
3. Add `custom_hooks = [dict(type='CheckInvalidLossHook', interval=50)]` in the config file.

```
import torch
from mmcv.runner.hooks import HOOKS, Hook


@HOOKS.register_module()
class CheckInvalidLossHook(Hook):
    """Check invalid loss hook.
    This hook will regularly check whether the loss is valid
```

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```
    during training.
    Args:
        interval (int): Checking interval (every k iterations).
            Default: 50.
    """

    def __init__(self, interval=50):
        self.interval = interval

    def after_train_iter(self, runner):
        if self.every_n_iters(runner, self.interval):
            assert torch.isfinite(runner.outputs['loss']), \
                runner.logger.info('loss become infinite or NaN!')
```

Please read customize_runtime for more about implementing a custom hook.

Apart from training/testing scripts, We provide lots of useful tools under the `tools/` directory.

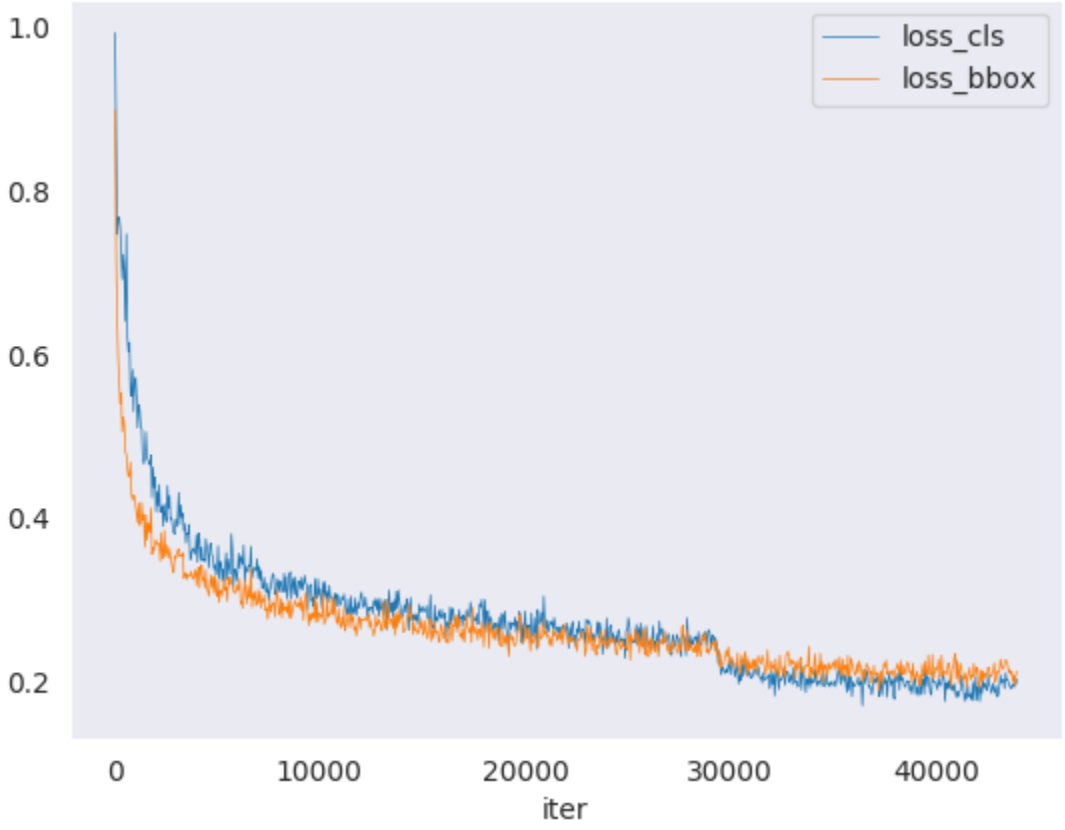
CHAPTER

TWENTY

LOG ANALYSIS

`tools/analysis_tools/analyze_logs.py` plots loss/mAP curves given a training log file. Run `pip install seaborn` first to install the dependency.

```
python tools/analysis_tools/analyze_logs.py plot_curve [--keys ${KEYS}] [--eval-interval
↪${EVALUATION_INTERVAL}] [--title ${TITLE}] [--legend ${LEGEND}] [--backend ${BACKEND}]␣
↪[--style ${STYLE}] [--out ${OUT_FILE}]
```



Examples:

- Plot the classification loss of some run.

```
python tools/analysis_tools/analyze_logs.py plot_curve log.json --keys loss_cls --
↪legend loss_cls
```

- Plot the classification and regression loss of some run, and save the figure to a pdf.

```
python tools/analysis_tools/analyze_logs.py plot_curve log.json --keys loss_cls␣
↪loss_bbox --out losses.pdf
```

- Compare the bbox mAP of two runs in the same figure.

```
python tools/analysis_tools/analyze_logs.py plot_curve log1.json log2.json --keys␣
↪bbox_mAP --legend run1 run2
```

- Compute the average training speed.

```
python tools/analysis_tools/analyze_logs.py cal_train_time log.json [--include-
↪outliers]
```

The output is expected to be like the following.

```
-----Analyze train time of work_dirs/some_exp/20190611_192040.log.json-----
slowest epoch 11, average time is 1.2024
fastest epoch 1, average time is 1.1909
time std over epochs is 0.0028
average iter time: 1.1959 s/iter
```

CHAPTER

TWENTYONE

RESULT ANALYSIS

`tools/analysis_tools/analyze_results.py` calculates single image mAP and saves or shows the topk images with the highest and lowest scores based on prediction results.

Usage

```
python tools/analysis_tools/analyze_results.py \
      ${CONFIG} \
      ${PREDICTION_PATH} \
      ${SHOW_DIR} \
      [--show] \
      [--wait-time ${WAIT_TIME}] \
      [--topk ${TOPK}] \
      [--show-score-thr ${SHOW_SCORE_THR}] \
      [--cfg-options ${CFG_OPTIONS}]
```

Description of all arguments:

- `config` : The path of a model config file.
- `prediction_path`: Output result file in pickle format from `tools/test.py`
- `show_dir`: Directory where painted GT and detection images will be saved
- `--show`Determines whether to show painted images, If not specified, it will be set to `False`
- `--wait-time`: The interval of show (s), 0 is block
- `--topk`: The number of saved images that have the highest and lowest `topk` scores after sorting. If not specified, it will be set to `20`.
- `--show-score-thr`: Show score threshold. If not specified, it will be set to `0`.
- `--cfg-options`: If specified, the key-value pair optional cfg will be merged into config file

Examples:

Assume that you have got result file in pickle format from `tools/test.py` in the path './result.pkl'.

1. Test Faster R-CNN and visualize the results, save images to the directory `results/`

```
python tools/analysis_tools/analyze_results.py \
       configs/faster_rcnn/faster_rcnn_r50_fpn_1x_coco.py \
       result.pkl \
       results \
       --show
```

2. Test Faster R-CNN and specified topk to 50, save images to the directory `results/`

```
python tools/analysis_tools/analyze_results.py \
       configs/faster_rcnn/faster_rcnn_r50_fpn_1x_coco.py \
       result.pkl \
       results \
       --topk 50
```

3. If you want to filter the low score prediction results, you can specify the `show-score-thr` parameter

```
python tools/analysis_tools/analyze_results.py \
       configs/faster_rcnn/faster_rcnn_r50_fpn_1x_coco.py \
       result.pkl \
       results \
       --show-score-thr 0.3
```

CHAPTER

TWENTYTWO

VISUALIZATION

22.1 Visualize Datasets

`tools/misc/browse_dataset.py` helps the user to browse a detection dataset (both images and bounding box annotations) visually, or save the image to a designated directory.

```
python tools/misc/browse_dataset.py ${CONFIG} [-h] [--skip-type ${SKIP_TYPE[SKIP_TYPE...
↪]}] [--output-dir ${OUTPUT_DIR}] [--not-show] [--show-interval ${SHOW_INTERVAL}]
```

22.2 Visualize Models

First, convert the model to ONNX as described here. Note that currently only RetinaNet is supported, support for other models will be coming in later versions. The converted model could be visualized by tools like Netron.

22.3 Visualize Predictions

If you need a lightweight GUI for visualizing the detection results, you can refer DetVisGUI project.

CHAPTER

TWENTYTHREE

ERROR ANALYSIS

`tools/analysis_tools/coco_error_analysis.py` analyzes COCO results per category and by different criterion. It can also make a plot to provide useful information.

```
python tools/analysis_tools/coco_error_analysis.py ${RESULT} ${OUT_DIR} [-h] [--ann ${ANN}] [--types ${TYPES[TYPES...]}]
```

Example:

Assume that you have got Mask R-CNN checkpoint file in the path 'checkpoint'. For other checkpoints, please refer to our *model zoo*. You can use the following command to get the results bbox and segmentation json file.

```
# out: results.bbox.json and results.segm.json
python tools/test.py \
       configs/mask_rcnn/mask_rcnn_r50_fpn_1x_coco.py \
       checkpoint/mask_rcnn_r50_fpn_1x_coco_20200205-d4b0c5d6.pth \
       --format-only \
       --options "jsonfile_prefix=./results"
```

1. Get COCO bbox error results per category , save analyze result images to the directory `results/`

```
python tools/analysis_tools/coco_error_analysis.py \
       results.bbox.json \
       results \
       --ann=data/coco/annotations/instances_val2017.json \
```

2. Get COCO segmentation error results per category , save analyze result images to the directory `results/`

```
python tools/analysis_tools/coco_error_analysis.py \
       results.segm.json \
       results \
       --ann=data/coco/annotations/instances_val2017.json \
       --types='segm'
```

CHAPTER

TWENTYFOUR

MODEL SERVING

In order to serve an `MMDetection` model with TorchServe, you can follow the steps:

24.1 1. Convert model from MMDetection to TorchServe

```
python tools/deployment/mmdet2torchserve.py ${CONFIG_FILE} ${CHECKPOINT_FILE} \
--output-folder ${MODEL_STORE} \
--model-name ${MODEL_NAME}
```

Note: ${MODEL_STORE} needs to be an absolute path to a folder.

24.2 2. Build `mmdet-serve` docker image

```
docker build -t mmdet-serve:latest docker/serve/
```

24.3 3. Run `mmdet-serve`

Check the official docs for running TorchServe with docker.

In order to run in GPU, you need to install nvidia-docker. You can omit the `--gpus` argument in order to run in CPU.

Example:

```
docker run --rm \
--cpus 8 \
--gpus device=0 \
-p8080:8080 -p8081:8081 -p8082:8082 \
--mount type=bind,source=$MODEL_STORE,target=/home/model-server/model-store \
mmdet-serve:latest
```

Read the docs about the Inference (8080), Management (8081) and Metrics (8082) APis

24.4 4. Test deployment

```
curl -O curl -O https://raw.githubusercontent.com/pytorch/serve/master/docs/images/3dogs.
↪jpg
curl http://127.0.0.1:8080/predictions/${MODEL_NAME} -T 3dogs.jpg
```

You should obtain a response similar to:

```
[
  {
    "class_name": "dog",
    "bbox": [
      294.63409423828125,
      203.99111938476562,
      417.048583984375,
      281.62744140625
    ],
    "score": 0.9987992644309998
  },
  {
    "class_name": "dog",
    "bbox": [
      404.26019287109375,
      126.0080795288086,
      574.5091552734375,
      293.6662292480469
    ],
    "score": 0.9979367256164551
  },
  {
    "class_name": "dog",
    "bbox": [
      197.2144775390625,
      93.3067855834961,
      307.8505554199219,
      276.7560119628906
    ],
    "score": 0.993338406085968
  }
]
```

And you can use `test_torchserver.py` to compare result of torchserver and pytorch, and visualize them.

```
python tools/deployment/test_torchserver.py ${IMAGE_FILE} ${CONFIG_FILE} ${CHECKPOINT_
↪FILE} ${MODEL_NAME}
[--inference-addr ${INFERENCE_ADDR}] [--device ${DEVICE}] [--score-thr ${SCORE_THR}]
```

Example:

```
python tools/deployment/test_torchserver.py \
demo/demo.jpg \
configs/yolo/yolov3_d53_320_273e_coco.py \
checkpoint/yolov3_d53_320_273e_coco-421362b6.pth \
```

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```
yolov3
```

CHAPTER

TWENTYFIVE

MODEL COMPLEXITY

`tools/analysis_tools/get_flops.py` is a script adapted from flops-counter.pytorch to compute the FLOPs and params of a given model.

```
python tools/analysis_tools/get_flops.py ${CONFIG_FILE} [--shape ${INPUT_SHAPE}]
```

You will get the results like this.

```
==============================
Input shape: (3, 1280, 800)
Flops: 239.32 GFLOPs
Params: 37.74 M
==============================
```

Note: This tool is still experimental and we do not guarantee that the number is absolutely correct. You may well use the result for simple comparisons, but double check it before you adopt it in technical reports or papers.

1. FLOPs are related to the input shape while parameters are not. The default input shape is (1, 3, 1280, 800).
2. Some operators are not counted into FLOPs like GN and custom operators. Refer to `mmcv.cnn.get_model_complexity_info()` for details.
3. The FLOPs of two-stage detectors is dependent on the number of proposals.

CHAPTER

TWENTYSIX

MODEL CONVERSION

26.1 MMDetection model to ONNX (experimental)

We provide a script to convert model to ONNX format. We also support comparing the output results between Pytorch and ONNX model for verification.

```
python tools/deployment/pytorch2onnx.py ${CONFIG_FILE} ${CHECKPOINT_FILE} --output-file $
↪{ONNX_FILE} [--shape ${INPUT_SHAPE} --verify]
```

Note: This tool is still experimental. Some customized operators are not supported for now. For a detailed description of the usage and the list of supported models, please refer to *pytorch2onnx*.

26.2 MMDetection 1.x model to MMDetection 2.x

`tools/model_converters/upgrade_model_version.py` upgrades a previous MMDetection checkpoint to the new version. Note that this script is not guaranteed to work as some breaking changes are introduced in the new version. It is recommended to directly use the new checkpoints.

```
python tools/model_converters/upgrade_model_version.py ${IN_FILE} ${OUT_FILE} [-h] [--
↪num-classes NUM_CLASSES]
```

26.3 RegNet model to MMDetection

`tools/model_converters/regnet2mmdet.py` convert keys in pycls pretrained RegNet models to MMDetection style.

```
python tools/model_converters/regnet2mmdet.py ${SRC} ${DST} [-h]
```

26.4 Detectron ResNet to Pytorch

`tools/model_converters/detectron2pytorch.py` converts keys in the original detectron pretrained ResNet models to PyTorch style.

```
python tools/model_converters/detectron2pytorch.py ${SRC} ${DST} ${DEPTH} [-h]
```

26.5 Prepare a model for publishing

`tools/model_converters/publish_model.py` helps users to prepare their model for publishing.

Before you upload a model to AWS, you may want to

1. convert model weights to CPU tensors
2. delete the optimizer states and
3. compute the hash of the checkpoint file and append the hash id to the filename.

```
python tools/model_converters/publish_model.py ${INPUT_FILENAME} ${OUTPUT_FILENAME}
```

E.g.,

```
python tools/model_converters/publish_model.py work_dirs/faster_rcnn/latest.pth faster_
↪rcnn_r50_fpn_1x_20190801.pth
```

The final output filename will be `faster_rcnn_r50_fpn_1x_20190801-{hash id}.pth`.

CHAPTER

TWENTYSEVEN

DATASET CONVERSION

tools/data_converters/ contains tools to convert the Cityscapes dataset and Pascal VOC dataset to the COCO format.

```
python tools/dataset_converters/cityscapes.py ${CITYSCAPES_PATH} [-h] [--img-dir ${IMG_
↪DIR}] [--gt-dir ${GT_DIR}] [-o ${OUT_DIR}] [--nproc ${NPROC}]
python tools/dataset_converters/pascal_voc.py ${DEVKIT_PATH} [-h] [-o ${OUT_DIR}]
```

CHAPTER

TWENTYEIGHT

DATASET DOWNLOAD

`tools/misc/download_dataset.py` supports downloading datasets such as COCO, VOC, and LVIS.

```
python tools/misc/download_dataset.py --dataset-name coco2017
python tools/misc/download_dataset.py --dataset-name voc2007
python tools/misc/download_dataset.py --dataset-name lvis
```

CHAPTER

TWENTYNINE

BENCHMARK

29.1 Robust Detection Benchmark

`tools/analysis_tools/test_robustness.py` and`tools/analysis_tools/robustness_eval.py` helps users to evaluate model robustness. The core idea comes from Benchmarking Robustness in Object Detection: Autonomous Driving when Winter is Coming. For more information how to evaluate models on corrupted images and results for a set of standard models please refer to robustness_benchmarking.md.

29.2 FPS Benchmark

`tools/analysis_tools/benchmark.py` helps users to calculate FPS. The FPS value includes model forward and post-processing. In order to get a more accurate value, currently only supports single GPU distributed startup mode.

```
python -m torch.distributed.launch --nproc_per_node=1 --master_port=${PORT} tools/
↪analysis_tools/benchmark.py \
    ${CONFIG} \
    ${CHECKPOINT} \
    [--repeat-num ${REPEAT_NUM}] \
    [--max-iter ${MAX_ITER}] \
    [--log-interval ${LOG_INTERVAL}] \
    --launcher pytorch
```

Examples: Assuming that you have already downloaded the `Faster R-CNN` model checkpoint to the directory `checkpoints/`.

```
python -m torch.distributed.launch --nproc_per_node=1 --master_port=29500 tools/analysis_
↪tools/benchmark.py \
       configs/faster_rcnn/faster_rcnn_r50_fpn_1x_coco.py \
       checkpoints/faster_rcnn_r50_fpn_1x_coco_20200130-047c8118.pth \
       --launcher pytorch
```

CHAPTER

THIRTY

MISCELLANEOUS

30.1 Evaluating a metric

`tools/analysis_tools/eval_metric.py` evaluates certain metrics of a pkl result file according to a config file.

```
python tools/analysis_tools/eval_metric.py ${CONFIG} ${PKL_RESULTS} [-h] [--format-only]␣
↪[--eval ${EVAL[EVAL ...]}]
                      [--cfg-options ${CFG_OPTIONS [CFG_OPTIONS ...]}]
                      [--eval-options ${EVAL_OPTIONS [EVAL_OPTIONS ...]}]
```

30.2 Print the entire config

`tools/misc/print_config.py` prints the whole config verbatim, expanding all its imports.

```
python tools/misc/print_config.py ${CONFIG} [-h] [--options ${OPTIONS [OPTIONS...]}]
```

CHAPTER

THIRTYONE

HYPER-PARAMETER OPTIMIZATION

31.1 YOLO Anchor Optimization

`tools/analysis_tools/optimize_anchors.py` provides two method to optimize YOLO anchors.

One is k-means anchor cluster which refers from darknet.

```
python tools/analysis_tools/optimize_anchors.py ${CONFIG} --algorithm k-means --input-
↪shape ${INPUT_SHAPE [WIDTH HEIGHT]} --output-dir ${OUTPUT_DIR}
```

Another is using differential evolution to optimize anchors.

```
python tools/analysis_tools/optimize_anchors.py ${CONFIG} --algorithm differential_
↪evolution --input-shape ${INPUT_SHAPE [WIDTH HEIGHT]} --output-dir ${OUTPUT_DIR}
```

E.g.,

```
python tools/analysis_tools/optimize_anchors.py configs/yolo/yolov3_d53_320_273e_coco.py␣
↪--algorithm differential_evolution --input-shape 608 608 --device cuda --output-dir␣
↪work_dirs
```

You will get:

```
loading annotations into memory...
Done (t=9.70s)
creating index...
index created!
2021-07-19 19:37:20,951 - mmdet - INFO - Collecting bboxes from annotation...
[>>>>>>>>>>>>>>>>>>>>>>>>>>>>>>>>>>>>>>>>>>>>>>>>>>>>>>>>] 117266/117266, 15874.5 task/s,␣
↪elapsed: 7s, ETA:     0s

2021-07-19 19:37:28,753 - mmdet - INFO - Collected 849902 bboxes.
differential_evolution step 1: f(x)= 0.506055
differential_evolution step 2: f(x)= 0.506055
......

differential_evolution step 489: f(x)= 0.386625
2021-07-19 19:46:40,775 - mmdet - INFO Anchor evolution finish. Average IOU: 0.
↪6133754253387451
2021-07-19 19:46:40,776 - mmdet - INFO Anchor differential evolution result:[[10, 12],␣
↪[15, 30], [32, 22], [29, 59], [61, 46], [57, 116], [112, 89], [154, 198], [349, 336]]
2021-07-19 19:46:40,798 - mmdet - INFO Result saved in work_dirs/anchor_optimize_result.
↪json
```

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CHAPTER

THIRTYTWO

CONFUSION MATRIX

A confusion matrix is a summary of prediction results.

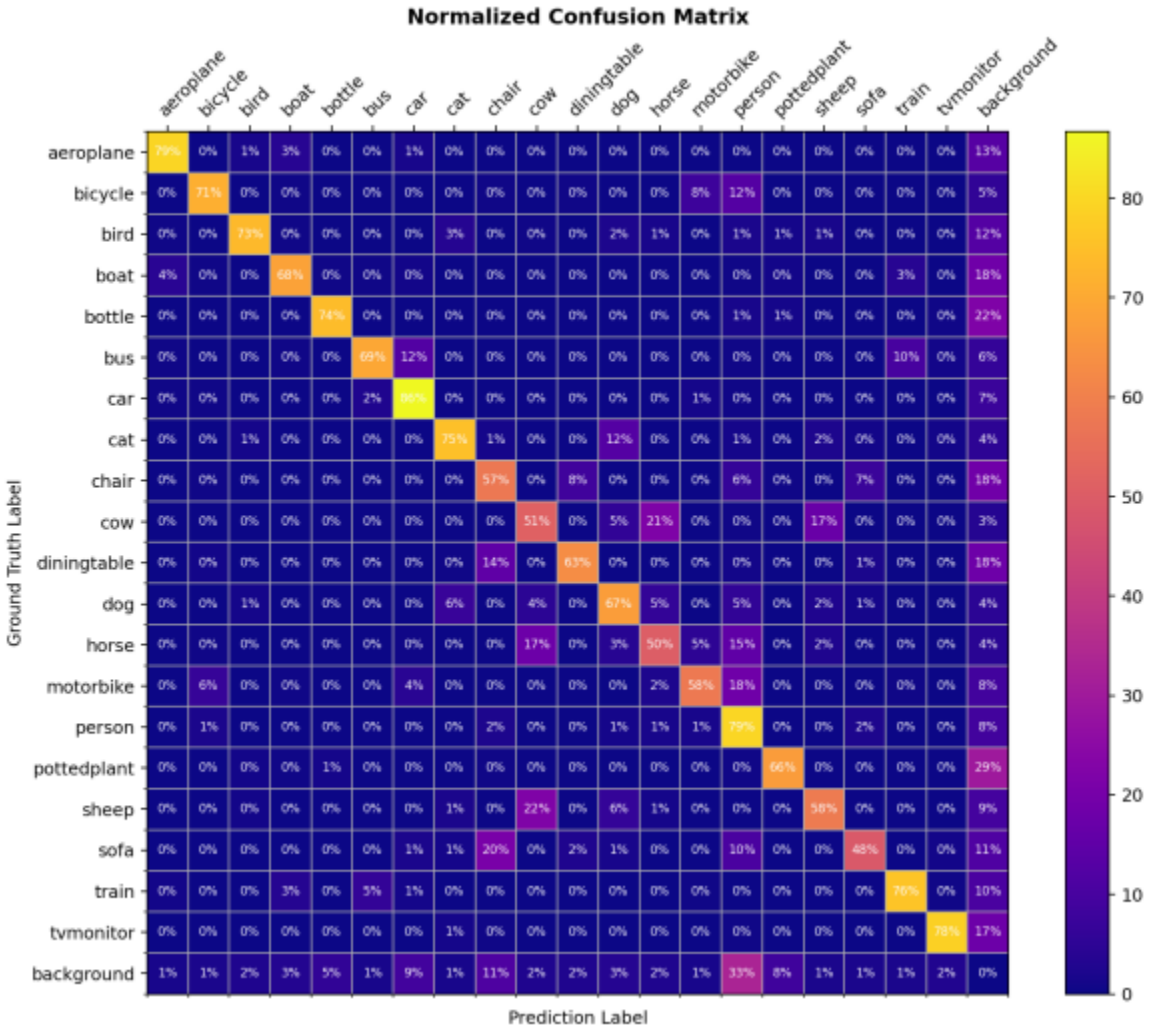
`tools/analysis_tools/confusion_matrix.py` can analyze the prediction results and plot a confusion matrix table.

First, run `tools/test.py` to save the `.pkl` detection results.

Then, run

```
python tools/analysis_tools/confusion_matrix.py ${CONFIG}  ${DETECTION_RESULTS}  ${SAVE_
↪DIR} --show
```

And you will get a confusion matrix like this:


Normalized Confusion Matrix
aeroplane
bicycle
bird
boat
bottle
bus
car
cat
chair
cow
diningtable
dog
horse
motorbike
person
pottedplant
sheep
sofa
train
tvmonitor
background
Ground Truth Label
Prediction Label
80
70
60
50
40
30
20
10
0

CHAPTER

THIRTYTHREE

CONVENTIONS

Please check the following conventions if you would like to modify MMDetection as your own project.

33.1 Loss

In MMDetection, a `dict` containing losses and metrics will be returned by `model(**data)`.

For example, in bbox head,

```
class BBoxHead(nn.Module):
    ...
    def loss(self, ...):
        losses = dict()
        # classification loss
        losses['loss_cls'] = self.loss_cls(...)
        # classification accuracy
        losses['acc'] = accuracy(...)
        # bbox regression loss
        losses['loss_bbox'] = self.loss_bbox(...)
        return losses
```

`bbox_head.loss()` will be called during model forward. The returned dict contains `'loss_bbox'`, `'loss_cls'`, `'acc'` . Only `'loss_bbox'`, `'loss_cls'` will be used during back propagation, `'acc'` will only be used as a metric to monitor training process.

By default, only values whose keys contain `'loss'` will be back propagated. This behavior could be changed by modifying `BaseDetector.train_step()`.

33.2 Empty Proposals

In MMDetection, We have added special handling and unit test for empty proposals of two-stage. We need to deal with the empty proposals of the entire batch and single image at the same time. For example, in CascadeRoIHead,

```
# simple_test method
...
# There is no proposal in the whole batch
if rois.shape[0] == 0:
    bbox_results = [[
        np.zeros((0, 5), dtype=np.float32)
```

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```
        for _ in range(self.bbox_head[-1].num_classes)
    ]] * num_imgs
    if self.with_mask:
        mask_classes = self.mask_head[-1].num_classes
        segm_results = [[[] for _ in range(mask_classes)]
                        for _ in range(num_imgs)]
        results = list(zip(bbox_results, segm_results))
    else:
        results = bbox_results
    return results
...

# There is no proposal in the single image
for i in range(self.num_stages):
    ...
    if i < self.num_stages - 1:
          for j in range(num_imgs):
                  # Handle empty proposal
                  if rois[j].shape[0] > 0:
                      bbox_label = cls_score[j][:, :-1].argmax(dim=1)
                      refine_roi = self.bbox_head[i].regress_by_class(
                           rois[j], bbox_label, bbox_pred[j], img_metas[j])
                      refine_roi_list.append(refine_roi)
```

If you have customized `RoIHead`, you can refer to the above method to deal with empty proposals.

33.3 Coco Panoptic Dataset

In MMDetection, we have supported COCO Panoptic dataset. We clarify a few conventions about the implementation of `CocoPanopticDataset` here.

1. For mmdet<=2.16.0, the range of foreground and background labels in semantic segmentation are different from the default setting of MMDetection. The label `0` stands for `VOID` label and the category labels start from `1`. Since mmdet=2.17.0, the category labels of semantic segmentation start from `0` and label `255` stands for `VOID` for consistency with labels of bounding boxes. To achieve that, the `Pad` pipeline supports setting the padding value for `seg`.
2. In the evaluation, the panoptic result is a map with the same shape as the original image. Each value in the result map has the format of `instance_id * INSTANCE_OFFSET + category_id`.

CHAPTER

THIRTYFOUR

COMPATIBILITY OF MMDETECTION 2.X

34.1 MMDetection 2.25.0

In order to support Mask2Former for instance segmentation, the original config files of Mask2Former for panpotic segmentation need to be renamed PR #7571.

```
'mask2former_xxx_coco.py' represents config files for **panoptic segmentation**.
```

```
'mask2former_xxx_coco.py' represents config files for **instance segmentation**.
'mask2former_xxx_coco-panoptic.py' represents config files for **panoptic segmentation**.
```

34.2 MMDetection 2.21.0

In order to support CPU training, the logic of scatter in batch collating has been changed. We recommend to use MMCV v1.4.4 or higher. For more details, please refer to MMCV PR #1621.

34.3 MMDetection 2.18.1

34.3.1 MMCV compatibility

In order to fix the wrong weight reference bug in BaseTransformerLayer, the logic in batch first mode of MultiheadAttention has been changed. We recommend to use MMCV v1.3.17 or higher. For more details, please refer to MMCV PR #1418.

34.4 MMDetection 2.18.0

34.4.1 DIIHead compatibility

In order to support QueryInst, attn_feats is added into the returned tuple of DIIHead.

34.5 MMDetection 2.14.0

34.5.1 MMCV Version

In order to fix the problem that the priority of EvalHook is too low, all hook priorities have been re-adjusted in 1.3.8, so MMDetection 2.14.0 needs to rely on the latest MMCV 1.3.8 version. For related information, please refer to #1120, for related issues, please refer to #5343.

34.5.2 SSD compatibility

In v2.14.0, to make SSD more flexible to use, PR5291 refactored its backbone, neck and head. The users can use the script `tools/model_converters/upgrade_ssd_version.py` to convert their models.

```
python tools/model_converters/upgrade_ssd_version.py ${OLD_MODEL_PATH} ${NEW_MODEL_PATH}
```

- OLD_MODEL_PATH: the path to load the old version SSD model.
- NEW_MODEL_PATH: the path to save the converted model weights.

34.6 MMDetection 2.12.0

MMDetection is going through big refactoring for more general and convenient usages during the releases from v2.12.0 to v2.18.0 (maybe longer). In v2.12.0 MMDetection inevitably brings some BC-breakings, including the MMCV dependency, model initialization, model registry, and mask AP evaluation.

34.6.1 MMCV Version

MMDetection v2.12.0 relies on the newest features in MMCV 1.3.3, including `BaseModule` for unified parameter initialization, model registry, and the CUDA operator `MultiScaleDeformableAttn` for Deformable DETR. Note that MMCV 1.3.2 already contains all the features used by MMDet but has known issues. Therefore, we recommend users to skip MMCV v1.3.2 and use v1.3.2, though v1.3.2 might work for most of the cases.

34.6.2 Unified model initialization

To unify the parameter initialization in OpenMMLab projects, MMCV supports `BaseModule` that accepts `init_cfg` to allow the modules' parameters initialized in a flexible and unified manner. Now the users need to explicitly call `model.init_weights()` in the training script to initialize the model (as in here, previously this was handled by the detector. **The downstream projects must update their model initialization accordingly to use MMDetection v2.12.0**. Please refer to PR #4750 for details.

34.6.3 Unified model registry

To easily use backbones implemented in other OpenMMLab projects, MMDetection v2.12.0 inherits the model registry created in MMCV (#760). In this way, as long as the backbone is supported in an OpenMMLab project and that project also uses the registry in MMCV, users can use that backbone in MMDetection by simply modifying the config without copying the code of that backbone into MMDetection. Please refer to PR #5059 for more details.

34.6.4 Mask AP evaluation

Before PR 4898 and V2.12.0, the mask AP of small, medium, and large instances is calculated based on the bounding box area rather than the real mask area. This leads to higher `APs` and `APm` but lower `APl` but will not affect the overall mask AP. PR 4898 change it to use mask areas by deleting `bbox` in mask AP calculation. The new calculation does not affect the overall mask AP evaluation and is consistent with Detectron2.

34.7 Compatibility with MMDetection 1.x

MMDetection 2.0 goes through a big refactoring and addresses many legacy issues. It is not compatible with the 1.x version, i.e., running inference with the same model weights in these two versions will produce different results. Thus, MMDetection 2.0 re-benchmarks all the models and provides their links and logs in the model zoo.

The major differences are in four folds: coordinate system, codebase conventions, training hyperparameters, and modular design.

34.7.1 Coordinate System

The new coordinate system is consistent with Detectron2 and treats the center of the most left-top pixel as (0, 0) rather than the left-top corner of that pixel. Accordingly, the system interprets the coordinates in COCO bounding box and segmentation annotations as coordinates in range `[0, width]` or `[0, height]`. This modification affects all the computation related to the bbox and pixel selection, which is more natural and accurate.

- The height and width of a box with corners (x1, y1) and (x2, y2) in the new coordinate system is computed as `width = x2 - x1` and `height = y2 - y1`. In MMDetection 1.x and previous version, a "+ 1" was added both height and width. This modification are in three folds:
  1. Box transformation and encoding/decoding in regression.
  2. IoU calculation. This affects the matching process between ground truth and bounding box and the NMS process. The effect to compatibility is very negligible, though.
  3. The corners of bounding box is in float type and no longer quantized. This should provide more accurate bounding box results. This also makes the bounding box and RoIs not required to have minimum size of 1, whose effect is small, though.
- The anchors are center-aligned to feature grid points and in float type. In MMDetection 1.x and previous version, the anchors are in `int` type and not center-aligned. This affects the anchor generation in RPN and all the anchor-based methods.
- ROIAlign is better aligned with the image coordinate system. The new implementation is adopted from Detectron2. The RoIs are shifted by half a pixel by default when they are used to cropping RoI features, compared to MMDetection 1.x. The old behavior is still available by setting `aligned=False` instead of `aligned=True`.
- Mask cropping and pasting are more accurate.

1. We use the new RoIAlign to crop mask targets. In MMDetection 1.x, the bounding box is quantized before it is used to crop mask target, and the crop process is implemented by numpy. In new implementation, the bounding box for crop is not quantized and sent to RoIAlign. This implementation accelerates the training speed by a large margin (~0.1s per iter, ~2 hour when training Mask R50 for 1x schedule) and should be more accurate.
2. In MMDetection 2.0, the "`paste_mask()`" function is different and should be more accurate than those in previous versions. This change follows the modification in Detectron2 and can improve mask AP on COCO by ~0.5% absolute.

34.7.2 Codebase Conventions

- MMDetection 2.0 changes the order of class labels to reduce unused parameters in regression and mask branch more naturally (without +1 and -1). This effect all the classification layers of the model to have a different ordering of class labels. The final layers of regression branch and mask head no longer keep K+1 channels for K categories, and their class orders are consistent with the classification branch.
  - In MMDetection 2.0, label "K" means background, and labels [0, K-1] correspond to the K = num_categories object categories.
  - In MMDetection 1.x and previous version, label "0" means background, and labels [1, K] correspond to the K categories.
  - **Note**: The class order of softmax RPN is still the same as that in 1.x in versions<=2.4.0 while sigmoid RPN is not affected. The class orders in all heads are unified since MMDetection v2.5.0.
- Low quality matching in R-CNN is not used. In MMDetection 1.x and previous versions, the `max_iou_assigner` will match low quality boxes for each ground truth box in both RPN and R-CNN training. We observe this sometimes does not assign the most perfect GT box to some bounding boxes, thus MMDetection 2.0 do not allow low quality matching by default in R-CNN training in the new system. This sometimes may slightly improve the box AP (~0.1% absolute).
- Separate scale factors for width and height. In MMDetection 1.x and previous versions, the scale factor is a single float in mode `keep_ratio=True`. This is slightly inaccurate because the scale factors for width and height have slight difference. MMDetection 2.0 adopts separate scale factors for width and height, the improvement on AP ~0.1% absolute.
- Configs name conventions are changed. MMDetection V2.0 adopts the new name convention to maintain the gradually growing model zoo as the following:

```
[model]_(model setting)_[backbone]_[neck]_(norm setting)_(misc)_(gpu x batch)_
↪[schedule]_[dataset].py,
```

  where the (`misc`) includes DCN and GCBlock, etc. More details are illustrated in the *documentation for config*
- MMDetection V2.0 uses new ResNet Caffe backbones to reduce warnings when loading pre-trained models. Most of the new backbones' weights are the same as the former ones but do not have `conv.bias`, except that they use a different `img_norm_cfg`. Thus, the new backbone will not cause warning of unexpected keys.

34.7.3 Training Hyperparameters

The change in training hyperparameters does not affect model-level compatibility but slightly improves the performance. The major ones are:

- The number of proposals after nms is changed from 2000 to 1000 by setting `nms_post=1000` and `max_num=1000`. This slightly improves both mask AP and bbox AP by ~0.2% absolute.
- The default box regression losses for Mask R-CNN, Faster R-CNN and RetinaNet are changed from smooth L1 Loss to L1 loss. This leads to an overall improvement in box AP (~0.6% absolute). However, using L1-loss for other methods such as Cascade R-CNN and HTC does not improve the performance, so we keep the original settings for these methods.
- The sample num of RoIAlign layer is set to be 0 for simplicity. This leads to slightly improvement on mask AP (~0.2% absolute).
- The default setting does not use gradient clipping anymore during training for faster training speed. This does not degrade performance of the most of models. For some models such as RepPoints we keep using gradient clipping to stabilize the training process and to obtain better performance.
- The default warmup ratio is changed from 1/3 to 0.001 for a more smooth warming up process since the gradient clipping is usually not used. The effect is found negligible during our re-benchmarking, though.

34.7.4 Upgrade Models from 1.x to 2.0

To convert the models trained by MMDetection V1.x to MMDetection V2.0, the users can use the script `tools/model_converters/upgrade_model_version.py` to convert their models. The converted models can be run in MMDetection V2.0 with slightly dropped performance (less than 1% AP absolute). Details can be found in `configs/legacy`.

34.8 pycocotools compatibility

`mmpycocotools` is the OpenMMlab's fork of official `pycocotools`, which works for both MMDetection and Detectron2. Before PR 4939, since `pycocotools` and `mmpycocotool` have the same package name, if users already installed `pycocotools` (installed Detectron2 first under the same environment), then the setup of MMDetection will skip installing `mmpycocotool`. Thus MMDetection fails due to the missing `mmpycocotools`. If MMDetection is installed before Detectron2, they could work under the same environment. PR 4939 deprecates mmpycocotools in favor of official pycocotools. Users may install MMDetection and Detectron2 under the same environment after PR 4939, no matter what the installation order is.

CHAPTER

THIRTYFIVE

PROJECTS BASED ON MMDETECTION

There are many projects built upon MMDetection. We list some of them as examples of how to extend MMDetection for your own projects. As the page might not be completed, please feel free to create a PR to update this page.

35.1 Projects as an extension

Some projects extend the boundary of MMDetection for deployment or other research fields. They reveal the potential of what MMDetection can do. We list several of them as below.

- OTEDetection: OpenVINO training extensions for object detection.
- MMDetection3d: OpenMMLab's next-generation platform for general 3D object detection.

35.2 Projects of papers

There are also projects released with papers. Some of the papers are published in top-tier conferences (CVPR, ICCV, and ECCV), the others are also highly influential. To make this list also a reference for the community to develop and compare new object detection algorithms, we list them following the time order of top-tier conferences. Methods already supported and maintained by MMDetection are not listed.

- Anchor Pruning for Object Detection, CVIU 2022. [paper][github]
- Involution: Inverting the Inherence of Convolution for Visual Recognition, CVPR21. [paper][github]
- Multiple Instance Active Learning for Object Detection, CVPR 2021. [paper][github]
- Adaptive Class Suppression Loss for Long-Tail Object Detection, CVPR 2021. [paper][github]
- Generalizable Pedestrian Detection: The Elephant In The Room, CVPR2021. [paper][github]
- Group Fisher Pruning for Practical Network Compression, ICML2021. [paper][github]
- Overcoming Classifier Imbalance for Long-tail Object Detection with Balanced Group Softmax, CVPR2020. [paper][github]
- Coherent Reconstruction of Multiple Humans from a Single Image, CVPR2020. [paper][github]
- Look-into-Object: Self-supervised Structure Modeling for Object Recognition, CVPR 2020. [paper][github]
- Video Panoptic Segmentation, CVPR2020. [paper][github]
- D2Det: Towards High Quality Object Detection and Instance Segmentation, CVPR2020. [paper][github]
- CentripetalNet: Pursuing High-quality Keypoint Pairs for Object Detection, CVPR2020. [paper][github]
- Learning a Unified Sample Weighting Network for Object Detection, CVPR 2020. [paper][github]

- Scale-equalizing Pyramid Convolution for Object Detection, CVPR2020. [paper] [github]
- Revisiting the Sibling Head in Object Detector, CVPR2020. [paper][github]
- PolarMask: Single Shot Instance Segmentation with Polar Representation, CVPR2020. [paper][github]
- Hit-Detector: Hierarchical Trinity Architecture Search for Object Detection, CVPR2020. [paper][github]
- ZeroQ: A Novel Zero Shot Quantization Framework, CVPR2020. [paper][github]
- CBNet: A Novel Composite Backbone Network Architecture for Object Detection, AAAI2020. [paper][github]
- RDSNet: A New Deep Architecture for Reciprocal Object Detection and Instance Segmentation, AAAI2020. [paper][github]
- Training-Time-Friendly Network for Real-Time Object Detection, AAAI2020. [paper][github]
- Cascade RPN: Delving into High-Quality Region Proposal Network with Adaptive Convolution, NeurIPS 2019. [paper][github]
- Reasoning R-CNN: Unifying Adaptive Global Reasoning into Large-scale Object Detection, CVPR2019. [paper][github]
- Learning RoI Transformer for Oriented Object Detection in Aerial Images, CVPR2019. [paper][github]
- SOLO: Segmenting Objects by Locations. [paper][github]
- SOLOv2: Dynamic, Faster and Stronger. [paper][github]
- Dense Peppoints: Representing Visual Objects with Dense Point Sets. [paper][github]
- IterDet: Iterative Scheme for Object Detection in Crowded Environments. [paper][github]
- Cross-Iteration Batch Normalization. [paper][github]
- A Ranking-based, Balanced Loss Function Unifying Classification and Localisation in Object Detection, NeurIPS2020 [paper][github]
- RelationNet++: Bridging Visual Representations for Object Detection via Transformer Decoder, NeurIPS2020 [paper][github]
- Generalized Focal Loss V2: Learning Reliable Localization Quality Estimation for Dense Object Detection, CVPR2021[paper][github]
- Swin Transformer: Hierarchical Vision Transformer using Shifted Windows, ICCV2021[paper][github]
- Focal Transformer: Focal Self-attention for Local-Global Interactions in Vision Transformers, NeurIPS2021[paper][github]
- End-to-End Semi-Supervised Object Detection with Soft Teacher, ICCV2021[paper][github]
- CBNetV2: A Novel Composite Backbone Network Architecture for Object Detection [paper][github]
- Instances as Queries, ICCV2021 [paper][github]

CHAPTER

THIRTYSIX

CHANGELOG

36.1 v2.25.1 (29/7/2022)

36.1.1 Bug Fixes

- Fix single GPU distributed training of cuda device specifying (#8176)
- Fix PolygonMask bug in FilterAnnotations (#8136)
- Fix mdformat version to support python3.6 (#8195)
- Fix GPG key error in Dockerfile (#8215)
- Fix `WandbLoggerHook` error (#8273)
- Fix Pytorch 1.10 incompatibility issues (#8439)

36.1.2 Improvements

- Add `mim` to `extras_require` in setup.py (#8194)
- Support get image shape on macOS (#8434)
- Add test commands of `mim` in CI (#8230 & #8240)
- Update `maskformer` to be compatible when cfg is a dictionary (#8263)
- Clean `Pillow` version check in CI (#8229)

36.1.3 Documents

- Change example hook name in tutorials (#8118)
- Update projects (#8120)
- Update metafile and release new models (#8294)
- Add download link in tutorials (#8391)

36.1.4 Contributors

A total of 15 developers contributed to this release. Thanks @ZwwWayne, @ayulockin, @Mxbonn, @p-mishra1, @Youth-Got, @MiXaiLL76, @chhluo, @jbwang1997, @atinfinity, @shinya7y, @duanzhihua, @STLAND-admin, @BIGWangYuDong, @grimoire, @xiaoyuan0203

36.2 v2.25.0 (31/5/2022)

36.2.1 Highlights

- Support dedicated `WandbLogger` hook
- Support ConvNeXt, DDOD, SOLOv2
- Support Mask2Former for instance segmentation
- Rename config files of Mask2Former

36.2.2 Backwards incompatible changes

- Rename config files of Mask2Former (#7571)
  - `mask2former_xxx_coco.py` represents config files for **panoptic segmentation**.
  - `mask2former_xxx_coco.py` represents config files for **instance segmentation**.
  - `mask2former_xxx_coco-panoptic.py` represents config files for **panoptic segmentation**.

36.2.3 New Features

- Support ConvNeXt (#7281)
- Support DDOD (#7279)
- Support SOLOv2 (#7441)
- Support Mask2Former for instance segmentation (#7571, #8032)

36.2.4 Bug Fixes

- Enable YOLOX training on different devices (#7912)
- Fix the log plot error when evaluation with `interval != 1` (#7784)
- Fix RuntimeError of HTC (#8083)

36.2.5 Improvements

- Support dedicated `WandbLogger` hook (#7459)

  Users can set

```
cfg.log_config.hooks = [
  dict(type='MMDetWandbHook',
       init_kwargs={'project': 'MMDetection-tutorial'},
       interval=10,
       log_checkpoint=True,
       log_checkpoint_metadata=True,
       num_eval_images=10)]
```

  in the config to use `MMDetWandbHook`. Example can be found in this colab tutorial

- Add `AvoidOOM` to avoid OOM (#7434, #8091)

  Try to use `AvoidCUDAOOM` to avoid GPU out of memory. It will first retry after calling `torch.cuda.empty_cache()`. If it still fails, it will then retry by converting the type of inputs to FP16 format. If it still fails, it will try to copy inputs from GPUs to CPUs to continue computing. Try AvoidOOM in code to make the code continue to run when GPU memory runs out:

```
from mmdet.utils import AvoidCUDAOOM

output = AvoidCUDAOOM.retry_if_cuda_oom(some_function)(input1, input2)
```

  Users can also try `AvoidCUDAOOM` as a decorator to make the code continue to run when GPU memory runs out:

```
from mmdet.utils import AvoidCUDAOOM

@AvoidCUDAOOM.retry_if_cuda_oom
def function(*args, **kwargs):
    ...
    return xxx
```

- Support reading `gpu_collect` from `cfg.evaluation.gpu_collect` (#7672)
- Speedup the Video Inference by Accelerating data-loading Stage (#7832)
- Support replacing the `${key}` with the value of `cfg.key` (#7492)
- Accelerate result analysis in `analyze_result.py`. The evaluation time is speedup by 10 ~ 15 times and only tasks 10 ~ 15 minutes now. (#7891)
- Support to set `block_dilations` in `DilatedEncoder` (#7812)
- Support panoptic segmentation result analysis (#7922)
- Release DyHead with Swin-Large backbone (#7733)
- Documentations updating and adding
  - Fix wrong default type of `act_cfg` in `SwinTransformer` (#7794)
  - Fix text errors in the tutorials (#7959)
  - Rewrite the installation guide (#7897)
  - Useful hooks (#7810)
  - Fix heading anchor in documentation (#8006)

  - Replace `markdownlint` with `mdformat` for avoiding installing ruby (#8009)

36.2.6 Contributors

A total of 20 developers contributed to this release.

Thanks @ZwwWayne, @DarthThomas, @solyaH, @LutingWang, @chenxinfeng4, @Czm369, @Chenastron, @chhluo, @austinmw, @Shanyaliux @hellock, @Y-M-Y, @jbwang1997, @hhaAndroid, @Irvingao, @zhanggefan, @BIGWangYuDong, @Keiku, @PeterVennerstrom, @ayulockin

36.3 v2.24.0 (26/4/2022)

36.3.1 Highlights

- Support Simple Copy-Paste is a Strong Data Augmentation Method for Instance Segmentation
- Support automatically scaling LR according to GPU number and samples per GPU
- Support Class Aware Sampler that improves performance on OpenImages Dataset

36.3.2 New Features

- Support Simple Copy-Paste is a Strong Data Augmentation Method for Instance Segmentation, see example configs (#7501)
- Support Class Aware Sampler, users can set

```
data=dict(train_dataloader=dict(class_aware_sampler=dict(num_sample_class=1))))
```

  in the config to use `ClassAwareSampler`. Examples can be found in the configs of OpenImages Dataset. (#7436)

- Support automatically scaling LR according to GPU number and samples per GPU. (#7482) In each config, there is a corresponding config of auto-scaling LR as below,

```
auto_scale_lr = dict(enable=True, base_batch_size=N)
```

  where `N` is the batch size used for the current learning rate in the config (also equals to `samples_per_gpu` * gpu number to train this config). By default, we set `enable=False` so that the original usages will not be affected. Users can set `enable=True` in each config or add `--auto-scale-lr` after the command line to enable this feature and should check the correctness of `base_batch_size` in customized configs.

- Support setting dataloader arguments in config and add functions to handle config compatibility. (#7668) The comparison between the old and new usages is as below.

```
data = dict(
    samples_per_gpu=64, workers_per_gpu=4,
    train=dict(type='xxx', ...),
    val=dict(type='xxx', samples_per_gpu=4, ...),
    test=dict(type='xxx', ...),
)
```

```
# A recommended config that is clear
data = dict(
    train=dict(type='xxx', ...),
    val=dict(type='xxx', ...),
    test=dict(type='xxx', ...),
    # Use different batch size during inference.
    train_dataloader=dict(samples_per_gpu=64, workers_per_gpu=4),
    val_dataloader=dict(samples_per_gpu=8, workers_per_gpu=2),
    test_dataloader=dict(samples_per_gpu=8, workers_per_gpu=2),
)

# Old style still works but allows to set more arguments about data loaders
data = dict(
    samples_per_gpu=64,  # only works for train_dataloader
    workers_per_gpu=4,  # only works for train_dataloader
    train=dict(type='xxx', ...),
    val=dict(type='xxx', ...),
    test=dict(type='xxx', ...),
    # Use different batch size during inference.
    val_dataloader=dict(samples_per_gpu=8, workers_per_gpu=2),
    test_dataloader=dict(samples_per_gpu=8, workers_per_gpu=2),
)
```

- Support memory profile hook. Users can use it to monitor the memory usages during training as below (#7560)

```
custom_hooks = [
    dict(type='MemoryProfilerHook', interval=50)
]
```

- Support to run on PyTorch with MLU chip (#7578)
- Support re-spliting data batch with tag (#7641)
- Support the `DiceCost` used by K-Net in `MaskHungarianAssigner` (#7716)
- Support splitting COCO data for Semi-supervised object detection (#7431)
- Support Pathlib for Config.fromfile (#7685)
- Support to use file client in OpenImages dataset (#7433)
- Add a probability parameter to Mosaic transformation (#7371)
- Support specifying interpolation mode in `Resize` pipeline (#7585)

36.3.3 Bug Fixes

- Avoid invalid bbox after deform_sampling (#7567)
- Fix the issue that argument color_theme does not take effect when exporting confusion matrix (#7701)
- Fix the `end_level` in Necks, which should be the index of the end input backbone level (#7502)
- Fix the bug that `mix_results` may be None in `MultiImageMixDataset` (#7530)
- Fix the bug in ResNet plugin when two plugins are used (#7797)

36.3.4 Improvements

- Enhance `load_json_logs` of analyze_logs.py for resumed training logs (#7732)
- Add argument `out_file` in image_demo.py (#7676)
- Allow mixed precision training with `SimOTAAssigner` (#7516)
- Updated INF to 100000.0 to be the same as that in the official YOLOX (#7778)
- Add documentations of:
  - how to get channels of a new backbone (#7642)
  - how to unfreeze the backbone network (#7570)
  - how to train fast_rcnn model (#7549)
  - proposals in Deformable DETR (#7690)
  - from-scratch install script in get_started.md (#7575)
- Release pre-trained models of
  - Mask2Former (#7595, #7709)
  - RetinaNet with ResNet-18 and release models (#7387)
  - RetinaNet with EfficientNet backbone (#7646)

36.3.5 Contributors

A total of 27 developers contributed to this release. Thanks @jovialio, @zhangsanfeng2022, @HarryZJ, @jamiechoi1995, @nestiank, @PeterH0323, @RangeKing, @Y-M-Y, @mattcasey02, @weiji14, @Yulvgit, @xiefeifeihu, @FANG-MING, @meng976537406, @nijkah, @sudz123, @CCODING04, @SheffieldCao, @Czm369, @BIGWangYuDong, @zytx121, @jbwang1997, @chhluo, @jshilong, @RangiLyu, @hhaAndroid, @ZwwWayne

36.4 v2.23.0 (28/3/2022)

36.4.1 Highlights

- Support Mask2Former: Masked-attention Mask Transformer for Universal Image Segmentation
- Support EfficientNet: EfficientNet: Rethinking Model Scaling for Convolutional Neural Networks
- Support setting data root through environment variable `MMDET_DATASETS`, users don't have to modify the corresponding path in config files anymore.
- Find a good recipe for fine-tuning high precision ResNet backbone pre-trained by Torchvision.

36.4.2 New Features

- Support Mask2Former(#6938)(#7466)(#7471)
- Support EfficientNet (#7514)
- Support setting data root through environment variable `MMDET_DATASETS`, users don't have to modify the corresponding path in config files anymore. (#7386)
- Support setting different seeds to different ranks (#7432)
- Update the `dist_train.sh` so that the script can be used to support launching multi-node training on machines without slurm (#7415)
- Find a good recipe for fine-tuning high precision ResNet backbone pre-trained by Torchvision (#7489)

36.4.3 Bug Fixes

- Fix bug in VOC unit test which removes the data directory (#7270)
- Adjust the order of `get_classes` and `FileClient` (#7276)
- Force the inputs of `get_bboxes` in yolox_head to float32 (#7324)
- Fix misplaced arguments in LoadPanopticAnnotations (#7388)
- Fix reduction=mean in CELoss. (#7449)
- Update unit test of CrossEntropyCost (#7537)
- Fix memory leaking in panpotic segmentation evaluation (#7538)
- Fix the bug of shape broadcast in YOLOv3 (#7551)

36.4.4 Improvements

- Add Chinese version of onnx2tensorrt.md (#7219)
- Update colab tutorials (#7310)
- Update information about Localization Distillation (#7350)
- Add Chinese version of `finetune.md` (#7178)
- Update YOLOX log for non square input (#7235)
- Add `nproc` in `coco_panoptic.py` for panoptic quality computing (#7315)
- Allow to set channel_order in LoadImageFromFile (#7258)
- Take point sample related functions out of mask_point_head (#7353)
- Add instance evaluation for coco_panoptic (#7313)
- Enhance the robustness of analyze_logs.py (#7407)
- Supplementary notes of sync_random_seed (#7440)
- Update docstring of cross entropy loss (#7472)
- Update pascal voc result (#7503)
- We create How-to documentation to record any questions about How to xxx. In this version, we added
  - How to use Mosaic augmentation (#7507)

  - How to use backbone in mmcls (#7438)
  - How to produce and submit the prediction results of panoptic segmentation models on COCO test-dev set (#7430))

36.4.5 Contributors

A total of 27 developers contributed to this release. Thanks @ZwwWayne, @haofanwang, @shinya7y, @chhluo, @yangrisheng, @triple-Mu, @jbwang1997, @HikariTJU, @imflash217, @274869388, @zytx121, @matrixgame2018, @jamiechoi1995, @BIGWangYuDong, @JingweiZhang12, @Xiangxu-0103, @hhaAndroid, @jshilong, @osbm, @ceroytres, @bunge-bedstraw-herb, @Youth-Got, @daavoo, @jiangyitong, @RangiLyu, @CCODING04, @yarkable

36.5 v2.22.0 (24/2/2022)

36.5.1 Highlights

- Support MaskFormer: Per-Pixel Classification is Not All You Need for Semantic Segmentation (#7212)
- Support DyHead: Dynamic Head: Unifying Object Detection Heads with Attentions (#6823)
- Release a good recipe of using ResNet in object detectors pre-trained by ResNet Strikes Back, which consistently brings about 3~4 mAP improvements over RetinaNet, Faster/Mask/Cascade Mask R-CNN (#7001)
- Support Open Images Dataset (#6331)
- Support TIMM backbone: PyTorch Image Models (#7020)

36.5.2 New Features

- Support MaskFormer (#7212)
- Support DyHead (#6823)
- Support ResNet Strikes Back (#7001)
- Support OpenImages Dataset (#6331)
- Support TIMM backbone (#7020)
- Support visualization for Panoptic Segmentation (#7041)

36.5.3 Breaking Changes

In order to support the visualization for Panoptic Segmentation, the `num_classes` can not be `None` when using the `get_palette` function to determine whether to use the panoptic palette.

36.5.4 Bug Fixes

- Fix bug for the best checkpoints can not be saved when the `key_score` is None (#7101)
- Fix MixUp transform filter boxes failing case (#7080)
- Add missing properties in SABLHead (#7091)
- Fix bug when NaNs exist in confusion matrix (#7147)
- Fix PALETTE AttributeError in downstream task (#7230)

36.5.5 Improvements

- Speed up SimOTA matching (#7098)
- Add Chinese translation of `docs_zh-CN/tutorials/init_cfg.md` (#7188)

36.5.6 Contributors

A total of 20 developers contributed to this release. Thanks @ZwwWayne, @hhaAndroid, @RangiLyu, @Aron-Lin, @BIGWangYuDong, @jbwang1997, @zytx121, @chhluo, @shinya7y, @LuooChen, @dvansa, @siatwang-min, @del-zhenwu, @vikashranjan26, @haofanwang, @jamiechoi1995, @HJoonKwon, @yarkable, @zhijian-liu, @RangeKing

36.6 v2.21.0 (8/2/2022)

36.7 Breaking Changes

To standardize the contents in config READMEs and meta files of OpenMMLab projects, the READMEs and meta files in each config directory have been significantly changed. The template will be released in the future, for now, you can refer to the examples of README for algorithm, dataset and backbone. To align with the standard, the configs in dcn are put into to two directories named `dcn` and `dcnv2`.

36.7.1 New Features

- Allow to customize colors of different classes during visualization (#6716)
- Support CPU training (#7016)
- Add download script of COCO, LVIS, and VOC dataset (#7015)

36.7.2 Bug Fixes

- Fix weight conversion issue of RetinaNet with Swin-S (#6973)
- Update `__repr__` of `Compose` (#6951)
- Fix BadZipFile Error when build docker (#6966)
- Fix bug in non-distributed multi-gpu training/testing (#7019)
- Fix bbox clamp in PyTorch 1.10 (#7074)
- Relax the requirement of PALETTE in dataset wrappers (#7085)
- Keep the same weights before reassign in the PAA head (#7032)
- Update code demo in doc (#7092)

36.7.3 Improvements

- Speed-up training by allow to set variables of multi-processing (#6974, #7036)
- Add links of Chinese tutorials in readme (#6897)
- Disable cv2 multiprocessing by default for acceleration (#6867)
- Deprecate the support for "python setup.py test" (#6998)
- Re-organize metafiles and config readmes (#7051)
- Fix None grad problem during training TOOD by adding `SigmoidGeometricMean` (#7090)

36.7.4 Contributors

A total of 26 developers contributed to this release. Thanks @del-zhenwu, @zimoqingfeng, @srishilesh, @imyhxy, @jenhaoyang, @jliu-ac, @kimnamu, @ShengliLiu, @garvan2021, @ciusji, @DIYer22, @kimnamu, @q3394101, @zhouzaida, @gaotongxiao, @topsy404, @AntoAndGar, @jbwang1997, @nijkah, @ZwwWayne, @Czm369, @jshilong, @RangiLyu, @BIGWangYuDong, @hhaAndroid, @AronLin

36.8 v2.20.0 (27/12/2021)

36.8.1 New Features

- Support TOOD: Task-aligned One-stage Object Detection (ICCV 2021 Oral) (#6746)
- Support resuming from the latest checkpoint automatically (#6727)

36.8.2 Bug Fixes

- Fix wrong bbox `loss_weight` of the PAA head (#6744)
- Fix the padding value of `gt_semantic_seg` in batch collating (#6837)
- Fix test error of lvis when using `classwise` (#6845)
- Avoid BC-breaking of `get_local_path` (#6719)
- Fix bug in `sync_norm_hook` when the BN layer does not exist (#6852)
- Use pycocotools directly no matter what platform it is (#6838)

36.8.3 Improvements

- Add unit test for SimOTA with no valid bbox (#6770)
- Use precommit to check readme (#6802)
- Support selecting GPU-ids in non-distributed testing time (#6781)

36.8.4 Contributors

A total of 16 developers contributed to this release. Thanks @ZwwWayne, @Czm369, @jshilong, @RangiLyu, @BIGWangYuDong, @hhaAndroid, @jamiechoi1995, @AronLin, @Keiku, @gkagkos, @fcakyon, @www516717402, @vansin, @zactodd, @kimnamu, @jenhaoyang

36.9 v2.19.1 (14/12/2021)

36.9.1 New Features

- Release YOLOX COCO pretrained models (#6698)

36.9.2 Bug Fixes

- Fix DCN initialization in DenseHead (#6625)
- Fix initialization of ConvFCHead (#6624)
- Fix PseudoSampler in RCNN (#6622)
- Fix weight initialization in Swin and PVT (#6663)
- Fix dtype bug in BaseDenseHead (#6767)
- Fix SimOTA with no valid bbox (#6733)

36.9.3 Improvements

- Add an example of combining swin and one-stage models (#6621)
- Add `get_ann_info` to dataset_wrappers (#6526)
- Support keeping image ratio in the multi-scale training of YOLOX (#6732)
- Support `bbox_clip_border` for the augmentations of YOLOX (#6730)

36.9.4 Documents

- Update metafile (#6717)
- Add mmhuman3d in readme (#6699)
- Update FAQ docs (#6587)
- Add doc for `detect_anomalous_params` (#6697)

36.9.5 Contributors

A total of 11 developers contributed to this release. Thanks @ZwwWayne, @LJoson, @Czm369, @jshilong, @ZCMax, @RangiLyu, @BIGWangYuDong, @hhaAndroid, @zhaoxin111, @GT9505, @shinya7y

36.10 v2.19.0 (29/11/2021)

36.10.1 Highlights

- Support Label Assignment Distillation
- Support `persistent_workers` for Pytorch >= 1.7
- Align accuracy to the updated official YOLOX

36.10.2 New Features

- Support Label Assignment Distillation (#6342)
- Support `persistent_workers` for Pytorch >= 1.7 (#6435)

36.10.3 Bug Fixes

- Fix repeatedly output warning message (#6584)
- Avoid infinite GPU waiting in dist training (#6501)
- Fix SSD512 config error (#6574)
- Fix MMDetection model to ONNX command (#6558)

36.10.4 Improvements

- Refactor configs of FP16 models (#6592)
- Align accuracy to the updated official YOLOX (#6443)
- Speed up training and reduce memory cost when using PhotoMetricDistortion. (#6442)
- Make OHEM work with seesaw loss (#6514)

36.10.5 Documents

- Update README.md (#6567)

36.10.6 Contributors

A total of 11 developers contributed to this release. Thanks @FloydHsiu, @RangiLyu, @ZwwWayne, @AndreaPi, @st9007a, @hachreak, @BIGWangYuDong, @hhaAndroid, @AronLin, @chhluo, @vealocia, @HarborYuan, @st9007a, @jshilong

36.11 v2.18.1 (15/11/2021)

36.11.1 Highlights

- Release QueryInst pre-trained weights (#6460)
- Support plot confusion matrix (#6344)

36.11.2 New Features

- Release QueryInst pre-trained weights (#6460)
- Support plot confusion matrix (#6344)

36.11.3 Bug Fixes

- Fix aug test error when the number of prediction bboxes is 0 (#6398)
- Fix SpatialReductionAttention in PVT (#6488)
- Fix wrong use of `trunc_normal_init` in PVT and Swin-Transformer (#6432)

36.11.4 Improvements

- Save the printed AP information of COCO API to logger (#6505)
- Always map location to cpu when load checkpoint (#6405)
- Set a random seed when the user does not set a seed (#6457)

36.11.5 Documents

- Chinese version of Corruption Benchmarking (#6375)
- Fix config path in docs (#6396)
- Update GRoIE readme (#6401)

36.11.6 Contributors

A total of 11 developers contributed to this release. Thanks @st9007a, @hachreak, @HarborYuan, @vealocia, @chhluo, @AndreaPi, @AronLin, @BIGWangYuDong, @hhaAndroid, @RangiLyu, @ZwwWayne

36.12 v2.18.0 (27/10/2021)

36.12.1 Highlights

- Support QueryInst (#6050)
- Refactor dense heads to decouple onnx export logics from `get_bboxes` and speed up inference (#5317, #6003, #6369, #6268, #6315)

36.12.2 New Features

- Support QueryInst (#6050)
- Support infinite sampler (#5996)

36.12.3 Bug Fixes

- Fix init_weight in fcn_mask_head (#6378)
- Fix type error in imshow_bboxes of RPN (#6386)
- Fix broken colab link in MMDetection Tutorial (#6382)
- Make sure the device and dtype of scale_factor are the same as bboxes (#6374)
- Remove sampling hardcode (#6317)
- Fix RandomAffine bbox coordinate recorrection (#6293)
- Fix init bug of final cls/reg layer in convfc head (#6279)
- Fix img_shape broken in auto_augment (#6259)
- Fix kwargs parameter missing error in two_stage (#6256)

36.12.4 Improvements

- Unify the interface of stuff head and panoptic head (#6308)
- Polish readme (#6243)
- Add code-spell pre-commit hook and fix a typo (#6306)
- Fix typo (#6245, #6190)
- Fix sampler unit test (#6284)
- Fix `forward_dummy` of YOLACT to enable `get_flops` (#6079)
- Fix link error in the config documentation (#6252)
- Adjust the order to beautify the document (#6195)

36.12.5 Refactors

- Refactor one-stage get_bboxes logic (#5317)
- Refactor ONNX export of One-Stage models (#6003, #6369)
- Refactor dense_head and speedup (#6268)
- Migrate to use prior_generator in training of dense heads (#6315)

36.12.6 Contributors

A total of 18 developers contributed to this release. Thanks @Boyden, @onnkeat, @st9007a, @vealocia, @yhcao6, @DapangpangX, @yellowdolphin, @cclauss, @kennymckormick, @pingguokiller, @collinzrj, @AndreaPi, @Aron-Lin, @BIGWangYuDong, @hhaAndroid, @jshilong, @RangiLyu, @ZwwWayne

36.13 v2.17.0 (28/9/2021)

36.13.1 Highlights

- Support PVT and PVTv2
- Support SOLO
- Support large scale jittering and New Mask R-CNN baselines
- Speed up `YOLOv3` inference

36.13.2 New Features

- Support PVT and PVTv2 (#5780)
- Support SOLO (#5832)
- Support large scale jittering and New Mask R-CNN baselines (#6132)
- Add a general data structrue for the results of models (#5508)
- Added a base class for one-stage instance segmentation (#5904)

- Speed up YOLOv3 inference (#5991)
- Release Swin Transformer pre-trained models (#6100)
- Support mixed precision training in YOLOX (#5983)
- Support val workflow in YOLACT (#5986)
- Add script to test torchserve (#5936)
- Support onnxsim with dynamic input shape (#6117)

36.13.3 Bug Fixes

- Fix the function naming errors in model_wrappers (#5975)
- Fix regression loss bug when the input is an empty tensor (#5976)
- Fix scores not contiguous error in centernet_head (#6016)
- Fix missing parameters bug in imshow_bboxes (#6034)
- Fix bug in aug_test of HTC when the length of det_bboxes is 0 (#6088)
- Fix empty proposal errors in the training of some two-stage models (#5941)
- Fix dynamic_axes parameter error in ONNX dynamic shape export (#6104)
- Fix dynamic_shape bug of SyncRandomSizeHook (#6144)
- Fix the Swin Transformer config link error in the configuration (#6172)

36.13.4 Improvements

- Add filter rules in Mosaic transform (#5897)
- Add size divisor in get flops to avoid some potential bugs (#6076)
- Add Chinese translation of docs_zh-CN/tutorials/customize_dataset.md (#5915)
- Add Chinese translation of conventions.md (#5825)
- Add description of the output of data pipeline (#5886)
- Add dataset information in the README file for PanopticFPN (#5996)
- Add extra_repr for DropBlock layer to get details in the model printing (#6140)
- Fix CI out of memory and add PyTorch1.9 Python3.9 unit tests (#5862)
- Fix download links error of some model (#6069)
- Improve the generalization of XML dataset (#5943)
- Polish assertion error messages (#6017)
- Remove opencv-python-headless dependency by albumentations (#5868)
- Check dtype in transform unit tests (#5969)
- Replace the default theme of documentation with PyTorch Sphinx Theme (#6146)
- Update the paper and code fields in the metafile (#6043)
- Support to customize padding value of segmentation map (#6152)
- Support to resize multiple segmentation maps (#5747)

36.13.5 Contributors

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36.14 v2.16.0 (30/8/2021)

36.14.1 Highlights

- Support Panoptic FPN and Swin Transformer

36.14.2 New Features

- Support Panoptic FPN and release models (#5577, #5902)
- Support Swin Transformer backbone (#5748)
- Release RetinaNet models pre-trained with multi-scale 3x schedule (#5636)
- Add script to convert unlabeled image list to coco format (#5643)
- Add hook to check whether the loss value is valid (#5674)
- Add YOLO anchor optimizing tool (#5644)
- Support export onnx models without post process. (#5851)
- Support classwise evaluation in CocoPanopticDataset (#5896)
- Adapt browse_dataset for concatenated datasets. (#5935)
- Add `PatchEmbed` and `PatchMerging` with `AdaptivePadding` (#5952)

36.14.3 Bug Fixes

- Fix unit tests of YOLOX (#5859)
- Fix lose randomness in `imshow_det_bboxes` (#5845)
- Make output result of `ImageToTensor` contiguous (#5756)
- Fix inference bug when calling `regress_by_class` in RoIHead in some cases (#5884)
- Fix bug in CIoU loss where alpha should not have gradient. (#5835)
- Fix the bug that `multiscale_output` is defined but not used in HRNet (#5887)
- Set the priority of EvalHook to LOW. (#5882)
- Fix a YOLOX bug when applying bbox rescaling in test mode (#5899)
- Fix mosaic coordinate error (#5947)
- Fix dtype of bbox in RandomAffine. (#5930)

36.14.4 Improvements

- Add Chinese version of `data_pipeline` and (#5662)
- Support to remove state dicts of EMA when publishing models. (#5858)
- Refactor the loss function in HTC and SCNet (#5881)
- Use warnings instead of logger.warning (#5540)
- Use legacy coordinate in metric of VOC (#5627)
- Add Chinese version of customize_losses (#5826)
- Add Chinese version of model_zoo (#5827)

36.14.5 Contributors

A total of 19 developers contributed to this release. Thanks @ypwhs, @zywvvd, @collinzrj, @OceanPang, @ddonatien, @@haotian-liu, @viibridges, @Muyun99, @guigarfr, @zhaojinjian0000, @jbwang1997,@wangbo-zhao, @xvjiarui, @RangiLyu, @jshilong, @AronLin, @BIGWangYuDong, @hhaAndroid, @ZwwWayne

36.15 v2.15.1 (11/8/2021)

36.15.1 Highlights

- Support YOLOX

36.15.2 New Features

- Support YOLOX(#5756, #5758, #5760, #5767, #5770, #5774, #5777, #5808, #5828, #5848)

36.15.3 Bug Fixes

- Update correct SSD models. (#5789)
- Fix casting error in mask structure (#5820)
- Fix MMCV deployment documentation links. (#5790)

36.15.4 Improvements

- Use dynamic MMCV download link in TorchServe dockerfile (#5779)
- Rename the function `upsample_like` to `interpolate_as` for more general usage (#5788)

36.15.5 Contributors

A total of 14 developers contributed to this release. Thanks @HAOCHENYE, @xiaohu2015, @HsLOL, @zhiqwang, @Adamdad, @shinya7y, @Johnson-Wang, @RangiLyu, @jshilong, @mmeendez8, @AronLin, @BIGWangYuDong, @hhaAndroid, @ZwwWayne

36.16 v2.15.0 (02/8/2021)

36.16.1 Highlights

- Support adding MIM dependencies during pip installation
- Support MobileNetV2 for SSD-Lite and YOLOv3
- Support Chinese Documentation

36.16.2 New Features

- Add function `upsample_like` (#5732)
- Support to output pdf and epub format documentation (#5738)
- Support and release Cascade Mask R-CNN 3x pre-trained models (#5645)
- Add `ignore_index` to CrossEntropyLoss (#5646)
- Support adding MIM dependencies during pip installation (#5676)
- Add MobileNetV2 config and models for YOLOv3 (#5510)
- Support COCO Panoptic Dataset (#5231)
- Support ONNX export of cascade models (#5486)
- Support DropBlock with RetinaNet (#5544)
- Support MobileNetV2 SSD-Lite (#5526)

36.16.3 Bug Fixes

- Fix the device of label in multiclass_nms (#5673)
- Fix error of backbone initialization from pre-trained checkpoint in config file (#5603, #5550)
- Fix download links of RegNet pretrained weights (#5655)
- Fix two-stage runtime error given empty proposal (#5559)
- Fix flops count error in DETR (#5654)
- Fix unittest for `NumClassCheckHook` when it is not used. (#5626)
- Fix description bug of using custom dataset (#5546)
- Fix bug of `multiclass_nms` that returns the global indices (#5592)
- Fix `valid_mask` logic error in RPNHead (#5562)
- Fix unit test error of pretrained configs (#5561)
- Fix typo error in anchor_head.py (#5555)

- Fix bug when using dataset wrappers (#5552)
- Fix a typo error in demo/MMDet_Tutorial.ipynb (#5511)
- Fixing crash in `get_root_logger` when `cfg.log_level` is not None (#5521)
- Fix docker version (#5502)
- Fix optimizer parameter error when using `IterBasedRunner` (#5490)

36.16.4 Improvements

- Add unit tests for MMTracking (#5620)
- Add Chinese translation of documentation (#5718, #5618, #5558, #5423, #5593, #5421, #5408. #5369, #5419, #5530, #5531)
- Update resource limit (#5697)
- Update docstring for InstaBoost (#5640)
- Support key `reduction_override` in all loss functions (#5515)
- Use repeatdataset to accelerate CenterNet training (#5509)
- Remove unnecessary code in autoassign (#5519)
- Add documentation about `init_cfg` (#5273)

36.16.5 Contributors

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36.17 v2.14.0 (29/6/2021)

36.17.1 Highlights

- Add `simple_test` to dense heads to improve the consistency of single-stage and two-stage detectors
- Revert the `test_mixins` to single image test to improve efficiency and readability
- Add Faster R-CNN and Mask R-CNN config using multi-scale training with 3x schedule

36.17.2 New Features

- Support pretrained models from MoCo v2 and SwAV (#5286)
- Add Faster R-CNN and Mask R-CNN config using multi-scale training with 3x schedule (#5179, #5233)
- Add `reduction_override` in MSELoss (#5437)
- Stable support of exporting DETR to ONNX with dynamic shapes and batch inference (#5168)
- Stable support of exporting PointRend to ONNX with dynamic shapes and batch inference (#5440)

36.17.3 Bug Fixes

- Fix size mismatch bug in `multiclass_nms` (#4980)
- Fix the import path of `MultiScaleDeformableAttention` (#5338)
- Fix errors in config of GCNet ResNext101 models (#5360)
- Fix Grid-RCNN error when there is no bbox result (#5357)
- Fix errors in `onnx_export` of bbox_head when setting reg_class_agnostic (#5468)
- Fix type error of AutoAssign in the document (#5478)
- Fix web links ending with `.md` (#5315)

36.17.4 Improvements

- Add `simple_test` to dense heads to improve the consistency of single-stage and two-stage detectors (#5264)
- Add support for mask diagonal flip in TTA (#5403)
- Revert the `test_mixins` to single image test to improve efficiency and readability (#5249)
- Make YOLOv3 Neck more flexible (#5218)
- Refactor SSD to make it more general (#5291)
- Refactor `anchor_generator` and `point_generator` (#5349)
- Allow to configure out the `mask_head` of the HTC algorithm (#5389)
- Delete deprecated warning in FPN (#5311)
- Move `model.pretrained` to `model.backbone.init_cfg` (#5370)
- Make deployment tools more friendly to use (#5280)
- Clarify installation documentation (#5316)
- Add ImageNet Pretrained Models docs (#5268)
- Add FAQ about training loss=nan solution and COCO AP or AR =-1 (# 5312, #5313)
- Change all weight links of http to https (#5328)

36.18 v2.13.0 (01/6/2021)

36.18.1 Highlights

- Support new methods: CenterNet, Seesaw Loss, MobileNetV2

36.18.2 New Features

- Support paper Objects as Points (#4602)
- Support paper Seesaw Loss for Long-Tailed Instance Segmentation (CVPR 2021) (#5128)
- Support MobileNetV2 backbone and inverted residual block (#5122)
- Support MIM (#5143)
- ONNX exportation with dynamic shapes of CornerNet (#5136)
- Add `mask_soft` config option to allow non-binary masks (#4615)
- Add PWC metafile (#5135)

36.18.3 Bug Fixes

- Fix YOLOv3 FP16 training error (#5172)
- Fix Cacscade R-CNN TTA test error when `det_bboxes` length is 0 (#5221)
- Fix `iou_thr` variable naming errors in VOC recall calculation function (#5195)
- Fix Faster R-CNN performance dropped in ONNX Runtime (#5197)
- Fix DETR dict changed error when using python 3.8 during iteration (#5226)

36.18.4 Improvements

- Refactor ONNX export of two stage detector (#5205)
- Replace MMDetection's EvalHook with MMCV's EvalHook for consistency (#4806)
- Update RoI extractor for ONNX (#5194)
- Use better parameter initialization in YOLOv3 head for higher performance (#5181)
- Release new DCN models of Mask R-CNN by mixed-precision training (#5201)
- Update YOLOv3 model weights (#5229)
- Add DetectoRS ResNet-101 model weights (#4960)
- Discard bboxes with sizes equals to `min_bbox_size` (#5011)
- Remove duplicated code in DETR head (#5129)
- Remove unnecessary object in class definition (#5180)
- Fix doc link (#5192)

36.19 v2.12.0 (01/5/2021)

36.19.1 Highlights

- Support new methods: AutoAssign, YOLOF, and Deformable DETR
- Stable support of exporting models to ONNX with batched images and dynamic shape (#5039)

36.19.2 Backwards Incompatible Changes

MMDetection is going through big refactoring for more general and convenient usages during the releases from v2.12.0 to v2.15.0 (maybe longer). In v2.12.0 MMDetection inevitably brings some BC-breakings, including the MMCV dependency, model initialization, model registry, and mask AP evaluation.

- MMCV version. MMDetection v2.12.0 relies on the newest features in MMCV 1.3.3, including `BaseModule` for unified parameter initialization, model registry, and the CUDA operator `MultiScaleDeformableAttn` for Deformable DETR. Note that MMCV 1.3.2 already contains all the features used by MMDet but has known issues. Therefore, we recommend users skip MMCV v1.3.2 and use v1.3.3, though v1.3.2 might work for most cases.
- Unified model initialization (#4750). To unify the parameter initialization in OpenMMLab projects, MMCV supports `BaseModule` that accepts `init_cfg` to allow the modules' parameters initialized in a flexible and unified manner. Now the users need to explicitly call `model.init_weights()` in the training script to initialize the model (as in here, previously this was handled by the detector. The models in MMDetection have been re-benchmarked to ensure accuracy based on PR #4750. **The downstream projects should update their code accordingly to use MMDetection v2.12.0**.
- Unified model registry (#5059). To easily use backbones implemented in other OpenMMLab projects, MMDetection migrates to inherit the model registry created in MMCV (#760). In this way, as long as the backbone is supported in an OpenMMLab project and that project also uses the registry in MMCV, users can use that backbone in MMDetection by simply modifying the config without copying the code of that backbone into MMDetection.
- Mask AP evaluation (#4898). Previous versions calculate the areas of masks through the bounding boxes when calculating the mask AP of small, medium, and large instances. To indeed use the areas of masks, we pop the key `bbox` during mask AP calculation. This change does not affect the overall mask AP evaluation and aligns the mask AP of similar models in other projects like Detectron2.

36.19.3 New Features

- Support paper AutoAssign: Differentiable Label Assignment for Dense Object Detection (#4295)
- Support paper You Only Look One-level Feature (#4295)
- Support paper Deformable DETR: Deformable Transformers for End-to-End Object Detection (#4778)
- Support calculating IoU with FP16 tensor in `bbox_overlaps` to save memory and keep speed (#4889)
- Add `__repr__` in custom dataset to count the number of instances (#4756)
- Add windows support by updating requirements.txt (#5052)
- Stable support of exporting models to ONNX with batched images and dynamic shape, including SSD, FSAF,FCOS, YOLOv3, RetinaNet, Faster R-CNN, and Mask R-CNN (#5039)

36.19.4 Improvements

- Use MMCV `MODEL_REGISTRY` (#5059)
- Unified parameter initialization for more flexible usage (#4750)
- Rename variable names and fix docstring in anchor head (#4883)
- Support training with empty GT in Cascade RPN (#4928)
- Add more details of usage of `test_robustness` in documentation (#4917)
- Changing to use `pycocotools` instead of `mmpycocotools` to fully support Detectron2 and MMDetection in one environment (#4939)
- Update torch serve dockerfile to support dockers of more versions (#4954)
- Add check for training with single class dataset (#4973)
- Refactor transformer and DETR Head (#4763)
- Update FPG model zoo (#5079)
- More accurate mask AP of small/medium/large instances (#4898)

36.19.5 Bug Fixes

- Fix bug in mean_ap.py when calculating mAP by 11 points (#4875)
- Fix error when key `meta` is not in old checkpoints (#4936)
- Fix hanging bug when training with empty GT in VFNet, GFL, and FCOS by changing the place of `reduce_mean` (#4923, #4978, #5058)
- Fix asyncronized inference error and provide related demo (#4941)
- Fix IoU losses dimensionality unmatch error (#4982)
- Fix torch.randperm whtn using PyTorch 1.8 (#5014)
- Fix empty bbox error in `mask_head` when using CARAFE (#5062)
- Fix `supplement_mask` bug when there are zero-size RoIs (#5065)
- Fix testing with empty rois in RoI Heads (#5081)

36.20 v2.11.0 (01/4/2021)

Highlights

- Support new method: Localization Distillation for Object Detection
- Support Pytorch2ONNX with batch inference and dynamic shape

New Features

- Support Localization Distillation for Object Detection (#4758)
- Support Pytorch2ONNX with batch inference and dynamic shape for Faster-RCNN and mainstream one-stage detectors (#4796)

Improvements

- Support batch inference in head of RetinaNet (#4699)

- Add batch dimension in second stage of Faster-RCNN (#4785)
- Support batch inference in bbox coder (#4721)
- Add check for `ann_ids` in `COCODataset` to ensure it is unique (#4789)
- support for showing the FPN results (#4716)
- support dynamic shape for grid_anchor (#4684)
- Move pycocotools version check to when it is used (#4880)

Bug Fixes

- Fix a bug of TridentNet when doing the batch inference (#4717)
- Fix a bug of Pytorch2ONNX in FASF (#4735)
- Fix a bug when show the image with float type (#4732)

36.21 v2.10.0 (01/03/2021)

36.21.1 Highlights

- Support new methods: FPG
- Support ONNX2TensorRT for SSD, FSAF, FCOS, YOLOv3, and Faster R-CNN.

36.21.2 New Features

- Support ONNX2TensorRT for SSD, FSAF, FCOS, YOLOv3, and Faster R-CNN (#4569)
- Support Feature Pyramid Grids (FPG) (#4645)
- Support video demo (#4420)
- Add seed option for sampler (#4665)
- Support to customize type of runner (#4570, #4669)
- Support synchronizing BN buffer in `EvalHook` (#4582)
- Add script for GIF demo (#4573)

36.21.3 Bug Fixes

- Fix ConfigDict AttributeError and add Colab link (#4643)
- Avoid crash in empty gt training of GFL head (#4631)
- Fix `iou_thrs` bug in RPN evaluation (#4581)
- Fix syntax error of config when upgrading model version (#4584)

36.21.4 Improvements

- Refactor unit test file structures (#4600)
- Refactor nms config (#4636)
- Get loading pipeline by checking the class directly rather than through config strings (#4619)
- Add doctests for mask target generation and mask structures (#4614)
- Use deep copy when copying pipeline arguments (#4621)
- Update documentations (#4642, #4650, #4620, #4630)
- Remove redundant code calling `import_modules_from_strings` (#4601)
- Clean deprecated FP16 API (#4571)
- Check whether `CLASSES` is correctly initialized in the initialization of `XMLDataset` (#4555)
- Support batch inference in the inference API (#4462, #4526)
- Clean deprecated warning and fix 'meta' error (#4695)

36.22 v2.9.0 (01/02/2021)

36.22.1 Highlights

- Support new methods: SCNet, Sparse R-CNN
- Move `train_cfg` and `test_cfg` into model in configs
- Support to visualize results based on prediction quality

36.22.2 New Features

- Support SCNet (#4356)
- Support Sparse R-CNN (#4219)
- Support evaluate mAP by multiple IoUs (#4398)
- Support concatenate dataset for testing (#4452)
- Support to visualize results based on prediction quality (#4441)
- Add ONNX simplify option to Pytorch2ONNX script (#4468)
- Add hook for checking compatibility of class numbers in heads and datasets (#4508)

36.22.3 Bug Fixes

- Fix CPU inference bug of Cascade RPN (#4410)
- Fix NMS error of CornerNet when there is no prediction box (#4409)
- Fix TypeError in CornerNet inference (#4411)
- Fix bug of PAA when training with background images (#4391)
- Fix the error that the window data is not destroyed when `out_file is not None` and `show==False` (#4442)
- Fix order of NMS `score_factor` that will decrease the performance of YOLOv3 (#4473)
- Fix bug in HTC TTA when the number of detection boxes is 0 (#4516)
- Fix resize error in mask data structures (#4520)

36.22.4 Improvements

- Allow to customize classes in LVIS dataset (#4382)
- Add tutorials for building new models with existing datasets (#4396)
- Add CPU compatibility information in documentation (#4405)
- Add documentation of deprecated `ImageToTensor` for batch inference (#4408)
- Add more details in documentation for customizing dataset (#4430)
- Switch `imshow_det_bboxes` visualization backend from OpenCV to Matplotlib (#4389)
- Deprecate `ImageToTensor` in `image_demo.py` (#4400)
- Move train_cfg/test_cfg into model (#4347, #4489)
- Update docstring for `reg_decoded_bbox` option in bbox heads (#4467)
- Update dataset information in documentation (#4525)
- Release pre-trained R50 and R101 PAA detectors with multi-scale 3x training schedules (#4495)
- Add guidance for speed benchmark (#4537)

36.23 v2.8.0 (04/01/2021)

36.23.1 Highlights

- Support new methods: Cascade RPN, TridentNet

36.23.2 New Features

- Support Cascade RPN (#1900)
- Support TridentNet (#3313)

36.23.3 Bug Fixes

- Fix bug of show result in async_benchmark (#4367)
- Fix scale factor in MaskTestMixin (#4366)
- Fix but when returning indices in `multiclass_nms` (#4362)
- Fix bug of empirical attention in resnext backbone error (#4300)
- Fix bug of `img_norm_cfg` in FCOS-HRNet models with updated performance and models (#4250)
- Fix invalid checkpoint and log in Mask R-CNN models on Cityscapes dataset (#4287)
- Fix bug in distributed sampler when dataset is too small (#4257)
- Fix bug of 'PAFPN has no attribute extra_convs_on_inputs' (#4235)

36.23.4 Improvements

- Update model url from aws to aliyun (#4349)
- Update ATSS for PyTorch 1.6+ (#4359)
- Update script to install ruby in pre-commit installation (#4360)
- Delete deprecated `mmdet.ops` (#4325)
- Refactor hungarian assigner for more general usage in Sparse R-CNN (#4259)
- Handle scipy import in DETR to reduce package dependencies (#4339)
- Update documentation of usages for config options after MMCV (1.2.3) supports overriding list in config (#4326)
- Update pre-train models of faster rcnn trained on COCO subsets (#4307)
- Avoid zero or too small value for beta in Dynamic R-CNN (#4303)
- Add doccumentation for Pytorch2ONNX (#4271)
- Add deprecated warning FPN arguments (#4264)
- Support returning indices of kept bboxes when using nms (#4251)
- Update type and device requirements when creating tensors `GFLHead` (#4210)
- Update device requirements when creating tensors in `CrossEntropyLoss` (#4224)

36.24 v2.7.0 (30/11/2020)

- Support new method: DETR, ResNest, Faster R-CNN DC5.
- Support YOLO, Mask R-CNN, and Cascade R-CNN models exportable to ONNX.

36.24.1 New Features

- Support DETR (#4201, #4206)
- Support to link the best checkpoint in training (#3773)
- Support to override config through options in inference.py (#4175)
- Support YOLO, Mask R-CNN, and Cascade R-CNN models exportable to ONNX (#4087, #4083)
- Support ResNeSt backbone (#2959)
- Support unclip border bbox regression (#4076)
- Add tpfp func in evaluating AP (#4069)
- Support mixed precision training of SSD detector with other backbones (#4081)
- Add Faster R-CNN DC5 models (#4043)

36.24.2 Bug Fixes

- Fix bug of `gpu_id` in distributed training mode (#4163)
- Support Albumentations with version higher than 0.5 (#4032)
- Fix num_classes bug in faster rcnn config (#4088)
- Update code in docs/2_new_data_model.md (#4041)

36.24.3 Improvements

- Ensure DCN offset to have similar type as features in VFNet (#4198)
- Add config links in README files of models (#4190)
- Add tutorials for loss conventions (#3818)
- Add solution to installation issues in 30-series GPUs (#4176)
- Update docker version in get_started.md (#4145)
- Add model statistics and polish some titles in configs README (#4140)
- Clamp neg probability in FreeAnchor (#4082)
- Speed up expanding large images (#4089)
- Fix Pytorch 1.7 incompatibility issues (#4103)
- Update trouble shooting page to resolve segmentation fault (#4055)
- Update aLRP-Loss in project page (#4078)
- Clean duplicated `reduce_mean` function (#4056)
- Refactor Q&A (#4045)

36.25 v2.6.0 (1/11/2020)

- Support new method: VarifocalNet.
- Refactored documentation with more tutorials.

36.25.1 New Features

- Support GIoU calculation in `BboxOverlaps2D`, and re-implement `giou_loss` using `bbox_overlaps` (#3936)
- Support random sampling in CPU mode (#3948)
- Support VarifocalNet (#3666, #4024)

36.25.2 Bug Fixes

- Fix SABL validating bug in Cascade R-CNN (#3913)
- Avoid division by zero in PAA head when num_pos=0 (#3938)
- Fix temporary directory bug of multi-node testing error (#4034, #4017)
- Fix `--show-dir` option in test script (#4025)
- Fix GA-RetinaNet r50 model url (#3983)
- Update code in docs and fix broken urls (#3947)

36.25.3 Improvements

- Refactor pytorch2onnx API into `mmdet.core.export` and use `generate_inputs_and_wrap_model` for pytorch2onnx (#3857, #3912)
- Update RPN upgrade scripts for v2.5.0 compatibility (#3986)
- Use mmcv `tensor2imgs` (#4010)
- Update test robustness (#4000)
- Update trouble shooting page (#3994)
- Accelerate PAA training speed (#3985)
- Support batch_size > 1 in validation (#3966)
- Use RoIAlign implemented in MMCV for inference in CPU mode (#3930)
- Documentation refactoring (#4031)

36.26 v2.5.0 (5/10/2020)

36.26.1 Highlights

- Support new methods: YOLACT, CentripetalNet.
- Add more documentations for easier and more clear usage.

36.26.2 Backwards Incompatible Changes

FP16 related methods are imported from mmcv instead of mmdet. (#3766, #3822) Mixed precision training utils in `mmdet.core.fp16` are moved to `mmcv.runner`, including `force_fp32`, `auto_fp16`, `wrap_fp16_model`, and `Fp16OptimizerHook`. A deprecation warning will be raised if users attempt to import those methods from `mmdet.core.fp16`, and will be finally removed in V2.10.0.

[0, N-1] represents foreground classes and N indicates background classes for all models. (#3221) Before v2.5.0, the background label for RPN is 0, and N for other heads. Now the behavior is consistent for all models. Thus `self.background_labels` in `dense_heads` is removed and all heads use `self.num_classes` to indicate the class index of background labels. This change has no effect on the pre-trained models in the v2.x model zoo, but will affect the training of all models with RPN heads. Two-stage detectors whose RPN head uses softmax will be affected because the order of categories is changed.

Only call `get_subset_by_classes` when `test_mode=True` and `self.filter_empty_gt=True` (#3695) Function `get_subset_by_classes` in dataset is refactored and only filters out images when `test_mode=True` and `self.filter_empty_gt=True`. In the original implementation, `get_subset_by_classes` is not related to the flag `self.filter_empty_gt` and will only be called when the classes is set during initialization no matter `test_mode` is `True` or `False`. This brings ambiguous behavior and potential bugs in many cases. After v2.5.0, if `filter_empty_gt=False`, no matter whether the classes are specified in a dataset, the dataset will use all the images in the annotations. If `filter_empty_gt=True` and `test_mode=True`, no matter whether the classes are specified, the dataset will call ``get_subset_by_classes` to check the images and filter out images containing no GT boxes. Therefore, the users should be responsible for the data filtering/cleaning process for the test dataset.

36.26.3 New Features

- Test time augmentation for single stage detectors (#3844, #3638)
- Support to show the name of experiments during training (#3764)
- Add `Shear`, `Rotate`, `Translate` Augmentation (#3656, #3619, #3687)
- Add image-only transformations including `Constrast`, `Equalize`, `Color`, and `Brightness`. (#3643)
- Support YOLACT (#3456)
- Support CentripetalNet (#3390)
- Support PyTorch 1.6 in docker (#3905)

36.26.4 Bug Fixes

- Fix the bug of training ATSS when there is no ground truth boxes (#3702)
- Fix the bug of using Focal Loss when there is `num_pos` is 0 (#3702)
- Fix the label index mapping in dataset browser (#3708)
- Fix Mask R-CNN training stuck problem when their is no positive rois (#3713)
- Fix the bug of `self.rpn_head.test_cfg` in `RPNTestMixin` by using `self.rpn_head` in rpn head (#3808)
- Fix deprecated `Conv2d` from mmcv.ops (#3791)
- Fix device bug in RepPoints (#3836)
- Fix SABL validating bug (#3849)
- Use `https://download.openmmlab.com/mmcv/dist/index.html` for installing MMCV (#3840)
- Fix nonzero in NMS for PyTorch 1.6.0 (#3867)
- Fix the API change bug of PAA (#3883)
- Fix typo in bbox_flip (#3886)
- Fix cv2 import error of ligGL.so.1 in Dockerfile (#3891)

36.26.5 Improvements

- Change to use `mmcv.utils.collect_env` for collecting environment information to avoid duplicate codes (#3779)
- Update checkpoint file names to v2.0 models in documentation (#3795)
- Update tutorials for changing runtime settings (#3778), modifying loss (#3777)
- Improve the function of `simple_test_bboxes` in SABL (#3853)
- Convert mask to bool before using it as img's index for robustness and speedup (#3870)
- Improve documentation of modules and dataset customization (#3821)

36.27 v2.4.0 (5/9/2020)

Highlights

- Fix lots of issues/bugs and reorganize the trouble shooting page
- Support new methods SABL, YOLOv3, and PAA Assign
- Support Batch Inference
- Start to publish `mmdet` package to PyPI since v2.3.0
- Switch model zoo to download.openmmlab.com

Backwards Incompatible Changes

- Support Batch Inference (#3564, #3686, #3705): Since v2.4.0, MMDetection could inference model with multiple images in a single GPU. This change influences all the test APIs in MMDetection and downstream codebases. To help the users migrate their code, we use `replace_ImageToTensor` (#3686) to convert legacy test data pipelines during dataset initialization.

- Support RandomFlip with horizontal/vertical/diagonal direction (#3608): Since v2.4.0, MMDetection supports horizontal/vertical/diagonal flip in the data augmentation. This influences bounding box, mask, and image transformations in data augmentation process and the process that will map those data back to the original format.
- Migrate to use `mmlvis` and `mmpycocotools` for COCO and LVIS dataset (#3727). The APIs are fully compatible with the original `lvis` and `pycocotools`. Users need to uninstall the existing pycocotools and lvis packages in their environment first and install `mmlvis` & `mmpycocotools`.

Bug Fixes

- Fix default mean/std for onnx (#3491)
- Fix coco evaluation and add metric items (#3497)
- Fix typo for install.md (#3516)
- Fix atss when sampler per gpu is 1 (#3528)
- Fix import of fuse_conv_bn (#3529)
- Fix bug of gaussian_target, update unittest of heatmap (#3543)
- Fixed VOC2012 evaluate (#3553)
- Fix scale factor bug of rescale (#3566)
- Fix with_xxx_attributes in base detector (#3567)
- Fix boxes scaling when number is 0 (#3575)
- Fix rfp check when neck config is a list (#3591)
- Fix import of fuse conv bn in benchmark.py (#3606)
- Fix webcam demo (#3634)
- Fix typo and itemize issues in tutorial (#3658)
- Fix error in distributed training when some levels of FPN are not assigned with bounding boxes (#3670)
- Fix the width and height orders of stride in valid flag generation (#3685)
- Fix weight initialization bug in Res2Net DCN (#3714)
- Fix bug in OHEMSampler (#3677)

New Features

- Support Cutout augmentation (#3521)
- Support evaluation on multiple datasets through ConcatDataset (#3522)
- Support PAA assign #(3547)
- Support eval metric with pickle results (#3607)
- Support YOLOv3 (#3083)
- Support SABL (#3603)
- Support to publish to Pypi in github-action (#3510)
- Support custom imports (#3641)

Improvements

- Refactor common issues in documentation (#3530)
- Add pytorch 1.6 to CI config (#3532)

- Add config to runner meta (#3534)
- Add eval-option flag for testing (#3537)
- Add init_eval to evaluation hook (#3550)
- Add include_bkg in ClassBalancedDataset (#3577)
- Using config's loading in inference_detector (#3611)
- Add ATSS ResNet-101 models in model zoo (#3639)
- Update urls to download.openmmlab.com (#3665)
- Support non-mask training for CocoDataset (#3711)

36.28 v2.3.0 (5/8/2020)

Highlights

- The CUDA/C++ operators have been moved to `mmcv.ops`. For backward compatibility `mmdet.ops` is kept as warppers of `mmcv.ops`.
- Support new methods CornerNet, DIOU/CIOU loss, and new dataset: LVIS V1
- Provide more detailed colab training tutorials and more complete documentation.
- Support to convert RetinaNet from Pytorch to ONNX.

Bug Fixes

- Fix the model initialization bug of DetectoRS (#3187)
- Fix the bug of module names in NASFCOSHead (#3205)
- Fix the filename bug in publish_model.py (#3237)
- Fix the dimensionality bug when `inside_flags.any()` is `False` in dense heads (#3242)
- Fix the bug of forgetting to pass flip directions in `MultiScaleFlipAug` (#3262)
- Fixed the bug caused by default value of `stem_channels` (#3333)
- Fix the bug of model checkpoint loading for CPU inference (#3318, #3316)
- Fix topk bug when box number is smaller than the expected topk number in ATSSAssigner (#3361)
- Fix the gt priority bug in center_region_assigner.py (#3208)
- Fix NaN issue of iou calculation in iou_loss.py (#3394)
- Fix the bug that `iou_thrs` is not actually used during evaluation in coco.py (#3407)
- Fix test-time augmentation of RepPoints (#3435)
- Fix runtimeError caused by incontiguous tensor in Res2Net+DCN (#3412)

New Features

- Support CornerNet (#3036)
- Support DIOU/CIOU loss (#3151)
- Support LVIS V1 dataset (#)
- Support customized hooks in training (#3395)
- Support fp16 training of generalized focal loss (#3410)

- Support to convert RetinaNet from Pytorch to ONNX (#3075)

Improvements

- Support to process ignore boxes in ATSS assigner (#3082)
- Allow to crop images without ground truth in `RandomCrop` (#3153)
- Enable the the `Accuracy` module to set threshold (#3155)
- Refactoring unit tests (#3206)
- Unify the training settings of `to_float32` and `norm_cfg` in RegNets configs (#3210)
- Add colab training tutorials for beginners (#3213, #3273)
- Move CUDA/C++ operators into `mmcv.ops` and keep `mmdet.ops` as warppers for backward compatibility (#3232)(#3457)
- Update installation scripts in documentation (#3290) and dockerfile (#3320)
- Support to set image resize backend (#3392)
- Remove git hash in version file (#3466)
- Check mmcv version to force version compatibility (#3460)

36.29 v2.2.0 (1/7/2020)

Highlights

- Support new methods: DetectoRS, PointRend, Generalized Focal Loss, Dynamic R-CNN

Bug Fixes

- Fix FreeAnchor when no gt in image (#3176)
- Clean up deprecated usage of `register_module()` (#3092, #3161)
- Fix pretrain bug in NAS FCOS (#3145)
- Fix `num_classes` in SSD (#3142)
- Fix FCOS warmup (#3119)
- Fix `rstrip` in `tools/publish_model.py`
- Fix `flip_ratio` default value in RandomFLip pipeline (#3106)
- Fix cityscapes eval with ms_rcnn (#3112)
- Fix RPN softmax (#3056)
- Fix filename of LVIS@v0.5 (#2998)
- Fix nan loss by filtering out-of-frame gt_bboxes in COCO (#2999)
- Fix bug in FSAF (#3018)
- Add FocalLoss `num_classes` check (#2964)
- Fix PISA Loss when there are no gts (#2992)
- Avoid nan in `iou_calculator` (#2975)
- Prevent possible bugs in loading and transforms caused by shallow copy (#2967)

New Features

- Add DetectoRS (#3064)
- Support Generalize Focal Loss (#3097)
- Support PointRend (#2752)
- Support Dynamic R-CNN (#3040)
- Add DeepFashion dataset (#2968)
- Implement FCOS training tricks (#2935)
- Use BaseDenseHead as base class for anchor-base heads (#2963)
- Add `with_cp` for BasicBlock (#2891)
- Add `stem_channels` argument for ResNet (#2954)

Improvements

- Add anchor free base head (#2867)
- Migrate to github action (#3137)
- Add docstring for datasets, pipelines, core modules and methods (#3130, #3125, #3120)
- Add VOC benchmark (#3060)
- Add `concat` mode in GRoI (#3098)
- Remove cmd arg `autorescale-lr` (#3080)
- Use `len(data['img_metas'])` to indicate `num_samples` (#3073, #3053)
- Switch to EpochBasedRunner (#2976)

36.30 v2.1.0 (8/6/2020)

Highlights

- Support new backbones: RegNetX, Res2Net
- Support new methods: NASFCOS, PISA, GRoIE
- Support new dataset: LVIS

Bug Fixes

- Change the CLI argument `--validate` to `--no-validate` to enable validation after training epochs by default. (#2651)
- Add missing cython to docker file (#2713)
- Fix bug in nms cpu implementation (#2754)
- Fix bug when showing mask results (#2763)
- Fix gcc requirement (#2806)
- Fix bug in async test (#2820)
- Fix mask encoding-decoding bugs in test API (#2824)
- Fix bug in test time augmentation (#2858, #2921, #2944)
- Fix a typo in comment of apis/train (#2877)

- Fix the bug of returning None when no gt bboxes are in the original image in `RandomCrop`. Fix the bug that misses to handle `gt_bboxes_ignore`, `gt_label_ignore`, and `gt_masks_ignore` in `RandomCrop`, `MinIoURandomCrop` and `Expand` modules. (#2810)
- Fix bug of `base_channels` of regnet (#2917)
- Fix the bug of logger when loading pre-trained weights in base detector (#2936)

New Features

- Add IoU models (#2666)
- Add colab demo for inference
- Support class agnostic nms (#2553)
- Add benchmark gathering scripts for development only (#2676)
- Add mmdet-based project links (#2736, #2767, #2895)
- Add config dump in training (#2779)
- Add ClassBalancedDataset (#2721)
- Add res2net backbone (#2237)
- Support RegNetX models (#2710)
- Use `mmcv.FileClient` to support different storage backends (#2712)
- Add ClassBalancedDataset (#2721)
- Code Release: Prime Sample Attention in Object Detection (CVPR 2020) (#2626)
- Implement NASFCOS (#2682)
- Add class weight in CrossEntropyLoss (#2797)
- Support LVIS dataset (#2088)
- Support GRoIE (#2584)

Improvements

- Allow different x and y strides in anchor heads. (#2629)
- Make FSAF loss more robust to no gt (#2680)
- Compute pure inference time instead (#2657) and update inference speed (#2730)
- Avoided the possibility that a patch with 0 area is cropped. (#2704)
- Add warnings when deprecated `imgs_per_gpu` is used. (#2700)
- Add a mask rcnn example for config (#2645)
- Update model zoo (#2762, #2866, #2876, #2879, #2831)
- Add `ori_filename` to img_metas and use it in test show-dir (#2612)
- Use `img_fields` to handle multiple images during image transform (#2800)
- Add upsample_cfg support in FPN (#2787)
- Add `['img']` as default `img_fields` for back compatibility (#2809)
- Rename the pretrained model from `open-mmlab://resnet50_caffe` and `open-mmlab://resnet50_caffe_bgr` to `open-mmlab://detectron/resnet50_caffe` and `open-mmlab://detectron2/resnet50_caffe`. (#2832)

- Added sleep(2) in test.py to reduce hanging problem (#2847)
- Support `c10::half` in CARAFE (#2890)
- Improve documentations (#2918, #2714)
- Use optimizer constructor in mmcv and clean the original implementation in `mmdet.core.optimizer` (#2947)

36.31 v2.0.0 (6/5/2020)

In this release, we made lots of major refactoring and modifications.

1. **Faster speed**. We optimize the training and inference speed for common models, achieving up to 30% speedup for training and 25% for inference. Please refer to *model zoo* for details.
2. **Higher performance**. We change some default hyperparameters with no additional cost, which leads to a gain of performance for most models. Please refer to *compatibility* for details.
3. **More documentation and tutorials**. We add a bunch of documentation and tutorials to help users get started more smoothly. Read it here.
4. **Support PyTorch 1.5**. The support for 1.1 and 1.2 is dropped, and we switch to some new APIs.
5. **Better configuration system**. Inheritance is supported to reduce the redundancy of configs.
6. **Better modular design**. Towards the goal of simplicity and flexibility, we simplify some encapsulation while add more other configurable modules like BBoxCoder, IoUCalculator, OptimizerConstructor, RoIHead. Target computation is also included in heads and the call hierarchy is simpler.
7. Support new methods: FSAF and PAFPN (part of PAFPN).

Breaking Changes Models training with MMDetection 1.x are not fully compatible with 2.0, please refer to the *compatibility doc* for the details and how to migrate to the new version.

Improvements

- Unify cuda and cpp API for custom ops. (#2277)
- New config files with inheritance. (#2216)
- Encapsulate the second stage into RoI heads. (#1999)
- Refactor GCNet/EmpericalAttention into plugins. (#2345)
- Set low quality match as an option in IoU-based bbox assigners. (#2375)
- Change the codebase's coordinate system. (#2380)
- Refactor the category order in heads. 0 means the first positive class instead of background now. (#2374)
- Add bbox sampler and assigner registry. (#2419)
- Speed up the inference of RPN. (#2420)
- Add `train_cfg` and `test_cfg` as class members in all anchor heads. (#2422)
- Merge target computation methods into heads. (#2429)
- Add bbox coder to support different bbox encoding and losses. (#2480)
- Unify the API for regression loss. (#2156)
- Refactor Anchor Generator. (#2474)
- Make `lr` an optional argument for optimizers. (#2509)

- Migrate to modules and methods in MMCV. (#2502, #2511, #2569, #2572)
- Support PyTorch 1.5. (#2524)
- Drop the support for Python 3.5 and use F-string in the codebase. (#2531)

Bug Fixes

- Fix the scale factors for resized images without keep the aspect ratio. (#2039)
- Check if max_num > 0 before slicing in NMS. (#2486)
- Fix Deformable RoIPool when there is no instance. (#2490)
- Fix the default value of assigned labels. (#2536)
- Fix the evaluation of Cityscapes. (#2578)

New Features

- Add deep_stem and avg_down option to ResNet, i.e., support ResNetV1d. (#2252)
- Add L1 loss. (#2376)
- Support both polygon and bitmap for instance masks. (#2353, #2540)
- Support CPU mode for inference. (#2385)
- Add optimizer constructor for complicated configuration of optimizers. (#2397, #2488)
- Implement PAFPN. (#2392)
- Support empty tensor input for some modules. (#2280)
- Support for custom dataset classes without overriding it. (#2408, #2443)
- Support to train subsets of coco dataset. (#2340)
- Add iou_calculator to potentially support more IoU calculation methods. (2405)
- Support class wise mean AP (was removed in the last version). (#2459)
- Add option to save the testing result images. (#2414)
- Support MomentumUpdaterHook. (#2571)
- Add a demo to inference a single image. (#2605)

36.32 v1.1.0 (24/2/2020)

Highlights

- Dataset evaluation is rewritten with a unified api, which is used by both evaluation hooks and test scripts.
- Support new methods: CARAFE.

Breaking Changes

- The new MMDDP inherits from the official DDP, thus the `__init__` api is changed to be the same as official DDP.
- The `mask_head` field in HTC config files is modified.
- The evaluation and testing script is updated.
- In all transforms, instance masks are stored as a numpy array shaped (n, h, w) instead of a list of (h, w) arrays, where n is the number of instances.

Bug Fixes

- Fix IOU assigners when ignore_iof_thr > 0 and there is no pred boxes. (#2135)
- Fix mAP evaluation when there are no ignored boxes. (#2116)
- Fix the empty RoI input for Deformable RoI Pooling. (#2099)
- Fix the dataset settings for multiple workflows. (#2103)
- Fix the warning related to `torch.uint8` in PyTorch 1.4. (#2105)
- Fix the inference demo on devices other than gpu:0. (#2098)
- Fix Dockerfile. (#2097)
- Fix the bug that `pad_val` is unused in Pad transform. (#2093)
- Fix the albumentation transform when there is no ground truth bbox. (#2032)

Improvements

- Use torch instead of numpy for random sampling. (#2094)
- Migrate to the new MMDDP implementation in MMCV v0.3. (#2090)
- Add meta information in logs. (#2086)
- Rewrite Soft NMS with pytorch extension and remove cython as a dependency. (#2056)
- Rewrite dataset evaluation. (#2042, #2087, #2114, #2128)
- Use numpy array for masks in transforms. (#2030)

New Features

- Implement "CARAFE: Content-Aware ReAssembly of FEatures". (#1583)
- Add `worker_init_fn()` in data_loader when seed is set. (#2066, #2111)
- Add logging utils. (#2035)

36.33 v1.0.0 (30/1/2020)

This release mainly improves the code quality and add more docstrings.

Highlights

- Documentation is online now: https://mmdetection.readthedocs.io.
- Support new models: ATSS.
- DCN is now available with the api `build_conv_layer` and `ConvModule` like the normal conv layer.
- A tool to collect environment information is available for trouble shooting.

Bug Fixes

- Fix the incompatibility of the latest numpy and pycocotools. (#2024)
- Fix the case when distributed package is unavailable, e.g., on Windows. (#1985)
- Fix the dimension issue for `refine_bboxes()`. (#1962)
- Fix the typo when `seg_prefix` is a list. (#1906)
- Add segmentation map cropping to RandomCrop. (#1880)

- Fix the return value of `ga_shape_target_single()`. (#1853)
- Fix the loaded shape of empty proposals. (#1819)
- Fix the mask data type when using albumentation. (#1818)

Improvements

- Enhance AssignResult and SamplingResult. (#1995)
- Add ability to overwrite existing module in Registry. (#1982)
- Reorganize requirements and make albumentations and imagecorruptions optional. (#1969)
- Check NaN in `SSDHead`. (#1935)
- Encapsulate the DCN in ResNe(X)t into a ConvModule & Conv_layers. (#1894)
- Refactoring for mAP evaluation and support multiprocessing and logging. (#1889)
- Init the root logger before constructing Runner to log more information. (#1865)
- Split `SegResizeFlipPadRescale` into different existing transforms. (#1852)
- Move `init_dist()` to MMCV. (#1851)
- Documentation and docstring improvements. (#1971, #1938, #1869, #1838)
- Fix the color of the same class for mask visualization. (#1834)
- Remove the option `keep_all_stages` in HTC and Cascade R-CNN. (#1806)

New Features

- Add two test-time options `crop_mask` and `rle_mask_encode` for mask heads. (#2013)
- Support loading grayscale images as single channel. (#1975)
- Implement "Bridging the Gap Between Anchor-based and Anchor-free Detection via Adaptive Training Sample Selection". (#1872)
- Add sphinx generated docs. (#1859, #1864)
- Add GN support for flops computation. (#1850)
- Collect env info for trouble shooting. (#1812)

36.34 v1.0rc1 (13/12/2019)

The RC1 release mainly focuses on improving the user experience, and fixing bugs.

Highlights

- Support new models: FoveaBox, RepPoints and FreeAnchor.
- Add a Dockerfile.
- Add a jupyter notebook demo and a webcam demo.
- Setup the code style and CI.
- Add lots of docstrings and unit tests.
- Fix lots of bugs.

Breaking Changes

- There was a bug for computing COCO-style mAP w.r.t different scales (AP_s, AP_m, AP_l), introduced by #621. (#1679)

Bug Fixes

- Fix a sampling interval bug in Libra R-CNN. (#1800)
- Fix the learning rate in SSD300 WIDER FACE. (#1781)
- Fix the scaling issue when `keep_ratio=False`. (#1730)
- Fix typos. (#1721, #1492, #1242, #1108, #1107)
- Fix the shuffle argument in `build_dataloader`. (#1693)
- Clip the proposal when computing mask targets. (#1688)
- Fix the "index out of range" bug for samplers in some corner cases. (#1610, #1404)
- Fix the NMS issue on devices other than GPU:0. (#1603)
- Fix SSD Head and GHM Loss on CPU. (#1578)
- Fix the OOM error when there are too many gt bboxes. (#1575)
- Fix the wrong keyword argument `nms_cfg` in HTC. (#1573)
- Process masks and semantic segmentation in Expand and MinIoUCrop transforms. (#1550, #1361)
- Fix a scale bug in the Non Local op. (#1528)
- Fix a bug in transforms when `gt_bboxes_ignore` is None. (#1498)
- Fix a bug when `img_prefix` is None. (#1497)
- Pass the device argument to `grid_anchors` and `valid_flags`. (#1478)
- Fix the data pipeline for test_robustness. (#1476)
- Fix the argument type of deformable pooling. (#1390)
- Fix the coco_eval when there are only two classes. (#1376)
- Fix a bug in Modulated DeformableConv when deformable_group>1. (#1359)
- Fix the mask cropping in RandomCrop. (#1333)
- Fix zero outputs in DeformConv when not running on cuda:0. (#1326)
- Fix the type issue in Expand. (#1288)
- Fix the inference API. (#1255)
- Fix the inplace operation in Expand. (#1249)
- Fix the from-scratch training config. (#1196)
- Fix inplace add in RoIExtractor which cause an error in PyTorch 1.2. (#1160)
- Fix FCOS when input images has no positive sample. (#1136)
- Fix recursive imports. (#1099)

Improvements

- Print the config file and mmdet version in the log. (#1721)
- Lint the code before compiling in travis CI. (#1715)
- Add a probability argument for the `Expand` transform. (#1651)

- Update the PyTorch and CUDA version in the docker file. (#1615)
- Raise a warning when specifying `--validate` in non-distributed training. (#1624, #1651)
- Beautify the mAP printing. (#1614)
- Add pre-commit hook. (#1536)
- Add the argument `in_channels` to backbones. (#1475)
- Add lots of docstrings and unit tests, thanks to @Erotemic. (#1603, #1517, #1506, #1505, #1491, #1479, #1477, #1475, #1474)
- Add support for multi-node distributed test when there is no shared storage. (#1399)
- Optimize Dockerfile to reduce the image size. (#1306)
- Update new results of HRNet. (#1284, #1182)
- Add an argument `no_norm_on_lateral` in FPN. (#1240)
- Test the compiling in CI. (#1235)
- Move docs to a separate folder. (#1233)
- Add a jupyter notebook demo. (#1158)
- Support different type of dataset for training. (#1133)
- Use int64_t instead of long in cuda kernels. (#1131)
- Support unsquare RoIs for bbox and mask heads. (#1128)
- Manually add type promotion to make compatible to PyTorch 1.2. (#1114)
- Allowing validation dataset for computing validation loss. (#1093)
- Use `.scalar_type()` instead of `.type()` to suppress some warnings. (#1070)

New Features

- Add an option `--with_ap` to compute the AP for each class. (#1549)
- Implement "FreeAnchor: Learning to Match Anchors for Visual Object Detection". (#1391)
- Support Albumentations for augmentations in the data pipeline. (#1354)
- Implement "FoveaBox: Beyond Anchor-based Object Detector". (#1339)
- Support horizontal and vertical flipping. (#1273, #1115)
- Implement "RepPoints: Point Set Representation for Object Detection". (#1265)
- Add test-time augmentation to HTC and Cascade R-CNN. (#1251)
- Add a COCO result analysis tool. (#1228)
- Add Dockerfile. (#1168)
- Add a webcam demo. (#1155, #1150)
- Add FLOPs counter. (#1127)
- Allow arbitrary layer order for ConvModule. (#1078)

36.35 v1.0rc0 (27/07/2019)

- Implement lots of new methods and components (Mixed Precision Training, HTC, Libra R-CNN, Guided Anchoring, Empirical Attention, Mask Scoring R-CNN, Grid R-CNN (Plus), GHM, GCNet, FCOS, HRNet, Weight Standardization, etc.). Thank all collaborators!
- Support two additional datasets: WIDER FACE and Cityscapes.
- Refactoring for loss APIs and make it more flexible to adopt different losses and related hyper-parameters.
- Speed up multi-gpu testing.
- Integrate all compiling and installing in a single script.

36.36 v0.6.0 (14/04/2019)

- Up to 30% speedup compared to the model zoo.
- Support both PyTorch stable and nightly version.
- Replace NMS and SigmoidFocalLoss with Pytorch CUDA extensions.

36.37 v0.6rc0(06/02/2019)

- Migrate to PyTorch 1.0.

36.38 v0.5.7 (06/02/2019)

- Add support for Deformable ConvNet v2. (Many thanks to the authors and @chengdazhi)
- This is the last release based on PyTorch 0.4.1.

36.39 v0.5.6 (17/01/2019)

- Add support for Group Normalization.
- Unify RPNHead and single stage heads (RetinaHead, SSDHead) with AnchorHead.

36.40 v0.5.5 (22/12/2018)

- Add SSD for COCO and PASCAL VOC.
- Add ResNeXt backbones and detection models.
- Refactoring for Samplers/Assigners and add OHEM.
- Add VOC dataset and evaluation scripts.

36.41 v0.5.4 (27/11/2018)

- Add SingleStageDetector and RetinaNet.

36.42 v0.5.3 (26/11/2018)

- Add Cascade R-CNN and Cascade Mask R-CNN.
- Add support for Soft-NMS in config files.

36.43 v0.5.2 (21/10/2018)

- Add support for custom datasets.
- Add a script to convert PASCAL VOC annotations to the expected format.

36.44 v0.5.1 (20/10/2018)

- Add BBoxAssigner and BBoxSampler, the `train_cfg` field in config files are restructured.
- `ConvFCRoIHead` / `SharedFCRoIHead` are renamed to `ConvFCBBoxHead` / `SharedFCBBoxHead` for consistency.

CHAPTER

THIRTYSEVEN

FREQUENTLY ASKED QUESTIONS

We list some common troubles faced by many users and their corresponding solutions here. Feel free to enrich the list if you find any frequent issues and have ways to help others to solve them. If the contents here do not cover your issue, please create an issue using the provided templates and make sure you fill in all required information in the template.

37.1 Installation

- Compatibility issue between MMCV and MMDetection; "ConvWS is already registered in conv layer"; "AssertionError: MMCV==xxx is used but incompatible. Please install mmcv>=xxx, <=xxx."

  Compatible MMDetection and MMCV versions are shown as below. Please choose the correct version of MMCV to avoid installation issues.

- "No module named 'mmcv.ops'"; "No module named 'mmcv._ext'".

  1. Uninstall existing mmcv in the environment using `pip uninstall mmcv`.
  2. Install mmcv-full following the installation instruction.

- Using albumentations

  If you would like to use `albumentations`, we suggest using `pip install -r requirements/albu.txt` or `pip install -U albumentations --no-binary qudida,albumentations`. If you simply use `pip install albumentations>=0.3.2`, it will install `opencv-python-headless` simultaneously (even though you have already installed `opencv-python`). Please refer to the official documentation for details.

- ModuleNotFoundError is raised when using some algorithms

  Some extra dependencies are required for Instaboost, Panoptic Segmentation, LVIS dataset, etc. Please note the error message and install corresponding packages, e.g.,

```
# for instaboost
pip install instaboostfast
# for panoptic segmentation
pip install git+https://github.com/cocodataset/panopticapi.git
# for LVIS dataset
pip install git+https://github.com/lvis-dataset/lvis-api.git
```

37.2 Coding

- Do I need to reinstall mmdet after some code modifications

  If you follow the best practice and install mmdet with `pip install -e .`, any local modifications made to the code will take effect without reinstallation.

- How to develop with multiple MMDetection versions

  You can have multiple folders like mmdet-2.21, mmdet-2.22. When you run the train or test script, it will adopt the mmdet package in the current folder.

  To use the default MMDetection installed in the environment rather than the one you are working with, you can remove the following line in those scripts:

```
PYTHONPATH="$(dirname $0)/..":$PYTHONPATH
```

37.3 PyTorch/CUDA Environment

- "RTX 30 series card fails when building MMCV or MMDet"

  1. Temporary work-around: do `MMCV_WITH_OPS=1 MMCV_CUDA_ARGS='-gencode=arch=compute_80,code=sm_80' pip install -e .`. The common issue is `nvcc fatal : Unsupported gpu architecture 'compute_86'`. This means that the compiler should optimize for sm_86, i.e., nvidia 30 series card, but such optimizations have not been supported by CUDA toolkit 11.0. This work-around modifies the compile flag by adding `MMCV_CUDA_ARGS='-gencode=arch=compute_80,code=sm_80'`, which tells `nvcc` to optimize for **sm_80**, i.e., Nvidia A100. Although A100 is different from the 30 series card, they use similar ampere architecture. This may hurt the performance but it works.
  2. PyTorch developers have updated that the default compiler flags should be fixed by pytorch/pytorch#47585. So using PyTorch-nightly may also be able to solve the problem, though we have not tested it yet.

- "invalid device function" or "no kernel image is available for execution".

  1. Check if your cuda runtime version (under `/usr/local/`), `nvcc --version` and `conda list cudatoolkit` version match.
  2. Run `python mmdet/utils/collect_env.py` to check whether PyTorch, torchvision, and MMCV are built for the correct GPU architecture. You may need to set `TORCH_CUDA_ARCH_LIST` to reinstall MMCV. The GPU arch table could be found here, i.e. run `TORCH_CUDA_ARCH_LIST=7.0 pip install mmcv-full` to build MMCV for Volta GPUs. The compatibility issue could happen when using old GPUS, e.g., Tesla K80 (3.7) on colab.
  3. Check whether the running environment is the same as that when mmcv/mmdet has compiled. For example, you may compile mmcv using CUDA 10.0 but run it on CUDA 9.0 environments.

- "undefined symbol" or "cannot open xxx.so".

  1. If those symbols are CUDA/C++ symbols (e.g., libcudart.so or GLIBCXX), check whether the CUDA/GCC runtimes are the same as those used for compiling mmcv, i.e. run `python mmdet/utils/collect_env.py` to see if `"MMCV Compiler"/"MMCV CUDA Compiler"` is the same as `"GCC"/"CUDA_HOME"`.
  2. If those symbols are PyTorch symbols (e.g., symbols containing caffe, aten, and TH), check whether the PyTorch version is the same as that used for compiling mmcv.
  3. Run `python mmdet/utils/collect_env.py` to check whether PyTorch, torchvision, and MMCV are built by and running on the same environment.

- setuptools.sandbox.UnpickleableException: DistutilsSetupError("each element of 'ext_modules' option must be an Extension instance or 2-tuple")

  1. If you are using miniconda rather than anaconda, check whether Cython is installed as indicated in #3379. You need to manually install Cython first and then run command `pip install -r requirements.txt`.
  2. You may also need to check the compatibility between the `setuptools`, `Cython`, and `PyTorch` in your environment.

- "Segmentation fault".

  1. Check you GCC version and use GCC 5.4. This usually caused by the incompatibility between PyTorch and the environment (e.g., GCC < 4.9 for PyTorch). We also recommend the users to avoid using GCC 5.5 because many feedbacks report that GCC 5.5 will cause "segmentation fault" and simply changing it to GCC 5.4 could solve the problem.
  2. Check whether PyTorch is correctly installed and could use CUDA op, e.g. type the following command in your terminal.

     ```
     python -c 'import torch; print(torch.cuda.is_available())'
     ```

     And see whether they could correctly output results.
  3. If Pytorch is correctly installed, check whether MMCV is correctly installed.

     ```
     python -c 'import mmcv; import mmcv.ops'
     ```

     If MMCV is correctly installed, then there will be no issue of the above two commands.
  4. If MMCV and Pytorch is correctly installed, you man use `ipdb`, `pdb` to set breakpoints or directly add 'print' in mmdetection code and see which part leads the segmentation fault.

37.4 Training

- "Loss goes Nan"

  1. Check if the dataset annotations are valid: zero-size bounding boxes will cause the regression loss to be Nan due to the commonly used transformation for box regression. Some small size (width or height are smaller than 1) boxes will also cause this problem after data augmentation (e.g., instaboost). So check the data and try to filter out those zero-size boxes and skip some risky augmentations on the small-size boxes when you face the problem.
  2. Reduce the learning rate: the learning rate might be too large due to some reasons, e.g., change of batch size. You can rescale them to the value that could stably train the model.
  3. Extend the warmup iterations: some models are sensitive to the learning rate at the start of the training. You can extend the warmup iterations, e.g., change the `warmup_iters` from 500 to 1000 or 2000.
  4. Add gradient clipping: some models requires gradient clipping to stabilize the training process. The default of `grad_clip` is `None`, you can add gradient clippint to avoid gradients that are too large, i.e., set `optimizer_config=dict(_delete_=True, grad_clip=dict(max_norm=35, norm_type=2))` in your config file. If your config does not inherits from any basic config that contains `optimizer_config=dict(grad_clip=None)`, you can simply add `optimizer_config=dict(grad_clip=dict(max_norm=35, norm_type=2))`.

- "GPU out of memory"

1. There are some scenarios when there are large amount of ground truth boxes, which may cause OOM during target assignment. You can set `gpu_assign_thr=N` in the config of assigner thus the assigner will calculate box overlaps through CPU when there are more than N GT boxes.
2. Set `with_cp=True` in the backbone. This uses the sublinear strategy in PyTorch to reduce GPU memory cost in the backbone.
3. Try mixed precision training using following the examples in `config/fp16`. The `loss_scale` might need further tuning for different models.
4. Try to use `AvoidCUDAOOM` to avoid GPU out of memory. It will first retry after calling `torch.cuda.empty_cache()`. If it still fails, it will then retry by converting the type of inputs to FP16 format. If it still fails, it will try to copy inputs from GPUs to CPUs to continue computing. Try AvoidOOM in you code to make the code continue to run when GPU memory runs out:

```
from mmdet.utils import AvoidCUDAOOM

output = AvoidCUDAOOM.retry_if_cuda_oom(some_function)(input1, input2)
```

You can also try `AvoidCUDAOOM` as a decorator to make the code continue to run when GPU memory runs out:

```
from mmdet.utils import AvoidCUDAOOM

@AvoidCUDAOOM.retry_if_cuda_oom
def function(*args, **kwargs):
    ...
    return xxx
```

- "RuntimeError: Expected to have finished reduction in the prior iteration before starting a new one"
  1. This error indicates that your module has parameters that were not used in producing loss. This phenomenon may be caused by running different branches in your code in DDP mode.
  2. You can set `find_unused_parameters = True` in the config to solve the above problems(but this will slow down the training speed.
  3. If the version of your MMCV >= 1.4.1, you can get the name of those unused parameters with `detect_anomalous_params=True` in `optimizer_config` of config.
- Save the best model

  It can be turned on by configuring `evaluation = dict(save_best='auto')`. In the case of the `auto` parameter, the first key in the returned evaluation result will be used as the basis for selecting the best model. You can also directly set the key in the evaluation result to manually set it, for example, `evaluation = dict(save_best='mAP' )`.
- Resume training with `ExpMomentumEMAHook`

  If you use `ExpMomentumEMAHook` in training, you can't just use command line parameters `--resume-from` nor `--cfg-options resume_from` to restore model parameters during resume, i.e., the command `python tools/train.py configs/yolox/yolox_s_8x8_300e_coco.py --resume-from ./work_dir/yolox_s_8x8_300e_coco/epoch_x.pth` will not work. Since `ExpMomentumEMAHook` needs to reload the weights, taking the `yolox_s` algorithm as an example, you should modify the values of `resume_from` in two places of the config as below:

```
# Open configs/yolox/yolox_s_8x8_300e_coco.py directly and modify all resume_from␣
↪fields
resume_from=./work_dir/yolox_s_8x8_300e_coco/epoch_x.pth
```

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```
custom_hooks=[...
    dict(
        type='ExpMomentumEMAHook',
        resume_from=./work_dir/yolox_s_8x8_300e_coco/epoch_x.pth,
        momentum=0.0001,
        priority=49)
    ]
```

37.5 Evaluation

- COCO Dataset, AP or AR = -1

  1. According to the definition of COCO dataset, the small and medium areas in an image are less than 1024 (32*32), 9216 (96*96), respectively.
  2. If the corresponding area has no object, the result of AP and AR will set to -1.

37.6 Model

- `style` in ResNet

  The `style` parameter in ResNet allows either `pytorch` or `caffe` style. It indicates the difference in the Bottleneck module. Bottleneck is a stacking structure of `1x1-3x3-1x1` convolutional layers. In the case of `caffe` mode, the convolution layer with `stride=2` is the first `1x1` convolution, while in `pyorch` mode, it is the second `3x3` convolution has `stride=2`. A sample code is as below:

```
if self.style == 'pytorch':
      self.conv1_stride = 1
      self.conv2_stride = stride
else:
      self.conv1_stride = stride
      self.conv2_stride = 1
```

- ResNeXt parameter description

  ResNeXt comes from the paper `Aggregated Residual Transformations for Deep Neural Networks`. It introduces group and uses "cardinality" to control the number of groups to achieve a balance between accuracy and complexity. It controls the basic width and grouping parameters of the internal Bottleneck module through two hyperparameters `baseWidth` and `cardinality`. An example configuration name in MMDetection is `mask_rcnn_x101_64x4d_fpn_mstrain-poly_3x_coco.py`, where `mask_rcnn` represents the algorithm using Mask R-CNN, `x101` represents the backbone network using ResNeXt-101, and `64x4d` represents that the bottleneck block has 64 group and each group has basic width of 4.

- `norm_eval` in backbone

  Since the detection model is usually large and the input image resolution is high, this will result in a small batch of the detection model, which will make the variance of the statistics calculated by BatchNorm during the training process very large and not as stable as the statistics obtained during the pre-training of the backbone network . Therefore, the `norm_eval=True` mode is generally used in training, and the BatchNorm statistics in the pre-trained backbone network are directly used. The few algorithms that use large batches are the `norm_eval=False` mode, such as NASFPN. For the backbone network without ImageNet pre-training and the batch is relatively small, you can consider using `SyncBN`.

CHAPTER

THIRTYEIGHT

ENGLISH

CHAPTER

THIRTYNINE

CHAPTER

FORTY

MMDET.APIS

CHAPTER

FORTYONE

MMDET.CORE

41.1 anchor

class mmdet.core.anchor.**AnchorGenerator**(*strides*, *ratios*, *scales=None*, *base_sizes=None*, *scale_major=True*, *octave_base_scale=None*, *scales_per_octave=None*, *centers=None*, *center_offset=0.0*)

Standard anchor generator for 2D anchor-based detectors.

Parameters

- **strides** (*list[int] | list[tuple[int, int]]*) – Strides of anchors in multiple feature levels in order (w, h).
- **ratios** (*list[float]*) – The list of ratios between the height and width of anchors in a single level.
- **scales** (*list[int] | None*) – Anchor scales for anchors in a single level. It cannot be set at the same time if *octave_base_scale* and *scales_per_octave* are set.
- **base_sizes** (*list[int] | None*) – The basic sizes of anchors in multiple levels. If None is given, strides will be used as base_sizes. (If strides are non square, the shortest stride is taken.)
- **scale_major** (*bool*) – Whether to multiply scales first when generating base anchors. If true, the anchors in the same row will have the same scales. By default it is True in V2.0
- **octave_base_scale** (*int*) – The base scale of octave.
- **scales_per_octave** (*int*) – Number of scales for each octave. *octave_base_scale* and *scales_per_octave* are usually used in retinanet and the *scales* should be None when they are set.
- **centers** (*list[tuple[float, float]] | None*) – The centers of the anchor relative to the feature grid center in multiple feature levels. By default it is set to be None and not used. If a list of tuple of float is given, they will be used to shift the centers of anchors.
- **center_offset** (*float*) – The offset of center in proportion to anchors' width and height. By default it is 0 in V2.0.

Examples

```
>>> from mmdet.core import AnchorGenerator
>>> self = AnchorGenerator([16], [1.], [1.], [9])
>>> all_anchors = self.grid_priors([(2, 2)], device='cpu')
>>> print(all_anchors)
[tensor([[-4.5000, -4.5000,  4.5000,  4.5000],
        [11.5000, -4.5000, 20.5000,  4.5000],
        [-4.5000, 11.5000,  4.5000, 20.5000],
        [11.5000, 11.5000, 20.5000, 20.5000]])]
>>> self = AnchorGenerator([16, 32], [1.], [1.], [9, 18])
>>> all_anchors = self.grid_priors([(2, 2), (1, 1)], device='cpu')
>>> print(all_anchors)
[tensor([[-4.5000, -4.5000,  4.5000,  4.5000],
        [11.5000, -4.5000, 20.5000,  4.5000],
        [-4.5000, 11.5000,  4.5000, 20.5000],
        [11.5000, 11.5000, 20.5000, 20.5000]]),         tensor([[-9., -9., 9., 9.
↪]])]
```

gen_base_anchors()
Generate base anchors.

Returns Base anchors of a feature grid in multiple feature levels.

Return type list(torch.Tensor)

gen_single_level_base_anchors(*base_size*, *scales*, *ratios*, *center=None*)
Generate base anchors of a single level.

Parameters

- **base_size** (*int | float*) – Basic size of an anchor.
- **scales** (*torch.Tensor*) – Scales of the anchor.
- **ratios** (*torch.Tensor*) – The ratio between between the height and width of anchors in a single level.
- **center** (*tuple[float], optional*) – The center of the base anchor related to a single feature grid. Defaults to None.

Returns Anchors in a single-level feature maps.

Return type torch.Tensor

grid_anchors(*featmap_sizes*, *device='cuda'*)
Generate grid anchors in multiple feature levels.

Parameters

- **featmap_sizes** (*list[tuple]*) – List of feature map sizes in multiple feature levels.
- **device** (*str*) – Device where the anchors will be put on.

Returns Anchors in multiple feature levels. The sizes of each tensor should be [N, 4], where N = width * height * num_base_anchors, width and height are the sizes of the corresponding feature level, num_base_anchors is the number of anchors for that level.

Return type list[torch.Tensor]

grid_priors(*featmap_sizes*, *dtype=torch.float32*, *device='cuda'*)
Generate grid anchors in multiple feature levels.

Parameters

- **featmap_sizes** (*list[tuple]*) – List of feature map sizes in multiple feature levels.
- **dtype** (torch.dtype) – Dtype of priors. Default: torch.float32.
- **device** (*str*) – The device where the anchors will be put on.

Returns Anchors in multiple feature levels. The sizes of each tensor should be [N, 4], where N = width * height * num_base_anchors, width and height are the sizes of the corresponding feature level, num_base_anchors is the number of anchors for that level.

Return type list[torch.Tensor]

property num_base_anchors
total number of base anchors in a feature grid

Type list[int]

property num_base_priors
The number of priors (anchors) at a point on the feature grid

Type list[int]

property num_levels
number of feature levels that the generator will be applied

Type int

single_level_grid_anchors(*base_anchors*, *featmap_size*, *stride=(16, 16)*, *device='cuda'*)
Generate grid anchors of a single level.

Note: This function is usually called by method `self.grid_anchors`.

Parameters

- **base_anchors** (*torch.Tensor*) – The base anchors of a feature grid.
- **featmap_size** (*tuple[int]*) – Size of the feature maps.
- **stride** (*tuple[int], optional*) – Stride of the feature map in order (w, h). Defaults to (16, 16).
- **device** (*str, optional*) – Device the tensor will be put on. Defaults to 'cuda'.

Returns Anchors in the overall feature maps.

Return type torch.Tensor

single_level_grid_priors(*featmap_size*, *level_idx*, *dtype=torch.float32*, *device='cuda'*)
Generate grid anchors of a single level.

Note: This function is usually called by method `self.grid_priors`.

Parameters

- **featmap_size** (*tuple[int]*) – Size of the feature maps.
- **level_idx** (*int*) – The index of corresponding feature map level.
- **(obj** (*dtype*) – *torch.dtype*): Date type of points.Defaults to `torch.float32`.

- **device** (*str, optional*) – The device the tensor will be put on. Defaults to 'cuda'.

Returns Anchors in the overall feature maps.

Return type torch.Tensor

single_level_valid_flags(*featmap_size*, *valid_size*, *num_base_anchors*, *device='cuda'*)
Generate the valid flags of anchor in a single feature map.

Parameters

- **featmap_size** (*tuple[int]*) – The size of feature maps, arrange as (h, w).
- **valid_size** (*tuple[int]*) – The valid size of the feature maps.
- **num_base_anchors** (*int*) – The number of base anchors.
- **device** (*str, optional*) – Device where the flags will be put on. Defaults to 'cuda'.

Returns The valid flags of each anchor in a single level feature map.

Return type torch.Tensor

sparse_priors(*prior_idxs*, *featmap_size*, *level_idx*, *dtype=torch.float32*, *device='cuda'*)
Generate sparse anchors according to the `prior_idxs`.

Parameters

- **prior_idxs** (*Tensor*) – The index of corresponding anchors in the feature map.
- **featmap_size** (*tuple[int]*) – feature map size arrange as (h, w).
- **level_idx** (*int*) – The level index of corresponding feature map.
- **(obj** (*device*) – *torch.dtype*): Date type of points.Defaults to `torch.float32`.
- **(obj** – *torch.device*): The device where the points is located.

Returns

Anchor with shape (N, 4), N should be equal to the length of `prior_idxs`.

Return type Tensor

valid_flags(*featmap_sizes*, *pad_shape*, *device='cuda'*)
Generate valid flags of anchors in multiple feature levels.

Parameters

- **featmap_sizes** (*list(tuple)*) – List of feature map sizes in multiple feature levels.
- **pad_shape** (*tuple*) – The padded shape of the image.
- **device** (*str*) – Device where the anchors will be put on.

Returns Valid flags of anchors in multiple levels.

Return type list(torch.Tensor)

class mmdet.core.anchor.**LegacyAnchorGenerator**(*strides*, *ratios*, *scales=None*, *base_sizes=None*, *scale_major=True*, *octave_base_scale=None*, *scales_per_octave=None*, *centers=None*, *center_offset=0.0*)
Legacy anchor generator used in MMDetection V1.x.

Note: Difference to the V2.0 anchor generator:

1. The center offset of V1.x anchors are set to be 0.5 rather than 0.
2. The width/height are minused by 1 when calculating the anchors' centers and corners to meet the V1.x coordinate system.
3. The anchors' corners are quantized.

Parameters

- **strides** (*list[int] | list[tuple[int]]*) – Strides of anchors in multiple feature levels.
- **ratios** (*list[float]*) – The list of ratios between the height and width of anchors in a single level.
- **scales** (*list[int] | None*) – Anchor scales for anchors in a single level. It cannot be set at the same time if *octave_base_scale* and *scales_per_octave* are set.
- **base_sizes** (*list[int]*) – The basic sizes of anchors in multiple levels. If None is given, strides will be used to generate base_sizes.
- **scale_major** (*bool*) – Whether to multiply scales first when generating base anchors. If true, the anchors in the same row will have the same scales. By default it is True in V2.0
- **octave_base_scale** (*int*) – The base scale of octave.
- **scales_per_octave** (*int*) – Number of scales for each octave. *octave_base_scale* and *scales_per_octave* are usually used in retinanet and the *scales* should be None when they are set.
- **centers** (*list[tuple[float, float]] | None*) – The centers of the anchor relative to the feature grid center in multiple feature levels. By default it is set to be None and not used. It a list of float is given, this list will be used to shift the centers of anchors.
- **center_offset** (*float*) – The offset of center in proportion to anchors' width and height. By default it is 0.5 in V2.0 but it should be 0.5 in v1.x models.

Examples

```
>>> from mmdet.core import LegacyAnchorGenerator
>>> self = LegacyAnchorGenerator(
>>>     [16], [1.], [1.], [9], center_offset=0.5)
>>> all_anchors = self.grid_anchors(((2, 2),), device='cpu')
>>> print(all_anchors)
[tensor([[ 0.,  0.,  8.,  8.],
        [16.,  0., 24.,  8.],
        [ 0., 16.,  8., 24.],
        [16., 16., 24., 24.]])]
```

gen_single_level_base_anchors(*base_size*, *scales*, *ratios*, *center=None*)

Generate base anchors of a single level.

Note: The width/height of anchors are minused by 1 when calculating the centers and corners to meet the V1.x coordinate system.

Parameters

- **base_size** (*int | float*) – Basic size of an anchor.
- **scales** (*torch.Tensor*) – Scales of the anchor.
- **ratios** (*torch.Tensor*) – The ratio between between the height. and width of anchors in a single level.
- **center** (*tuple[float], optional*) – The center of the base anchor related to a single feature grid. Defaults to None.

Returns Anchors in a single-level feature map.

Return type torch.Tensor

class mmdet.core.anchor.**MlvlPointGenerator**(*strides*, *offset=0.5*)

Standard points generator for multi-level (Mlvl) feature maps in 2D points-based detectors.

Parameters

- **strides** (*list[int] | list[tuple[int, int]]*) – Strides of anchors in multiple feature levels in order (w, h).
- **offset** (*float*) – The offset of points, the value is normalized with corresponding stride. Defaults to 0.5.

grid_priors(*featmap_sizes*, *dtype=torch.float32*, *device='cuda'*, *with_stride=False*)

Generate grid points of multiple feature levels.

Parameters

- **featmap_sizes** (*list[tuple]*) – List of feature map sizes in multiple feature levels, each size arrange as as (h, w).
- **dtype** (dtype) – Dtype of priors. Default: torch.float32.
- **device** (*str*) – The device where the anchors will be put on.
- **with_stride** (*bool*) – Whether to concatenate the stride to the last dimension of points.

Returns Points of multiple feature levels. The sizes of each tensor should be (N, 2) when with stride is `False`, where N = width * height, width and height are the sizes of the corresponding feature level, and the last dimension 2 represent (coord_x, coord_y), otherwise the shape should be (N, 4), and the last dimension 4 represent (coord_x, coord_y, stride_w, stride_h).

Return type list[torch.Tensor]

property num_base_priors

The number of priors (points) at a point on the feature grid

Type list[int]

property num_levels

number of feature levels that the generator will be applied

Type int

single_level_grid_priors(*featmap_size*, *level_idx*, *dtype=torch.float32*, *device='cuda'*, *with_stride=False*)

Generate grid Points of a single level.

Note: This function is usually called by method `self.grid_priors`.

Parameters

- **featmap_size** (*tuple[int]*) – Size of the feature maps, arrange as (h, w).
- **level_idx** (*int*) – The index of corresponding feature map level.
- **dtype** (dtype) – Dtype of priors. Default: torch.float32.
- **device** (*str, optional*) – The device the tensor will be put on. Defaults to 'cuda'.
- **with_stride** (*bool*) – Concatenate the stride to the last dimension of points.

Returns Points of single feature levels. The shape of tensor should be (N, 2) when with stride is `False`, where N = width * height, width and height are the sizes of the corresponding feature level, and the last dimension 2 represent (coord_x, coord_y), otherwise the shape should be (N, 4), and the last dimension 4 represent (coord_x, coord_y, stride_w, stride_h).

Return type Tensor

single_level_valid_flags(*featmap_size*, *valid_size*, *device='cuda'*)
Generate the valid flags of points of a single feature map.

Parameters

- **featmap_size** (*tuple[int]*) – The size of feature maps, arrange as as (h, w).
- **valid_size** (*tuple[int]*) – The valid size of the feature maps. The size arrange as as (h, w).
- **device** (*str, optional*) – The device where the flags will be put on. Defaults to 'cuda'.

Returns The valid flags of each points in a single level feature map.

Return type torch.Tensor

sparse_priors(*prior_idxs*, *featmap_size*, *level_idx*, *dtype=torch.float32*, *device='cuda'*)
Generate sparse points according to the `prior_idxs`.

Parameters

- **prior_idxs** (*Tensor*) – The index of corresponding anchors in the feature map.
- **featmap_size** (*tuple[int]*) – feature map size arrange as (w, h).
- **level_idx** (*int*) – The level index of corresponding feature map.
- **(obj** (*device*) – *torch.dtype*): Date type of points. Defaults to `torch.float32`.
- **(obj** – *torch.device*): The device where the points is located.

Returns Anchor with shape (N, 2), N should be equal to the length of `prior_idxs`. And last dimension 2 represent (coord_x, coord_y).

Return type Tensor

valid_flags(*featmap_sizes*, *pad_shape*, *device='cuda'*)
Generate valid flags of points of multiple feature levels.

Parameters

- **featmap_sizes** (*list(tuple)*) – List of feature map sizes in multiple feature levels, each size arrange as as (h, w).
- **pad_shape** (*tuple(int)*) – The padded shape of the image, arrange as (h, w).
- **device** (*str*) – The device where the anchors will be put on.

Returns Valid flags of points of multiple levels.

Return type list(torch.Tensor)

class mmdet.core.anchor.YOLOAnchorGenerator(*strides*, *base_sizes*)
Anchor generator for YOLO.

Parameters

- **strides** (*list[int] | list[tuple[int, int]]*) – Strides of anchors in multiple feature levels.
- **base_sizes** (*list[list[tuple[int, int]]]*) – The basic sizes of anchors in multiple levels.

gen_base_anchors()
Generate base anchors.

Returns Base anchors of a feature grid in multiple feature levels.

Return type list(torch.Tensor)

gen_single_level_base_anchors(*base_sizes_per_level*, *center=None*)
Generate base anchors of a single level.

Parameters

- **base_sizes_per_level** (*list[tuple[int, int]]*) – Basic sizes of anchors.
- **center** (*tuple[float], optional*) – The center of the base anchor related to a single feature grid. Defaults to None.

Returns Anchors in a single-level feature maps.

Return type torch.Tensor

property num_levels
number of feature levels that the generator will be applied

Type int

responsible_flags(*featmap_sizes*, *gt_bboxes*, *device='cuda'*)
Generate responsible anchor flags of grid cells in multiple scales.

Parameters

- **featmap_sizes** (*list(tuple)*) – List of feature map sizes in multiple feature levels.
- **gt_bboxes** (*Tensor*) – Ground truth boxes, shape (n, 4).
- **device** (*str*) – Device where the anchors will be put on.

Returns responsible flags of anchors in multiple level

Return type list(torch.Tensor)

single_level_responsible_flags(*featmap_size*, *gt_bboxes*, *stride*, *num_base_anchors*, *device='cuda'*)
Generate the responsible flags of anchor in a single feature map.

Parameters

- **featmap_size** (*tuple[int]*) – The size of feature maps.
- **gt_bboxes** (*Tensor*) – Ground truth boxes, shape (n, 4).
- **stride** (*tuple(int)*) – stride of current level
- **num_base_anchors** (*int*) – The number of base anchors.
- **device** (*str, optional*) – Device where the flags will be put on. Defaults to 'cuda'.

Returns The valid flags of each anchor in a single level feature map.

Return type torch.Tensor

mmdet.core.anchor.**anchor_inside_flags**(*flat_anchors*, *valid_flags*, *img_shape*, *allowed_border=0*)
Check whether the anchors are inside the border.

Parameters

- **flat_anchors** (*torch.Tensor*) – Flatten anchors, shape (n, 4).
- **valid_flags** (*torch.Tensor*) – An existing valid flags of anchors.
- **img_shape** (*tuple(int)*) – Shape of current image.
- **allowed_border** (*int, optional*) – The border to allow the valid anchor. Defaults to 0.

Returns Flags indicating whether the anchors are inside a valid range.

Return type torch.Tensor

mmdet.core.anchor.**calc_region**(*bbox*, *ratio*, *featmap_size=None*)
Calculate a proportional bbox region.

The bbox center are fixed and the new h' and w' is h * ratio and w * ratio.

Parameters

- **bbox** (*Tensor*) – Bboxes to calculate regions, shape (n, 4).
- **ratio** (*float*) – Ratio of the output region.
- **featmap_size** (*tuple*) – Feature map size used for clipping the boundary.

Returns x1, y1, x2, y2

Return type tuple

mmdet.core.anchor.**images_to_levels**(*target*, *num_levels*)
Convert targets by image to targets by feature level.

[target_img0, target_img1] -> [target_level0, target_level1, ...]

41.2 bbox

class mmdet.core.bbox.**AssignResult**(*num_gts*, *gt_inds*, *max_overlaps*, *labels=None*)
Stores assignments between predicted and truth boxes.

num_gts
the number of truth boxes considered when computing this assignment

Type int

gt_inds
for each predicted box indicates the 1-based index of the assigned truth box. 0 means unassigned and -1 means ignore.

Type LongTensor

max_overlaps
the iou between the predicted box and its assigned truth box.

Type FloatTensor

labels
If specified, for each predicted box indicates the category label of the assigned truth box.

Type None | LongTensor

Example

```
>>> # An assign result between 4 predicted boxes and 9 true boxes
>>> # where only two boxes were assigned.
>>> num_gts = 9
>>> max_overlaps = torch.LongTensor([0, .5, .9, 0])
>>> gt_inds = torch.LongTensor([-1, 1, 2, 0])
>>> labels = torch.LongTensor([0, 3, 4, 0])
>>> self = AssignResult(num_gts, gt_inds, max_overlaps, labels)
>>> print(str(self))  # xdoctest: +IGNORE_WANT
<AssignResult(num_gts=9, gt_inds.shape=(4,), max_overlaps.shape=(4,),
              labels.shape=(4,))>
>>> # Force addition of gt labels (when adding gt as proposals)
>>> new_labels = torch.LongTensor([3, 4, 5])
>>> self.add_gt_(new_labels)
>>> print(str(self))  # xdoctest: +IGNORE_WANT
<AssignResult(num_gts=9, gt_inds.shape=(7,), max_overlaps.shape=(7,),
              labels.shape=(7,))>
```

add_gt_(*gt_labels*)
Add ground truth as assigned results.

Parameters **gt_labels** (*torch.Tensor*) – Labels of gt boxes

get_extra_property(*key*)
Get user-defined property.

property info
a dictionary of info about the object

Type dict

property num_preds
the number of predictions in this assignment

Type int

classmethod random(***kwargs*)
Create random AssignResult for tests or debugging.

Parameters

- **num_preds** – number of predicted boxes
- **num_gts** – number of true boxes
- **p_ignore** (*float*) – probability of a predicted box assigned to an ignored truth
- **p_assigned** (*float*) – probability of a predicted box not being assigned
- **p_use_label** (*float | bool*) – with labels or not
- **rng** (*None | int | numpy.random.RandomState*) – seed or state

Returns Randomly generated assign results.

Return type *AssignResult*

Example

```
>>> from mmdet.core.bbox.assigners.assign_result import *  # NOQA
>>> self = AssignResult.random()
>>> print(self.info)
```

set_extra_property(*key*, *value*)
Set user-defined new property.

class mmdet.core.bbox.**BaseAssigner**
Base assigner that assigns boxes to ground truth boxes.

abstract assign(*bboxes*, *gt_bboxes*, *gt_bboxes_ignore=None*, *gt_labels=None*)
Assign boxes to either a ground truth boxes or a negative boxes.

class mmdet.core.bbox.**BaseBBoxCoder**(***kwargs*)
Base bounding box coder.

abstract decode(*bboxes*, *bboxes_pred*)
Decode the predicted bboxes according to prediction and base boxes.

abstract encode(*bboxes*, *gt_bboxes*)
Encode deltas between bboxes and ground truth boxes.

class mmdet.core.bbox.**BaseSampler**(*num*, *pos_fraction*, *neg_pos_ub=- 1*, *add_gt_as_proposals=True*, ***kwargs*)
Base class of samplers.

sample(*assign_result*, *bboxes*, *gt_bboxes*, *gt_labels=None*, ***kwargs*)
Sample positive and negative bboxes.

This is a simple implementation of bbox sampling given candidates, assigning results and ground truth bboxes.

Parameters

- **assign_result** (*AssignResult*) – Bbox assigning results.
- **bboxes** (*Tensor*) – Boxes to be sampled from.
- **gt_bboxes** (*Tensor*) – Ground truth bboxes.
- **gt_labels** (*Tensor, optional*) – Class labels of ground truth bboxes.

Returns Sampling result.

Return type *SamplingResult*

Example

```
>>> from mmdet.core.bbox import RandomSampler
>>> from mmdet.core.bbox import AssignResult
>>> from mmdet.core.bbox.demodata import ensure_rng, random_boxes
>>> rng = ensure_rng(None)
>>> assign_result = AssignResult.random(rng=rng)
>>> bboxes = random_boxes(assign_result.num_preds, rng=rng)
>>> gt_bboxes = random_boxes(assign_result.num_gts, rng=rng)
>>> gt_labels = None
>>> self = RandomSampler(num=32, pos_fraction=0.5, neg_pos_ub=-1,
```

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```
>>>                         add_gt_as_proposals=False)
>>> self = self.sample(assign_result, bboxes, gt_bboxes, gt_labels)
```

class mmdet.core.bbox.**BboxOverlaps2D**(*scale=1.0*, *dtype=None*)

2D Overlaps (e.g. IoUs, GIoUs) Calculator.

class mmdet.core.bbox.**CenterRegionAssigner**(*pos_scale*, *neg_scale*, *min_pos_iof=0.01*, *ignore_gt_scale=0.5*, *foreground_dominate=False*, *iou_calculator={'type': 'BboxOverlaps2D'}*)

Assign pixels at the center region of a bbox as positive.

Each proposals will be assigned with *-1*, *0*, or a positive integer indicating the ground truth index. - -1: negative samples - semi-positive numbers: positive sample, index (0-based) of assigned gt

Parameters

- **pos_scale** (*float*) – Threshold within which pixels are labelled as positive.
- **neg_scale** (*float*) – Threshold above which pixels are labelled as positive.
- **min_pos_iof** (*float*) – Minimum iof of a pixel with a gt to be labelled as positive. Default: 1e-2
- **ignore_gt_scale** (*float*) – Threshold within which the pixels are ignored when the gt is labelled as shadowed. Default: 0.5
- **foreground_dominate** (*bool*) – If True, the bbox will be assigned as positive when a gt's kernel region overlaps with another's shadowed (ignored) region, otherwise it is set as ignored. Default to False.

assign(*bboxes*, *gt_bboxes*, *gt_bboxes_ignore=None*, *gt_labels=None*)

Assign gt to bboxes.

This method assigns gts to every bbox (proposal/anchor), each bbox will be assigned with -1, or a semi-positive number. -1 means negative sample, semi-positive number is the index (0-based) of assigned gt.

Parameters

- **bboxes** (*Tensor*) – Bounding boxes to be assigned, shape(n, 4).
- **gt_bboxes** (*Tensor*) – Groundtruth boxes, shape (k, 4).
- **gt_bboxes_ignore** (*tensor, optional*) – Ground truth bboxes that are labelled as *ignored*, e.g., crowd boxes in COCO.
- **gt_labels** (*tensor, optional*) – Label of gt_bboxes, shape (num_gts,).

Returns The assigned result. Note that shadowed_labels of shape (N, 2) is also added as an *assign_result* attribute. *shadowed_labels* is a tensor composed of N pairs of anchor_ind, class_label], where N is the number of anchors that lie in the outer region of a gt, anchor_ind is the shadowed anchor index and class_label is the shadowed class label.

Return type *AssignResult*

Example

```
>>> self = CenterRegionAssigner(0.2, 0.2)
>>> bboxes = torch.Tensor([[0, 0, 10, 10], [10, 10, 20, 20]])
>>> gt_bboxes = torch.Tensor([[0, 0, 10, 10]])
>>> assign_result = self.assign(bboxes, gt_bboxes)
>>> expected_gt_inds = torch.LongTensor([1, 0])
>>> assert torch.all(assign_result.gt_inds == expected_gt_inds)
```

assign_one_hot_gt_indices(*is_bbox_in_gt_core*, *is_bbox_in_gt_shadow*, *gt_priority=None*)

Assign only one gt index to each prior box.

Gts with large gt_priority are more likely to be assigned.

Parameters

- **is_bbox_in_gt_core** (*Tensor*) – Bool tensor indicating the bbox center is in the core area of a gt (e.g. 0-0.2). Shape: (num_prior, num_gt).
- **is_bbox_in_gt_shadow** (*Tensor*) – Bool tensor indicating the bbox center is in the shadowed area of a gt (e.g. 0.2-0.5). Shape: (num_prior, num_gt).
- **gt_priority** (*Tensor*) – Priorities of gts. The gt with a higher priority is more likely to be assigned to the bbox when the bbox match with multiple gts. Shape: (num_gt,).

Returns

Returns (assigned_gt_inds, shadowed_gt_inds).

- assigned_gt_inds: The assigned gt index of each prior bbox (i.e. index from 1 to num_gts). Shape: (num_prior,).
- shadowed_gt_inds: shadowed gt indices. It is a tensor of shape (num_ignore, 2) with first column being the shadowed prior bbox indices and the second column the shadowed gt indices (1-based).

Return type tuple

get_gt_priorities(*gt_bboxes*)

Get gt priorities according to their areas.

Smaller gt has higher priority.

Parameters **gt_bboxes** (*Tensor*) – Ground truth boxes, shape (k, 4).

Returns The priority of gts so that gts with larger priority is more likely to be assigned. Shape (k,)

Return type Tensor

class mmdet.core.bbox.**CombinedSampler**(*pos_sampler*, *neg_sampler*, ***kwargs*)

A sampler that combines positive sampler and negative sampler.

class mmdet.core.bbox.**DeltaXYWHBBoxCoder**(*target_means=(0.0, 0.0, 0.0, 0.0)*, *target_stds=(1.0, 1.0, 1.0, 1.0)*, *clip_border=True*, *add_ctr_clamp=False*, *ctr_clamp=32*)

Delta XYWH BBox coder.

Following the practice in R-CNN, this coder encodes bbox (x1, y1, x2, y2) into delta (dx, dy, dw, dh) and decodes delta (dx, dy, dw, dh) back to original bbox (x1, y1, x2, y2).

Parameters

- **target_means** (*Sequence[float]*) – Denormalizing means of target for delta coordinates

- **target_stds** (*Sequence[float]*) – Denormalizing standard deviation of target for delta coordinates
- **clip_border** (*bool, optional*) – Whether clip the objects outside the border of the image. Defaults to True.
- **add_ctr_clamp** (*bool*) – Whether to add center clamp, when added, the predicted box is clamped is its center is too far away from the original anchor's center. Only used by YOLOF. Default False.
- **ctr_clamp** (*int*) – the maximum pixel shift to clamp. Only used by YOLOF. Default 32.

decode(*bboxes*, *pred_bboxes*, *max_shape=None*, *wh_ratio_clip=0.016*)

Apply transformation *pred_bboxes* to *boxes*.

Parameters

- **bboxes** (*torch.Tensor*) – Basic boxes. Shape (B, N, 4) or (N, 4)
- **pred_bboxes** (*Tensor*) – Encoded offsets with respect to each roi. Has shape (B, N, num_classes * 4) or (B, N, 4) or (N, num_classes * 4) or (N, 4). Note N = num_anchors * W * H when rois is a grid of anchors.Offset encoding follows[1].
- **(Sequence[int] or torch.Tensor or Sequence[** (*max_shape*) – Sequence[int]],optional): Maximum bounds for boxes, specifies (H, W, C) or (H, W). If bboxes shape is (B, N, 4), then the max_shape should be a Sequence[Sequence[int]] and the length of max_shape should also be B.
- **wh_ratio_clip** (*float, optional*) – The allowed ratio between width and height.

Returns Decoded boxes.

Return type torch.Tensor

encode(*bboxes*, *gt_bboxes*)

Get box regression transformation deltas that can be used to transform the `bboxes` into the `gt_bboxes`.

Parameters

- **bboxes** (*torch.Tensor*) – Source boxes, e.g., object proposals.
- **gt_bboxes** (*torch.Tensor*) – Target of the transformation, e.g., ground-truth boxes.

Returns Box transformation deltas

Return type torch.Tensor

class mmdet.core.bbox.**DistancePointBBoxCoder**(*clip_border=True*)

Distance Point BBox coder.

This coder encodes gt bboxes (x1, y1, x2, y2) into (top, bottom, left, right) and decode it back to the original.

Parameters **clip_border** (*bool, optional*) – Whether clip the objects outside the border of the image. Defaults to True.

decode(*points*, *pred_bboxes*, *max_shape=None*)

Decode distance prediction to bounding box.

Parameters

- **points** (*Tensor*) – Shape (B, N, 2) or (N, 2).
- **pred_bboxes** (*Tensor*) – Distance from the given point to 4 boundaries (left, top, right, bottom). Shape (B, N, 4) or (N, 4)

[1] https://gitlab.kitware.com/computer-vision/kwimage/-/blob/928cae35ca8/kwimage/structs/polygon.py#L379 # noqa: E501

- **(Sequence[int] or torch.Tensor or Sequence[** (*max_shape*) – Sequence[int]],optional): Maximum bounds for boxes, specifies (H, W, C) or (H, W). If priors shape is (B, N, 4), then the max_shape should be a Sequence[Sequence[int]], and the length of max_shape should also be B. Default None.

Returns Boxes with shape (N, 4) or (B, N, 4)

Return type Tensor

encode(*points*, *gt_bboxes*, *max_dis=None*, *eps=0.1*)

Encode bounding box to distances.

Parameters

- **points** (*Tensor*) – Shape (N, 2), The format is [x, y].
- **gt_bboxes** (*Tensor*) – Shape (N, 4), The format is "xyxy"
- **max_dis** (*float*) – Upper bound of the distance. Default None.
- **eps** (*float*) – a small value to ensure target < max_dis, instead <=. Default 0.1.

Returns Box transformation deltas. The shape is (N, 4).

Return type Tensor

class mmdet.core.bbox.**InstanceBalancedPosSampler**(*num*, *pos_fraction*, *neg_pos_ub=- 1*, *add_gt_as_proposals=True*, ***kwargs*)

Instance balanced sampler that samples equal number of positive samples for each instance.

class mmdet.core.bbox.**IoUBalancedNegSampler**(*num*, *pos_fraction*, *floor_thr=- 1*, *floor_fraction=0*, *num_bins=3*, ***kwargs*)

IoU Balanced Sampling.

arXiv: https://arxiv.org/pdf/1904.02701.pdf (CVPR 2019)

Sampling proposals according to their IoU. *floor_fraction* of needed RoIs are sampled from proposals whose IoU are lower than *floor_thr* randomly. The others are sampled from proposals whose IoU are higher than *floor_thr*. These proposals are sampled from some bins evenly, which are split by *num_bins* via IoU evenly.

Parameters

- **num** (*int*) – number of proposals.
- **pos_fraction** (*float*) – fraction of positive proposals.
- **floor_thr** (*float*) – threshold (minimum) IoU for IoU balanced sampling, set to -1 if all using IoU balanced sampling.
- **floor_fraction** (*float*) – sampling fraction of proposals under floor_thr.
- **num_bins** (*int*) – number of bins in IoU balanced sampling.

sample_via_interval(*max_overlaps*, *full_set*, *num_expected*)

Sample according to the iou interval.

Parameters

- **max_overlaps** (*torch.Tensor*) – IoU between bounding boxes and ground truth boxes.
- **full_set** (*set(int)*) – A full set of indices of boxes
- **num_expected** (*int*) – Number of expected samples

Returns Indices of samples

Return type np.ndarray

class mmdet.core.bbox.**MaxIoUAssigner**(*pos_iou_thr*, *neg_iou_thr*, *min_pos_iou=0.0*, *gt_max_assign_all=True*, *ignore_iof_thr=-1*, *ignore_wrt_candidates=True*, *match_low_quality=True*, *gpu_assign_thr=-1*, *iou_calculator={'type': 'BboxOverlaps2D'}*)

Assign a corresponding gt bbox or background to each bbox.

Each proposals will be assigned with *-1*, or a semi-positive integer indicating the ground truth index.

- -1: negative sample, no assigned gt
- semi-positive integer: positive sample, index (0-based) of assigned gt

Parameters

- **pos_iou_thr** (*float*) – IoU threshold for positive bboxes.
- **neg_iou_thr** (*float or tuple*) – IoU threshold for negative bboxes.
- **min_pos_iou** (*float*) – Minimum iou for a bbox to be considered as a positive bbox. Positive samples can have smaller IoU than pos_iou_thr due to the 4th step (assign max IoU sample to each gt). *min_pos_iou* is set to avoid assigning bboxes that have extremely small iou with GT as positive samples. It brings about 0.3 mAP improvements in 1x schedule but does not affect the performance of 3x schedule. More comparisons can be found in PR #7464.
- **gt_max_assign_all** (*bool*) – Whether to assign all bboxes with the same highest overlap with some gt to that gt.
- **ignore_iof_thr** (*float*) – IoF threshold for ignoring bboxes (if *gt_bboxes_ignore* is specified). Negative values mean not ignoring any bboxes.
- **ignore_wrt_candidates** (*bool*) – Whether to compute the iof between *bboxes* and *gt_bboxes_ignore*, or the contrary.
- **match_low_quality** (*bool*) – Whether to allow low quality matches. This is usually allowed for RPN and single stage detectors, but not allowed in the second stage. Details are demonstrated in Step 4.
- **gpu_assign_thr** (*int*) – The upper bound of the number of GT for GPU assign. When the number of gt is above this threshold, will assign on CPU device. Negative values mean not assign on CPU.

assign(*bboxes*, *gt_bboxes*, *gt_bboxes_ignore=None*, *gt_labels=None*)

Assign gt to bboxes.

This method assign a gt bbox to every bbox (proposal/anchor), each bbox will be assigned with -1, or a semi-positive number. -1 means negative sample, semi-positive number is the index (0-based) of assigned gt. The assignment is done in following steps, the order matters.

1. assign every bbox to the background
2. assign proposals whose iou with all gts < neg_iou_thr to 0
3. for each bbox, if the iou with its nearest gt >= pos_iou_thr, assign it to that bbox
4. for each gt bbox, assign its nearest proposals (may be more than one) to itself

Parameters

- **bboxes** (*Tensor*) – Bounding boxes to be assigned, shape(n, 4).
- **gt_bboxes** (*Tensor*) – Groundtruth boxes, shape (k, 4).

- **gt_bboxes_ignore** (*Tensor, optional*) – Ground truth bboxes that are labelled as *ignored*, e.g., crowd boxes in COCO.
- **gt_labels** (*Tensor, optional*) – Label of gt_bboxes, shape (k,).

Returns The assign result.

Return type *AssignResult*

Example

```
>>> self = MaxIoUAssigner(0.5, 0.5)
>>> bboxes = torch.Tensor([[0, 0, 10, 10], [10, 10, 20, 20]])
>>> gt_bboxes = torch.Tensor([[0, 0, 10, 9]])
>>> assign_result = self.assign(bboxes, gt_bboxes)
>>> expected_gt_inds = torch.LongTensor([1, 0])
>>> assert torch.all(assign_result.gt_inds == expected_gt_inds)
```

assign_wrt_overlaps(*overlaps*, *gt_labels=None*)
Assign w.r.t. the overlaps of bboxes with gts.

Parameters

- **overlaps** (*Tensor*) – Overlaps between k gt_bboxes and n bboxes, shape(k, n).
- **gt_labels** (*Tensor, optional*) – Labels of k gt_bboxes, shape (k,).

Returns The assign result.

Return type *AssignResult*

class mmdet.core.bbox.**OHEMSampler**(*num*, *pos_fraction*, *context*, *neg_pos_ub=-1*, *add_gt_as_proposals=True*, *loss_key='loss_cls'*, ***kwargs*)
Online Hard Example Mining Sampler described in Training Region-based Object Detectors with Online Hard Example Mining.

class mmdet.core.bbox.**PseudoBBoxCoder**(***kwargs*)
Pseudo bounding box coder.

decode(*bboxes*, *pred_bboxes*)
torch.Tensor: return the given `pred_bboxes`

encode(*bboxes*, *gt_bboxes*)
torch.Tensor: return the given `bboxes`

class mmdet.core.bbox.**PseudoSampler**(***kwargs*)
A pseudo sampler that does not do sampling actually.

sample(*assign_result*, *bboxes*, *gt_bboxes*, **args*, ***kwargs*)
Directly returns the positive and negative indices of samples.

Parameters

- **assign_result** (*AssignResult*) – Assigned results
- **bboxes** (*torch.Tensor*) – Bounding boxes
- **gt_bboxes** (*torch.Tensor*) – Ground truth boxes

Returns sampler results

Return type *SamplingResult*

class mmdet.core.bbox.**RandomSampler**(*num*, *pos_fraction*, *neg_pos_ub=- 1*, *add_gt_as_proposals=True*, ***kwargs*)

Random sampler.

Parameters

- **num** (*int*) – Number of samples
- **pos_fraction** (*float*) – Fraction of positive samples
- **neg_pos_up** (*int, optional*) – Upper bound number of negative and positive samples. Defaults to -1.
- **add_gt_as_proposals** (*bool, optional*) – Whether to add ground truth boxes as proposals. Defaults to True.

random_choice(*gallery*, *num*)

Random select some elements from the gallery.

If *gallery* is a Tensor, the returned indices will be a Tensor; If *gallery* is a ndarray or list, the returned indices will be a ndarray.

Parameters

- **gallery** (*Tensor | ndarray | list*) – indices pool.
- **num** (*int*) – expected sample num.

Returns sampled indices.

Return type Tensor or ndarray

class mmdet.core.bbox.**RegionAssigner**(*center_ratio=0.2*, *ignore_ratio=0.5*)

Assign a corresponding gt bbox or background to each bbox.

Each proposals will be assigned with *-1*, *0*, or a positive integer indicating the ground truth index.

- -1: don't care
- 0: negative sample, no assigned gt
- positive integer: positive sample, index (1-based) of assigned gt

Parameters

- **center_ratio** – ratio of the region in the center of the bbox to define positive sample.
- **ignore_ratio** – ratio of the region to define ignore samples.

assign(*mlvl_anchors*, *mlvl_valid_flags*, *gt_bboxes*, *img_meta*, *featmap_sizes*, *anchor_scale*, *anchor_strides*, *gt_bboxes_ignore=None*, *gt_labels=None*, *allowed_border=0*)

Assign gt to anchors.

This method assign a gt bbox to every bbox (proposal/anchor), each bbox will be assigned with -1, 0, or a positive number. -1 means don't care, 0 means negative sample, positive number is the index (1-based) of assigned gt.

The assignment is done in following steps, and the order matters.

1. Assign every anchor to 0 (negative)
2. (For each gt_bboxes) Compute ignore flags based on ignore_region then assign -1 to anchors w.r.t. ignore flags
3. (For each gt_bboxes) Compute pos flags based on center_region then assign gt_bboxes to anchors w.r.t. pos flags

4. (For each gt_bboxes) Compute ignore flags based on adjacent anchor level then assign -1 to anchors w.r.t. ignore flags
5. Assign anchor outside of image to -1

Parameters

- **mlvl_anchors** (*list[Tensor]*) – Multi level anchors.
- **mlvl_valid_flags** (*list[Tensor]*) – Multi level valid flags.
- **gt_bboxes** (*Tensor*) – Ground truth bboxes of image
- **img_meta** (*dict*) – Meta info of image.
- **featmap_sizes** (*list[Tensor]*) – Feature mapsize each level
- **anchor_scale** (*int*) – Scale of the anchor.
- **anchor_strides** (*list[int]*) – Stride of the anchor.
- **gt_bboxes** – Groundtruth boxes, shape (k, 4).
- **gt_bboxes_ignore** (*Tensor, optional*) – Ground truth bboxes that are labelled as *ignored*, e.g., crowd boxes in COCO.
- **gt_labels** (*Tensor, optional*) – Label of gt_bboxes, shape (k,).
- **allowed_border** (*int, optional*) – The border to allow the valid anchor. Defaults to 0.

Returns The assign result.

Return type *AssignResult*

class mmdet.core.bbox.**SamplingResult**(*pos_inds*, *neg_inds*, *bboxes*, *gt_bboxes*, *assign_result*, *gt_flags*)

Bbox sampling result.

Example

```
>>> # xdoctest: +IGNORE_WANT
>>> from mmdet.core.bbox.samplers.sampling_result import *  # NOQA
>>> self = SamplingResult.random(rng=10)
>>> print(f'self = {self}')
self = <SamplingResult({
    'neg_bboxes': torch.Size([12, 4]),
    'neg_inds': tensor([ 0,  1,  2,  4,  5,  6,  7,  8,  9, 10, 11, 12]),
    'num_gts': 4,
    'pos_assigned_gt_inds': tensor([], dtype=torch.int64),
    'pos_bboxes': torch.Size([0, 4]),
    'pos_inds': tensor([], dtype=torch.int64),
    'pos_is_gt': tensor([], dtype=torch.uint8)
})>
```

property bboxes

concatenated positive and negative boxes

Type torch.Tensor

property info

Returns a dictionary of info about the object.

classmethod random(*rng=None*, ***kwargs*)

Parameters

- **rng** (*None | int | numpy.random.RandomState*) – seed or state.
- **kwargs** (*keyword arguments*) –
  - num_preds: number of predicted boxes
  - num_gts: number of true boxes
  - p_ignore (float): probability of a predicted box assigned to an ignored truth.
  - p_assigned (float): probability of a predicted box not being assigned.
  - p_use_label (float | bool): with labels or not.

Returns Randomly generated sampling result.

Return type *SamplingResult*

Example

```
>>> from mmdet.core.bbox.samplers.sampling_result import *  # NOQA
>>> self = SamplingResult.random()
>>> print(self.__dict__)
```

to(*device*)

Change the device of the data inplace.

Example

```
>>> self = SamplingResult.random()
>>> print(f'self = {self.to(None)}')
>>> # xdoctest: +REQUIRES(--gpu)
>>> print(f'self = {self.to(0)}')
```

class mmdet.core.bbox.**ScoreHLRSampler**(*num*, *pos_fraction*, *context*, *neg_pos_ub=-1*, *add_gt_as_proposals=True*, *k=0.5*, *bias=0*, *score_thr=0.05*, *iou_thr=0.5*, ***kwargs*)

Importance-based Sample Reweighting (ISR_N), described in Prime Sample Attention in Object Detection.

Score hierarchical local rank (HLR) differentiates with RandomSampler in negative part. It firstly computes Score-HLR in a two-step way, then linearly maps score hlr to the loss weights.

Parameters

- **num** (*int*) – Total number of sampled RoIs.
- **pos_fraction** (*float*) – Fraction of positive samples.
- **context** (BaseRoIHead) – RoI head that the sampler belongs to.
- **neg_pos_ub** (*int*) – Upper bound of the ratio of num negative to num positive, -1 means no upper bound.
- **add_gt_as_proposals** (*bool*) – Whether to add ground truth as proposals.
- **k** (*float*) – Power of the non-linear mapping.

- **bias** (*float*) – Shift of the non-linear mapping.
- **score_thr** (*float*) – Minimum score that a negative sample is to be considered as valid bbox.

static random_choice(*gallery*, *num*)
Randomly select some elements from the gallery.

If *gallery* is a Tensor, the returned indices will be a Tensor; If *gallery* is a ndarray or list, the returned indices will be a ndarray.

Parameters

- **gallery** (*Tensor | ndarray | list*) – indices pool.
- **num** (*int*) – expected sample num.

Returns sampled indices.

Return type Tensor or ndarray

sample(*assign_result*, *bboxes*, *gt_bboxes*, *gt_labels=None*, *img_meta=None*, ***kwargs*)
Sample positive and negative bboxes.

This is a simple implementation of bbox sampling given candidates, assigning results and ground truth bboxes.

Parameters

- **assign_result** (*AssignResult*) – Bbox assigning results.
- **bboxes** (*Tensor*) – Boxes to be sampled from.
- **gt_bboxes** (*Tensor*) – Ground truth bboxes.
- **gt_labels** (*Tensor, optional*) – Class labels of ground truth bboxes.

Returns

Sampling result and negative label weights.

Return type tuple[*SamplingResult*, Tensor]

class mmdet.core.bbox.**TBLRBBoxCoder**(*normalizer=4.0*, *clip_border=True*)
TBLR BBox coder.

Following the practice in FSAF, this coder encodes gt bboxes (x1, y1, x2, y2) into (top, bottom, left, right) and decode it back to the original.

Parameters

- **normalizer** (*list | float*) – Normalization factor to be divided with when coding the coordinates. If it is a list, it should have length of 4 indicating normalization factor in tblr dims. Otherwise it is a unified float factor for all dims. Default: 4.0
- **clip_border** (*bool, optional*) – Whether clip the objects outside the border of the image. Defaults to True.

decode(*bboxes*, *pred_bboxes*, *max_shape=None*)
Apply transformation *pred_bboxes* to *boxes*.

Parameters

- **bboxes** (*torch.Tensor*) – Basic boxes.Shape (B, N, 4) or (N, 4)
- **pred_bboxes** (*torch.Tensor*) – Encoded boxes with shape (B, N, 4) or (N, 4)

- **(Sequence[int] or torch.Tensor or Sequence[** (*max_shape*) – Sequence[int]],optional): Maximum bounds for boxes, specifies (H, W, C) or (H, W). If bboxes shape is (B, N, 4), then the max_shape should be a Sequence[Sequence[int]] and the length of max_shape should also be B.

Returns Decoded boxes.

Return type torch.Tensor

encode(*bboxes*, *gt_bboxes*)

Get box regression transformation deltas that can be used to transform the `bboxes` into the `gt_bboxes` in the (top, left, bottom, right) order.

Parameters

- **bboxes** (*torch.Tensor*) – source boxes, e.g., object proposals.
- **gt_bboxes** (*torch.Tensor*) – target of the transformation, e.g., ground truth boxes.

Returns Box transformation deltas

Return type torch.Tensor

mmdet.core.bbox.**bbox2distance**(*points*, *bbox*, *max_dis=None*, *eps=0.1*)

Decode bounding box based on distances.

Parameters

- **points** (*Tensor*) – Shape (n, 2), [x, y].
- **bbox** (*Tensor*) – Shape (n, 4), "xyxy" format
- **max_dis** (*float*) – Upper bound of the distance.
- **eps** (*float*) – a small value to ensure target < max_dis, instead <=

Returns Decoded distances.

Return type Tensor

mmdet.core.bbox.**bbox2result**(*bboxes*, *labels*, *num_classes*)

Convert detection results to a list of numpy arrays.

Parameters

- **bboxes** (*torch.Tensor | np.ndarray*) – shape (n, 5)
- **labels** (*torch.Tensor | np.ndarray*) – shape (n,)
- **num_classes** (*int*) – class number, including background class

Returns bbox results of each class

Return type list(ndarray)

mmdet.core.bbox.**bbox2roi**(*bbox_list*)

Convert a list of bboxes to roi format.

Parameters **bbox_list** (*list[Tensor]*) – a list of bboxes corresponding to a batch of images.

Returns shape (n, 5), [batch_ind, x1, y1, x2, y2]

Return type Tensor

mmdet.core.bbox.**bbox_cxcywh_to_xyxy**(*bbox*)

Convert bbox coordinates from (cx, cy, w, h) to (x1, y1, x2, y2).

Parameters **bbox** (*Tensor*) – Shape (n, 4) for bboxes.

Returns Converted bboxes.

Return type Tensor

mmdet.core.bbox.**bbox_flip**(*bboxes*, *img_shape*, *direction='horizontal'*)
Flip bboxes horizontally or vertically.

Parameters

- **bboxes** (*Tensor*) – Shape (..., 4*k)
- **img_shape** (*tuple*) – Image shape.
- **direction** (*str*) – Flip direction, options are "horizontal", "vertical", "diagonal". Default: "horizontal"

Returns Flipped bboxes.

Return type Tensor

mmdet.core.bbox.**bbox_mapping**(*bboxes*, *img_shape*, *scale_factor*, *flip*, *flip_direction='horizontal'*)
Map bboxes from the original image scale to testing scale.

mmdet.core.bbox.**bbox_mapping_back**(*bboxes*, *img_shape*, *scale_factor*, *flip*, *flip_direction='horizontal'*)
Map bboxes from testing scale to original image scale.

mmdet.core.bbox.**bbox_overlaps**(*bboxes1*, *bboxes2*, *mode='iou'*, *is_aligned=False*, *eps=1e-06*)
Calculate overlap between two set of bboxes.

FP16 Contributed by https://github.com/open-mmlab/mmdetection/pull/4889 .. note:

```
Assume bboxes1 is M x 4, bboxes2 is N x 4, when mode is 'iou',
there are some new generated variable when calculating IOU
using bbox_overlaps function:

1) is_aligned is False
    area1: M x 1
    area2: N x 1
    lt: M x N x 2
    rb: M x N x 2
    wh: M x N x 2
    overlap: M x N x 1
    union: M x N x 1
    ious: M x N x 1

    Total memory:
        S = (9 x N x M + N + M) * 4 Byte,

    When using FP16, we can reduce:
        R = (9 x N x M + N + M) * 4 / 2 Byte
        R large than (N + M) * 4 * 2 is always true when N and M >= 1.
        Obviously, N + M <= N * M < 3 * N * M, when N >=2 and M >=2,
                   N + 1 < 3 * N, when N or M is 1.

    Given M = 40 (ground truth), N = 400000 (three anchor boxes
    in per grid, FPN, R-CNNs),
        R = 275 MB (one times)

    A special case (dense detection), M = 512 (ground truth),
```

(continues on next page)

(continued from previous page)

```
        R = 3516 MB = 3.43 GB

    When the batch size is B, reduce:
        B x R

    Therefore, CUDA memory runs out frequently.

    Experiments on GeForce RTX 2080Ti (11019 MiB):

    |   dtype   |   M   |   N   |   Use    |   Real   |   Ideal   |
    |:----:|:----:|:----:|:----:|:----:|:----:|
    |   FP32   |   512 | 400000 | 8020 MiB |   --   |   --   |
    |   FP16   |   512 | 400000 |   4504 MiB | 3516 MiB | 3516 MiB |
    |   FP32   |   40 | 400000 |   1540 MiB |   --   |   --   |
    |   FP16   |   40 | 400000 |   1264 MiB |   276MiB   | 275 MiB |

2) is_aligned is True
    area1: N x 1
    area2: N x 1
    lt: N x 2
    rb: N x 2
    wh: N x 2
    overlap: N x 1
    union: N x 1
    ious: N x 1

    Total memory:
        S = 11 x N * 4 Byte

    When using FP16, we can reduce:
        R = 11 x N * 4 / 2 Byte

So do the 'giou' (large than 'iou').

Time-wise, FP16 is generally faster than FP32.

When gpu_assign_thr is not -1, it takes more time on cpu
but not reduce memory.
There, we can reduce half the memory and keep the speed.
```

If `is_aligned` is `False`, then calculate the overlaps between each bbox of bboxes1 and bboxes2, otherwise the overlaps between each aligned pair of bboxes1 and bboxes2.

Parameters

- **bboxes1** (*Tensor*) – shape (B, m, 4) in <x1, y1, x2, y2> format or empty.
- **bboxes2** (*Tensor*) – shape (B, n, 4) in <x1, y1, x2, y2> format or empty. B indicates the batch dim, in shape (B1, B2, ..., Bn). If `is_aligned` is `True`, then m and n must be equal.
- **mode** (*str*) – "iou" (intersection over union), "iof" (intersection over foreground) or "giou" (generalized intersection over union). Default "iou".
- **is_aligned** (*bool, optional*) – If True, then m and n must be equal. Default False.

- **eps** (*float, optional*) – A value added to the denominator for numerical stability. Default 1e-6.

Returns shape (m, n) if `is_aligned` is False else shape (m,)

Return type Tensor

Example

```
>>> bboxes1 = torch.FloatTensor([
>>>     [0, 0, 10, 10],
>>>     [10, 10, 20, 20],
>>>     [32, 32, 38, 42],
>>> ])
>>> bboxes2 = torch.FloatTensor([
>>>     [0, 0, 10, 20],
>>>     [0, 10, 10, 19],
>>>     [10, 10, 20, 20],
>>> ])
>>> overlaps = bbox_overlaps(bboxes1, bboxes2)
>>> assert overlaps.shape == (3, 3)
>>> overlaps = bbox_overlaps(bboxes1, bboxes2, is_aligned=True)
>>> assert overlaps.shape == (3, )
```

Example

```
>>> empty = torch.empty(0, 4)
>>> nonempty = torch.FloatTensor([[0, 0, 10, 9]])
>>> assert tuple(bbox_overlaps(empty, nonempty).shape) == (0, 1)
>>> assert tuple(bbox_overlaps(nonempty, empty).shape) == (1, 0)
>>> assert tuple(bbox_overlaps(empty, empty).shape) == (0, 0)
```

mmdet.core.bbox.**bbox_rescale**(*bboxes*, *scale_factor=1.0*)

Rescale bounding box w.r.t. scale_factor.

Parameters

- **bboxes** (*Tensor*) – Shape (n, 4) for bboxes or (n, 5) for rois
- **scale_factor** (*float*) – rescale factor

Returns Rescaled bboxes.

Return type Tensor

mmdet.core.bbox.**bbox_xyxy_to_cxcywh**(*bbox*)

Convert bbox coordinates from (x1, y1, x2, y2) to (cx, cy, w, h).

Parameters **bbox** (*Tensor*) – Shape (n, 4) for bboxes.

Returns Converted bboxes.

Return type Tensor

mmdet.core.bbox.**build_assigner**(*cfg*, ***default_args*)

Builder of box assigner.

mmdet.core.bbox.**build_bbox_coder**(*cfg*, ***default_args*)
Builder of box coder.

mmdet.core.bbox.**build_sampler**(*cfg*, ***default_args*)
Builder of box sampler.

mmdet.core.bbox.**distance2bbox**(*points*, *distance*, *max_shape=None*)
Decode distance prediction to bounding box.

Parameters

- **points** (*Tensor*) – Shape (B, N, 2) or (N, 2).
- **distance** (*Tensor*) – Distance from the given point to 4 boundaries (left, top, right, bottom). Shape (B, N, 4) or (N, 4)
- **(Sequence[int] or torch.Tensor or Sequence[** (*max_shape*) – Sequence[int]],optional): Maximum bounds for boxes, specifies (H, W, C) or (H, W). If priors shape is (B, N, 4), then the max_shape should be a Sequence[Sequence[int]] and the length of max_shape should also be B.

Returns Boxes with shape (N, 4) or (B, N, 4)

Return type Tensor

mmdet.core.bbox.**find_inside_bboxes**(*bboxes*, *img_h*, *img_w*)
Find bboxes as long as a part of bboxes is inside the image.

Parameters

- **bboxes** (*Tensor*) – Shape (N, 4).
- **img_h** (*int*) – Image height.
- **img_w** (*int*) – Image width.

Returns Index of the remaining bboxes.

Return type Tensor

mmdet.core.bbox.**roi2bbox**(*rois*)
Convert rois to bounding box format.

Parameters **rois** (*torch.Tensor*) – RoIs with the shape (n, 5) where the first column indicates batch id of each RoI.

Returns Converted boxes of corresponding rois.

Return type list[torch.Tensor]

41.3 export

41.4 mask

class mmdet.core.mask.**BaseInstanceMasks**
Base class for instance masks.

abstract property areas
areas of each instance.

Type ndarray

abstract crop(*bbox*)
Crop each mask by the given bbox.

Parameters **bbox** (*ndarray*) – Bbox in format [x1, y1, x2, y2], shape (4,).

Returns The cropped masks.

Return type *BaseInstanceMasks*

abstract crop_and_resize(*bboxes*, *out_shape*, *inds*, *device*, *interpolation='bilinear'*, *binarize=True*)
Crop and resize masks by the given bboxes.

This function is mainly used in mask targets computation. It firstly align mask to bboxes by assigned_inds, then crop mask by the assigned bbox and resize to the size of (mask_h, mask_w)

Parameters

- **bboxes** (*Tensor*) – Bboxes in format [x1, y1, x2, y2], shape (N, 4)
- **out_shape** (*tuple[int]*) – Target (h, w) of resized mask
- **inds** (*ndarray*) – Indexes to assign masks to each bbox, shape (N,) and values should be between [0, num_masks - 1].
- **device** (*str*) – Device of bboxes
- **interpolation** (*str*) – See *mmcv.imresize*
- **binarize** (*bool*) – if True fractional values are rounded to 0 or 1 after the resize operation. if False and unsupported an error will be raised. Defaults to True.

Returns the cropped and resized masks.

Return type *BaseInstanceMasks*

abstract expand(*expanded_h*, *expanded_w*, *top*, *left*)
see Expand.

abstract flip(*flip_direction='horizontal'*)
Flip masks alone the given direction.

Parameters **flip_direction** (*str*) – Either 'horizontal' or 'vertical'.

Returns The flipped masks.

Return type *BaseInstanceMasks*

abstract pad(*out_shape*, *pad_val*)
Pad masks to the given size of (h, w).

Parameters

- **out_shape** (*tuple[int]*) – Target (h, w) of padded mask.
- **pad_val** (*int*) – The padded value.

Returns The padded masks.

Return type *BaseInstanceMasks*

abstract rescale(*scale*, *interpolation='nearest'*)
Rescale masks as large as possible while keeping the aspect ratio. For details can refer to *mmcv.imrescale*.

Parameters

- **scale** (*tuple[int]*) – The maximum size (h, w) of rescaled mask.
- **interpolation** (*str*) – Same as `mmcv.imrescale()`.

Returns The rescaled masks.

Return type *BaseInstanceMasks*

abstract resize(*out_shape*, *interpolation='nearest'*)
Resize masks to the given out_shape.

Parameters

- **out_shape** – Target (h, w) of resized mask.
- **interpolation** (*str*) – See `mmcv.imresize()`.

Returns The resized masks.

Return type *BaseInstanceMasks*

abstract rotate(*out_shape*, *angle*, *center=None*, *scale=1.0*, *fill_val=0*)
Rotate the masks.

Parameters

- **out_shape** (*tuple[int]*) – Shape for output mask, format (h, w).
- **angle** (*int | float*) – Rotation angle in degrees. Positive values mean counter-clockwise rotation.
- **center** (*tuple[float], optional*) – Center point (w, h) of the rotation in source image. If not specified, the center of the image will be used.
- **scale** (*int | float*) – Isotropic scale factor.
- **fill_val** (*int | float*) – Border value. Default 0 for masks.

Returns Rotated masks.

shear(*out_shape*, *magnitude*, *direction='horizontal'*, *border_value=0*, *interpolation='bilinear'*)
Shear the masks.

Parameters

- **out_shape** (*tuple[int]*) – Shape for output mask, format (h, w).
- **magnitude** (*int | float*) – The magnitude used for shear.
- **direction** (*str*) – The shear direction, either "horizontal" or "vertical".
- **border_value** (*int | tuple[int]*) – Value used in case of a constant border. Default 0.
- **interpolation** (*str*) – Same as in `mmcv.imshear()`.

Returns Sheared masks.

Return type ndarray

abstract to_ndarray()
Convert masks to the format of ndarray.

Returns Converted masks in the format of ndarray.

Return type ndarray

abstract to_tensor(*dtype*, *device*)
Convert masks to the format of Tensor.

Parameters

- **dtype** (*str*) – Dtype of converted mask.

- **device** (*torch.device*) – Device of converted masks.

Returns Converted masks in the format of Tensor.

Return type Tensor

abstract translate(*out_shape*, *offset*, *direction='horizontal'*, *fill_val=0*, *interpolation='bilinear'*)

Translate the masks.

Parameters

- **out_shape** (*tuple[int]*) – Shape for output mask, format (h, w).
- **offset** (*int | float*) – The offset for translate.
- **direction** (*str*) – The translate direction, either "horizontal" or "vertical".
- **fill_val** (*int | float*) – Border value. Default 0.
- **interpolation** (*str*) – Same as `mmcv.imtranslate()`.

Returns Translated masks.

class mmdet.core.mask.**BitmapMasks**(*masks*, *height*, *width*)

This class represents masks in the form of bitmaps.

Parameters

- **masks** (*ndarray*) – ndarray of masks in shape (N, H, W), where N is the number of objects.
- **height** (*int*) – height of masks
- **width** (*int*) – width of masks

Example

```
>>> from mmdet.core.mask.structures import *  # NOQA
>>> num_masks, H, W = 3, 32, 32
>>> rng = np.random.RandomState(0)
>>> masks = (rng.rand(num_masks, H, W) > 0.1).astype(np.int)
>>> self = BitmapMasks(masks, height=H, width=W)
```

```
>>> # demo crop_and_resize
>>> num_boxes = 5
>>> bboxes = np.array([[0, 0, 30, 10.0]] * num_boxes)
>>> out_shape = (14, 14)
>>> inds = torch.randint(0, len(self), size=(num_boxes,))
>>> device = 'cpu'
>>> interpolation = 'bilinear'
>>> new = self.crop_and_resize(
...     bboxes, out_shape, inds, device, interpolation)
>>> assert len(new) == num_boxes
>>> assert new.height, new.width == out_shape
```

property areas

See *BaseInstanceMasks.areas*.

crop(*bbox*)

See *BaseInstanceMasks.crop()*.

crop_and_resize(*bboxes*, *out_shape*, *inds*, *device='cpu'*, *interpolation='bilinear'*, *binarize=True*)
See *BaseInstanceMasks.crop_and_resize()*.

expand(*expanded_h*, *expanded_w*, *top*, *left*)
See *BaseInstanceMasks.expand()*.

flip(*flip_direction='horizontal'*)
See *BaseInstanceMasks.flip()*.

pad(*out_shape*, *pad_val=0*)
See *BaseInstanceMasks.pad()*.

classmethod random(*num_masks=3*, *height=32*, *width=32*, *dtype=<class 'numpy.uint8'>*, *rng=None*)
Generate random bitmap masks for demo / testing purposes.

Example

```
>>> from mmdet.core.mask.structures import BitmapMasks
>>> self = BitmapMasks.random()
>>> print('self = {}'.format(self))
self = BitmapMasks(num_masks=3, height=32, width=32)
```

rescale(*scale*, *interpolation='nearest'*)
See *BaseInstanceMasks.rescale()*.

resize(*out_shape*, *interpolation='nearest'*)
See *BaseInstanceMasks.resize()*.

rotate(*out_shape*, *angle*, *center=None*, *scale=1.0*, *fill_val=0*)
Rotate the BitmapMasks.

Parameters

- **out_shape** (*tuple[int]*) – Shape for output mask, format (h, w).
- **angle** (*int | float*) – Rotation angle in degrees. Positive values mean counter-clockwise rotation.
- **center** (*tuple[float], optional*) – Center point (w, h) of the rotation in source image. If not specified, the center of the image will be used.
- **scale** (*int | float*) – Isotropic scale factor.
- **fill_val** (*int | float*) – Border value. Default 0 for masks.

Returns Rotated BitmapMasks.

Return type *BitmapMasks*

shear(*out_shape*, *magnitude*, *direction='horizontal'*, *border_value=0*, *interpolation='bilinear'*)
Shear the BitmapMasks.

Parameters

- **out_shape** (*tuple[int]*) – Shape for output mask, format (h, w).
- **magnitude** (*int | float*) – The magnitude used for shear.
- **direction** (*str*) – The shear direction, either "horizontal" or "vertical".
- **border_value** (*int | tuple[int]*) – Value used in case of a constant border.
- **interpolation** (*str*) – Same as in `mmcv.imshear()`.

Returns The sheared masks.

Return type *BitmapMasks*

to_ndarray()
See *BaseInstanceMasks.to_ndarray()*.

to_tensor(*dtype*, *device*)
See *BaseInstanceMasks.to_tensor()*.

translate(*out_shape*, *offset*, *direction='horizontal'*, *fill_val=0*, *interpolation='bilinear'*)
Translate the BitmapMasks.

Parameters

- **out_shape** (*tuple[int]*) – Shape for output mask, format (h, w).
- **offset** (*int | float*) – The offset for translate.
- **direction** (*str*) – The translate direction, either "horizontal" or "vertical".
- **fill_val** (*int | float*) – Border value. Default 0 for masks.
- **interpolation** (*str*) – Same as `mmcv.imtranslate()`.

Returns Translated BitmapMasks.

Return type *BitmapMasks*

Example

```
>>> from mmdet.core.mask.structures import BitmapMasks
>>> self = BitmapMasks.random(dtype=np.uint8)
>>> out_shape = (32, 32)
>>> offset = 4
>>> direction = 'horizontal'
>>> fill_val = 0
>>> interpolation = 'bilinear'
>>> # Note, There seem to be issues when:
>>> # * out_shape is different than self's shape
>>> # * the mask dtype is not supported by cv2.AffineWarp
>>> new = self.translate(out_shape, offset, direction, fill_val,
>>>                      interpolation)
>>> assert len(new) == len(self)
>>> assert new.height, new.width == out_shape
```

class mmdet.core.mask.**PolygonMasks**(*masks*, *height*, *width*)
This class represents masks in the form of polygons.

Polygons is a list of three levels. The first level of the list corresponds to objects, the second level to the polys that compose the object, the third level to the poly coordinates

Parameters

- **masks** (*list[list[ndarray]]*) – The first level of the list corresponds to objects, the second level to the polys that compose the object, the third level to the poly coordinates
- **height** (*int*) – height of masks
- **width** (*int*) – width of masks

Example

```
>>> from mmdet.core.mask.structures import *  # NOQA
>>> masks = [
>>>     [ np.array([0, 0, 10, 0, 10, 10., 0, 10, 0, 0]) ]
>>> ]
>>> height, width = 16, 16
>>> self = PolygonMasks(masks, height, width)
```

```
>>> # demo translate
>>> new = self.translate((16, 16), 4., direction='horizontal')
>>> assert np.all(new.masks[0][0][1::2] == masks[0][0][1::2])
>>> assert np.all(new.masks[0][0][0::2] == masks[0][0][0::2] + 4)
```

```
>>> # demo crop_and_resize
>>> num_boxes = 3
>>> bboxes = np.array([[0, 0, 30, 10.0]] * num_boxes)
>>> out_shape = (16, 16)
>>> inds = torch.randint(0, len(self), size=(num_boxes,))
>>> device = 'cpu'
>>> interpolation = 'bilinear'
>>> new = self.crop_and_resize(
...     bboxes, out_shape, inds, device, interpolation)
>>> assert len(new) == num_boxes
>>> assert new.height, new.width == out_shape
```

property areas
Compute areas of masks.

This func is modified from detectron2. The function only works with Polygons using the shoelace formula.

Returns areas of each instance

Return type ndarray

crop(*bbox*)
see *BaseInstanceMasks.crop()*

crop_and_resize(*bboxes*, *out_shape*, *inds*, *device='cpu'*, *interpolation='bilinear'*, *binarize=True*)
see *BaseInstanceMasks.crop_and_resize()*

expand(**args*, ***kwargs*)
TODO: Add expand for polygon

flip(*flip_direction='horizontal'*)
see *BaseInstanceMasks.flip()*

pad(*out_shape*, *pad_val=0*)
padding has no effect on polygons`

classmethod random(*num_masks=3*, *height=32*, *width=32*, *n_verts=5*, *dtype=<class 'numpy.float32'>*, *rng=None*)
Generate random polygon masks for demo / testing purposes.

Adapted from[Page 232, 1]

References

Example

```
>>> from mmdet.core.mask.structures import PolygonMasks
>>> self = PolygonMasks.random()
>>> print('self = {}'.format(self))
```

rescale(*scale*, *interpolation=None*)
see *BaseInstanceMasks.rescale()*

resize(*out_shape*, *interpolation=None*)
see *BaseInstanceMasks.resize()*

rotate(*out_shape*, *angle*, *center=None*, *scale=1.0*, *fill_val=0*)
See *BaseInstanceMasks.rotate()*.

shear(*out_shape*, *magnitude*, *direction='horizontal'*, *border_value=0*, *interpolation='bilinear'*)
See *BaseInstanceMasks.shear()*.

to_bitmap()
convert polygon masks to bitmap masks.

to_ndarray()
Convert masks to the format of ndarray.

to_tensor(*dtype*, *device*)
See *BaseInstanceMasks.to_tensor()*.

translate(*out_shape*, *offset*, *direction='horizontal'*, *fill_val=None*, *interpolation=None*)
Translate the PolygonMasks.

Example

```
>>> self = PolygonMasks.random(dtype=np.int)
>>> out_shape = (self.height, self.width)
>>> new = self.translate(out_shape, 4., direction='horizontal')
>>> assert np.all(new.masks[0][0][1::2] == self.masks[0][0][1::2])
>>> assert np.all(new.masks[0][0][0::2] == self.masks[0][0][0::2] + 4)  # noqa:␣
↪E501
```

mmdet.core.mask.**encode_mask_results**(*mask_results*)
Encode bitmap mask to RLE code.

Parameters **mask_results** (*list | tuple[list]*) – bitmap mask results. In mask scoring rcnn, mask_results is a tuple of (segm_results, segm_cls_score).

Returns RLE encoded mask.

Return type list | tuple

mmdet.core.mask.**mask2bbox**(*masks*)
Obtain tight bounding boxes of binary masks.

Parameters **masks** (*Tensor*) – Binary mask of shape (n, h, w).

Returns Bboxe with shape (n, 4) of positive region in binary mask.

Return type Tensor

mmdet.core.mask.**mask_target**(*pos_proposals_list*, *pos_assigned_gt_inds_list*, *gt_masks_list*, *cfg*)
Compute mask target for positive proposals in multiple images.

Parameters

- **pos_proposals_list** (*list[Tensor]*) – Positive proposals in multiple images.
- **pos_assigned_gt_inds_list** (*list[Tensor]*) – Assigned GT indices for each positive proposals.
- **gt_masks_list** (list[*BaseInstanceMasks*]) – Ground truth masks of each image.
- **cfg** (*dict*) – Config dict that specifies the mask size.

Returns Mask target of each image.

Return type list[Tensor]

Example

```
>>> import mmcv
>>> import mmdet
>>> from mmdet.core.mask import BitmapMasks
>>> from mmdet.core.mask.mask_target import *
>>> H, W = 17, 18
>>> cfg = mmcv.Config({'mask_size': (13, 14)})
>>> rng = np.random.RandomState(0)
>>> # Positive proposals (tl_x, tl_y, br_x, br_y) for each image
>>> pos_proposals_list = [
>>>     torch.Tensor([
>>>         [ 7.2425,  5.5929, 13.9414, 14.9541],
>>>         [ 7.3241,  3.6170, 16.3850, 15.3102],
>>>     ]),
>>>     torch.Tensor([
>>>         [ 4.8448, 6.4010, 7.0314, 9.7681],
>>>         [ 5.9790, 2.6989, 7.4416, 4.8580],
>>>         [ 0.0000, 0.0000, 0.1398, 9.8232],
>>>     ]),
>>> ]
>>> # Corresponding class index for each proposal for each image
>>> pos_assigned_gt_inds_list = [
>>>     torch.LongTensor([7, 0]),
>>>     torch.LongTensor([5, 4, 1]),
>>> ]
>>> # Ground truth mask for each true object for each image
>>> gt_masks_list = [
>>>     BitmapMasks(rng.rand(8, H, W), height=H, width=W),
>>>     BitmapMasks(rng.rand(6, H, W), height=H, width=W),
>>> ]
>>> mask_targets = mask_target(
>>>     pos_proposals_list, pos_assigned_gt_inds_list,
>>>     gt_masks_list, cfg)
>>> assert mask_targets.shape == (5,) + cfg['mask_size']
```

mmdet.core.mask.**split_combined_polys**(*polys*, *poly_lens*, *polys_per_mask*)
Split the combined 1-D polys into masks.

A mask is represented as a list of polys, and a poly is represented as a 1-D array. In dataset, all masks are concatenated into a single 1-D tensor. Here we need to split the tensor into original representations.

Parameters

- **polys** (*list*) – a list (length = image num) of 1-D tensors
- **poly_lens** (*list*) – a list (length = image num) of poly length
- **polys_per_mask** (*list*) – a list (length = image num) of poly number of each mask

Returns a list (length = image num) of list (length = mask num) of list (length = poly num) of numpy array.

Return type list

41.5 evaluation

class mmdet.core.evaluation.**DistEvalHook**(**args*, *dynamic_intervals=None*, ***kwargs*)

before_train_epoch(*runner*)
Evaluate the model only at the start of training by epoch.

before_train_iter(*runner*)
Evaluate the model only at the start of training by iteration.

class mmdet.core.evaluation.**EvalHook**(**args*, *dynamic_intervals=None*, ***kwargs*)

before_train_epoch(*runner*)
Evaluate the model only at the start of training by epoch.

before_train_iter(*runner*)
Evaluate the model only at the start of training by iteration.

mmdet.core.evaluation.**average_precision**(*recalls*, *precisions*, *mode='area'*)
Calculate average precision (for single or multiple scales).

Parameters

- **recalls** (*ndarray*) – shape (num_scales, num_dets) or (num_dets,)
- **precisions** (*ndarray*) – shape (num_scales, num_dets) or (num_dets,)
- **mode** (*str*) – 'area' or '11points', 'area' means calculating the area under precision-recall curve, '11points' means calculating the average precision of recalls at [0, 0.1, . . . , 1]

Returns calculated average precision

Return type float or ndarray

mmdet.core.evaluation.**eval_map**(*det_results*, *annotations*, *scale_ranges=None*, *iou_thr=0.5*, *ioa_thr=None*, *dataset=None*, *logger=None*, *tpfp_fn=None*, *nproc=4*, *use_legacy_coordinate=False*, *use_group_of=False*)
Evaluate mAP of a dataset.

Parameters

- **det_results** (*list[list]*) – [[cls1_det, cls2_det, . . .], . . .]. The outer list indicates images, and the inner list indicates per-class detected bboxes.

- **annotations** (*list[dict]*) – Ground truth annotations where each item of the list indicates an image. Keys of annotations are:
  - *bboxes*: numpy array of shape (n, 4)
  - *labels*: numpy array of shape (n,)
  - *bboxes_ignore* (optional): numpy array of shape (k, 4)
  - *labels_ignore* (optional): numpy array of shape (k,)
- **scale_ranges** (*list[tuple] | None*) – Range of scales to be evaluated, in the format [(min1, max1), (min2, max2), ...]. A range of (32, 64) means the area range between (32**2, 64**2). Default: None.
- **iou_thr** (*float*) – IoU threshold to be considered as matched. Default: 0.5.
- **ioa_thr** (*float | None*) – IoA threshold to be considered as matched, which only used in OpenImages evaluation. Default: None.
- **dataset** (*list[str] | str | None*) – Dataset name or dataset classes, there are minor differences in metrics for different datasets, e.g. "voc07", "imagenet_det", etc. Default: None.
- **logger** (*logging.Logger | str | None*) – The way to print the mAP summary. See *mmcv.utils.print_log()* for details. Default: None.
- **tpfp_fn** (*callable | None*) – The function used to determine true/ false positives. If None, `tpfp_default()` is used as default unless dataset is 'det' or 'vid' (`tpfp_imagenet()` in this case). If it is given as a function, then this function is used to evaluate tp & fp. Default None.
- **nproc** (*int*) – Processes used for computing TP and FP. Default: 4.
- **use_legacy_coordinate** (*bool*) – Whether to use coordinate system in mmdet v1.x. which means width, height should be calculated as 'x2 - x1 + 1` and 'y2 - y1 + 1' respectively. Default: False.
- **use_group_of** (*bool*) – Whether to use group of when calculate TP and FP, which only used in OpenImages evaluation. Default: False.

Returns (mAP, [dict, dict, ...])

Return type tuple

mmdet.core.evaluation.**eval_recalls**(*gts*, *proposals*, *proposal_nums=None*, *iou_thrs=0.5*, *logger=None*, *use_legacy_coordinate=False*)

Calculate recalls.

Parameters

- **gts** (*list[ndarray]*) – a list of arrays of shape (n, 4)
- **proposals** (*list[ndarray]*) – a list of arrays of shape (k, 4) or (k, 5)
- **proposal_nums** (*int | Sequence[int]*) – Top N proposals to be evaluated.
- **iou_thrs** (*float | Sequence[float]*) – IoU thresholds. Default: 0.5.
- **logger** (*logging.Logger | str | None*) – The way to print the recall summary. See *mmcv.utils.print_log()* for details. Default: None.
- **use_legacy_coordinate** (*bool*) – Whether use coordinate system in mmdet v1.x. "1" was added to both height and width which means w, h should be computed as 'x2 - x1 + 1` and 'y2 - y1 + 1'. Default: False.

Returns recalls of different ious and proposal nums

Return type ndarray

mmdet.core.evaluation.**get_classes**(*dataset*)
Get class names of a dataset.

mmdet.core.evaluation.**plot_iou_recall**(*recalls*, *iou_thrs*)
Plot IoU-Recalls curve.

Parameters

- **recalls** (*ndarray or list*) – shape (k,)
- **iou_thrs** (*ndarray or list*) – same shape as *recalls*

mmdet.core.evaluation.**plot_num_recall**(*recalls*, *proposal_nums*)
Plot Proposal_num-Recalls curve.

Parameters

- **recalls** (*ndarray or list*) – shape (k,)
- **proposal_nums** (*ndarray or list*) – same shape as *recalls*

mmdet.core.evaluation.**print_map_summary**(*mean_ap*, *results*, *dataset=None*, *scale_ranges=None*, *logger=None*)
Print mAP and results of each class.

A table will be printed to show the gts/dets/recall/AP of each class and the mAP.

Parameters

- **mean_ap** (*float*) – Calculated from *eval_map()*.
- **results** (*list[dict]*) – Calculated from *eval_map()*.
- **dataset** (*list[str] | str | None*) – Dataset name or dataset classes.
- **scale_ranges** (*list[tuple] | None*) – Range of scales to be evaluated.
- **logger** (*logging.Logger | str | None*) – The way to print the mAP summary. See *mmcv.utils.print_log()* for details. Default: None.

mmdet.core.evaluation.**print_recall_summary**(*recalls*, *proposal_nums*, *iou_thrs*, *row_idxs=None*, *col_idxs=None*, *logger=None*)
Print recalls in a table.

Parameters

- **recalls** (*ndarray*) – calculated from *bbox_recalls*
- **proposal_nums** (*ndarray or list*) – top N proposals
- **iou_thrs** (*ndarray or list*) – iou thresholds
- **row_idxs** (*ndarray*) – which rows(proposal nums) to print
- **col_idxs** (*ndarray*) – which cols(iou thresholds) to print
- **logger** (*logging.Logger | str | None*) – The way to print the recall summary. See *mmcv.utils.print_log()* for details. Default: None.

41.6 post_processing

mmdet.core.post_processing.**fast_nms**(*multi_bboxes*, *multi_scores*, *multi_coeffs*, *score_thr*, *iou_thr*, *top_k*, *max_num=- 1*)

Fast NMS in YOLACT.

Fast NMS allows already-removed detections to suppress other detections so that every instance can be decided to be kept or discarded in parallel, which is not possible in traditional NMS. This relaxation allows us to implement Fast NMS entirely in standard GPU-accelerated matrix operations.

Parameters

- **multi_bboxes** (*Tensor*) – shape (n, #class*4) or (n, 4)
- **multi_scores** (*Tensor*) – shape (n, #class+1), where the last column contains scores of the background class, but this will be ignored.
- **multi_coeffs** (*Tensor*) – shape (n, #class*coeffs_dim).
- **score_thr** (*float*) – bbox threshold, bboxes with scores lower than it will not be considered.
- **iou_thr** (*float*) – IoU threshold to be considered as conflicted.
- **top_k** (*int*) – if there are more than top_k bboxes before NMS, only top top_k will be kept.
- **max_num** (*int*) – if there are more than max_num bboxes after NMS, only top max_num will be kept. If -1, keep all the bboxes. Default: -1.

Returns

(dets, labels, coefficients), tensors of shape (k, 5), (k, 1), and (k, coeffs_dim). Dets are boxes with scores. Labels are 0-based.

Return type tuple

mmdet.core.post_processing.**mask_matrix_nms**(*masks*, *labels*, *scores*, *filter_thr=- 1*, *nms_pre=- 1*, *max_num=- 1*, *kernel='gaussian'*, *sigma=2.0*, *mask_area=None*)

Matrix NMS for multi-class masks.

Parameters

- **masks** (*Tensor*) – Has shape (num_instances, h, w)
- **labels** (*Tensor*) – Labels of corresponding masks, has shape (num_instances,).
- **scores** (*Tensor*) – Mask scores of corresponding masks, has shape (num_instances).
- **filter_thr** (*float*) – Score threshold to filter the masks after matrix nms. Default: -1, which means do not use filter_thr.
- **nms_pre** (*int*) – The max number of instances to do the matrix nms. Default: -1, which means do not use nms_pre.
- **max_num** (*int, optional*) – If there are more than max_num masks after matrix, only top max_num will be kept. Default: -1, which means do not use max_num.
- **kernel** (*str*) – 'linear' or 'gaussian'.
- **sigma** (*float*) – std in gaussian method.
- **mask_area** (*Tensor*) – The sum of seg_masks.

Returns

Processed mask results.

- scores (Tensor): Updated scores, has shape (n,).
- labels (Tensor): Remained labels, has shape (n,).
- masks (Tensor): Remained masks, has shape (n, w, h).
- **keep_inds (Tensor): The indices number of** the remaining mask in the input mask, has shape (n,).

Return type tuple(Tensor)

mmdet.core.post_processing.**merge_aug_bboxes**(*aug_bboxes*, *aug_scores*, *img_metas*, *rcnn_test_cfg*)
Merge augmented detection bboxes and scores.

Parameters

- **aug_bboxes** (*list[Tensor]*) – shape (n, 4*#class)
- **aug_scores** (*list[Tensor] or None*) – shape (n, #class)
- **img_shapes** (*list[Tensor]*) – shape (3,).
- **rcnn_test_cfg** (*dict*) – rcnn test config.

Returns (bboxes, scores)

Return type tuple

mmdet.core.post_processing.**merge_aug_masks**(*aug_masks*, *img_metas*, *rcnn_test_cfg*, *weights=None*)
Merge augmented mask prediction.

Parameters

- **aug_masks** (*list[ndarray]*) – shape (n, #class, h, w)
- **img_shapes** (*list[ndarray]*) – shape (3,).
- **rcnn_test_cfg** (*dict*) – rcnn test config.

Returns (bboxes, scores)

Return type tuple

mmdet.core.post_processing.**merge_aug_proposals**(*aug_proposals*, *img_metas*, *cfg*)
Merge augmented proposals (multiscale, flip, etc.)

Parameters

- **aug_proposals** (*list[Tensor]*) – proposals from different testing schemes, shape (n, 5). Note that they are not rescaled to the original image size.
- **img_metas** (*list[dict]*) – list of image info dict where each dict has: 'img_shape', 'scale_factor', 'flip', and may also contain 'filename', 'ori_shape', 'pad_shape', and 'img_norm_cfg'. For details on the values of these keys see *mmdet/datasets/pipelines/formatting.py:Collect*.
- **cfg** (*dict*) – rpn test config.

Returns shape (n, 4), proposals corresponding to original image scale.

Return type Tensor

mmdet.core.post_processing.**merge_aug_scores**(*aug_scores*)
Merge augmented bbox scores.

mmdet.core.post_processing.**multiclass_nms**(*multi_bboxes*, *multi_scores*, *score_thr*, *nms_cfg*, *max_num=-1*, *score_factors=None*, *return_inds=False*)

NMS for multi-class bboxes.

Parameters

- **multi_bboxes** (*Tensor*) – shape (n, #class*4) or (n, 4)
- **multi_scores** (*Tensor*) – shape (n, #class), where the last column contains scores of the background class, but this will be ignored.
- **score_thr** (*float*) – bbox threshold, bboxes with scores lower than it will not be considered.
- **nms_cfg** (*dict*) – a dict that contains the arguments of nms operations
- **max_num** (*int, optional*) – if there are more than max_num bboxes after NMS, only top max_num will be kept. Default to -1.
- **score_factors** (*Tensor, optional*) – The factors multiplied to scores before applying NMS. Default to None.
- **return_inds** (*bool, optional*) – Whether return the indices of kept bboxes. Default to False.

Returns

(dets, labels, indices (optional)), tensors of shape (k, 5), (k), and (k). Dets are boxes with scores. Labels are 0-based.

Return type tuple

41.7 utils

CHAPTER

FORTYTWO

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CHAPTER

FORTYTHREE

MMDET.MODELS

43.1 detectors

43.2 backbones

class mmdet.models.backbones.**CSPDarknet**(*arch='P5'*, *deepen_factor=1.0*, *widen_factor=1.0*, *out_indices=(2, 3, 4)*, *frozen_stages=- 1*, *use_depthwise=False*, *arch_ovewrite=None*, *spp_kernal_sizes=(5, 9, 13)*, *conv_cfg=None*, *norm_cfg={'eps': 0.001, 'momentum': 0.03, 'type': 'BN'}*, *act_cfg={'type': 'Swish'}*, *norm_eval=False*, *init_cfg={'a': 2.23606797749979, 'distribution': 'uniform', 'layer': 'Conv2d', 'mode': 'fan_in', 'nonlinearity': 'leaky_relu', 'type': 'Kaiming'}*)

CSP-Darknet backbone used in YOLOv5 and YOLOX.

Parameters

- **arch** (*str*) – Architecture of CSP-Darknet, from {P5, P6}. Default: P5.
- **deepen_factor** (*float*) – Depth multiplier, multiply number of blocks in CSP layer by this amount. Default: 1.0.
- **widen_factor** (*float*) – Width multiplier, multiply number of channels in each layer by this amount. Default: 1.0.
- **out_indices** (*Sequence[int]*) – Output from which stages. Default: (2, 3, 4).
- **frozen_stages** (*int*) – Stages to be frozen (stop grad and set eval mode). -1 means not freezing any parameters. Default: -1.
- **use_depthwise** (*bool*) – Whether to use depthwise separable convolution. Default: False.
- **arch_ovewrite** (*list*) – Overwrite default arch settings. Default: None.
- **spp_kernal_sizes** – (tuple[int]): Sequential of kernel sizes of SPP layers. Default: (5, 9, 13).
- **conv_cfg** (*dict*) – Config dict for convolution layer. Default: None.
- **norm_cfg** (*dict*) – Dictionary to construct and config norm layer. Default: dict(type='BN', requires_grad=True).
- **act_cfg** (*dict*) – Config dict for activation layer. Default: dict(type='LeakyReLU', negative_slope=0.1).
- **norm_eval** (*bool*) – Whether to set norm layers to eval mode, namely, freeze running stats (mean and var). Note: Effect on Batch Norm and its variants only.

- **init_cfg** (*dict or list[dict], optional*) – Initialization config dict. Default: None.

Example

```
>>> from mmdet.models import CSPDarknet
>>> import torch
>>> self = CSPDarknet(depth=53)
>>> self.eval()
>>> inputs = torch.rand(1, 3, 416, 416)
>>> level_outputs = self.forward(inputs)
>>> for level_out in level_outputs:
...     print(tuple(level_out.shape))
...
(1, 256, 52, 52)
(1, 512, 26, 26)
(1, 1024, 13, 13)
```

forward(*x*)

Defines the computation performed at every call.

Should be overridden by all subclasses.

Note: Although the recipe for forward pass needs to be defined within this function, one should call the `Module` instance afterwards instead of this since the former takes care of running the registered hooks while the latter silently ignores them.

---

train(*mode=True*)

Sets the module in training mode.

This has any effect only on certain modules. See documentations of particular modules for details of their behaviors in training/evaluation mode, if they are affected, e.g. `Dropout`, `BatchNorm`, etc.

Parameters **mode** (*bool*) – whether to set training mode (`True`) or evaluation mode (`False`). Default: `True`.

Returns self

Return type Module

class mmdet.models.backbones.**Darknet**(*depth=53*, *out_indices=(3, 4, 5)*, *frozen_stages=-1*, *conv_cfg=None*, *norm_cfg={'requires_grad': True, 'type': 'BN'}*, *act_cfg={'negative_slope': 0.1, 'type': 'LeakyReLU'}*, *norm_eval=True*, *pretrained=None*, *init_cfg=None*)

Darknet backbone.

Parameters

- **depth** (*int*) – Depth of Darknet. Currently only support 53.
- **out_indices** (*Sequence[int]*) – Output from which stages.
- **frozen_stages** (*int*) – Stages to be frozen (stop grad and set eval mode). -1 means not freezing any parameters. Default: -1.
- **conv_cfg** (*dict*) – Config dict for convolution layer. Default: None.

- **norm_cfg** (*dict*) – Dictionary to construct and config norm layer. Default: dict(type='BN', requires_grad=True)
- **act_cfg** (*dict*) – Config dict for activation layer. Default: dict(type='LeakyReLU', negative_slope=0.1).
- **norm_eval** (*bool*) – Whether to set norm layers to eval mode, namely, freeze running stats (mean and var). Note: Effect on Batch Norm and its variants only.
- **pretrained** (*str, optional*) – model pretrained path. Default: None
- **init_cfg** (*dict or list[dict], optional*) – Initialization config dict. Default: None

Example

```
>>> from mmdet.models import Darknet
>>> import torch
>>> self = Darknet(depth=53)
>>> self.eval()
>>> inputs = torch.rand(1, 3, 416, 416)
>>> level_outputs = self.forward(inputs)
>>> for level_out in level_outputs:
...     print(tuple(level_out.shape))
...
(1, 256, 52, 52)
(1, 512, 26, 26)
(1, 1024, 13, 13)
```

forward(*x*)

Defines the computation performed at every call.

Should be overridden by all subclasses.

Note: Although the recipe for forward pass needs to be defined within this function, one should call the `Module` instance afterwards instead of this since the former takes care of running the registered hooks while the latter silently ignores them.

---

static make_conv_res_block(*in_channels*, *out_channels*, *res_repeat*, *conv_cfg=None*, *norm_cfg={'requires_grad': True, 'type': 'BN'}*, *act_cfg={'negative_slope': 0.1, 'type': 'LeakyReLU'}*)

In Darknet backbone, ConvLayer is usually followed by ResBlock. This function will make that. The Conv layers always have 3x3 filters with stride=2. The number of the filters in Conv layer is the same as the out channels of the ResBlock.

Parameters

- **in_channels** (*int*) – The number of input channels.
- **out_channels** (*int*) – The number of output channels.
- **res_repeat** (*int*) – The number of ResBlocks.
- **conv_cfg** (*dict*) – Config dict for convolution layer. Default: None.
- **norm_cfg** (*dict*) – Dictionary to construct and config norm layer. Default: dict(type='BN', requires_grad=True)

- **act_cfg** (*dict*) – Config dict for activation layer. Default: dict(type='LeakyReLU', negative_slope=0.1).

train(*mode=True*)
Sets the module in training mode.

This has any effect only on certain modules. See documentations of particular modules for details of their behaviors in training/evaluation mode, if they are affected, e.g. `Dropout`, `BatchNorm`, etc.

Parameters **mode** (*bool*) – whether to set training mode (`True`) or evaluation mode (`False`). Default: `True`.

Returns self

Return type Module

class mmdet.models.backbones.**DetectoRS_ResNeXt**(*groups=1*, *base_width=4*, ***kwargs*)
ResNeXt backbone for DetectoRS.

Parameters

- **groups** (*int*) – The number of groups in ResNeXt.
- **base_width** (*int*) – The base width of ResNeXt.

make_res_layer(***kwargs*)
Pack all blocks in a stage into a `ResLayer` for DetectoRS.

class mmdet.models.backbones.**DetectoRS_ResNet**(*sac=None*, *stage_with_sac=(False, False, False, False)*, *rfp_inplanes=None*, *output_img=False*, *pretrained=None*, *init_cfg=None*, ***kwargs*)
ResNet backbone for DetectoRS.

Parameters

- **sac** (*dict, optional*) – Dictionary to construct SAC (Switchable Atrous Convolution). Default: None.
- **stage_with_sac** (*list*) – Which stage to use sac. Default: (False, False, False, False).
- **rfp_inplanes** (*int, optional*) – The number of channels from RFP. Default: None. If specified, an additional conv layer will be added for `rfp_feat`. Otherwise, the structure is the same as base class.
- **output_img** (*bool*) – If `True`, the input image will be inserted into the starting position of output. Default: False.

forward(*x*)
Forward function.

init_weights()
Initialize the weights.

make_res_layer(***kwargs*)
Pack all blocks in a stage into a `ResLayer` for DetectoRS.

rfp_forward(*x*, *rfp_feats*)
Forward function for RFP.

class mmdet.models.backbones.**EfficientNet**(*arch='b0'*, *drop_path_rate=0.0*, *out_indices=(6)*, *frozen_stages=0*, *conv_cfg={'type': 'Conv2dAdaptivePadding'}*, *norm_cfg={'eps': 0.001, 'type': 'BN'}*, *act_cfg={'type': 'Swish'}*, *norm_eval=False*, *with_cp=False*, *init_cfg=[{'type': 'Kaiming', 'layer': 'Conv2d'}, {'type': 'Constant', 'layer': ['_BatchNorm', 'GroupNorm'], 'val': 1}]*)

EfficientNet backbone.

Parameters

- **arch** (*str*) – Architecture of efficientnet. Defaults to b0.
- **out_indices** (*Sequence[int]*) – Output from which stages. Defaults to (6,).
- **frozen_stages** (*int*) – Stages to be frozen (all param fixed). Defaults to 0, which means not freezing any parameters.
- **conv_cfg** (*dict*) – Config dict for convolution layer. Defaults to None, which means using conv2d.
- **norm_cfg** (*dict*) – Config dict for normalization layer. Defaults to dict(type='BN').
- **act_cfg** (*dict*) – Config dict for activation layer. Defaults to dict(type='Swish').
- **norm_eval** (*bool*) – Whether to set norm layers to eval mode, namely, freeze running stats (mean and var). Note: Effect on Batch Norm and its variants only. Defaults to False.
- **with_cp** (*bool*) – Use checkpoint or not. Using checkpoint will save some memory while slowing down the training speed. Defaults to False.

forward(*x*)

Defines the computation performed at every call.

Should be overridden by all subclasses.

Note: Although the recipe for forward pass needs to be defined within this function, one should call the `Module` instance afterwards instead of this since the former takes care of running the registered hooks while the latter silently ignores them.

---

train(*mode=True*)

Sets the module in training mode.

This has any effect only on certain modules. See documentations of particular modules for details of their behaviors in training/evaluation mode, if they are affected, e.g. `Dropout`, `BatchNorm`, etc.

Parameters **mode** (*bool*) – whether to set training mode (`True`) or evaluation mode (`False`). Default: `True`.

Returns self

Return type Module

class mmdet.models.backbones.**HRNet**(*extra*, *in_channels=3*, *conv_cfg=None*, *norm_cfg={'type': 'BN'}*, *norm_eval=True*, *with_cp=False*, *zero_init_residual=False*, *multiscale_output=True*, *pretrained=None*, *init_cfg=None*)

HRNet backbone.

High-Resolution Representations for Labeling Pixels and Regions arXiv:.

Parameters

- **extra** (*dict*) – Detailed configuration for each stage of HRNet. There must be 4 stages, the configuration for each stage must have 5 keys:
  - num_modules(int): The number of HRModule in this stage.
  - num_branches(int): The number of branches in the HRModule.
  - block(str): The type of convolution block.
  - **num_blocks(tuple): The number of blocks in each branch.** The length must be equal to num_branches.
  - **num_channels(tuple): The number of channels in each branch.** The length must be equal to num_branches.
- **in_channels** (*int*) – Number of input image channels. Default: 3.
- **conv_cfg** (*dict*) – Dictionary to construct and config conv layer.
- **norm_cfg** (*dict*) – Dictionary to construct and config norm layer.
- **norm_eval** (*bool*) – Whether to set norm layers to eval mode, namely, freeze running stats (mean and var). Note: Effect on Batch Norm and its variants only. Default: True.
- **with_cp** (*bool*) – Use checkpoint or not. Using checkpoint will save some memory while slowing down the training speed. Default: False.
- **zero_init_residual** (*bool*) – Whether to use zero init for last norm layer in resblocks to let them behave as identity. Default: False.
- **multiscale_output** (*bool*) – Whether to output multi-level features produced by multiple branches. If False, only the first level feature will be output. Default: True.
- **pretrained** (*str, optional*) – Model pretrained path. Default: None.
- **init_cfg** (*dict or list[dict], optional*) – Initialization config dict. Default: None.

Example

```
>>> from mmdet.models import HRNet
>>> import torch
>>> extra = dict(
>>>     stage1=dict(
>>>         num_modules=1,
>>>         num_branches=1,
>>>         block='BOTTLENECK',
>>>         num_blocks=(4, ),
>>>         num_channels=(64, )),
>>>     stage2=dict(
>>>         num_modules=1,
>>>         num_branches=2,
>>>         block='BASIC',
>>>         num_blocks=(4, 4),
>>>         num_channels=(32, 64)),
>>>     stage3=dict(
>>>         num_modules=4,
>>>         num_branches=3,
>>>         block='BASIC',
```

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```
>>>         num_blocks=(4, 4, 4),
>>>         num_channels=(32, 64, 128)),
>>>     stage4=dict(
>>>         num_modules=3,
>>>         num_branches=4,
>>>         block='BASIC',
>>>         num_blocks=(4, 4, 4, 4),
>>>         num_channels=(32, 64, 128, 256)))
>>> self = HRNet(extra, in_channels=1)
>>> self.eval()
>>> inputs = torch.rand(1, 1, 32, 32)
>>> level_outputs = self.forward(inputs)
>>> for level_out in level_outputs:
...     print(tuple(level_out.shape))
(1, 32, 8, 8)
(1, 64, 4, 4)
(1, 128, 2, 2)
(1, 256, 1, 1)
```

forward(*x*)
Forward function.

property norm1
the normalization layer named "norm1"

Type nn.Module

property norm2
the normalization layer named "norm2"

Type nn.Module

train(*mode=True*)
Convert the model into training mode will keeping the normalization layer freezed.

class mmdet.models.backbones.**HourglassNet**(*downsample_times=5*, *num_stacks=2*, *stage_channels=(256, 256, 384, 384, 384, 512)*, *stage_blocks=(2, 2, 2, 2, 2, 4)*, *feat_channel=256*, *norm_cfg={'requires_grad': True, 'type': 'BN'}*, *pretrained=None*, *init_cfg=None*)

HourglassNet backbone.

Stacked Hourglass Networks for Human Pose Estimation. More details can be found in the paper .

Parameters

- **downsample_times** (*int*) – Downsample times in a HourglassModule.
- **num_stacks** (*int*) – Number of HourglassModule modules stacked, 1 for Hourglass-52, 2 for Hourglass-104.
- **stage_channels** (*list[int]*) – Feature channel of each sub-module in a HourglassModule.
- **stage_blocks** (*list[int]*) – Number of sub-modules stacked in a HourglassModule.
- **feat_channel** (*int*) – Feature channel of conv after a HourglassModule.
- **norm_cfg** (*dict*) – Dictionary to construct and config norm layer.
- **pretrained** (*str, optional*) – model pretrained path. Default: None

- **init_cfg** (*dict or list[dict], optional*) – Initialization config dict. Default: None

Example

```
>>> from mmdet.models import HourglassNet
>>> import torch
>>> self = HourglassNet()
>>> self.eval()
>>> inputs = torch.rand(1, 3, 511, 511)
>>> level_outputs = self.forward(inputs)
>>> for level_output in level_outputs:
...     print(tuple(level_output.shape))
(1, 256, 128, 128)
(1, 256, 128, 128)
```

forward(*x*)
Forward function.

init_weights()
Init module weights.

class mmdet.models.backbones.**MobileNetV2**(*widen_factor=1.0*, *out_indices=(1, 2, 4, 7)*, *frozen_stages=-1*, *conv_cfg=None*, *norm_cfg={'type': 'BN'}*, *act_cfg={'type': 'ReLU6'}*, *norm_eval=False*, *with_cp=False*, *pretrained=None*, *init_cfg=None*)

MobileNetV2 backbone.

Parameters

- **widen_factor** (*float*) – Width multiplier, multiply number of channels in each layer by this amount. Default: 1.0.
- **out_indices** (*Sequence[int], optional*) – Output from which stages. Default: (1, 2, 4, 7).
- **frozen_stages** (*int*) – Stages to be frozen (all param fixed). Default: -1, which means not freezing any parameters.
- **conv_cfg** (*dict, optional*) – Config dict for convolution layer. Default: None, which means using conv2d.
- **norm_cfg** (*dict*) – Config dict for normalization layer. Default: dict(type='BN').
- **act_cfg** (*dict*) – Config dict for activation layer. Default: dict(type='ReLU6').
- **norm_eval** (*bool*) – Whether to set norm layers to eval mode, namely, freeze running stats (mean and var). Note: Effect on Batch Norm and its variants only. Default: False.
- **with_cp** (*bool*) – Use checkpoint or not. Using checkpoint will save some memory while slowing down the training speed. Default: False.
- **pretrained** (*str, optional*) – model pretrained path. Default: None
- **init_cfg** (*dict or list[dict], optional*) – Initialization config dict. Default: None

forward(*x*)
Forward function.

make_layer(*out_channels*, *num_blocks*, *stride*, *expand_ratio*)
Stack InvertedResidual blocks to build a layer for MobileNetV2.

Parameters

- **out_channels** (*int*) – out_channels of block.
- **num_blocks** (*int*) – number of blocks.
- **stride** (*int*) – stride of the first block. Default: 1
- **expand_ratio** (*int*) – Expand the number of channels of the hidden layer in InvertedResidual by this ratio. Default: 6.

train(*mode=True*)

Convert the model into training mode while keep normalization layer frozen.

class mmdet.models.backbones.**PyramidVisionTransformer**(*pretrain_img_size=224*, *in_channels=3*, *embed_dims=64*, *num_stages=4*, *num_layers=[3, 4, 6, 3]*, *num_heads=[1, 2, 5, 8]*, *patch_sizes=[4, 2, 2, 2]*, *strides=[4, 2, 2, 2]*, *paddings=[0, 0, 0, 0]*, *sr_ratios=[8, 4, 2, 1]*, *out_indices=(0, 1, 2, 3)*, *mlp_ratios=[8, 8, 4, 4]*, *qkv_bias=True*, *drop_rate=0.0*, *attn_drop_rate=0.0*, *drop_path_rate=0.1*, *use_abs_pos_embed=True*, *norm_after_stage=False*, *use_conv_ffn=False*, *act_cfg={'type': 'GELU'}*, *norm_cfg={'eps': 1e-06, 'type': 'LN'}*, *pretrained=None*, *convert_weights=True*, *init_cfg=None*)

Pyramid Vision Transformer (PVT)

Implementation of Pyramid Vision Transformer: A Versatile Backbone for Dense Prediction without Convolutions.

Parameters

- **pretrain_img_size** (*int | tuple[int]*) – The size of input image when pretrain. Defaults: 224.
- **in_channels** (*int*) – Number of input channels. Default: 3.
- **embed_dims** (*int*) – Embedding dimension. Default: 64.
- **num_stags** (*int*) – The num of stages. Default: 4.
- **num_layers** (*Sequence[int]*) – The layer number of each transformer encode layer. Default: [3, 4, 6, 3].
- **num_heads** (*Sequence[int]*) – The attention heads of each transformer encode layer. Default: [1, 2, 5, 8].
- **patch_sizes** (*Sequence[int]*) – The patch_size of each patch embedding. Default: [4, 2, 2, 2].
- **strides** (*Sequence[int]*) – The stride of each patch embedding. Default: [4, 2, 2, 2].
- **paddings** (*Sequence[int]*) – The padding of each patch embedding. Default: [0, 0, 0, 0].
- **sr_ratios** (*Sequence[int]*) – The spatial reduction rate of each transformer encode layer. Default: [8, 4, 2, 1].
- **out_indices** (*Sequence[int] | int*) – Output from which stages. Default: (0, 1, 2, 3).
- **mlp_ratios** (*Sequence[int]*) – The ratio of the mlp hidden dim to the embedding dim of each transformer encode layer. Default: [8, 8, 4, 4].

- **qkv_bias** (*bool*) – Enable bias for qkv if True. Default: True.
- **drop_rate** (*float*) – Probability of an element to be zeroed. Default 0.0.
- **attn_drop_rate** (*float*) – The drop out rate for attention layer. Default 0.0.
- **drop_path_rate** (*float*) – stochastic depth rate. Default 0.1.
- **use_abs_pos_embed** (*bool*) – If True, add absolute position embedding to the patch embedding. Defaults: True.
- **use_conv_ffn** (*bool*) – If True, use Convolutional FFN to replace FFN. Default: False.
- **act_cfg** (*dict*) – The activation config for FFNs. Default: dict(type='GELU').
- **norm_cfg** (*dict*) – Config dict for normalization layer. Default: dict(type='LN').
- **pretrained** (*str, optional*) – model pretrained path. Default: None.
- **convert_weights** (*bool*) – The flag indicates whether the pre-trained model is from the original repo. We may need to convert some keys to make it compatible. Default: True.
- **init_cfg** (*dict or list[dict], optional*) – Initialization config dict. Default: None.

forward(*x*)

Defines the computation performed at every call.

Should be overridden by all subclasses.

Note: Although the recipe for forward pass needs to be defined within this function, one should call the `Module` instance afterwards instead of this since the former takes care of running the registered hooks while the latter silently ignores them.

---

init_weights()

Initialize the weights.

class mmdet.models.backbones.**PyramidVisionTransformerV2**(***kwargs*)

Implementation of PVTv2: Improved Baselines with Pyramid Vision Transformer.

class mmdet.models.backbones.**RegNet**(*arch*, *in_channels=3*, *stem_channels=32*, *base_channels=32*, *strides=(2, 2, 2, 2)*, *dilations=(1, 1, 1, 1)*, *out_indices=(0, 1, 2, 3)*, *style='pytorch'*, *deep_stem=False*, *avg_down=False*, *frozen_stages=-1*, *conv_cfg=None*, *norm_cfg={'requires_grad': True, 'type': 'BN'}*, *norm_eval=True*, *dcn=None*, *stage_with_dcn=(False, False, False, False)*, *plugins=None*, *with_cp=False*, *zero_init_residual=True*, *pretrained=None*, *init_cfg=None*)

RegNet backbone.

More details can be found in paper .

Parameters

- **arch** (*dict*) – The parameter of RegNets.
  - w0 (int): initial width
  - wa (float): slope of width
  - wm (float): quantization parameter to quantize the width
  - depth (int): depth of the backbone
  - group_w (int): width of group

  - bot_mul (float): bottleneck ratio, i.e. expansion of bottleneck.
- **strides** (*Sequence[int]*) – Strides of the first block of each stage.
- **base_channels** (*int*) – Base channels after stem layer.
- **in_channels** (*int*) – Number of input image channels. Default: 3.
- **dilations** (*Sequence[int]*) – Dilation of each stage.
- **out_indices** (*Sequence[int]*) – Output from which stages.
- **style** (*str*) – *pytorch* or *caffe*. If set to "pytorch", the stride-two layer is the 3x3 conv layer, otherwise the stride-two layer is the first 1x1 conv layer.
- **frozen_stages** (*int*) – Stages to be frozen (all param fixed). -1 means not freezing any parameters.
- **norm_cfg** (*dict*) – dictionary to construct and config norm layer.
- **norm_eval** (*bool*) – Whether to set norm layers to eval mode, namely, freeze running stats (mean and var). Note: Effect on Batch Norm and its variants only.
- **with_cp** (*bool*) – Use checkpoint or not. Using checkpoint will save some memory while slowing down the training speed.
- **zero_init_residual** (*bool*) – whether to use zero init for last norm layer in resblocks to let them behave as identity.
- **pretrained** (*str, optional*) – model pretrained path. Default: None
- **init_cfg** (*dict or list[dict], optional*) – Initialization config dict. Default: None

Example

```
>>> from mmdet.models import RegNet
>>> import torch
>>> self = RegNet(
        arch=dict(
            w0=88,
            wa=26.31,
            wm=2.25,
            group_w=48,
            depth=25,
            bot_mul=1.0))
>>> self.eval()
>>> inputs = torch.rand(1, 3, 32, 32)
>>> level_outputs = self.forward(inputs)
>>> for level_out in level_outputs:
...     print(tuple(level_out.shape))
(1, 96, 8, 8)
(1, 192, 4, 4)
(1, 432, 2, 2)
(1, 1008, 1, 1)
```

adjust_width_group(*widths*, *bottleneck_ratio*, *groups*)

Adjusts the compatibility of widths and groups.

Parameters

- **widths** (*list[int]*) – Width of each stage.
- **bottleneck_ratio** (*float*) – Bottleneck ratio.
- **groups** (*int*) – number of groups in each stage

Returns The adjusted widths and groups of each stage.

Return type tuple(list)

forward(*x*)
Forward function.

generate_regnet(*initial_width*, *width_slope*, *width_parameter*, *depth*, *divisor=8*)
Generates per block width from RegNet parameters.

Parameters

- **initial_width** (*[int]*) – Initial width of the backbone
- **width_slope** (*[float]*) – Slope of the quantized linear function
- **width_parameter** (*[int]*) – Parameter used to quantize the width.
- **depth** (*[int]*) – Depth of the backbone.
- **divisor** (*int, optional*) – The divisor of channels. Defaults to 8.

Returns return a list of widths of each stage and the number of stages

Return type list, int

get_stages_from_blocks(*widths*)
Gets widths/stage_blocks of network at each stage.

Parameters **widths** (*list[int]*) – Width in each stage.

Returns width and depth of each stage

Return type tuple(list)

static quantize_float(*number*, *divisor*)
Converts a float to closest non-zero int divisible by divisor.

Parameters

- **number** (*int*) – Original number to be quantized.
- **divisor** (*int*) – Divisor used to quantize the number.

Returns quantized number that is divisible by devisor.

Return type int

class mmdet.models.backbones.**Res2Net**(*scales=4*, *base_width=26*, *style='pytorch'*, *deep_stem=True*, *avg_down=True*, *pretrained=None*, *init_cfg=None*, ***kwargs*)
Res2Net backbone.

Parameters

- **scales** (*int*) – Scales used in Res2Net. Default: 4
- **base_width** (*int*) – Basic width of each scale. Default: 26
- **depth** (*int*) – Depth of res2net, from {50, 101, 152}.
- **in_channels** (*int*) – Number of input image channels. Default: 3.
- **num_stages** (*int*) – Res2net stages. Default: 4.

- **strides** (*Sequence[int]*) – Strides of the first block of each stage.
- **dilations** (*Sequence[int]*) – Dilation of each stage.
- **out_indices** (*Sequence[int]*) – Output from which stages.
- **style** (*str*) – *pytorch* or *caffe*. If set to "pytorch", the stride-two layer is the 3x3 conv layer, otherwise the stride-two layer is the first 1x1 conv layer.
- **deep_stem** (*bool*) – Replace 7x7 conv in input stem with 3 3x3 conv
- **avg_down** (*bool*) – Use AvgPool instead of stride conv when downsampling in the bottle2neck.
- **frozen_stages** (*int*) – Stages to be frozen (stop grad and set eval mode). -1 means not freezing any parameters.
- **norm_cfg** (*dict*) – Dictionary to construct and config norm layer.
- **norm_eval** (*bool*) – Whether to set norm layers to eval mode, namely, freeze running stats (mean and var). Note: Effect on Batch Norm and its variants only.
- **plugins** (*list[dict]*) – List of plugins for stages, each dict contains:
  - cfg (dict, required): Cfg dict to build plugin.
  - position (str, required): Position inside block to insert plugin, options are 'after_conv1', 'after_conv2', 'after_conv3'.
  - stages (tuple[bool], optional): Stages to apply plugin, length should be same as 'num_stages'.
- **with_cp** (*bool*) – Use checkpoint or not. Using checkpoint will save some memory while slowing down the training speed.
- **zero_init_residual** (*bool*) – Whether to use zero init for last norm layer in resblocks to let them behave as identity.
- **pretrained** (*str, optional*) – model pretrained path. Default: None
- **init_cfg** (*dict or list[dict], optional*) – Initialization config dict. Default: None

Example

```
>>> from mmdet.models import Res2Net
>>> import torch
>>> self = Res2Net(depth=50, scales=4, base_width=26)
>>> self.eval()
>>> inputs = torch.rand(1, 3, 32, 32)
>>> level_outputs = self.forward(inputs)
>>> for level_out in level_outputs:
...     print(tuple(level_out.shape))
(1, 256, 8, 8)
(1, 512, 4, 4)
(1, 1024, 2, 2)
(1, 2048, 1, 1)
```

make_res_layer(***kwargs*)

Pack all blocks in a stage into a `ResLayer`.

class mmdet.models.backbones.**ResNeSt**(*groups=1*, *base_width=4*, *radix=2*, *reduction_factor=4*, *avg_down_stride=True*, ***kwargs*)

ResNeSt backbone.

Parameters

- **groups** (*int*) – Number of groups of Bottleneck. Default: 1
- **base_width** (*int*) – Base width of Bottleneck. Default: 4
- **radix** (*int*) – Radix of SplitAttentionConv2d. Default: 2
- **reduction_factor** (*int*) – Reduction factor of inter_channels in SplitAttentionConv2d. Default: 4.
- **avg_down_stride** (*bool*) – Whether to use average pool for stride in Bottleneck. Default: True.
- **kwargs** (*dict*) – Keyword arguments for ResNet.

make_res_layer(***kwargs*)

Pack all blocks in a stage into a ResLayer.

class mmdet.models.backbones.**ResNeXt**(*groups=1*, *base_width=4*, ***kwargs*)

ResNeXt backbone.

Parameters

- **depth** (*int*) – Depth of resnet, from {18, 34, 50, 101, 152}.
- **in_channels** (*int*) – Number of input image channels. Default: 3.
- **num_stages** (*int*) – Resnet stages. Default: 4.
- **groups** (*int*) – Group of resnext.
- **base_width** (*int*) – Base width of resnext.
- **strides** (*Sequence[int]*) – Strides of the first block of each stage.
- **dilations** (*Sequence[int]*) – Dilation of each stage.
- **out_indices** (*Sequence[int]*) – Output from which stages.
- **style** (*str*) – *pytorch* or *caffe*. If set to "pytorch", the stride-two layer is the 3x3 conv layer, otherwise the stride-two layer is the first 1x1 conv layer.
- **frozen_stages** (*int*) – Stages to be frozen (all param fixed). -1 means not freezing any parameters.
- **norm_cfg** (*dict*) – dictionary to construct and config norm layer.
- **norm_eval** (*bool*) – Whether to set norm layers to eval mode, namely, freeze running stats (mean and var). Note: Effect on Batch Norm and its variants only.
- **with_cp** (*bool*) – Use checkpoint or not. Using checkpoint will save some memory while slowing down the training speed.
- **zero_init_residual** (*bool*) – whether to use zero init for last norm layer in resblocks to let them behave as identity.

make_res_layer(***kwargs*)

Pack all blocks in a stage into a ResLayer

class mmdet.models.backbones.**ResNet**(*depth*, *in_channels=3*, *stem_channels=None*, *base_channels=64*, *num_stages=4*, *strides=(1, 2, 2, 2)*, *dilations=(1, 1, 1, 1)*, *out_indices=(0, 1, 2, 3)*, *style='pytorch'*, *deep_stem=False*, *avg_down=False*, *frozen_stages=- 1*, *conv_cfg=None*, *norm_cfg={'requires_grad': True, 'type': 'BN'}*, *norm_eval=True*, *dcn=None*, *stage_with_dcn=(False, False, False, False)*, *plugins=None*, *with_cp=False*, *zero_init_residual=True*, *pretrained=None*, *init_cfg=None*)

ResNet backbone.

Parameters

- **depth** (*int*) – Depth of resnet, from {18, 34, 50, 101, 152}.
- **stem_channels** (*int | None*) – Number of stem channels. If not specified, it will be the same as *base_channels*. Default: None.
- **base_channels** (*int*) – Number of base channels of res layer. Default: 64.
- **in_channels** (*int*) – Number of input image channels. Default: 3.
- **num_stages** (*int*) – Resnet stages. Default: 4.
- **strides** (*Sequence[int]*) – Strides of the first block of each stage.
- **dilations** (*Sequence[int]*) – Dilation of each stage.
- **out_indices** (*Sequence[int]*) – Output from which stages.
- **style** (*str*) – *pytorch* or *caffe*. If set to "pytorch", the stride-two layer is the 3x3 conv layer, otherwise the stride-two layer is the first 1x1 conv layer.
- **deep_stem** (*bool*) – Replace 7x7 conv in input stem with 3 3x3 conv
- **avg_down** (*bool*) – Use AvgPool instead of stride conv when downsampling in the bottleneck.
- **frozen_stages** (*int*) – Stages to be frozen (stop grad and set eval mode). -1 means not freezing any parameters.
- **norm_cfg** (*dict*) – Dictionary to construct and config norm layer.
- **norm_eval** (*bool*) – Whether to set norm layers to eval mode, namely, freeze running stats (mean and var). Note: Effect on Batch Norm and its variants only.
- **plugins** (*list[dict]*) – List of plugins for stages, each dict contains:
  - cfg (dict, required): Cfg dict to build plugin.
  - position (str, required): Position inside block to insert plugin, options are 'after_conv1', 'after_conv2', 'after_conv3'.
  - stages (tuple[bool], optional): Stages to apply plugin, length should be same as 'num_stages'.
- **with_cp** (*bool*) – Use checkpoint or not. Using checkpoint will save some memory while slowing down the training speed.
- **zero_init_residual** (*bool*) – Whether to use zero init for last norm layer in resblocks to let them behave as identity.
- **pretrained** (*str, optional*) – model pretrained path. Default: None
- **init_cfg** (*dict or list[dict], optional*) – Initialization config dict. Default: None

Example

```
>>> from mmdet.models import ResNet
>>> import torch
>>> self = ResNet(depth=18)
>>> self.eval()
>>> inputs = torch.rand(1, 3, 32, 32)
>>> level_outputs = self.forward(inputs)
>>> for level_out in level_outputs:
...     print(tuple(level_out.shape))
(1, 64, 8, 8)
(1, 128, 4, 4)
(1, 256, 2, 2)
(1, 512, 1, 1)
```

forward(*x*)
Forward function.

make_res_layer(***kwargs*)
Pack all blocks in a stage into a `ResLayer`.

make_stage_plugins(*plugins*, *stage_idx*)
Make plugins for ResNet `stage_idx` th stage.

Currently we support to insert `context_block`, `empirical_attention_block`, `nonlocal_block` into the backbone like ResNet/ResNeXt. They could be inserted after conv1/conv2/conv3 of Bottleneck.

An example of plugins format could be:

Examples

```
>>> plugins=[
...     dict(cfg=dict(type='xxx', arg1='xxx'),
...          stages=(False, True, True, True),
...          position='after_conv2'),
...     dict(cfg=dict(type='yyy'),
...          stages=(True, True, True, True),
...          position='after_conv3'),
...     dict(cfg=dict(type='zzz', postfix='1'),
...          stages=(True, True, True, True),
...          position='after_conv3'),
...     dict(cfg=dict(type='zzz', postfix='2'),
...          stages=(True, True, True, True),
...          position='after_conv3')
... ]
>>> self = ResNet(depth=18)
>>> stage_plugins = self.make_stage_plugins(plugins, 0)
>>> assert len(stage_plugins) == 3
```

Suppose `stage_idx=0`, the structure of blocks in the stage would be:

```
conv1-> conv2->conv3->yyy->zzz1->zzz2
```

Suppose 'stage_idx=1', the structure of blocks in the stage would be:

```
conv1-> conv2->xxx->conv3->yyy->zzz1->zzz2
```

If stages is missing, the plugin would be applied to all stages.

Parameters

- **plugins** (*list[dict]*) – List of plugins cfg to build. The postfix is required if multiple same type plugins are inserted.
- **stage_idx** (*int*) – Index of stage to build

Returns Plugins for current stage

Return type list[dict]

property norm1

the normalization layer named "norm1"

Type nn.Module

train(*mode=True*)

Convert the model into training mode while keep normalization layer freezed.

class mmdet.models.backbones.**ResNetV1d**(***kwargs*)

ResNetV1d variant described in Bag of Tricks.

Compared with default ResNet(ResNetV1b), ResNetV1d replaces the 7x7 conv in the input stem with three 3x3 convs. And in the downsampling block, a 2x2 avg_pool with stride 2 is added before conv, whose stride is changed to 1.

class mmdet.models.backbones.**SSDVGG**(*depth*, *with_last_pool=False*, *ceil_mode=True*, *out_indices=(3, 4)*, *out_feature_indices=(22, 34)*, *pretrained=None*, *init_cfg=None*, *input_size=None*, *l2_norm_scale=None*)

VGG Backbone network for single-shot-detection.

Parameters

- **depth** (*int*) – Depth of vgg, from {11, 13, 16, 19}.
- **with_last_pool** (*bool*) – Whether to add a pooling layer at the last of the model
- **ceil_mode** (*bool*) – When True, will use *ceil* instead of *floor* to compute the output shape.
- **out_indices** (*Sequence[int]*) – Output from which stages.
- **out_feature_indices** (*Sequence[int]*) – Output from which feature map.
- **pretrained** (*str, optional*) – model pretrained path. Default: None
- **init_cfg** (*dict or list[dict], optional*) – Initialization config dict. Default: None
- **input_size** (*int, optional*) – Deprecated argumment. Width and height of input, from {300, 512}.
- **l2_norm_scale** (*float, optional*) – Deprecated argumment. L2 normalization layer init scale.

Example

```
>>> self = SSDVGG(input_size=300, depth=11)
>>> self.eval()
>>> inputs = torch.rand(1, 3, 300, 300)
>>> level_outputs = self.forward(inputs)
>>> for level_out in level_outputs:
...     print(tuple(level_out.shape))
(1, 1024, 19, 19)
(1, 512, 10, 10)
(1, 256, 5, 5)
(1, 256, 3, 3)
(1, 256, 1, 1)
```

forward(*x*)
Forward function.

init_weights(*pretrained=None*)
Initialize the weights.

class mmdet.models.backbones.**SwinTransformer**(*pretrain_img_size=224*, *in_channels=3*, *embed_dims=96*, *patch_size=4*, *window_size=7*, *mlp_ratio=4*, *depths=(2, 2, 6, 2)*, *num_heads=(3, 6, 12, 24)*, *strides=(4, 2, 2, 2)*, *out_indices=(0, 1, 2, 3)*, *qkv_bias=True*, *qk_scale=None*, *patch_norm=True*, *drop_rate=0.0*, *attn_drop_rate=0.0*, *drop_path_rate=0.1*, *use_abs_pos_embed=False*, *act_cfg={'type': 'GELU'}*, *norm_cfg={'type': 'LN'}*, *with_cp=False*, *pretrained=None*, *convert_weights=False*, *frozen_stages=- 1*, *init_cfg=None*)

Swin Transformer A PyTorch implement of : *Swin Transformer: Hierarchical Vision Transformer using Shifted Windows* -

https://arxiv.org/abs/2103.14030

Inspiration from https://github.com/microsoft/Swin-Transformer

Parameters

- **pretrain_img_size** (*int | tuple[int]*) – The size of input image when pretrain. Defaults: 224.
- **in_channels** (*int*) – The num of input channels. Defaults: 3.
- **embed_dims** (*int*) – The feature dimension. Default: 96.
- **patch_size** (*int | tuple[int]*) – Patch size. Default: 4.
- **window_size** (*int*) – Window size. Default: 7.
- **mlp_ratio** (*int*) – Ratio of mlp hidden dim to embedding dim. Default: 4.
- **depths** (*tuple[int]*) – Depths of each Swin Transformer stage. Default: (2, 2, 6, 2).
- **num_heads** (*tuple[int]*) – Parallel attention heads of each Swin Transformer stage. Default: (3, 6, 12, 24).
- **strides** (*tuple[int]*) – The patch merging or patch embedding stride of each Swin Transformer stage. (In swin, we set kernel size equal to stride.) Default: (4, 2, 2, 2).
- **out_indices** (*tuple[int]*) – Output from which stages. Default: (0, 1, 2, 3).

- **qkv_bias** (*bool, optional*) – If True, add a learnable bias to query, key, value. Default: True
- **qk_scale** (*float | None, optional*) – Override default qk scale of head_dim ** -0.5 if set. Default: None.
- **patch_norm** (*bool*) – If add a norm layer for patch embed and patch merging. Default: True.
- **drop_rate** (*float*) – Dropout rate. Defaults: 0.
- **attn_drop_rate** (*float*) – Attention dropout rate. Default: 0.
- **drop_path_rate** (*float*) – Stochastic depth rate. Defaults: 0.1.
- **use_abs_pos_embed** (*bool*) – If True, add absolute position embedding to the patch embedding. Defaults: False.
- **act_cfg** (*dict*) – Config dict for activation layer. Default: dict(type='GELU').
- **norm_cfg** (*dict*) – Config dict for normalization layer at output of backone. Defaults: dict(type='LN').
- **with_cp** (*bool, optional*) – Use checkpoint or not. Using checkpoint will save some memory while slowing down the training speed. Default: False.
- **pretrained** (*str, optional*) – model pretrained path. Default: None.
- **convert_weights** (*bool*) – The flag indicates whether the pre-trained model is from the original repo. We may need to convert some keys to make it compatible. Default: False.
- **frozen_stages** (*int*) – Stages to be frozen (stop grad and set eval mode). Default: -1 (-1 means not freezing any parameters).
- **init_cfg** (*dict, optional*) – The Config for initialization. Defaults to None.

forward(*x*)

Defines the computation performed at every call.

Should be overridden by all subclasses.

Note: Although the recipe for forward pass needs to be defined within this function, one should call the `Module` instance afterwards instead of this since the former takes care of running the registered hooks while the latter silently ignores them.

---

init_weights()

Initialize the weights.

train(*mode=True*)

Convert the model into training mode while keep layers freezed.

class mmdet.models.backbones.**TridentResNet**(*depth*, *num_branch*, *test_branch_idx*, *trident_dilations*, ***kwargs*)

The stem layer, stage 1 and stage 2 in Trident ResNet are identical to ResNet, while in stage 3, Trident BottleBlock is utilized to replace the normal BottleBlock to yield trident output. Different branch shares the convolution weight but uses different dilations to achieve multi-scale output.

/ stage3(b0) x - stem - stage1 - stage2 - stage3(b1) - output stage3(b2) /

Parameters

- **depth** (*int*) – Depth of resnet, from {50, 101, 152}.

- **num_branch** (*int*) – Number of branches in TridentNet.
- **test_branch_idx** (*int*) – In inference, all 3 branches will be used if *test_branch_idx==-1*, otherwise only branch with index *test_branch_idx* will be used.
- **trident_dilations** (*tuple[int]*) – Dilations of different trident branch. len(trident_dilations) should be equal to num_branch.

43.3 necks

class mmdet.models.necks.**BFP**(*Balanced Feature Pyramids*)

BFP takes multi-level features as inputs and gather them into a single one, then refine the gathered feature and scatter the refined results to multi-level features. This module is used in Libra R-CNN (CVPR 2019), see the paper Libra R-CNN: Towards Balanced Learning for Object Detection for details.

Parameters

- **in_channels** (*int*) – Number of input channels (feature maps of all levels should have the same channels).
- **num_levels** (*int*) – Number of input feature levels.
- **conv_cfg** (*dict*) – The config dict for convolution layers.
- **norm_cfg** (*dict*) – The config dict for normalization layers.
- **refine_level** (*int*) – Index of integration and refine level of BSF in multi-level features from bottom to top.
- **refine_type** (*str*) – Type of the refine op, currently support [None, 'conv', 'non_local'].
- **init_cfg** (*dict or list[dict], optional*) – Initialization config dict.

forward(*inputs*)

Forward function.

class mmdet.models.necks.**CTResNetNeck**(*in_channel*, *num_deconv_filters*, *num_deconv_kernels*, *use_dcn=True*, *init_cfg=None*)

The neck used in CenterNet for object classification and box regression.

Parameters

- **in_channel** (*int*) – Number of input channels.
- **num_deconv_filters** (*tuple[int]*) – Number of filters per stage.
- **num_deconv_kernels** (*tuple[int]*) – Number of kernels per stage.
- **use_dcn** (*bool*) – If True, use DCNv2. Default: True.
- **init_cfg** (*dict or list[dict], optional*) – Initialization config dict.

forward(*inputs*)

Defines the computation performed at every call.

Should be overridden by all subclasses.

Note: Although the recipe for forward pass needs to be defined within this function, one should call the `Module` instance afterwards instead of this since the former takes care of running the registered hooks while the latter silently ignores them.

---

init_weights()
Initialize the weights.

class mmdet.models.necks.**ChannelMapper**(*in_channels*, *out_channels*, *kernel_size=3*, *conv_cfg=None*, *norm_cfg=None*, *act_cfg={'type': 'ReLU'}*, *num_outs=None*, *init_cfg={'distribution': 'uniform', 'layer': 'Conv2d', 'type': 'Xavier'}*)

Channel Mapper to reduce/increase channels of backbone features.

This is used to reduce/increase channels of backbone features.

Parameters

- **in_channels** (*List[int]*) – Number of input channels per scale.
- **out_channels** (*int*) – Number of output channels (used at each scale).
- **kernel_size** (*int, optional*) – kernel_size for reducing channels (used at each scale). Default: 3.
- **conv_cfg** (*dict, optional*) – Config dict for convolution layer. Default: None.
- **norm_cfg** (*dict, optional*) – Config dict for normalization layer. Default: None.
- **act_cfg** (*dict, optional*) – Config dict for activation layer in ConvModule. Default: dict(type='ReLU').
- **num_outs** (*int, optional*) – Number of output feature maps. There would be extra_convs when num_outs larger than the length of in_channels.
- **init_cfg** (*dict or list[dict], optional*) – Initialization config dict.

Example

```
>>> import torch
>>> in_channels = [2, 3, 5, 7]
>>> scales = [340, 170, 84, 43]
>>> inputs = [torch.rand(1, c, s, s)
...           for c, s in zip(in_channels, scales)]
>>> self = ChannelMapper(in_channels, 11, 3).eval()
>>> outputs = self.forward(inputs)
>>> for i in range(len(outputs)):
...     print(f'outputs[{i}].shape = {outputs[i].shape}')
outputs[0].shape = torch.Size([1, 11, 340, 340])
outputs[1].shape = torch.Size([1, 11, 170, 170])
outputs[2].shape = torch.Size([1, 11, 84, 84])
outputs[3].shape = torch.Size([1, 11, 43, 43])
```

forward(*inputs*)
Forward function.

class mmdet.models.necks.**DilatedEncoder**(*in_channels*, *out_channels*, *block_mid_channels*, *num_residual_blocks*, *block_dilations*)

Dilated Encoder for YOLOF <https://arxiv.org/abs/2103.09460>`.

This module contains two types of components:

- **the original FPN lateral convolution layer and fpn convolution layer,** which are 1x1 conv + 3x3 conv

- the dilated residual block

Parameters

- **in_channels** (*int*) – The number of input channels.
- **out_channels** (*int*) – The number of output channels.
- **block_mid_channels** (*int*) – The number of middle block output channels
- **num_residual_blocks** (*int*) – The number of residual blocks.
- **block_dilations** (*list*) – The list of residual blocks dilation.

forward(*feature*)

Defines the computation performed at every call.

Should be overridden by all subclasses.

Note: Although the recipe for forward pass needs to be defined within this function, one should call the `Module` instance afterwards instead of this since the former takes care of running the registered hooks while the latter silently ignores them.

---

class mmdet.models.necks.**DyHead**(*in_channels*, *out_channels*, *num_blocks=6*, *zero_init_offset=True*, *init_cfg=None*)

DyHead neck consisting of multiple DyHead Blocks.

See Dynamic Head: Unifying Object Detection Heads with Attentions for details.

Parameters

- **in_channels** (*int*) – Number of input channels.
- **out_channels** (*int*) – Number of output channels.
- **num_blocks** (*int, optional*) – Number of DyHead Blocks. Default: 6.
- **zero_init_offset** (*bool, optional*) – Whether to use zero init for *spatial_conv_offset*. Default: True.
- **init_cfg** (*dict or list[dict], optional*) – Initialization config dict. Default: None.

forward(*inputs*)

Forward function.

class mmdet.models.necks.**FPG**(*in_channels*, *out_channels*, *num_outs*, *stack_times*, *paths*, *inter_channels=None*, *same_down_trans=None*, *same_up_trans={'kernel_size': 3, 'padding': 1, 'stride': 2, 'type': 'conv'}*, *across_lateral_trans={'kernel_size': 1, 'type': 'conv'}*, *across_down_trans={'kernel_size': 3, 'type': 'conv'}*, *across_up_trans=None*, *across_skip_trans={'type': 'identity'}*, *output_trans={'kernel_size': 3, 'type': 'last_conv'}*, *start_level=0*, *end_level=- 1*, *add_extra_convs=False*, *norm_cfg=None*, *skip_inds=None*, *init_cfg=[{'type': 'Caffe2Xavier', 'layer': 'Conv2d'}, {'type': 'Constant', 'layer': ['_BatchNorm', '_InstanceNorm', 'GroupNorm', 'LayerNorm'], 'val': 1.0}]*)

FPG.

Implementation of Feature Pyramid Grids (FPG). This implementation only gives the basic structure stated in the paper. But users can implement different type of transitions to fully explore the the potential power of the structure of FPG.

Parameters

- **in_channels** (*int*) – Number of input channels (feature maps of all levels should have the same channels).
- **out_channels** (*int*) – Number of output channels (used at each scale)
- **num_outs** (*int*) – Number of output scales.
- **stack_times** (*int*) – The number of times the pyramid architecture will be stacked.
- **paths** (*list[str]*) – Specify the path order of each stack level. Each element in the list should be either 'bu' (bottom-up) or 'td' (top-down).
- **inter_channels** (*int*) – Number of inter channels.
- **same_up_trans** (*dict*) – Transition that goes down at the same stage.
- **same_down_trans** (*dict*) – Transition that goes up at the same stage.
- **across_lateral_trans** (*dict*) – Across-pathway same-stage
- **across_down_trans** (*dict*) – Across-pathway bottom-up connection.
- **across_up_trans** (*dict*) – Across-pathway top-down connection.
- **across_skip_trans** (*dict*) – Across-pathway skip connection.
- **output_trans** (*dict*) – Transition that trans the output of the last stage.
- **start_level** (*int*) – Index of the start input backbone level used to build the feature pyramid. Default: 0.
- **end_level** (*int*) – Index of the end input backbone level (exclusive) to build the feature pyramid. Default: -1, which means the last level.
- **add_extra_convs** (*bool*) – It decides whether to add conv layers on top of the original feature maps. Default to False. If True, its actual mode is specified by *extra_convs_on_inputs*.
- **norm_cfg** (*dict*) – Config dict for normalization layer. Default: None.
- **init_cfg** (*dict or list[dict], optional*) – Initialization config dict.

forward(*inputs*)

Defines the computation performed at every call.

Should be overridden by all subclasses.

Note: Although the recipe for forward pass needs to be defined within this function, one should call the `Module` instance afterwards instead of this since the former takes care of running the registered hooks while the latter silently ignores them.

---

class mmdet.models.necks.**FPN**(*in_channels*, *out_channels*, *num_outs*, *start_level=0*, *end_level=- 1*, *add_extra_convs=False*, *relu_before_extra_convs=False*, *no_norm_on_lateral=False*, *conv_cfg=None*, *norm_cfg=None*, *act_cfg=None*, *upsample_cfg={'mode': 'nearest'}*, *init_cfg={'distribution': 'uniform', 'layer': 'Conv2d', 'type': 'Xavier'}*)

Feature Pyramid Network.

This is an implementation of paper Feature Pyramid Networks for Object Detection.

Parameters

- **in_channels** (*list[int]*) – Number of input channels per scale.

- **out_channels** (*int*) – Number of output channels (used at each scale).
- **num_outs** (*int*) – Number of output scales.
- **start_level** (*int*) – Index of the start input backbone level used to build the feature pyramid. Default: 0.
- **end_level** (*int*) – Index of the end input backbone level (exclusive) to build the feature pyramid. Default: -1, which means the last level.
- **add_extra_convs** (*bool | str*) – If bool, it decides whether to add conv layers on top of the original feature maps. Default to False. If True, it is equivalent to *add_extra_convs='on_input'*. If str, it specifies the source feature map of the extra convs. Only the following options are allowed
  - 'on_input': Last feat map of neck inputs (i.e. backbone feature).
  - 'on_lateral': Last feature map after lateral convs.
  - 'on_output': The last output feature map after fpn convs.
- **relu_before_extra_convs** (*bool*) – Whether to apply relu before the extra conv. Default: False.
- **no_norm_on_lateral** (*bool*) – Whether to apply norm on lateral. Default: False.
- **conv_cfg** (*dict*) – Config dict for convolution layer. Default: None.
- **norm_cfg** (*dict*) – Config dict for normalization layer. Default: None.
- **act_cfg** (*dict*) – Config dict for activation layer in ConvModule. Default: None.
- **upsample_cfg** (*dict*) – Config dict for interpolate layer. Default: dict(mode='nearest').
- **init_cfg** (*dict or list[dict], optional*) – Initialization config dict.

Example

```
>>> import torch
>>> in_channels = [2, 3, 5, 7]
>>> scales = [340, 170, 84, 43]
>>> inputs = [torch.rand(1, c, s, s)
...           for c, s in zip(in_channels, scales)]
>>> self = FPN(in_channels, 11, len(in_channels)).eval()
>>> outputs = self.forward(inputs)
>>> for i in range(len(outputs)):
...     print(f'outputs[{i}].shape = {outputs[i].shape}')
outputs[0].shape = torch.Size([1, 11, 340, 340])
outputs[1].shape = torch.Size([1, 11, 170, 170])
outputs[2].shape = torch.Size([1, 11, 84, 84])
outputs[3].shape = torch.Size([1, 11, 43, 43])
```

forward(*inputs*)
Forward function.

class mmdet.models.necks.**FPN_CARAFE**(*in_channels*, *out_channels*, *num_outs*, *start_level=0*, *end_level=-1*, *norm_cfg=None*, *act_cfg=None*, *order=('conv', 'norm', 'act')*, *upsample_cfg={'encoder_dilation': 1, 'encoder_kernel': 3, 'type': 'carafe', 'up_group': 1, 'up_kernel': 5}*, *init_cfg=None*)

FPN_CARAFE is a more flexible implementation of FPN. It allows more choice for upsample methods during the top-down pathway.

It can reproduce the performance of ICCV 2019 paper CARAFE: Content-Aware ReAssembly of FEatures Please refer to https://arxiv.org/abs/1905.02188 for more details.

Parameters

- **in_channels** (*list[int]*) – Number of channels for each input feature map.
- **out_channels** (*int*) – Output channels of feature pyramids.
- **num_outs** (*int*) – Number of output stages.
- **start_level** (*int*) – Start level of feature pyramids. (Default: 0)
- **end_level** (*int*) – End level of feature pyramids. (Default: -1 indicates the last level).
- **norm_cfg** (*dict*) – Dictionary to construct and config norm layer.
- **activate** (*str*) – Type of activation function in ConvModule (Default: None indicates w/o activation).
- **order** (*dict*) – Order of components in ConvModule.
- **upsample** (*str*) – Type of upsample layer.
- **upsample_cfg** (*dict*) – Dictionary to construct and config upsample layer.
- **init_cfg** (*dict or list[dict], optional*) – Initialization config dict. Default: None

forward(*inputs*)
Forward function.

init_weights()
Initialize the weights of module.

slice_as(*src*, *dst*)
Slice `src` as `dst`

Note: `src` should have the same or larger size than `dst`.

Parameters

- **src** (*torch.Tensor*) – Tensors to be sliced.
- **dst** (*torch.Tensor*) – `src` will be sliced to have the same size as `dst`.

Returns Sliced tensor.

Return type torch.Tensor

tensor_add(*a*, *b*)
Add tensors `a` and `b` that might have different sizes.

class mmdet.models.necks.**HRFPN**(*High Resolution Feature Pyramids*)
paper: High-Resolution Representations for Labeling Pixels and Regions.

Parameters

- **in_channels** (*list*) – number of channels for each branch.
- **out_channels** (*int*) – output channels of feature pyramids.
- **num_outs** (*int*) – number of output stages.
- **pooling_type** (*str*) – pooling for generating feature pyramids from {MAX, AVG}.

- **conv_cfg** (*dict*) – dictionary to construct and config conv layer.
- **norm_cfg** (*dict*) – dictionary to construct and config norm layer.
- **with_cp** (*bool*) – Use checkpoint or not. Using checkpoint will save some memory while slowing down the training speed.
- **stride** (*int*) – stride of 3x3 convolutional layers
- **init_cfg** (*dict or list[dict], optional*) – Initialization config dict.

forward(*inputs*)
Forward function.

class mmdet.models.necks.**NASFCOS_FPN**(*in_channels*, *out_channels*, *num_outs*, *start_level=1*, *end_level=- 1*, *add_extra_convs=False*, *conv_cfg=None*, *norm_cfg=None*, *init_cfg=None*)

FPN structure in NASFPN.

Implementation of paper NAS-FCOS: Fast Neural Architecture Search for Object Detection

Parameters

- **in_channels** (*List[int]*) – Number of input channels per scale.
- **out_channels** (*int*) – Number of output channels (used at each scale)
- **num_outs** (*int*) – Number of output scales.
- **start_level** (*int*) – Index of the start input backbone level used to build the feature pyramid. Default: 0.
- **end_level** (*int*) – Index of the end input backbone level (exclusive) to build the feature pyramid. Default: -1, which means the last level.
- **add_extra_convs** (*bool*) – It decides whether to add conv layers on top of the original feature maps. Default to False. If True, its actual mode is specified by *extra_convs_on_inputs*.
- **conv_cfg** (*dict*) – dictionary to construct and config conv layer.
- **norm_cfg** (*dict*) – dictionary to construct and config norm layer.
- **init_cfg** (*dict or list[dict], optional*) – Initialization config dict. Default: None

forward(*inputs*)
Forward function.

init_weights()
Initialize the weights of module.

class mmdet.models.necks.**NASFPN**(*in_channels*, *out_channels*, *num_outs*, *stack_times*, *start_level=0*, *end_level=- 1*, *add_extra_convs=False*, *norm_cfg=None*, *init_cfg={'layer': 'Conv2d', 'type': 'Caffe2Xavier'}*)

NAS-FPN.

Implementation of NAS-FPN: Learning Scalable Feature Pyramid Architecture for Object Detection

Parameters

- **in_channels** (*List[int]*) – Number of input channels per scale.
- **out_channels** (*int*) – Number of output channels (used at each scale)
- **num_outs** (*int*) – Number of output scales.
- **stack_times** (*int*) – The number of times the pyramid architecture will be stacked.

- **start_level** (*int*) – Index of the start input backbone level used to build the feature pyramid. Default: 0.
- **end_level** (*int*) – Index of the end input backbone level (exclusive) to build the feature pyramid. Default: -1, which means the last level.
- **add_extra_convs** (*bool*) – It decides whether to add conv layers on top of the original feature maps. Default to False. If True, its actual mode is specified by *extra_convs_on_inputs*.
- **init_cfg** (*dict or list[dict], optional*) – Initialization config dict.

forward(*inputs*)
Forward function.

class mmdet.models.necks.**PAFPN**(*in_channels*, *out_channels*, *num_outs*, *start_level=0*, *end_level=-1*, *add_extra_convs=False*, *relu_before_extra_convs=False*, *no_norm_on_lateral=False*, *conv_cfg=None*, *norm_cfg=None*, *act_cfg=None*, *init_cfg={'distribution': 'uniform', 'layer': 'Conv2d', 'type': 'Xavier'}*)

Path Aggregation Network for Instance Segmentation.

This is an implementation of the PAFPN in Path Aggregation Network.

Parameters

- **in_channels** (*List[int]*) – Number of input channels per scale.
- **out_channels** (*int*) – Number of output channels (used at each scale)
- **num_outs** (*int*) – Number of output scales.
- **start_level** (*int*) – Index of the start input backbone level used to build the feature pyramid. Default: 0.
- **end_level** (*int*) – Index of the end input backbone level (exclusive) to build the feature pyramid. Default: -1, which means the last level.
- **add_extra_convs** (*bool | str*) – If bool, it decides whether to add conv layers on top of the original feature maps. Default to False. If True, it is equivalent to *add_extra_convs='on_input'*. If str, it specifies the source feature map of the extra convs. Only the following options are allowed
  - 'on_input': Last feat map of neck inputs (i.e. backbone feature).
  - 'on_lateral': Last feature map after lateral convs.
  - 'on_output': The last output feature map after fpn convs.
- **relu_before_extra_convs** (*bool*) – Whether to apply relu before the extra conv. Default: False.
- **no_norm_on_lateral** (*bool*) – Whether to apply norm on lateral. Default: False.
- **conv_cfg** (*dict*) – Config dict for convolution layer. Default: None.
- **norm_cfg** (*dict*) – Config dict for normalization layer. Default: None.
- **act_cfg** (*str*) – Config dict for activation layer in ConvModule. Default: None.
- **init_cfg** (*dict or list[dict], optional*) – Initialization config dict.

forward(*inputs*)
Forward function.

class mmdet.models.necks.**RFP**(*Recursive Feature Pyramid*)

This is an implementation of RFP in DetectoRS. Different from standard FPN, the input of RFP should be multi level features along with origin input image of backbone.

Parameters

- **rfp_steps** (*int*) – Number of unrolled steps of RFP.
- **rfp_backbone** (*dict*) – Configuration of the backbone for RFP.
- **aspp_out_channels** (*int*) – Number of output channels of ASPP module.
- **aspp_dilations** (*tuple[int]*) – Dilation rates of four branches. Default: (1, 3, 6, 1)
- **init_cfg** (*dict or list[dict], optional*) – Initialization config dict. Default: None

forward(*inputs*)

Forward function.

init_weights()

Initialize the weights.

class mmdet.models.necks.**SSDNeck**(*in_channels*, *out_channels*, *level_strides*, *level_paddings*, *l2_norm_scale=20.0*, *last_kernel_size=3*, *use_depthwise=False*, *conv_cfg=None*, *norm_cfg=None*, *act_cfg={'type': 'ReLU'}*, *init_cfg=[{'type': 'Xavier', 'distribution': 'uniform', 'layer': 'Conv2d'}, {'type': 'Constant', 'val': 1, 'layer': 'BatchNorm2d'}]*)

Extra layers of SSD backbone to generate multi-scale feature maps.

Parameters

- **in_channels** (*Sequence[int]*) – Number of input channels per scale.
- **out_channels** (*Sequence[int]*) – Number of output channels per scale.
- **level_strides** (*Sequence[int]*) – Stride of 3x3 conv per level.
- **level_paddings** (*Sequence[int]*) – Padding size of 3x3 conv per level.
- **l2_norm_scale** (*float|None*) – L2 normalization layer init scale. If None, not use L2 normalization on the first input feature.
- **last_kernel_size** (*int*) – Kernel size of the last conv layer. Default: 3.
- **use_depthwise** (*bool*) – Whether to use DepthwiseSeparableConv. Default: False.
- **conv_cfg** (*dict*) – Config dict for convolution layer. Default: None.
- **norm_cfg** (*dict*) – Dictionary to construct and config norm layer. Default: None.
- **act_cfg** (*dict*) – Config dict for activation layer. Default: dict(type='ReLU').
- **init_cfg** (*dict or list[dict], optional*) – Initialization config dict.

forward(*inputs*)

Forward function.

class mmdet.models.necks.**YOLOV3Neck**(*num_scales*, *in_channels*, *out_channels*, *conv_cfg=None*, *norm_cfg={'requires_grad': True, 'type': 'BN'}*, *act_cfg={'negative_slope': 0.1, 'type': 'LeakyReLU'}*, *init_cfg=None*)

The neck of YOLOV3.

It can be treated as a simplified version of FPN. It will take the result from Darknet backbone and do some upsampling and concatenation. It will finally output the detection result.

Note:

The input feats should be from top to bottom. i.e., from high-lvl to low-lvl

But YOLOV3Neck will process them in reversed order. i.e., from bottom (high-lvl) to top (low-lvl)

Parameters

- **num_scales** (*int*) – The number of scales / stages.
- **in_channels** (*List[int]*) – The number of input channels per scale.
- **out_channels** (*List[int]*) – The number of output channels per scale.
- **conv_cfg** (*dict, optional*) – Config dict for convolution layer. Default: None.
- **norm_cfg** (*dict, optional*) – Dictionary to construct and config norm layer. Default: dict(type='BN', requires_grad=True)
- **act_cfg** (*dict, optional*) – Config dict for activation layer. Default: dict(type='LeakyReLU', negative_slope=0.1).
- **init_cfg** (*dict or list[dict], optional*) – Initialization config dict. Default: None

forward(*feats*)

Defines the computation performed at every call.

Should be overridden by all subclasses.

Note: Although the recipe for forward pass needs to be defined within this function, one should call the `Module` instance afterwards instead of this since the former takes care of running the registered hooks while the latter silently ignores them.

class mmdet.models.necks.**YOLOXPAFPN**(*in_channels*, *out_channels*, *num_csp_blocks=3*, *use_depthwise=False*, *upsample_cfg={'mode': 'nearest', 'scale_factor': 2}*, *conv_cfg=None*, *norm_cfg={'eps': 0.001, 'momentum': 0.03, 'type': 'BN'}*, *act_cfg={'type': 'Swish'}*, *init_cfg={'a': 2.23606797749979, 'distribution': 'uniform', 'layer': 'Conv2d', 'mode': 'fan_in', 'nonlinearity': 'leaky_relu', 'type': 'Kaiming'}*)

Path Aggregation Network used in YOLOX.

Parameters

- **in_channels** (*List[int]*) – Number of input channels per scale.
- **out_channels** (*int*) – Number of output channels (used at each scale)
- **num_csp_blocks** (*int*) – Number of bottlenecks in CSPLayer. Default: 3
- **use_depthwise** (*bool*) – Whether to depthwise separable convolution in blocks. Default: False
- **upsample_cfg** (*dict*) – Config dict for interpolate layer. Default: *dict(scale_factor=2, mode='nearest')*
- **conv_cfg** (*dict, optional*) – Config dict for convolution layer. Default: None, which means using conv2d.
- **norm_cfg** (*dict*) – Config dict for normalization layer. Default: dict(type='BN')

- **act_cfg** (*dict*) – Config dict for activation layer. Default: dict(type='Swish')
- **init_cfg** (*dict or list[dict], optional*) – Initialization config dict. Default: None.

forward(*inputs*)

Parameters **inputs** (*tuple[Tensor]*) – input features.

Returns YOLOXPAFPN features.

Return type tuple[Tensor]

43.4 dense_heads

43.5 roi_heads

43.6 losses

43.7 utils

class mmdet.models.utils.**AdaptiveAvgPool2d**(*output_size: Union[int, None, Tuple[Optional[int], ...]]*)

Handle empty batch dimension to AdaptiveAvgPool2d.

forward(*x*)

Defines the computation performed at every call.

Should be overridden by all subclasses.

Note: Although the recipe for forward pass needs to be defined within this function, one should call the `Module` instance afterwards instead of this since the former takes care of running the registered hooks while the latter silently ignores them.

---

class mmdet.models.utils.**CSPLayer**(*in_channels*, *out_channels*, *expand_ratio=0.5*, *num_blocks=1*, *add_identity=True*, *use_depthwise=False*, *conv_cfg=None*, *norm_cfg={'eps': 0.001, 'momentum': 0.03, 'type': 'BN'}*, *act_cfg={'type': 'Swish'}*, *init_cfg=None*)

Cross Stage Partial Layer.

Parameters

- **in_channels** (*int*) – The input channels of the CSP layer.
- **out_channels** (*int*) – The output channels of the CSP layer.
- **expand_ratio** (*float*) – Ratio to adjust the number of channels of the hidden layer. Default: 0.5
- **num_blocks** (*int*) – Number of blocks. Default: 1
- **add_identity** (*bool*) – Whether to add identity in blocks. Default: True
- **use_depthwise** (*bool*) – Whether to depthwise separable convolution in blocks. Default: False

- **conv_cfg** (*dict, optional*) – Config dict for convolution layer. Default: None, which means using conv2d.
- **norm_cfg** (*dict*) – Config dict for normalization layer. Default: dict(type='BN')
- **act_cfg** (*dict*) – Config dict for activation layer. Default: dict(type='Swish')

forward(*x*)

Defines the computation performed at every call.

Should be overridden by all subclasses.

Note: Although the recipe for forward pass needs to be defined within this function, one should call the `Module` instance afterwards instead of this since the former takes care of running the registered hooks while the latter silently ignores them.

---

class mmdet.models.utils.**ConvUpsample**(*in_channels*, *inner_channels*, *num_layers=1*, *num_upsample=None*, *conv_cfg=None*, *norm_cfg=None*, *init_cfg=None*, ***kwargs*)

ConvUpsample performs 2x upsampling after Conv.

There are several *ConvModule* layers. In the first few layers, upsampling will be applied after each layer of convolution. The number of upsampling must be no more than the number of ConvModule layers.

Parameters

- **in_channels** (*int*) – Number of channels in the input feature map.
- **inner_channels** (*int*) – Number of channels produced by the convolution.
- **num_layers** (*int*) – Number of convolution layers.
- **num_upsample** (*int | optional*) – Number of upsampling layer. Must be no more than num_layers. Upsampling will be applied after the first `num_upsample` layers of convolution. Default: `num_layers`.
- **conv_cfg** (*dict*) – Config dict for convolution layer. Default: None, which means using conv2d.
- **norm_cfg** (*dict*) – Config dict for normalization layer. Default: None.
- **init_cfg** (*dict*) – Config dict for initialization. Default: None.
- **kwargs** (*key word augments*) – Other augments used in ConvModule.

forward(*x*)

Defines the computation performed at every call.

Should be overridden by all subclasses.

Note: Although the recipe for forward pass needs to be defined within this function, one should call the `Module` instance afterwards instead of this since the former takes care of running the registered hooks while the latter silently ignores them.

---

class mmdet.models.utils.**DetrTransformerDecoder**(**args*, *post_norm_cfg={'type': 'LN'}*, *return_intermediate=False*, ***kwargs*)

Implements the decoder in DETR transformer.

Parameters

- **return_intermediate** (*bool*) – Whether to return intermediate outputs.

- **post_norm_cfg** (*dict*) – Config of last normalization layer. Default *LN*.

forward(*query*, **args*, ***kwargs*)
Forward function for *TransformerDecoder*.

Parameters **query** (*Tensor*) – Input query with shape *(num_query, bs, embed_dims)*.

Returns

Results with shape [1, num_query, bs, embed_dims] when return_intermediate is *False*, otherwise it has shape [num_layers, num_query, bs, embed_dims].

Return type Tensor

class mmdet.models.utils.**DetrTransformerDecoderLayer**(*attn_cfgs*, *feedforward_channels*, *ffn_dropout=0.0*, *operation_order=None*, *act_cfg={'inplace': True, 'type': 'ReLU'}*, *norm_cfg={'type': 'LN'}*, *ffn_num_fcs=2*, ***kwargs*)
Implements decoder layer in DETR transformer.

Parameters

- **attn_cfgs** (list[*mmcv.ConfigDict*] | list[dict] | dict)) – Configs for self_attention or cross_attention, the order should be consistent with it in *operation_order*. If it is a dict, it would be expand to the number of attention in *operation_order*.
- **feedforward_channels** (*int*) – The hidden dimension for FFNs.
- **ffn_dropout** (*float*) – Probability of an element to be zeroed in ffn. Default 0.0.
- **operation_order** (*tuple[str]*) – The execution order of operation in transformer. Such as ('self_attn', 'norm', 'ffn', 'norm'). DefaultNone
- **act_cfg** (*dict*) – The activation config for FFNs. Default: *LN*
- **norm_cfg** (*dict*) – Config dict for normalization layer. Default: *LN*.
- **ffn_num_fcs** (*int*) – The number of fully-connected layers in FFNs. Default2.

class mmdet.models.utils.**DyReLU**(*channels*, *ratio=4*, *conv_cfg=None*, *act_cfg=({'type': 'ReLU'}, {'type': 'HSigmoid', 'bias': 3.0, 'divisor': 6.0})*, *init_cfg=None*)
Dynamic ReLU (DyReLU) module.

See Dynamic ReLU for details. Current implementation is specialized for task-aware attention in DyHead. HSigmoid arguments in default act_cfg follow DyHead official code. https://github.com/microsoft/DynamicHead/blob/master/dyhead/dyrelu.py

Parameters

- **channels** (*int*) – The input (and output) channels of DyReLU module.
- **ratio** (*int*) – Squeeze ratio in Squeeze-and-Excitation-like module, the intermediate channel will be `int(channels/ratio)`. Default: 4.
- **conv_cfg** (*None or dict*) – Config dict for convolution layer. Default: None, which means using conv2d.
- **act_cfg** (*dict or Sequence[dict]*) – Config dict for activation layer. If act_cfg is a dict, two activation layers will be configurated by this dict. If act_cfg is a sequence of dicts, the first activation layer will be configurated by the first dict and the second activation layer will be configurated by the second dict. Default: (dict(type='ReLU'), dict(type='HSigmoid', bias=3.0, divisor=6.0))
- **init_cfg**(*dict or list[dict], optional*) – Initialization config dict. Default: None

forward(*x*)
Forward function.

class mmdet.models.utils.**DynamicConv**(*in_channels=256*, *feat_channels=64*, *out_channels=None*, *input_feat_shape=7*, *with_proj=True*, *act_cfg={'inplace': True, 'type': 'ReLU'}*, *norm_cfg={'type': 'LN'}*, *init_cfg=None*)
Implements Dynamic Convolution.

This module generate parameters for each sample and use bmm to implement 1*1 convolution. Code is modified from the official github repo .

Parameters

- **in_channels** (*int*) – The input feature channel. Defaults to 256.
- **feat_channels** (*int*) – The inner feature channel. Defaults to 64.
- **out_channels** (*int, optional*) – The output feature channel. When not specified, it will be set to *in_channels* by default
- **input_feat_shape** (*int*) – The shape of input feature. Defaults to 7.
- **with_proj** (*bool*) – Project two-dimentional feature to one-dimentional feature. Default to True.
- **act_cfg** (*dict*) – The activation config for DynamicConv.
- **norm_cfg** (*dict*) – Config dict for normalization layer. Default layer normalization.
- **(obj** (*init_cfg*) – *mmcv.ConfigDict*): The Config for initialization. Default: None.

forward(*param_feature*, *input_feature*)
Forward function for *DynamicConv*.

Parameters

- **param_feature** (*Tensor*) – The feature can be used to generate the parameter, has shape (num_all_proposals, in_channels).
- **input_feature** (*Tensor*) – Feature that interact with parameters, has shape (num_all_proposals, in_channels, H, W).

Returns The output feature has shape (num_all_proposals, out_channels).

Return type Tensor

class mmdet.models.utils.**InvertedResidual**(*in_channels*, *out_channels*, *mid_channels*, *kernel_size=3*, *stride=1*, *se_cfg=None*, *with_expand_conv=True*, *conv_cfg=None*, *norm_cfg={'type': 'BN'}*, *act_cfg={'type': 'ReLU'}*, *drop_path_rate=0.0*, *with_cp=False*, *init_cfg=None*)
Inverted Residual Block.

Parameters

- **in_channels** (*int*) – The input channels of this Module.
- **out_channels** (*int*) – The output channels of this Module.
- **mid_channels** (*int*) – The input channels of the depthwise convolution.
- **kernel_size** (*int*) – The kernel size of the depthwise convolution. Default: 3.
- **stride** (*int*) – The stride of the depthwise convolution. Default: 1.
- **se_cfg** (*dict*) – Config dict for se layer. Default: None, which means no se layer.

- **with_expand_conv** (*bool*) – Use expand conv or not. If set False, mid_channels must be the same with in_channels. Default: True.
- **conv_cfg** (*dict*) – Config dict for convolution layer. Default: None, which means using conv2d.
- **norm_cfg** (*dict*) – Config dict for normalization layer. Default: dict(type='BN').
- **act_cfg** (*dict*) – Config dict for activation layer. Default: dict(type='ReLU').
- **drop_path_rate** (*float*) – stochastic depth rate. Defaults to 0.
- **with_cp** (*bool*) – Use checkpoint or not. Using checkpoint will save some memory while slowing down the training speed. Default: False.
- **init_cfg** (*dict or list[dict], optional*) – Initialization config dict. Default: None

Returns The output tensor.

Return type Tensor

forward(*x*)

Defines the computation performed at every call.

Should be overridden by all subclasses.

Note: Although the recipe for forward pass needs to be defined within this function, one should call the `Module` instance afterwards instead of this since the former takes care of running the registered hooks while the latter silently ignores them.

---

class mmdet.models.utils.**LearnedPositionalEncoding**(*num_feats*, *row_num_embed=50*, *col_num_embed=50*, *init_cfg={'layer': 'Embedding', 'type': 'Uniform'}*)

Position embedding with learnable embedding weights.

Parameters

- **num_feats** (*int*) – The feature dimension for each position along x-axis or y-axis. The final returned dimension for each position is 2 times of this value.
- **row_num_embed** (*int, optional*) – The dictionary size of row embeddings. Default 50.
- **col_num_embed** (*int, optional*) – The dictionary size of col embeddings. Default 50.
- **init_cfg** (*dict or list[dict], optional*) – Initialization config dict.

forward(*mask*)

Forward function for *LearnedPositionalEncoding*.

Parameters **mask** (*Tensor*) – ByteTensor mask. Non-zero values representing ignored positions, while zero values means valid positions for this image. Shape [bs, h, w].

Returns

Returned position embedding with shape [bs, num_feats*2, h, w].

Return type pos (Tensor)

class mmdet.models.utils.**NormedConv2d**(**args*, *tempearture=20*, *power=1.0*, *eps=1e-06*, *norm_over_kernel=False*, ***kwargs*)

Normalized Conv2d Layer.

Parameters

- **tempeature** (*float, optional*) – Tempeature term. Default to 20.
- **power** (*int, optional*) – Power term. Default to 1.0.
- **eps** (*float, optional*) – The minimal value of divisor to keep numerical stability. Default to 1e-6.
- **norm_over_kernel** (*bool, optional*) – Normalize over kernel. Default to False.

forward(*x*)

Defines the computation performed at every call.

Should be overridden by all subclasses.

Note: Although the recipe for forward pass needs to be defined within this function, one should call the `Module` instance afterwards instead of this since the former takes care of running the registered hooks while the latter silently ignores them.

---

class mmdet.models.utils.**NormedLinear**(**args*, *tempearture=20*, *power=1.0*, *eps=1e-06*, ***kwargs*)

Normalized Linear Layer.

Parameters

- **tempeature** (*float, optional*) – Tempeature term. Default to 20.
- **power** (*int, optional*) – Power term. Default to 1.0.
- **eps** (*float, optional*) – The minimal value of divisor to keep numerical stability. Default to 1e-6.

forward(*x*)

Defines the computation performed at every call.

Should be overridden by all subclasses.

Note: Although the recipe for forward pass needs to be defined within this function, one should call the `Module` instance afterwards instead of this since the former takes care of running the registered hooks while the latter silently ignores them.

---

class mmdet.models.utils.**PatchEmbed**(*in_channels=3*, *embed_dims=768*, *conv_type='Conv2d'*, *kernel_size=16*, *stride=16*, *padding='corner'*, *dilation=1*, *bias=True*, *norm_cfg=None*, *input_size=None*, *init_cfg=None*)

Image to Patch Embedding.

We use a conv layer to implement PatchEmbed.

Parameters

- **in_channels** (*int*) – The num of input channels. Default: 3
- **embed_dims** (*int*) – The dimensions of embedding. Default: 768
- **conv_type** (*str*) – The config dict for embedding conv layer type selection. Default: "Conv2d.
- **kernel_size** (*int*) – The kernel_size of embedding conv. Default: 16.
- **stride** (*int*) – The slide stride of embedding conv. Default: None (Would be set as *kernel_size*).

- **padding** (*int | tuple | string*) – The padding length of embedding conv. When it is a string, it means the mode of adaptive padding, support "same" and "corner" now. Default: "corner".
- **dilation** (*int*) – The dilation rate of embedding conv. Default: 1.
- **bias** (*bool*) – Bias of embed conv. Default: True.
- **norm_cfg** (*dict, optional*) – Config dict for normalization layer. Default: None.
- **input_size** (*int | tuple | None*) – The size of input, which will be used to calculate the out size. Only work when *dynamic_size* is False. Default: None.
- **init_cfg** (*mmcv.ConfigDict*, optional) – The Config for initialization. Default: None.

forward(*x*)

Parameters **x** (*Tensor*) – Has shape (B, C, H, W). In most case, C is 3.

Returns

Contains merged results and its spatial shape.

- x (Tensor): Has shape (B, out_h * out_w, embed_dims)
- **out_size (tuple[int]): Spatial shape of x, arrange as** (out_h, out_w).

Return type tuple

class mmdet.models.utils.**ResLayer**(*block*, *inplanes*, *planes*, *num_blocks*, *stride=1*, *avg_down=False*, *conv_cfg=None*, *norm_cfg={'type': 'BN'}*, *downsample_first=True*, ***kwargs*)

ResLayer to build ResNet style backbone.

Parameters

- **block** (*nn.Module*) – block used to build ResLayer.
- **inplanes** (*int*) – inplanes of block.
- **planes** (*int*) – planes of block.
- **num_blocks** (*int*) – number of blocks.
- **stride** (*int*) – stride of the first block. Default: 1
- **avg_down** (*bool*) – Use AvgPool instead of stride conv when downsampling in the bottleneck. Default: False
- **conv_cfg** (*dict*) – dictionary to construct and config conv layer. Default: None
- **norm_cfg** (*dict*) – dictionary to construct and config norm layer. Default: dict(type='BN')
- **downsample_first** (*bool*) – Downsample at the first block or last block. False for Hourglass, True for ResNet. Default: True

class mmdet.models.utils.**SELayer**(*channels*, *ratio=16*, *conv_cfg=None*, *act_cfg=({'type': 'ReLU'}, {'type': 'Sigmoid'})*, *init_cfg=None*)

Squeeze-and-Excitation Module.

Parameters

- **channels** (*int*) – The input (and output) channels of the SE layer.
- **ratio** (*int*) – Squeeze ratio in SELayer, the intermediate channel will be `int(channels/ratio)`. Default: 16.

- **conv_cfg** (*None or dict*) – Config dict for convolution layer. Default: None, which means using conv2d.
- **act_cfg** (*dict or Sequence[dict]*) – Config dict for activation layer. If act_cfg is a dict, two activation layers will be configurated by this dict. If act_cfg is a sequence of dicts, the first activation layer will be configurated by the first dict and the second activation layer will be configurated by the second dict. Default: (dict(type='ReLU'), dict(type='Sigmoid'))
- **init_cfg** (*dict or list[dict], optional*) – Initialization config dict. Default: None

forward(*x*)

Defines the computation performed at every call.

Should be overridden by all subclasses.

Note: Although the recipe for forward pass needs to be defined within this function, one should call the `Module` instance afterwards instead of this since the former takes care of running the registered hooks while the latter silently ignores them.

---

class mmdet.models.utils.**SimplifiedBasicBlock**(*inplanes*, *planes*, *stride=1*, *dilation=1*, *downsample=None*, *style='pytorch'*, *with_cp=False*, *conv_cfg=None*, *norm_cfg={'type': 'BN'}*, *dcn=None*, *plugins=None*, *init_fg=None*)

Simplified version of original basic residual block. This is used in SCNet.

- Norm layer is now optional
- Last ReLU in forward function is removed

forward(*x*)

Forward function.

property norm1

normalization layer after the first convolution layer

Type nn.Module

property norm2

normalization layer after the second convolution layer

Type nn.Module

class mmdet.models.utils.**SinePositionalEncoding**(*num_feats*, *temperature=10000*, *normalize=False*, *scale=6.283185307179586*, *eps=1e-06*, *offset=0.0*, *init_cfg=None*)

Position encoding with sine and cosine functions.

See End-to-End Object Detection with Transformers for details.

Parameters

- **num_feats** (*int*) – The feature dimension for each position along x-axis or y-axis. Note the final returned dimension for each position is 2 times of this value.
- **temperature** (*int, optional*) – The temperature used for scaling the position embedding. Defaults to 10000.
- **normalize** (*bool, optional*) – Whether to normalize the position embedding. Defaults to False.
- **scale** (*float, optional*) – A scale factor that scales the position embedding. The scale will be used only when *normalize* is True. Defaults to 2*pi.

- **eps** (*float, optional*) – A value added to the denominator for numerical stability. Defaults to 1e-6.
- **offset** (*float*) – offset add to embed when do the normalization. Defaults to 0.
- **init_cfg** (*dict or list[dict], optional*) – Initialization config dict. Default: None

forward(*mask*)

Forward function for *SinePositionalEncoding*.

Parameters **mask** (*Tensor*) – ByteTensor mask. Non-zero values representing ignored positions, while zero values means valid positions for this image. Shape [bs, h, w].

Returns

Returned position embedding with shape [bs, num_feats*2, h, w].

Return type pos (Tensor)

class mmdet.models.utils.**Transformer**(*encoder=None*, *decoder=None*, *init_cfg=None*)

Implements the DETR transformer.

Following the official DETR implementation, this module copy-paste from torch.nn.Transformer with modifications:

- positional encodings are passed in MultiheadAttention
- extra LN at the end of encoder is removed
- decoder returns a stack of activations from all decoding layers

See paper: End-to-End Object Detection with Transformers for details.

Parameters

- **encoder** (*mmcv.ConfigDict* | Dict) – Config of TransformerEncoder. Defaults to None.
- **decoder** ((*mmcv.ConfigDict* | Dict)) – Config of TransformerDecoder. Defaults to None
- **(obj** (*init_cfg*) – *mmcv.ConfigDict*): The Config for initialization. Defaults to None.

forward(*x*, *mask*, *query_embed*, *pos_embed*)

Forward function for *Transformer*.

Parameters

- **x** (*Tensor*) – Input query with shape [bs, c, h, w] where c = embed_dims.
- **mask** (*Tensor*) – The key_padding_mask used for encoder and decoder, with shape [bs, h, w].
- **query_embed** (*Tensor*) – The query embedding for decoder, with shape [num_query, c].
- **pos_embed** (*Tensor*) – The positional encoding for encoder and decoder, with the same shape as *x*.

Returns

results of decoder containing the following tensor.

- **out_dec: Output from decoder. If return_intermediate_dec is True output has shape [num_dec_layers, bs,** num_query, embed_dims], else has shape [1, bs, num_query, embed_dims].
- memory: Output results from encoder, with shape [bs, embed_dims, h, w].

Return type tuple[Tensor]

init_weights()
Initialize the weights.

mmdet.models.utils.**adaptive_avg_pool2d**(*input*, *output_size*)
Handle empty batch dimension to adaptive_avg_pool2d.

Parameters

- **input** (*tensor*) – 4D tensor.
- **output_size** (*int, tuple[int,int]*) – the target output size.

mmdet.models.utils.**build_linear_layer**(*cfg*, **args*, ***kwargs*)
Build linear layer. :param cfg: The linear layer config, which should contain:

- type (str): Layer type.
- layer args: Args needed to instantiate an linear layer.

Parameters

- **args** (*argument list*) – Arguments passed to the *__init__* method of the corresponding linear layer.
- **kwargs** (*keyword arguments*) – Keyword arguments passed to the *__init__* method of the corresponding linear layer.

Returns Created linear layer.

Return type nn.Module

mmdet.models.utils.**build_transformer**(*cfg*, *default_args=None*)
Builder for Transformer.

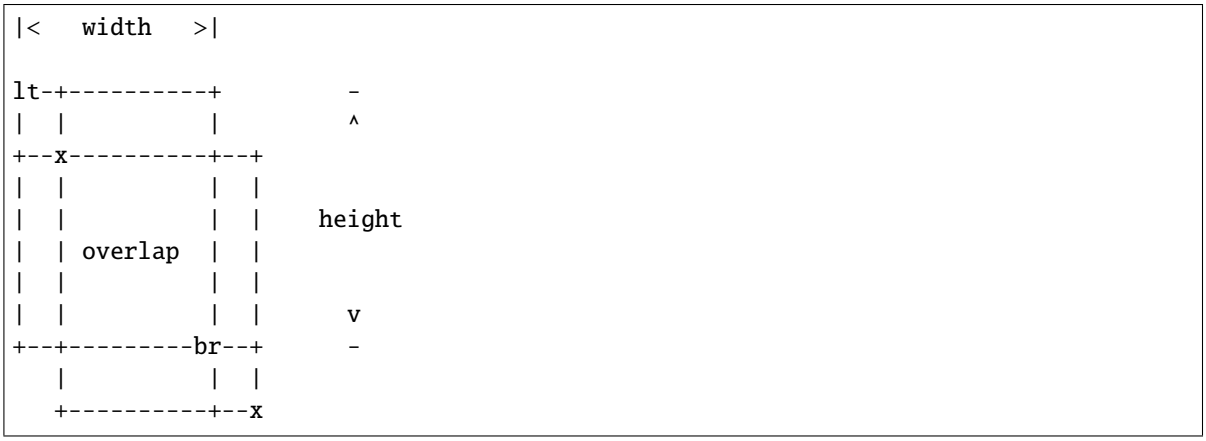
mmdet.models.utils.**gaussian_radius**(*det_size*, *min_overlap*)
Generate 2D gaussian radius.

This function is modified from the official github repo.

Given `min_overlap`, radius could computed by a quadratic equation according to Vieta's formulas.

There are 3 cases for computing gaussian radius, details are following:

- Explanation of figure: `lt` and `br` indicates the left-top and bottom-right corner of ground truth box. `x` indicates the generated corner at the limited position when `radius=r`.
- Case1: one corner is inside the gt box and the other is outside.

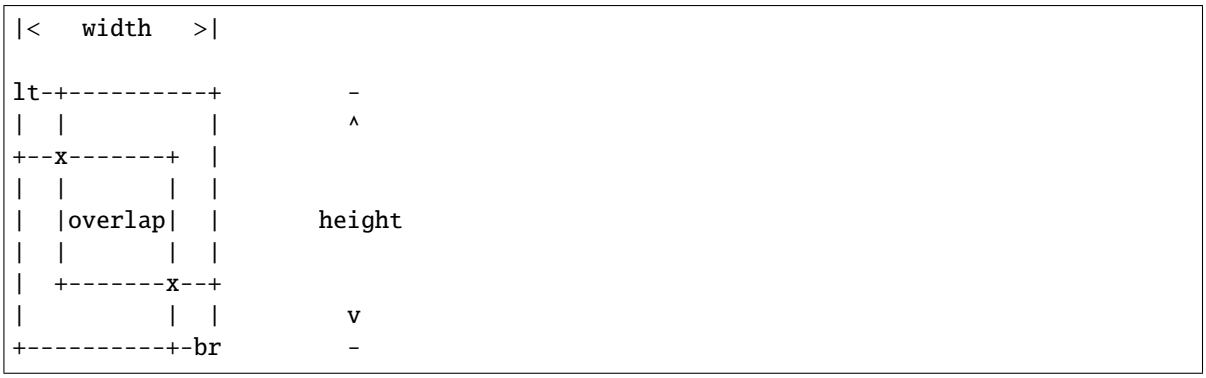


To ensure IoU of generated box and gt box is larger than `min_overlap`:

$$\frac{(w-r)*(h-r)}{w*h+(w+h)r-r^2} \geq iou \quad \Rightarrow \quad r^2-(w+h)r+\frac{1-iou}{1+iou}*w*h \geq 0$$

$$a=1, \quad b=-(w+h), \quad c=\frac{1-iou}{1+iou}*w*hr \leq \frac{-b-\sqrt{b^2-4*a*c}}{2*a}$$

- Case2: both two corners are inside the gt box.



To ensure IoU of generated box and gt box is larger than `min_overlap`:

$$\frac{(w-2*r)*(h-2*r)}{w*h} \geq iou \quad \Rightarrow \quad 4r^2-2(w+h)r+(1-iou)*w*h \geq 0$$

$$a=4, \quad b=-2(w+h), \quad c=(1-iou)*w*hr \leq \frac{-b-\sqrt{b^2-4*a*c}}{2*a}$$

- Case3: both two corners are outside the gt box.

To ensure IoU of generated box and gt box is larger than `min_overlap`:

$$\frac{w*h}{(w+2*r)*(h+2*r)} \geq iou \quad \Rightarrow \quad 4*iou*r^2+2*iou*(w+h)r+(iou-1)*w*h \leq 0$$

$$a=4*iou, \quad b=2*iou*(w+h), \quad c=(iou-1)*w*h$$

$$r \leq \frac{-b+\sqrt{b^2-4*a*c}}{2*a}$$

Parameters

- **det_size** (*list[int]*) – Shape of object.

- **min_overlap** (*float*) – Min IoU with ground truth for boxes generated by keypoints inside the gaussian kernel.

Returns Radius of gaussian kernel.

Return type radius (int)

mmdet.models.utils.**gen_gaussian_target**(*heatmap*, *center*, *radius*, *k=1*)
Generate 2D gaussian heatmap.

Parameters

- **heatmap** (*Tensor*) – Input heatmap, the gaussian kernel will cover on it and maintain the max value.
- **center** (*list[int]*) – Coord of gaussian kernel's center.
- **radius** (*int*) – Radius of gaussian kernel.
- **k** (*int*) – Coefficient of gaussian kernel. Default: 1.

Returns Updated heatmap covered by gaussian kernel.

Return type out_heatmap (Tensor)

mmdet.models.utils.**get_uncertain_point_coords_with_randomness**(*mask_pred*, *labels*, *num_points*, *oversample_ratio*, *importance_sample_ratio*)
Get num_points most uncertain points with random points during train.

Sample points in [0, 1] x [0, 1] coordinate space based on their uncertainty. The uncertainties are calculated for each point using 'get_uncertainty()' function that takes point's logit prediction as input.

Parameters

- **mask_pred** (*Tensor*) – A tensor of shape (num_rois, num_classes, mask_height, mask_width) for class-specific or class-agnostic prediction.
- **labels** (*list*) – The ground truth class for each instance.
- **num_points** (*int*) – The number of points to sample.
- **oversample_ratio** (*int*) – Oversampling parameter.
- **importance_sample_ratio** (*float*) – Ratio of points that are sampled via importnace sampling.

Returns

A tensor of shape (num_rois, num_points, 2) that contains the coordinates sampled points.

Return type point_coords (Tensor)

mmdet.models.utils.**get_uncertainty**(*mask_pred*, *labels*)
Estimate uncertainty based on pred logits.

We estimate uncertainty as L1 distance between 0.0 and the logits prediction in 'mask_pred' for the foreground class in *classes*.

Parameters

- **mask_pred** (*Tensor*) – mask predication logits, shape (num_rois, num_classes, mask_height, mask_width).
- **labels** (*list[Tensor]*) – Either predicted or ground truth label for each predicted mask, of length num_rois.

Returns

Uncertainty scores with the most uncertain locations having the highest uncertainty score, shape (num_rois, 1, mask_height, mask_width)

Return type scores (Tensor)

mmdet.models.utils.**interpolate_as**(*source*, *target*, *mode='bilinear'*, *align_corners=False*)
Interpolate the *source* to the shape of the *target*.

The *source* must be a Tensor, but the *target* can be a Tensor or a np.ndarray with the shape (..., target_h, target_w).

Parameters

- **source** (*Tensor*) – A 3D/4D Tensor with the shape (N, H, W) or (N, C, H, W).
- **target** (*Tensor | np.ndarray*) – The interpolation target with the shape (..., target_h, target_w).
- **mode** (*str*) – Algorithm used for interpolation. The options are the same as those in F.interpolate(). Default: `'bilinear'`.
- **align_corners** (*bool*) – The same as the argument in F.interpolate().

Returns The interpolated source Tensor.

Return type Tensor

mmdet.models.utils.**make_divisible**(*value*, *divisor*, *min_value=None*, *min_ratio=0.9*)
Make divisible function.

This function rounds the channel number to the nearest value that can be divisible by the divisor. It is taken from the original tf repo. It ensures that all layers have a channel number that is divisible by divisor. It can be seen here: https://github.com/tensorflow/models/blob/master/research/slim/nets/mobilenet/mobilenet.py # noqa

Parameters

- **value** (*int*) – The original channel number.
- **divisor** (*int*) – The divisor to fully divide the channel number.
- **min_value** (*int*) – The minimum value of the output channel. Default: None, means that the minimum value equal to the divisor.
- **min_ratio** (*float*) – The minimum ratio of the rounded channel number to the original channel number. Default: 0.9.

Returns The modified output channel number.

Return type int

mmdet.models.utils.**nchw_to_nlc**(*x*)
Flatten [N, C, H, W] shape tensor to [N, L, C] shape tensor.

Parameters **x** (*Tensor*) – The input tensor of shape [N, C, H, W] before conversion.

Returns The output tensor of shape [N, L, C] after conversion.

Return type Tensor

mmdet.models.utils.**nlc_to_nchw**(*x*, *hw_shape*)
Convert [N, L, C] shape tensor to [N, C, H, W] shape tensor.

Parameters

- **x** (*Tensor*) – The input tensor of shape [N, L, C] before conversion.
- **hw_shape** (*Sequence[int]*) – The height and width of output feature map.

Returns The output tensor of shape [N, C, H, W] after conversion.

Return type Tensor

mmdet.models.utils.**preprocess_panoptic_gt**(*gt_labels*, *gt_masks*, *gt_semantic_seg*, *num_things*, *num_stuff*, *img_metas*)

Preprocess the ground truth for a image.

Parameters

- **gt_labels** (*Tensor*) – Ground truth labels of each bbox, with shape (num_gts,).
- **gt_masks** (BitmapMasks) – Ground truth masks of each instances of a image, shape (num_gts, h, w).
- **gt_semantic_seg** (*Tensor | None*) – Ground truth of semantic segmentation with the shape (1, h, w). [0, num_thing_class - 1] means things, [num_thing_class, num_class-1] means stuff, 255 means VOID. It's None when training instance segmentation.
- **img_metas** (*dict*) – List of image meta information.

Returns

a tuple containing the following targets.

- **labels (Tensor): Ground truth class indices for a** image, with shape (n,), n is the sum of number of stuff type and number of instance in a image.
- **masks (Tensor): Ground truth mask for a image, with** shape (n, h, w). Contains stuff and things when training panoptic segmentation, and things only when training instance segmentation.

Return type tuple

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