MMOCR

Release 0.4.1

OpenMMLab

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CHAPTER

ONE

INSTALLATION

1.1 Prerequisites

- Linux (Windows is not officially supported)
- Python 3.7
- PyTorch 1.6 or higher
- torchvision 0.7.0
- CUDA 10.1
- NCCL 2
- GCC 5.4.0 or higher
- MMCV >= 1.3.8
- MMDetection >= 2.14.0

We have tested the following versions of OS and software:

- OS: Ubuntu 16.04
- CUDA: 10.1
- GCC(G++): 5.4.0
- MMCV 1.3.8
- MMDetection 2.14.0
- PyTorch 1.6.0
- torchvision 0.7.0

MMOCR depends on PyTorch and mmdetection.

1.2 Step-by-Step Installation Instructions

a. Create a Conda virtual environment and activate it.

```
conda create -n open-mmlab python=3.7 -y
conda activate open-mmlab
```

b. Install PyTorch and torchvision following the official instructions, e.g.,

```
conda install pytorch==1.6.0 torchvision==0.7.0 cudatoolkit=10.1 -c pytorch
```

Note: Make sure that your compilation CUDA version and runtime CUDA version matches. You can check the supported CUDA version for precompiled packages on the PyTorch website.

c. Install mmcv, we recommend you to install the pre-build mmcv as below.

```
pip install mmcv-full -f https://download.openmmlab.com/mmcv/dist/{cu_version}/{torch_
↪version}/index.html
```

Please replace `{cu_version}` and `{torch_version}` in the url with your desired one. For example, to install the latest `mmcv-full` with CUDA 11 and PyTorch 1.7.0, use the following command:

```
pip install mmcv-full -f https://download.openmmlab.com/mmcv/dist/cu110/torch1.7.0/index.
↪html
```

Note: Note that mmocr 0.2.1 or later requires mmcv 1.3.8 or later.

If it compiles during installation, then please check that the CUDA version and PyTorch version **exactly** matches the version in the `mmcv-full` installation command. For example, PyTorch 1.7.0 and 1.7.1 are treated differently.

See official installation guide for different versions of MMCV compatible to different PyTorch and CUDA versions.

Warning: You need to run `pip uninstall mmcv` first if you have `mmcv` installed. If `mmcv` and `mmcv-full` are both installed, there will be `ModuleNotFoundError`.

d. Install mmdet, we recommend you to install the latest `mmdet` with pip. See here for different versions of `mmdet`.

```
pip install mmdet
```

Optionally you can choose to install `mmdet` following the official installation guide.

e. Clone the MMOCR repository.

```
git clone https://github.com/open-mmlab/mmocr.git
cd mmocr
```

f. Install build requirements and then install MMOCR.

```
pip install -r requirements.txt
pip install -v -e . # or "python setup.py develop"
export PYTHONPATH=$(pwd):$PYTHONPATH
```

1.3 Full Set-up Script

Here is the full script for setting up MMOCR with Conda.

```
conda create -n open-mmlab python=3.7 -y
conda activate open-mmlab

# install latest pytorch prebuilt with the default prebuilt CUDA version (usually the␣
↪latest)
conda install pytorch==1.6.0 torchvision==0.7.0 cudatoolkit=10.1 -c pytorch

# install the latest mmcv-full
pip install mmcv-full -f https://download.openmmlab.com/mmcv/dist/cu101/torch1.6.0/index.
↪html

# install mmdetection
pip install mmdet

# install mmocr
git clone https://github.com/open-mmlab/mmocr.git
cd mmocr

pip install -r requirements.txt
pip install -v -e .  # or "python setup.py develop"
export PYTHONPATH=$(pwd):$PYTHONPATH
```

1.4 Another option: Docker Image

We provide a Dockerfile to build an image.

```
# build an image with PyTorch 1.6, CUDA 10.1
docker build -t mmocr docker/
```

Run it with

```
docker run --gpus all --shm-size=8g -it -v {DATA_DIR}:/mmocr/data mmocr
```

1.5 Prepare Datasets

It is recommended to symlink the dataset root to `mmocr/data`. Please refer to datasets.md to prepare your datasets. If your folder structure is different, you may need to change the corresponding paths in config files.

The `mmocr` folder is organized as follows:

```
├── configs/
├── demo/
├── docker/
├── docs/
├── LICENSE
```

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```
├── mmocr/
├── README.md
├── requirements/
├── requirements.txt
├── resources/
├── setup.cfg
├── setup.py
├── tests/
├── tools/
```

CHAPTER

TWO

GETTING STARTED

In this guide we will show you some useful commands and familiarize you with MMOCR. We also provide a notebook that can help you get the most out of MMOCR.

2.1 Installation

Check out our *installation guide* for full steps.

2.2 Dataset Preparation

MMOCR supports numerous datasets which are classified by the type of their corresponding tasks. You may find their preparation steps in these sections: *Detection Datasets*, *Recognition Datasets*, *KIE Datasets* and *NER Datasets*.

2.3 Inference with Pretrained Models

You can perform end-to-end OCR on our demo image with one simple line of command:

```
python mmocr/utils/ocr.py demo/demo_text_ocr.jpg --print-result --imshow
```

Its detection result will be printed out and a new window will pop up with result visualization. More demo and full instructions can be found in *Demo*.

2.4 Training

2.4.1 Training with Toy Dataset

We provide a toy dataset under `tests/data` on which you can get a sense of training before the academic dataset is prepared.

For example, to train a text recognition task with `seg` method and toy dataset,

```
python tools/train.py configs/textrecog/seg/seg_r31_1by16_fpnocr_toy_dataset.py --work-
↪dir seg
```

To train a text recognition task with `sar` method and toy dataset,

```
python tools/train.py configs/textrecog/sar/sar_r31_parallel_decoder_toy_dataset.py --
↪work-dir sar
```

2.4.2 Training with Academic Dataset

Once you have prepared required academic dataset following our instruction, the only last thing to check is if the model's config points MMOCR to the correct dataset path. Suppose we want to train DBNet on ICDAR 2015, and part of `configs/textdet/dbnet/dbnet_r18_fpnc_1200e_icdar2015.py` looks like the following:

```
dataset_type = 'IcdarDataset'
data_root = 'data/icdar2015'
data = dict(
    train=dict(
        type=dataset_type,
        ann_file=data_root + '/instances_training.json',
        img_prefix=data_root + '/imgs',
        pipeline=train_pipeline)
    val=dict(
        type=dataset_type,
        ann_file=data_root + '/instances_test.json',
        img_prefix=data_root + '/imgs',
        pipeline=test_pipeline),
    test=dict(
        type=dataset_type,
        ann_file=data_root + '/instances_test.json',
        img_prefix=data_root + '/imgs',
        pipeline=test_pipeline))
```

You would need to check if `data/icdar2015` is right. Then you can start training with the command:

```
python tools/train.py configs/textdet/dbnet/dbnet_r18_fpnc_1200e_icdar2015.py --work-dir␣
↪dbnet
```

You can find full training instructions, explanations and useful training configs in *Training*.

2.5 Testing

Suppose now you have finished the training of DBNet and the latest model has been saved in `dbnet/latest.pth`. You can evaluate its performance on the test set using the `hmean-iou` metric with the following command:

```
python tools/test.py configs/textdet/dbnet/dbnet_r18_fpnc_1200e_icdar2015.py dbnet/
↪latest.pth --eval hmean-iou
```

Evaluating any pretrained model accessible online is also allowed:

```
python tools/test.py configs/textdet/dbnet/dbnet_r18_fpnc_1200e_icdar2015.py https://
↪download.openmmlab.com/mmocr/textdet/dbnet/dbnet_r18_fpnc_sbn_1200e_icdar2015_20210329-
↪ba3ab597.pth --eval hmean-iou
```

More instructions on testing are available in *Testing*.

CHAPTER

THREE

DEMO

We provide an easy-to-use API for the demo and application purpose in ocr.py script.

The API can be called through command line (CL) or by calling it from another python script.

3.1 Example 1: Text Detection

Instruction: Perform detection inference on an image with the TextSnake recognition model, export the result in a json file (default) and save the visualization file.

- CL interface:

```
python mmocr/utils/ocr.py demo/demo_text_det.jpg --output demo/det_out.jpg --det␣
↪TextSnake --recog None --export demo/
```

- Python interface:

```
from mmocr.utils.ocr import MMOCR

# Load models into memory
ocr = MMOCR(det='TextSnake', recog=None)

# Inference
results = ocr.readtext('demo/demo_text_det.jpg', output='demo/det_out.jpg', export='demo/
↪')
```

3.2 Example 2: Text Recognition

Instruction: Perform batched recognition inference on a folder with hundreds of image with the CRNN_TPS recognition model and save the visualization results in another folder. *Batch size is set to 10 to prevent out of memory CUDA runtime errors.*

- CL interface:

```
python mmocr/utils/ocr.py %INPUT_FOLDER_PATH% --det None --recog CRNN_TPS --batch-mode --
↪single-batch-size 10 --output %OUPUT_FOLDER_PATH%
```

- Python interface:

```
from mmocr.utils.ocr import MMOCR

# Load models into memory
ocr = MMOCR(det=None, recog='CRNN_TPS')

# Inference
results = ocr.readtext(%INPUT_FOLDER_PATH%, output = %OUTPUT_FOLDER_PATH%, batch_
↪mode=True, single_batch_size = 10)
```

3.3 Example 3: Text Detection + Recognition

Instruction: Perform ocr (det + recog) inference on the demo/demo_text_det.jpg image with the PANet_IC15 (default) detection model and SAR (default) recognition model, print the result in the terminal and show the visualization.

- CL interface:

```
python mmocr/utils/ocr.py demo/demo_text_ocr.jpg --print-result --imshow
```

Note: When calling the script from the command line, the script assumes configs are saved in the `configs/` folder. User can customize the directory by specifying the value of `config_dir`.

- Python interface:

```
from mmocr.utils.ocr import MMOCR

# Load models into memory
ocr = MMOCR()

# Inference
results = ocr.readtext('demo/demo_text_ocr.jpg', print_result=True, imshow=True)
```

3.4 Example 4: Text Detection + Recognition + Key Information Extraction

Instruction: Perform end-to-end ocr (det + recog) inference first with PS_CTW detection model and SAR recognition model, then run KIE inference with SDMGR model on the ocr result and show the visualization.

- CL interface:

```
python mmocr/utils/ocr.py demo/demo_kie.jpeg  --det PS_CTW --recog SAR --kie SDMGR --
↪print-result --imshow
```

Note: Note: When calling the script from the command line, the script assumes configs are saved in the `configs/` folder. User can customize the directory by specifying the value of `config_dir`.

- Python interface:

```
from mmocr.utils.ocr import MMOCR

# Load models into memory
ocr = MMOCR(det='PS_CTW', recog='SAR', kie='SDMGR')

# Inference
results = ocr.readtext('demo/demo_kie.jpeg', print_result=True, imshow=True)
```

3.5 API Arguments

The API has an extensive list of arguments that you can use. The following tables are for the python interface.

MMOCR():

[1]: `kie` is only effective when both text detection and recognition models are specified.

Note: User can use default pretrained models by specifying `det` and/or `recog`, which is equivalent to specifying their corresponding `*_config` and `*_ckpt`. However, manually specifying `*_config` and `*_ckpt` will always override values set by `det` and/or `recog`. Similar rules also apply to `kie`, `kie_config` and `kie_ckpt`.

3.5.1 readtext():

[1]: Make sure that the model is compatible with batch mode.

[2]: Only effective when the script is running in det + recog mode.

All arguments are the same for the cli, all you need to do is add 2 hyphens at the beginning of the argument and replace underscores by hyphens. (*Example:* `det_batch_size` becomes `--det-batch-size`)

For bool type arguments, putting the argument in the command stores it as true. (*Example:* `python mmocr/utils/ocr.py demo/demo_text_det.jpg --batch_mode --print_result` means that `batch_mode` and `print_result` are set to `True`)

3.6 Models

Text detection:

Text recognition:

Warning: SAR_CN is the only model that supports Chinese character recognition and it requires a Chinese dictionary. Please download the dictionary from here for a successful run.

Key information extraction:

3.7 Additional info

- To perform det + recog inference (end2end ocr), both the `det` and `recog` arguments must be defined.
- To perform only detection set the `recog` argument to `None`.
- To perform only recognition set the `det` argument to `None`.
- `details` argument only works with end2end ocr.
- `det_batch_size` and `recog_batch_size` arguments define the number of images you want to forward to the model at the same time. For maximum speed, set this to the highest number you can. The max batch size is limited by the model complexity and the GPU VRAM size.

If you have any suggestions for new features, feel free to open a thread or even PR :)

CHAPTER

FOUR

TRAINING

4.1 Training on a Single Machine

You can use `tools/train.py` to train a model on a single machine with CPU and optionally GPU(s).

Here is the full usage of the script:

```
python tools/train.py ${CONFIG_FILE} [ARGS]
```

Note: By default, MMOCR prefers GPU(s) to CPU. If you want to train a model on CPU, please empty `CUDA_VISIBLE_DEVICES` or set it to -1 to make GPU(s) invisible to the program. Note that CPU training requires **MMCV >= 1.4.4**.

```
CUDA_VISIBLE_DEVICES= python tools/train.py ${CONFIG_FILE} [ARGS]
```

4.2 Training on Multiple Machines

MMOCR implements **distributed** training with `MMDistributedDataParallel`. (Please refer to datasets.md to prepare your datasets)

```
[PORT={PORT}] ./tools/dist_train.sh ${CONFIG_FILE} ${WORK_DIR} ${GPU_NUM} [PY_ARGS]
```

4.3 Training with Slurm

If you run MMOCR on a cluster managed with Slurm, you can use the script `slurm_train.sh`.

```
[GPUS=${GPUS}] [GPUS_PER_NODE=${GPUS_PER_NODE}] [CPUS_PER_TASK=${CPUS_PER_TASK}] [SRUN_
↪ARGS=${SRUN_ARGS}] ./tools/slurm_train.sh ${PARTITION} ${JOB_NAME} ${CONFIG_FILE} $
↪{WORK_DIR} [PY_ARGS]
```

Here is an example of using 8 GPUs to train a text detection model on the dev partition.

```
./tools/slurm_train.sh dev psenet-ic15 configs/textdet/psenet/psenet_r50_fpnf_sbn_1x_
↪icdar2015.py /nfs/xxxx/psenet-ic15
```

4.3.1 Running Multiple Training Jobs on a Single Machine

If you are launching multiple training jobs on a single machine with Slurm, you may need to modify the port in configs to avoid communication conflicts.

For example, in `config1.py`,

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

In `config2.py`,

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

Then you can launch two jobs with `config1.py` ang `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}
```

4.4 Commonly Used Training Configs

Here we list some configs that are frequently used during training for quick reference.

```
total_epochs = 1200
data = dict(
    # Note: User can configure general settings of train, val and test dataloader by␣
↪specifying them here. However, their values can be overridden in dataloader's config.
    samples_per_gpu=8, # Batch size per GPU
    workers_per_gpu=4, # Number of workers to process data for each GPU
    train_dataloader=dict(samples_per_gpu=10, drop_last=True),   # Batch size = 10,␣
↪workers_per_gpu = 4
    val_dataloader=dict(samples_per_gpu=6, workers_per_gpu=1),  # Batch size = 6,␣
↪workers_per_gpu = 1
    test_dataloader=dict(workers_per_gpu=16),  # Batch size = 8, workers_per_gpu = 16
    ...
)
# Evaluation
evaluation = dict(interval=1, by_epoch=True)  # Evaluate the model every epoch
# Saving and Logging
checkpoint_config = dict(interval=1)  # Save a checkpoint every epoch
log_config = dict(
    interval=5,  # Print out the model's performance every 5 iterations
    hooks=[
        dict(type='TextLoggerHook')
    ])
# Optimizer
optimizer = dict(type='SGD', lr=0.02, momentum=0.9, weight_decay=0.0001)  # Supports all␣
↪optimizers in PyTorch and shares the same parameters
optimizer_config = dict(grad_clip=None)  # Parameters for the optimizer hook. See https:/
↪/github.com/open-mmlab/mmcv/blob/master/mmcv/runner/hooks/optimizer.py for␣
↪implementation details
```

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```
# Learning policy
lr_config = dict(policy='poly', power=0.9, min_lr=1e-7, by_epoch=True)
```

CHAPTER

FIVE

TESTING

We introduce the way to test pretrained models on datasets here.

5.1 Testing with Single GPU

You can use `tools/test.py` to perform single CPU/GPU inference. For example, to evaluate DBNet on IC15: (You can download pretrained models from *Model Zoo*):

```
./tools/dist_test.sh configs/textdet/dbnet/dbnet_r18_fpnc_1200e_icdar2015.py dbnet_r18_
↪fpnc_sbn_1200e_icdar2015_20210329-ba3ab597.pth --eval hmean-iou
```

And here is the full usage of the script:

```
python tools/test.py ${CONFIG_FILE} ${CHECKPOINT_FILE} [ARGS]
```

Note: By default, MMOCR prefers GPU(s) to CPU. If you want to test a model on CPU, please empty `CUDA_VISIBLE_DEVICES` or set it to -1 to make GPU(s) invisible to the program. Note that running CPU tests requires **MMCV >= 1.4.4**.

```
CUDA_VISIBLE_DEVICES= python tools/test.py ${CONFIG_FILE} ${CHECKPOINT_FILE} [ARGS]
```

5.2 Testing with Multiple GPUs

MMOCR implements **distributed** testing with `MMDistributedDataParallel`.

You can use the following command to test a dataset with multiple GPUs.

```
[PORT={PORT}] ./tools/dist_test.sh ${CONFIG_FILE} ${CHECKPOINT_FILE} ${GPU_NUM} [PY_ARGS]
```

For example,

```
./tools/dist_test.sh configs/example_config.py work_dirs/example_exp/example_model_
↪20200202.pth 1 --eval hmean-iou
```

5.3 Testing with Slurm

If you run MMOCR on a cluster managed with Slurm, you can use the script `tools/slurm_test.sh`.

```
[GPUS=${GPUS}] [GPUS_PER_NODE=${GPUS_PER_NODE}] [SRUN_ARGS=${SRUN_ARGS}] ./tools/slurm_
↪test.sh ${PARTITION} ${JOB_NAME} ${CONFIG_FILE} ${CHECKPOINT_FILE} [PY_ARGS]
```

Here is an example of using 8 GPUs to test an example model on the 'dev' partition with job name 'test_job'.

```
GPUS=8 ./tools/slurm_test.sh dev test_job configs/example_config.py work_dirs/example_
↪exp/example_model_20200202.pth --eval hmean-iou
```

5.4 Batch Testing

By default, MMOCR tests the model image by image. For faster inference, you may change `data.val_dataloader.samples_per_gpu` and `data.test_dataloader.samples_per_gpu` in the config. For example,

```
data = dict(
    ...
    val_dataloader=dict(samples_per_gpu=16),
    test_dataloader=dict(samples_per_gpu=16),
    ...
)
```

will test the model with 16 images in a batch.

Warning: Batch testing may incur performance decrease of the model due to the different behavior of the data preprocessing pipeline.

CHAPTER

SIX

DEPLOYMENT

We provide deployment tools under `tools/deployment` directory.

6.1 Convert to ONNX (experimental)

We provide a script to convert the model to ONNX format. The converted model could be visualized by tools like Netron. Besides, we also support comparing the output results between PyTorch and ONNX model.

```
python tools/deployment/pytorch2onnx.py
    ${MODEL_CONFIG_PATH} \
    ${MODEL_CKPT_PATH} \
    ${MODEL_TYPE} \
    ${IMAGE_PATH} \
    --output-file ${OUTPUT_FILE} \
    --device-id ${DEVICE_ID} \
    --opset-version ${OPSET_VERSION} \
    --verify \
    --verbose \
    --show \
    --dynamic-export
```

Description of arguments:

Note: This tool is still experimental. For now, some customized operators are not supported, and we only support a subset of detection and recognition algorithms.

6.1.1 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.

Note:

- *All models above are tested with PyTorch==1.8.1 and onnxruntime-gpu == 1.8.1*
- If you meet any problem with the listed models above, please create an issue and it would be taken care of soon.
- Because this feature is experimental and may change fast, please always try with the latest `mmcv` and `mmocr`.

6.2 Convert ONNX to TensorRT (experimental)

We also provide a script to convert ONNX model to TensorRT format. Besides, we support comparing the output results between ONNX and TensorRT model.

```
python tools/deployment/onnx2tensorrt.py
    ${MODEL_CONFIG_PATH} \
    ${MODEL_TYPE} \
    ${IMAGE_PATH} \
    ${ONNX_FILE} \
    --trt-file ${OUT_TENSORRT} \
    --max-shape INT INT INT INT \
    --min-shape INT INT INT INT \
    --workspace-size INT \
    --fp16 \
    --verify \
    --show \
    --verbose
```

Description of arguments:

Note: This tool is still experimental. For now, some customized operators are not supported, and we only support a subset of detection and recognition algorithms.

6.2.1 List of supported models exportable to TensorRT

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

Note:

- *All models above are tested with PyTorch==1.8.1, onnxruntime-gpu==1.8.1 and tensorrt==7.2.1.6*
- If you meet any problem with the listed models above, please create an issue and it would be taken care of soon.
- Because this feature is experimental and may change fast, please always try with the latest `mmcv` and `mmocr`.

6.3 Evaluate ONNX and TensorRT Models (experimental)

We provide methods to evaluate TensorRT and ONNX models in `tools/deployment/deploy_test.py`.

6.3.1 Prerequisite

To evaluate ONNX and TensorRT models, ONNX, ONNXRuntime and TensorRT should be installed first. Install `mmcv-full` with ONNXRuntime custom ops and TensorRT plugins follow ONNXRuntime in mmcv and TensorRT plugin in mmcv.

6.3.2 Usage

```
python tools/deploy_test.py \
    ${CONFIG_FILE} \
    ${MODEL_PATH} \
    ${MODEL_TYPE} \
    ${BACKEND} \
    --eval ${METRICS} \
    --device ${DEVICE}
```

6.3.3 Description of all arguments

6.4 Results and Models

Note:

- TensorRT upsampling operation is a little different from PyTorch. For DBNet and PANet, we suggest replacing upsampling operations with the nearest mode to operations with bilinear mode. Here for PANet, here and here for DBNet. As is shown in the above table, networks with tag * mean the upsampling mode is changed.
- Note that changing upsampling mode reduces less performance compared with using the nearest mode. However, the weights of networks are trained through the nearest mode. To pursue the best performance, using bilinear mode for both training and TensorRT deployment is recommended.
- All ONNX and TensorRT models are evaluated with dynamic shapes on the datasets, and images are preprocessed according to the original config file.
- This tool is still experimental, and we only support a subset of detection and recognition algorithms for now.

6.5 C++ Inference example with OpenCV

The example below is tested with Visual Studio 2019 as console application, CPU inference only.

6.5.1 Prerequisites

1. Project should use OpenCV (tested with version 4.5.4), ONNX Runtime NuGet package (version 1.9.0).
2. Download *DBNet_r18* detector and *SATRN_small* recognizer models from our *Model Zoo*, and export them with the following python commands (you may change the paths accordingly):

```
python3.9 ../mmocr/tools/deployment/pytorch2onnx.py --verify --output-file detector.onnx␣
↪../mmocr/configs/textdet/dbnet/dbnet_r18_fpnc_1200e_icdar2015.py ./dbnet_r18_fpnc_sbn_
↪1200e_icdar2015_20210329-ba3ab597.pth --dynamic-export det ./sample_big_image_eg_
↪1920x1080.png

python3.9 ../mmocr/tools/deployment/pytorch2onnx.py --opset 14 --verify --output-file␣
↪recognizer.onnx ../mmocr/configs/textrecog/satrn/satrn_small.py ./satrn_small_20211009-
↪2cf13355.pth recog ./sample_small_image_eg_200x50.png
```

Note:

- Be aware, while exported `detector.onnx` file is relatively small (about 50 Mb), `recognizer.onnx` is pretty big (more than 600 Mb).
- *DBNet_r18* can use ONNX opset 11, *SATRN_small* can be exported with opset 14.

Warning: Be sure, that verifications of both models are successful - look through the export messages.

6.5.2 Example

Example usage of exported models with C++ is in the code below (don't forget to change paths to *.onnx files). It's applicable to these two models only, other models have another preprocessing and postprocessing logics.

```
#include <iostream>

#include <opencv2/core/core.hpp>
#include <opencv2/highgui.hpp>
#include <opencv2/imgproc.hpp>
#include <opencv2/dnn.hpp>

#include <onnxruntime_cxx_api.h>
#pragma comment(lib, "onnxruntime.lib")

// DB_r18
class Detector {
public:
        Detector(const std::string& model_path) {
                session = Ort::Session{ env, std::wstring(model_path.begin(), model_path.
↪end()).c_str(), Ort::SessionOptions{nullptr} };
        }

        std::vector<cv::Rect> inference(const cv::Mat& original, float threshold = 0.3f)
↪{
```

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```
                cv::Size original_size = original.size();

                const char* input_names[] = { "input" };
                const char* output_names[] = { "output" };

                std::array<int64_t, 4> input_shape{ 1, 3, height, width };

                cv::Mat image = cv::Mat::zeros(cv::Size(width, height), original.type());
                cv::resize(original, image, cv::Size(width, height), 0, 0, cv::INTER_
↪AREA);

                image.convertTo(image, CV_32FC3);

                cv::cvtColor(image, image, cv::COLOR_BGR2RGB);
                image = (image - cv::Scalar(123.675f, 116.28f, 103.53f)) / cv::Scalar(58.
↪395f, 57.12f, 57.375f);

                cv::Mat blob = cv::dnn::blobFromImage(image);

                auto memory_info = Ort::MemoryInfo::CreateCpu(OrtDeviceAllocator,␣
↪OrtMemTypeDefault);
                Ort::Value input_tensor = Ort::Value::CreateTensor<float>(memory_info,␣
↪(float*)blob.data, blob.total(), input_shape.data(), input_shape.size());

                std::vector<Ort::Value> output_tensor = session.Run(Ort::RunOptions{␣
↪nullptr }, input_names, &input_tensor, 1, output_names, 1);

                int sizes[] = { 1, 3, height, width };
                cv::Mat output(4, sizes, CV_32F, output_tensor.front().
↪GetTensorMutableData<float>());

                std::vector<cv::Mat> images;
                cv::dnn::imagesFromBlob(output, images);

                std::vector<cv::Rect> areas = get_detected(images[0], threshold);
                std::vector<cv::Rect> results;

                float x_ratio = original_size.width / (float)width;
                float y_ratio = original_size.height / (float)height;

                for (int index = 0; index < areas.size(); ++index) {
                        cv::Rect box = areas[index];

                        box.x = int(box.x * x_ratio);
                        box.width = int(box.width * x_ratio);
                        box.y = int(box.y * y_ratio);
                        box.height = int(box.height * y_ratio);

                        results.push_back(box);
                }

                return results;
```

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```
        }

private:
        Ort::Env env;
        Ort::Session session{ nullptr };

        const int width = 1312, height = 736;

        cv::Rect expand_box(const cv::Rect& original, int addition = 5) {
                cv::Rect box(original);
                box.x = std::max(0, box.x - addition);
                box.y = std::max(0, box.y - addition);
                box.width = (box.x + box.width + addition * 2 > width) ? (width - box.x)␣
↪: (box.width + addition * 2);
                box.height = (box.y + box.height + addition * 2) > height ? (height -␣
↪box.y) : (box.height + addition * 2);
                return box;
        }

        std::vector<cv::Rect> get_detected(const cv::Mat& output, float threshold) {
                cv::Mat text_mask = cv::Mat::zeros(height, width, CV_32F);
                std::vector<cv::Mat> maps;
                cv::split(output, maps);
                cv::Mat proba_map = maps[0];

                cv::threshold(proba_map, text_mask, threshold, 1.0f, cv::THRESH_BINARY);
                cv::multiply(text_mask, 255, text_mask);
                text_mask.convertTo(text_mask, CV_8U);

                std::vector<std::vector<cv::Point>> contours;
                cv::findContours(text_mask, contours, cv::RETR_EXTERNAL, cv::CHAIN_
↪APPROX_SIMPLE);
                std::vector<cv::Rect> boxes;

                for (int index = 0; index < contours.size(); ++index) {
                        cv::Rect box = expand_box(cv::boundingRect(contours[index]));
                        boxes.push_back(box);
                }

                return boxes;
        }
};

// SATRN_small
class Recognizer {
public:
        Recognizer(const std::string& model_path) {
                session = Ort::Session{ env, std::wstring(model_path.begin(), model_path.
↪end()).c_str(), Ort::SessionOptions{nullptr} };
        }

        std::string inference(const cv::Mat& original) {
```

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```
                const char* input_names[] = { "input" };
                const char* output_names[] = { "output" };

                std::array<int64_t, 4> input_shape{ 1, 3, height, width };

                cv::Mat image;
                cv::resize(original, image, cv::Size(width, height), 0, 0, cv::INTER_
↪AREA);
                image.convertTo(image, CV_32FC3);

                cv::cvtColor(image, image, cv::COLOR_BGR2RGB);
                image = (image / 255.0f - cv::Scalar(0.485f, 0.456f, 0.406f)) /␣
↪cv::Scalar(0.229f, 0.224f, 0.225f);

                cv::Mat blob = cv::dnn::blobFromImage(image);

                auto memory_info = Ort::MemoryInfo::CreateCpu(OrtDeviceAllocator,␣
↪OrtMemTypeDefault);
                Ort::Value input_tensor = Ort::Value::CreateTensor<float>(memory_info,␣
↪(float*)blob.data, blob.total(), input_shape.data(), input_shape.size());

                std::vector<Ort::Value> output_tensor = session.Run(Ort::RunOptions{␣
↪nullptr }, input_names, &input_tensor, 1, output_names, 1);

                int sequence_length = 25;
                std::string dictionary =
↪"0123456789abcdefghijklmnopqrstuvwxyzABCDEFGHIJKLMNOPQRSTUVWXYZ!\"#$%&'()*+,-./:;<=>?
↪@[\\]_`~";
                int characters = dictionary.length() + 2; // EOS + UNK

                std::vector<int> max_indices;
                for (int outer = 0; outer < sequence_length; ++outer) {
                        int character_index = -1;
                        float character_value = 0;
                        for (int inner = 0; inner < characters; ++inner) {
                                int counter = outer * characters + inner;
                                float value = output_tensor[0].GetTensorMutableData
↪<float>()[counter];
                                if (value > character_value) {
                                        character_value = value;
                                        character_index = inner;
                                }
                        }
                        max_indices.push_back(character_index);
                }

                std::string recognized;

                for (int index = 0; index < max_indices.size(); ++index) {
                        if (max_indices[index] == dictionary.length()) {
                                continue; // unk
                        }
```

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```
                        if (max_indices[index] == dictionary.length() + 1) {
                                break; // eos
                        }
                        recognized += dictionary[max_indices[index]];
                }

                return recognized;
        }

private:
        Ort::Env env;
        Ort::Session session{ nullptr };

        const int height = 32;
        const int width = 100;
};

int main(int argc, const char* argv[]) {
        if (argc < 2) {
                std::cout << "Usage: this_executable.exe c:/path/to/image.png" <<␣
↪std::endl;
                return 0;
        }

        std::chrono::steady_clock::time_point begin = std::chrono::steady_clock::now();
        std::cout << "Loading models..." << std::endl;

        Detector detector("d:/path/to/detector.onnx");
        Recognizer recognizer("d:/path/to/recognizer.onnx");

        std::chrono::steady_clock::time_point end = std::chrono::steady_clock::now();
        std::cout << "Loading models done in " << std::chrono::duration_cast
↪<std::chrono::milliseconds>(end - begin).count() << " ms" << std::endl;

        cv::Mat image = cv::imread(argv[1], cv::IMREAD_COLOR);

        begin = std::chrono::steady_clock::now();
        std::vector<cv::Rect> detections = detector.inference(image);
        for (int index = 0; index < detections.size(); ++index) {
                cv::Mat roi = image(detections[index]);
                std::string text = recognizer.inference(roi);
                cv::rectangle(image, detections[index], cv::Scalar(255, 255, 255), 2);
                cv::putText(image, text, cv::Point(detections[index].x,␣
↪detections[index].y - 10), cv::FONT_HERSHEY_COMPLEX, 0.4, cv::Scalar(255, 255, 255));
        }

        end = std::chrono::steady_clock::now();
        std::cout << "Inference time (with drawing): " << std::chrono::duration_cast
↪<std::chrono::milliseconds>(end - begin).count() << " ms" << std::endl;

        cv::imshow("Results", image);
        cv::waitKey(0);
```

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```
        return 0;
}
```

The output should look something like this.

```
Loading models...
Loading models done in 5715 ms
Inference time (with drawing): 3349 ms
```

And the sample result should look something like this.



CHAPTER

SEVEN

MODEL SERVING

MMOCR provides some utilities that facilitate the model serving process. Here is a quick walkthrough of necessary steps that let the models to serve through an API.

7.1 Install TorchServe

You can follow the steps on the official website to install `TorchServe` and `torch-model-archiver`.

7.2 Convert model from MMOCR to TorchServe

We provide a handy tool to convert any `.pth` model into `.mar` model for TorchServe.

```
python tools/deployment/mmocr2torchserve.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.

For example:

```
python tools/deployment/mmocr2torchserve.py \
  configs/textdet/dbnet/dbnet_r18_fpnc_1200e_icdar2015.py \
  checkpoints/dbnet_r18_fpnc_1200e_icdar2015.pth \
  --output-folder ./checkpoints \
  --model-name dbnet
```

7.3 Start Serving

7.3.1 From your Local Machine

Getting your models prepared, the next step is to start the service with a one-line command:

```
# To load all the models in ./checkpoints
torchserve --start --model-store ./checkpoints --models all
# Or, if you only want one model to serve, say dbnet
torchserve --start --model-store ./checkpoints --models dbnet=dbnet.mar
```

Then you can access inference, management and metrics services through TorchServe's REST API. You can find their usages in TorchServe REST API.

Note: By default, TorchServe binds port number `8080`, `8081` and `8082` to its services. You can change such behavior by modifying and saving the contents below to `config.properties`, and running TorchServe with option `--ts-config config.preperties`.

```
inference_address=http://0.0.0.0:8080
management_address=http://0.0.0.0:8081
metrics_address=http://0.0.0.0:8082
number_of_netty_threads=32
job_queue_size=1000
model_store=/home/model-server/model-store
```

7.3.2 From Docker

A better alternative to serve your models is through Docker. We provide a Dockerfile that frees you from those tedious and error-prone environmental setup steps.

Build `mmocr-serve` Docker image

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

Run `mmocr-serve` with Docker

In order to run Docker in GPU, you need to install nvidia-docker; or you can omit the `--gpus` argument for a CPU-only session.

The command below will run `mmocr-serve` with a gpu, bind the ports of `8080` (inference), `8081` (management) and `8082` (metrics) from container to `127.0.0.1`, and mount the checkpoint folder `./checkpoints` from the host machine to `/home/model-server/model-store` of the container. For more information, please check the official docs for running TorchServe with docker.

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

Note: `realpath ./checkpoints` points to the absolute path of "./checkpoints", and you can replace it with the absolute path where you store torchserve models.

Upon running the docker, you can access inference, management and metrics services through TorchServe's REST API. You can find their usages in TorchServe REST API.

7.4 4. Test deployment

Inference API allows user to post an image to a model and returns the prediction result.

```
curl http://127.0.0.1:8080/predictions/${MODEL_NAME} -T demo/demo_text_det.jpg
```

For example,

```
curl http://127.0.0.1:8080/predictions/dbnet -T demo/demo_text_det.jpg
```

For detection models, you should obtain a json with an object named `boundary_result`. Each array inside has float numbers representing x, y coordinates of boundary vertices in clockwise order, and the last float number as the confidence score.


```
{
  "boundary_result": [
    [
      221.18990004062653,
      226.875,
      221.18990004062653,
      212.625,
      244.05868631601334,
      212.625,
      244.05868631601334,
      226.875,
      0.80883354575186
    ]
  ]
}
```


For recognition models, the response should look like:


```
{
  "text": "sier",
  "score": 0.5247521847486496
}
```


And you can use `test_torchserve.py` to compare result of TorchServe and PyTorch by visualizing them.

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

Example:

```
python tools/deployment/test_torchserve.py \
  demo/demo_text_det.jpg \
  configs/textdet/dbnet/dbnet_r18_fpnc_1200e_icdar2015.py \
  checkpoints/dbnet_r18_fpnc_1200e_icdar2015.pth \
  dbnet
```

CHAPTER

EIGHT

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.

8.1 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 `'LoadImageFromNdarry'` in the pipeline, you may specify `--cfg-options data.train.pipeline.0.type=LoadImageFromNdarry`.

- 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.

8.2 Config Name Style

We follow the below style to name full config files (`configs/TASK/*.py`). Contributors are advised to follow the same style.

```
{model}_[ARCHITECTURE]_[schedule]_{dataset}.py
```

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

- `{model}`: model type like `dbnet`, `crnn`, etc.
- `[ARCHITECTURE]`: expands some invoked modules following the order of data flow, and the content depends on the model framework. The following examples show how it is generally expanded.

  - For text detection tasks, key information tasks, and SegOCR in text recognition task: `{model}_[backbone]_[neck]_[schedule]_{dataset}.py`
  - For other text recognition tasks, `{model}_[backbone]_[encoder]_[decoder]_[schedule]_{dataset}.py` Note that `backbone`, `neck`, `encoder`, `decoder` are the names of modules, e.g. `r50`, `fpnocr`, etc.
- `{schedule}`: training schedule. For instance, `1200e` denotes 1200 epochs.
- `{dataset}`: dataset. It can either be the name of a dataset (`icdar2015`), or a collection of datasets for brevity (e.g. `academic` usually refers to a common practice in academia, which uses MJSynth + SynthText as training set, and IIIT5K, SVT, IC13, IC15, SVTP and CT80 as test set).

Most configs are composed of basic *primitive* configs in `configs/_base_`, where each *primitive* config in different subdirectory has a slightly different name style. We present them as follows.

- det_datasets, recog_datasets: `{dataset_name(s)}_[train|test].py`. If [train|test] is not specified, the config should contain both training and test set.

  There are two exceptions: toy_data.py and seg_toy_data.py. In recog_datasets, the first one works for most while the second one contains character level annotations and works for seg baseline only as of Dec 2021.
- det_models, recog_models: `{model}_[ARCHITECTURE].py`.
- det_pipelines, recog_pipelines: `{model}_pipeline.py`.
- schedules: `schedule_{optimizer}_{num_epochs}e.py`.

8.3 Config Structure

For better config reusability, we break many of reusable sections of configs into `configs/_base_`. Now the directory tree of `configs/_base_` is organized as follows:

```
_base_
├── det_datasets
├── det_models
├── det_pipelines
├── recog_datasets
├── recog_models
├── recog_pipelines
└── schedules
```

These *primitive* configs are categorized by their roles in a complete config. Most of model configs are making full use of *primitive* configs by including them as parts of `_base_` section. For example, dbnet_r18_fpnc_1200e_icdar2015.py takes five *primitive* configs from `_base_`:

```
_base_ = [
    '../../_base_/runtime_10e.py',
    '../../_base_/schedules/schedule_sgd_1200e.py',
    '../../_base_/det_models/dbnet_r18_fpnc.py',
    '../../_base_/det_datasets/icdar2015.py',
    '../../_base_/det_pipelines/dbnet_pipeline.py'
]
```

From these configs' names we can roughly know this config trains dbnet_r18_fpnc with sgd optimizer in 1200 epochs. It uses the origin dbnet pipeline and icdar2015 as the dataset. We encourage users to follow and take advantage of this convention to organize the config clearly and facilitate fair comparison across different *primitive* configurations as well as models.

Please refer to mmcv for detailed documentation.

8.4 Config File Structure

8.4.1 Model

The parameter "model" is a python dictionary in the configuration file, which mainly includes information such as network structure and loss function.

Note: The 'type' in the configuration file is not a constructed parameter, but a class name.

Note: We can also use models from MMDetection by adding `mmdet.` prefix to type name, or from other OpenMMLab projects in a similar way if their backbones are registered in registries.

Shared Section

- `type`: Model name.

Text Detection / Text Recognition / Key Information Extraction Model

- `backbone`: Backbone configs. Common Backbones, TextRecog Backbones
- `neck`: Neck network name. TextDet Necks, TextRecog Necks.
- `bbox_head`: Head network name. Applicable to text detection, key information models and *some* text recognition models. TextDet Heads, TextRecog Heads, KIE Heads.
  - `loss`: Loss function type. TextDet Losses, KIE Losses
  - `postprocessor`: (TextDet only) Postprocess type. TextDet Postprocessors

Text Recognition / Named Entity Extraction Model

- `encoder`: Encoder configs. TextRecog Encoders
- `decoder`: Decoder configs. Applicable to text recognition models. TextRecog Decoders
- `loss`: Loss configs. Applicable to some text recognition models. TextRecog Losses
- `label_convertor`: Convert outputs between text, index and tensor. Applicable to text recognition models. Label Convertors
- `max_seq_len`: The maximum sequence length of recognition results. Applicable to text recognition models.

8.4.2 Data & Pipeline

The parameter "data" is a python dictionary in the configuration file, which mainly includes information to construct dataloader:

- samples_per_gpu : the BatchSize of each GPU when building the dataloader
- workers_per_gpu : the number of threads per GPU when building dataloader
- train | val | test : config to construct dataset
  - type: Dataset name. Check dataset types for supported datasets.

The parameter evaluation is also a dictionary, which is the configuration information of evaluation hook, mainly including evaluation interval, evaluation index, etc.

```
# dataset settings
dataset_type = 'IcdarDataset'  # dataset name
data_root = 'data/icdar2015'  # dataset root
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)                     # Whether to invert the color channel, rgb2bgr or␣
↪bgr2rgb.
# train data pipeline
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
    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
```

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```
    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=32,     # Batch size of a single GPU
    workers_per_gpu=2,      # Worker to pre-fetch data for each single GPU
    train=dict(             # train data config
        type=dataset_type,                  # dataset name
        ann_file=f'{data_root}/instances_training.json',  # Path to annotation file
        img_prefix=f'{data_root}/imgs',  # Path to images
        pipeline=train_pipeline),           # train data pipeline
    test=dict(              # test data config
        type=dataset_type,
        ann_file=f'{data_root}/instances_test.json',  # Path to annotation file
        img_prefix=f'{data_root}/imgs',  # Path to images
        pipeline=test_pipeline))
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.
```

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```
    interval=1,          # Evaluation interval
    metric='hmean-iou')   # Metrics used during evaluation
```

8.4.3 Training Schedule

Mainly include optimizer settings, `optimizer hook` settings, learning rate schedule and `runner` settings:

- `optimizer`: optimizer setting , support all optimizers in `pytorch`, refer to related mmcv documentation.
- `optimizer_config`: `optimizer hook` configuration file, such as setting gradient limit, refer to related mmcv code.
- `lr_config`: Learning rate scheduler, supports "CosineAnnealing", "Step", "Cyclic", etc. Refer to related mmcv documentation for more options.
- `runner`: For `runner`, please refer to `mmcv` for `runner` introduction document.

```
# he configuration file used to build the optimizer, support all optimizers in PyTorch.
optimizer = dict(type='SGD',         # Optimizer type
                 lr=0.1,             # 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
# 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.
optimizer_config = dict(grad_clip=None)  # Most of the methods do not use gradient clip
# Learning rate scheduler config used to register LrUpdater hook
lr_config = dict(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.
                 step=[30, 60, 90])      # Steps to decay the learning rate
runner = dict(type='EpochBasedRunner',   # Type of runner to use (i.e. IterBasedRunner␣
↪or EpochBasedRunner)
              max_epochs=100)    # Runner that runs the workflow in total max_epochs. For␣
↪IterBasedRunner use `max_iters`
```

8.4.4 Runtime Setting

This part mainly includes saving the checkpoint strategy, log configuration, training parameters, breakpoint weight path, working directory, etc..

```
# Config to set the checkpoint hook, Refer to https://github.com/open-mmlab/mmcv/blob/
↪master/mmcv/runner/hooks/checkpoint.py for implementation.
checkpoint_config = dict(interval=1)    # The save interval is 1
# config to register logger hook
log_config = dict(
    interval=100,                       # Interval to print the log
    hooks=[
        dict(type='TextLoggerHook'),           # The Tensorboard logger is also supported
        # dict(type='TensorboardLoggerHook')
    ])
```

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```
dist_params = dict(backend='nccl')   # Parameters to setup distributed training, the␣
↪port can also be set.
log_level = 'INFO'              # The output level of the log.
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.
work_dir = 'work_dir'           # Directory to save the model checkpoints and logs for␣
↪the current experiments.
```

8.5 FAQ

8.5.1 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.

8.5.2 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 usually want the data path to be a variable so that we

```
dataset_type = 'IcdarDataset'
data_root = 'data/icdar2015'

train = dict(
    type=dataset_type,
    ann_file=f'{data_root}/instances_training.json',
    img_prefix=f'{data_root}/imgs',
    pipeline=None)

test = dict(
    type=dataset_type,
    ann_file=f'{data_root}/instances_test.json',
    img_prefix=f'{data_root}/imgs',
    pipeline=None)
```

8.5.3 Use some fields in the base configs

Sometimes, you may refer to some fields in the `_base_` config, so as to avoid duplication of definitions. You can refer to mmcv for some more instructions.

This technique has been widely used in MMOCR's configs, where the main configs refer to the dataset and pipeline defined in *base* configs by:

```
train_list = {{_base_.train_list}}
test_list = {{_base_.test_list}}
```

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```
train_pipeline = {{_base_.train_pipeline}}
test_pipeline = {{_base_.test_pipeline}}
```

Which assumes that its *base* configs export datasets and pipelines in a way like:

```
#  base dataset config
dataset_type = 'IcdarDataset'
data_root = 'data/icdar2015'

train = dict(
    type=dataset_type,
    ann_file=f'{data_root}/instances_training.json',
    img_prefix=f'{data_root}/imgs',
    pipeline=None)

test = dict(
    type=dataset_type,
    ann_file=f'{data_root}/instances_test.json',
    img_prefix=f'{data_root}/imgs',
    pipeline=None)

train_list = [train]
test_list = [test]
```

```
#  base pipeline config
train_pipeline = dict(...)
test_pipeline = dict(...)
```

8.6 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(...),
)
```

CHAPTER

NINE

DATASET TYPES

9.1 General Introduction

To support the tasks of text detection, text recognition and key information extraction, we have designed some new types of dataset which consist of **loader** and **parser** to load and parse different types of annotation files.

- **loader**: Load the annotation file. There are two types of loader, `HardDiskLoader` and `LmdbLoader`
  - `HardDiskLoader`: Load `txt` format annotation file from hard disk to memory.
  - `LmdbLoader`: Load `lmdb` format annotation file with lmdb backend, which is very useful for **extremely large** annotation files to avoid out-of-memory problem when ten or more GPUs are used, since each GPU will start multiple processes to load annotation file to memory.
- **parser**: Parse the annotation file line-by-line and return with `dict` format. There are two types of parser, `LineStrParser` and `LineJsonParser`.
  - `LineStrParser`: Parse one line in ann file while treating it as a string and separating it to several parts by a `separator`. It can be used on tasks with simple annotation files such as text recognition where each line of the annotation files contains the `filename` and `label` attribute only.
  - `LineJsonParser`: Parse one line in ann file while treating it as a json-string and using `json.loads` to convert it to `dict`. It can be used on tasks with complex annotation files such as text detection where each line of the annotation files contains multiple attributes (e.g. `filename`, `height`, `width`, `box`, `segmentation`, `iscrowd`, `category_id`, etc.).

Here we show some examples of using different combination of `loader` and `parser`.

9.2 General Task

9.2.1 UniformConcatDataset

`UniformConcatDataset` is a dataset wrapper which allows users to apply a universal pipeline on multiple datasets without specifying the pipeline for each of them.

For example, to apply `train_pipeline` on both `train1` and `train2`,

```
data = dict(
    ...
    train=dict(
        type='UniformConcatDataset',
        datasets=[train1, train2],
        pipeline=train_pipeline))
```

Also, it support apply different `pipeline` to different `datasets`,

```
train_list1 = [train1, train2]
train_list2 = [train3, train4]

data = dict(
    ...
    train=dict(
        type='UniformConcatDataset',
        datasets=[train_list1, train_list2],
        pipeline=[train_pipeline1, train_pipeline2]))
```

Here, `train_pipeline1` will be applied to `train1` and `train2`, and `train_pipeline2` will be applied to `train3` and `train4`.

9.3 Text Detection Task

9.3.1 TextDetDataset

Dataset with annotation file in line-json txt format

```
dataset_type = 'TextDetDataset'
img_prefix = 'tests/data/toy_dataset/imgs'
test_anno_file = 'tests/data/toy_dataset/instances_test.txt'
test = dict(
    type=dataset_type,
    img_prefix=img_prefix,
    ann_file=test_anno_file,
    loader=dict(
        type='HardDiskLoader',
        repeat=4,
        parser=dict(
            type='LineJsonParser',
            keys=['file_name', 'height', 'width', 'annotations'])),
    pipeline=test_pipeline,
    test_mode=True)
```

The results are generated in the same way as the segmentation-based text recognition task above. You can check the content of the annotation file in `tests/data/toy_dataset/instances_test.txt`. The combination of `HardDiskLoader` and `LineJsonParser` will return a dict for each file by calling `__getitem__`:

```
{"file_name": "test/img_10.jpg", "height": 720, "width": 1280, "annotations": [{"iscrowd
↪": 1, "category_id": 1, "bbox": [260.0, 138.0, 24.0, 20.0], "segmentation": [[261, 138,
↪ 284, 140, 279, 158, 260, 158]]}, {"iscrowd": 0, "category_id": 1, "bbox": [288.0, 138.
↪0, 129.0, 23.0], "segmentation": [[288, 138, 417, 140, 416, 161, 290, 157]]}, {"iscrowd
↪": 0, "category_id": 1, "bbox": [743.0, 145.0, 37.0, 18.0], "segmentation": [[743, 145,
↪ 779, 146, 780, 163, 746, 163]]}, {"iscrowd": 0, "category_id": 1, "bbox": [783.0, 129.
↪0, 50.0, 26.0], "segmentation": [[783, 129, 831, 132, 833, 155, 785, 153]]}, {"iscrowd
↪": 1, "category_id": 1, "bbox": [831.0, 133.0, 43.0, 23.0], "segmentation": [[831, 133,
↪ 870, 135, 874, 156, 835, 155]]}, {"iscrowd": 1, "category_id": 1, "bbox": [159.0, 204.
↪0, 72.0, 15.0], "segmentation": [[159, 205, 230, 204, 231, 218, 159, 219]]}, {"iscrowd
↪": 1, "category_id": 1, "bbox": [785.0, 158.0, 75.0, 21.0], "segmentation": [[785, 158,
↪ 856, 158, 860, 178, 787, 179]]}, {"iscrowd": 1, "category_id": 1, "bbox": [1011.0,
↪157.0, 68.0, 16.0], "segmentation": [[1011, 157, 1079, 160, 1076, 173, 1011, 170]]}]}
```

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9.3.2 IcdarDataset

Dataset with annotation file in coco-like json format

For text detection, you can also use an annotation file in a COCO format that is defined in MMDetection:

```
dataset_type = 'IcdarDataset'
prefix = 'tests/data/toy_dataset/'
test=dict(
        type=dataset_type,
        ann_file=prefix + 'instances_test.json',
        img_prefix=prefix + 'imgs',
        pipeline=test_pipeline)
```

You can check the content of the annotation file in `tests/data/toy_dataset/instances_test.json`.

Note: Icdar 2015/2017 and ctw1500 annotations need to be converted into the COCO format following the steps in datasets.md.

9.4 Text Recognition Task

9.4.1 OCRDataset

Dataset for encoder-decoder based recognizer

```
dataset_type = 'OCRDataset'
img_prefix = 'tests/data/ocr_toy_dataset/imgs'
train_anno_file = 'tests/data/ocr_toy_dataset/label.txt'
train = dict(
    type=dataset_type,
    img_prefix=img_prefix,
    ann_file=train_anno_file,
    loader=dict(
        type='HardDiskLoader',
        repeat=10,
        parser=dict(
            type='LineStrParser',
            keys=['filename', 'text'],
            keys_idx=[0, 1],
            separator=' ')),
    pipeline=train_pipeline,
    test_mode=False)
```

You can check the content of the annotation file in `tests/data/ocr_toy_dataset/label.txt`. The combination of `HardDiskLoader` and `LineStrParser` will return a dict for each file by calling `__getitem__`: `{'filename': '1223731.jpg', 'text': 'GRAND'}`.

Optional Arguments:

- `repeat`: The number of repeated lines in the annotation files. For example, if there are `10` lines in the annotation file, setting `repeat=10` will generate a corresponding annotation file with size `100`.

If the annotation file is extremely large, you can convert it from txt format to lmdb format with the following command:

```
python tools/data_converter/txt2lmdb.py -i ann_file.txt -o ann_file.lmdb
```

After that, you can use `LmdbLoader` in dataset like below.

```
img_prefix = 'tests/data/ocr_toy_dataset/imgs'
train_anno_file = 'tests/data/ocr_toy_dataset/label.lmdb'
train = dict(
    type=dataset_type,
    img_prefix=img_prefix,
    ann_file=train_anno_file,
    loader=dict(
        type='LmdbLoader',
        repeat=10,
        parser=dict(
            type='LineStrParser',
            keys=['filename', 'text'],
            keys_idx=[0, 1],
            separator=' ')),
    pipeline=train_pipeline,
    test_mode=False)
```

9.4.2 OCRSegDataset

Dataset for segmentation-based recognizer

```
prefix = 'tests/data/ocr_char_ann_toy_dataset/'
train = dict(
    type='OCRSegDataset',
    img_prefix=prefix + 'imgs',
    ann_file=prefix + 'instances_train.txt',
    loader=dict(
        type='HardDiskLoader',
        repeat=10,
        parser=dict(
            type='LineJsonParser',
            keys=['file_name', 'annotations', 'text'])),
    pipeline=train_pipeline,
    test_mode=True)
```

You can check the content of the annotation file in `tests/data/ocr_char_ann_toy_dataset/instances_train.txt`. The combination of `HardDiskLoader` and `LineJsonParser` will return a dict for each file by calling `__getitem__` each time:

```
{"file_name": "resort_88_101_1.png", "annotations": [{"char_text": "F", "char_box": [11.
↪0, 0.0, 22.0, 0.0, 12.0, 12.0, 0.0, 12.0]}, {"char_text": "r", "char_box": [23.0, 2.0,␣
↪31.0, 1.0, 24.0, 11.0, 16.0, 11.0]}, {"char_text": "o", "char_box": [33.0, 2.0, 43.0,␣
↪2.0, 36.0, 12.0, 25.0, 12.0]}, {"char_text": "m", "char_box": [46.0, 2.0, 61.0, 2.0,␣
↪53.0, 12.0, 39.0, 12.0]}, {"char_text": ":", "char_box": [61.0, 2.0, 69.0, 2.0, 63.0,␣
↪12.0, 55.0, 12.0]}], "text": "From:"}
```

CHAPTER

TEN

KIE: DIFFERENCE BETWEEN CLOSESET & OPENSET

Being trained on WildReceipt, SDMG-R, or other KIE models, can identify the types of text boxes on a receipt picture. But what SDMG-R can do is far more beyond that. For example, it's able to identify key-value pairs on the picture. To demonstrate such ability and hopefully facilitate future research, we release a demonstrative version of WildReceiptOpenset annotated in OpenSet format, and provide a full training/testing pipeline for KIE models such as SDMG-R. Since it might be a *confusing* update, we'll elaborate on the key differences between the OpenSet and CloseSet format, taking WildReceipt as an example.

10.1 CloseSet

WildReceipt ("CloseSet") divides text boxes into 26 categories. There are 12 key-value pairs of fine-grained key information categories, such as (`Prod_item_value`, `Prod_item_key`), (`Prod_price_value`, `Prod_price_key`) and (`Tax_value`, `Tax_key`), plus two more "do not care" categories: `Ignore` and `Others`.

The objective of CloseSet SDMGR is to predict which category fits the text box best, but it will not predict the relations among text boxes. For instance, if there are four text boxes "Hamburger", "Hotdog", "$1" and "$2" on the receipt, the model may assign `Prod_item_value` to the first two boxes and `Prod_price_value` to the last two, but it can't tell if Hamburger sells for $1 or $2. However, this could be achieved in the open-set variant.

Warning: A `*_key` and `*_value` pair do not necessarily have to both appear on the receipt. For example, we usually won't see `Prod_item_key` appearing on the receipt, while there can be multiple boxes annotated as `Pred_item_value`. In contrast, `Tax_key` and `Tax_value` are likely to appear together since they're usually structured as `Tax: 11.02` on the receipt.

10.2 OpenSet

In OpenSet, all text boxes, or nodes, have only 4 possible categories: `background`, `key`, `value`, and `others`. The connectivity between nodes are annotated as *edge labels*. If a pair of key-value nodes have the same edge label, they are connected by an valid edge.

Multiple nodes can have the same edge label. However, only key and value nodes will be linked by edges. The nodes of same category will never be connected.

When making OpenSet annotations, each node must have an edge label. It should be an unique one if it falls into non-`key` non-`value` categories.

Note: You can merge `background` to `others` if telling background apart is not important, and we provide this choice in the conversion script for WildReceipt .

10.2.1 Converting WildReceipt from CloseSet to OpenSet

We provide a *conversion script* that converts WildRecipt-like dataset to OpenSet format. This script links every `key-value` pairs following the rules above. Here's an example illustration: (For better understanding, all the node labels are presented as texts)

Warning: A common request from our community is to extract the relations between food items and food prices. In this case, this conversion script ***is not you need***. Wildrecipt doesn't provide necessary information to recover this relation. For instance, there are four text boxes "Hamburger", "Hotdog", "$1" and "$2" on the receipt, and here's how they actually look like before and after the conversion:

So there won't be any valid edges connecting them. Nevertheless, OpenSet format is far more general than CloseSet, so this task can be achieved by annotating the data from scratch.

CHAPTER

ELEVEN

STATISTICS

- Number of checkpoints: 31
- Number of configs: 22
- Number of papers: 17
  - ALGORITHM: 17

11.1 Key Information Extraction Models

- Number of checkpoints: 3
- Number of configs: 3
- Number of papers: 1
  - [ALGORITHM] Spatial Dual-Modality Graph Reasoning for Key Information Extraction

11.2 Named Entity Recognition Models

- Number of checkpoints: 1
- Number of configs: 1
- Number of papers: 1
  - [ALGORITHM] Bert: Pre-Training of Deep Bidirectional Transformers for Language Understanding

11.3 Text Detection Models

- Number of checkpoints: 14
- Number of configs: 8
- Number of papers: 7
  - [ALGORITHM] Deep Relational Reasoning Graph Network for Arbitrary Shape Text Detection
  - [ALGORITHM] Efficient and Accurate Arbitrary-Shaped Text Detection With Pixel Aggregation Network
  - [ALGORITHM] Fourier Contour Embedding for Arbitrary-Shaped Text Detection
  - [ALGORITHM] Mask R-CNN

  - [ALGORITHM] Real-Time Scene Text Detection With Differentiable Binarization
  - [ALGORITHM] Shape Robust Text Detection With Progressive Scale Expansion Network
  - [ALGORITHM] Textsnake: A Flexible Representation for Detecting Text of Arbitrary Shapes

11.4 Text Recognition Models

- Number of checkpoints: 13
- Number of configs: 10
- Number of papers: 8
  - [ALGORITHM] An End-to-End Trainable Neural Network for Image-Based Sequence Recognition and Its Application to Scene Text Recognition
  - [ALGORITHM] Nrtr: A No-Recurrence Sequence-to-Sequence Model for Scene Text Recognition
  - [ALGORITHM] On Recognizing Texts of Arbitrary Shapes With 2d Self-Attention
  - [ALGORITHM] Read Like Humans: Autonomous, Bidirectional and Iterative Language Modeling for Scene Text Recognition
  - [ALGORITHM] Robust Scene Text Recognition With Automatic Rectification
  - [ALGORITHM] Robustscanner: Dynamically Enhancing Positional Clues for Robust Text Recognition
  - [ALGORITHM] Segocr Simple Baseline.
  - [ALGORITHM] Show, Attend and Read: A Simple and Strong Baseline for Irregular Text Recognition

CHAPTER

TWELVE

MODEL ARCHITECTURE SUMMARY

MMOCR has implemented many models that support various tasks. Depending on the type of tasks, these models have different architectural designs and, therefore, might be a bit confusing for beginners to master. We release a primary design doc to clearly illustrate the basic task-specific architectures and provide quick pointers to docstrings of model components to aid users' understanding.

12.1 Text Detection Models

The design of text detectors is similar to SingleStageDetector in MMDetection. The feature of an image was first extracted by `backbone` (e.g., ResNet), and `neck` further processes raw features into a head-ready format, where the models in MMOCR usually adapt the variants of FPN to extract finer-grained multi-level features. `bbox_head` is the core of text detectors, and its implementation varies in different models.

When training, the output of `bbox_head` is directly fed into the `loss` module, which compares the output with the ground truth and generates a loss dictionary for optimizer's use. When testing, `Postprocessor` converts the outputs from `bbox_head` to bounding boxes, which will be used for evaluation metrics (e.g., hmean-iou) and visualization.

12.1.1 DBNet

- Backbone: mmdet.ResNet
- Neck: FPNC
- Bbox_head: DBHead
- Loss: DBLoss
- Postprocessor: DBPostprocessor

12.1.2 DRRG

- Backbone: mmdet.ResNet
- Neck: FPN_UNet
- Bbox_head: DRRGHead
- Loss: DRRGLoss
- Postprocessor: DRRGPostprocessor

12.1.3 FCENet

- Backbone: mmdet.ResNet
- Neck: mmdet.FPN
- Bbox_head: FCEHead
- Loss: FCELoss
- Postprocessor: FCEPostprocessor

12.1.4 Mask R-CNN

We use the same architecture as in MMDetection. See MMDetection's config documentation for details.

12.1.5 PANet

- Backbone: mmdet.ResNet
- Neck: FPEM_FFM
- Bbox_head: PANHead
- Loss: PANLoss
- Postprocessor: PANPostprocessor

12.1.6 PSENet

- Backbone: mmdet.ResNet
- Neck: FPNF
- Bbox_head: PSEHead
- Loss: PSELoss
- Postprocessor: PSEPostprocessor

12.1.7 Textsnake

- Backbone: mmdet.ResNet
- Neck: FPN_UNet
- Bbox_head: TextSnakeHead
- Loss: TextSnakeLoss
- Postprocessor: TextSnakePostprocessor

12.2 Text Recognition Models

Most of the implemented recognizers use the following architecture:

`preprocessor` refers to any network that processes images before they are fed to `backbone`. `encoder` encodes images features into a hidden vector, which is then transcribed into text tokens by `decoder`.

The architecture diverges at training and test phases. The loss module returns a dictionary during training. In testing, `converter` is invoked to convert raw features into texts, which are wrapped into a dictionary together with confidence scores. Users can access the dictionary with the `text` and `score` keys to query the recognition result.

12.2.1 ABINet

- Preprocessor: None
- Backbone: ResNetABI
- Encoder: ABIVisionModel
- Decoder: ABIVisionDecoder
- Fuser: ABIFuser
- Loss: ABILoss
- Converter: ABIConvertor

Note: Fuser fuses the feature output from encoder and decoder before generating the final text outputs and computing the loss in full ABINet.

12.2.2 CRNN

- Preprocessor: None
- Backbone: VeryDeepVgg
- Encoder: None
- Decoder: CRNNDecoder
- Loss: CTCLoss
- Converter: CTCConvertor

12.2.3 CRNN with TPS-based STN

- Preprocessor: TPSPreprocessor
- Backbone: VeryDeepVgg
- Encoder: None
- Decoder: CRNNDecoder
- Loss: CTCLoss
- Converter: CTCConvertor

12.2.4 NRTR

- Preprocessor: None
- Backbone: ResNet31OCR
- Encoder: NRTREncoder
- Decoder: NRTRDecoder
- Loss: TFLoss
- Converter: AttnConvertor

12.2.5 RobustScanner

- Preprocessor: None
- Backbone: ResNet31OCR
- Encoder: ChannelReductionEncoder
- Decoder: ChannelReductionEncoder
- Loss: SARLoss
- Converter: AttnConvertor

12.2.6 SAR

- Preprocessor: None
- Backbone: ResNet31OCR
- Encoder: SAREncoder
- Decoder: ParallelSARDecoder
- Loss: SARLoss
- Converter: AttnConvertor

12.2.7 SATRN

- Preprocessor: None
- Backbone: ShallowCNN
- Encoder: SatrnEncoder
- Decoder: NRTRDecoder
- Loss: TFLoss
- Converter: AttnConvertor

12.2.8 SegOCR

- Backbone: ResNet31OCR
- Neck: FPNOCR
- Head: SegHead
- Loss: SegLoss
- Converter: SegConvertor

Note: SegOCR's architecture is an exception - it is closer to text detection models.

12.3 Key Information Extraction Models

The architecture of key information extraction (KIE) models is similar to text detection models, except for the extra feature extractor. As a downstream task of OCR, KIE models are required to run with bounding box annotations indicating the locations of text instances, from which an ROI extractor extracts the cropped features for `bbox_head` to discover relations among them.

The output containing edges and nodes information from `bbox_head` is sufficient for test and inference. Computation of loss also relies on such information.

12.3.1 SDMGR

- Backbone: UNet
- Neck: None
- Extractor: mmdet.SingleRoIExtractor
- Bbox_head: SDMGRHead
- Loss: SDMGRLoss

CHAPTER

THIRTEEN

TEXT DETECTION MODELS

13.1 DBNet

Real-time Scene Text Detection with Differentiable Binarization

13.1.1 Abstract

Recently, segmentation-based methods are quite popular in scene text detection, as the segmentation results can more accurately describe scene text of various shapes such as curve text. However, the post-processing of binarization is essential for segmentation-based detection, which converts probability maps produced by a segmentation method into bounding boxes/regions of text. In this paper, we propose a module named Differentiable Binarization (DB), which can perform the binarization process in a segmentation network. Optimized along with a DB module, a segmentation network can adaptively set the thresholds for binarization, which not only simplifies the post-processing but also enhances the performance of text detection. Based on a simple segmentation network, we validate the performance improvements of DB on five benchmark datasets, which consistently achieves state-of-the-art results, in terms of both detection accuracy and speed. In particular, with a light-weight backbone, the performance improvements by DB are significant so that we can look for an ideal tradeoff between detection accuracy and efficiency. Specifically, with a backbone of ResNet-18, our detector achieves an F-measure of 82.8, running at 62 FPS, on the MSRA-TD500 dataset.

13.1.2 Results and models

ICDAR2015

13.1.3 Citation

```
@article{Liao_Wan_Yao_Chen_Bai_2020,
    title={Real-Time Scene Text Detection with Differentiable Binarization},
    journal={Proceedings of the AAAI Conference on Artificial Intelligence},
    author={Liao, Minghui and Wan, Zhaoyi and Yao, Cong and Chen, Kai and Bai, Xiang},
    year={2020},
    pages={11474-11481}}
```

13.2 DRRG

Deep relational reasoning graph network for arbitrary shape text detection

13.2.1 Abstract

Arbitrary shape text detection is a challenging task due to the high variety and complexity of scenes texts. In this paper, we propose a novel unified relational reasoning graph network for arbitrary shape text detection. In our method, an innovative local graph bridges a text proposal model via Convolutional Neural Network (CNN) and a deep relational reasoning network via Graph Convolutional Network (GCN), making our network end-to-end trainable. To be concrete, every text instance will be divided into a series of small rectangular components, and the geometry attributes (e.g., height, width, and orientation) of the small components will be estimated by our text proposal model. Given the geometry attributes, the local graph construction model can roughly establish linkages between different text components. For further reasoning and deducing the likelihood of linkages between the component and its neighbors, we adopt a graph-based network to perform deep relational reasoning on local graphs. Experiments on public available datasets demonstrate the state-of-the-art performance of our method.

13.2.2 Results and models

CTW1500

Note: We've upgraded our IoU backend from `Polygon3` to `shapely`. There are some performance differences for some models due to the backends' different logics to handle invalid polygons (more info here). **New evaluation result is presented in brackets** and new logs will be uploaded soon.

13.2.3 Citation

```
@article{zhang2020drrg,
  title={Deep relational reasoning graph network for arbitrary shape text detection},
  author={Zhang, Shi-Xue and Zhu, Xiaobin and Hou, Jie-Bo and Liu, Chang and Yang, Chun␣
↪and Wang, Hongfa and Yin, Xu-Cheng},
  booktitle={CVPR},
  pages={9699-9708},
  year={2020}
}
```

13.3 FCENet

Fourier Contour Embedding for Arbitrary-Shaped Text Detection

13.3.1 Abstract

One of the main challenges for arbitrary-shaped text detection is to design a good text instance representation that allows networks to learn diverse text geometry variances. Most of existing methods model text instances in image spatial domain via masks or contour point sequences in the Cartesian or the polar coordinate system. However, the mask representation might lead to expensive post-processing, while the point sequence one may have limited capability to model texts with highly-curved shapes. To tackle these problems, we model text instances in the Fourier domain and propose one novel Fourier Contour Embedding (FCE) method to represent arbitrary shaped text contours as compact signatures. We further construct FCENet with a backbone, feature pyramid networks (FPN) and a simple post-processing with the Inverse Fourier Transformation (IFT) and Non-Maximum Suppression (NMS). Different from previous methods, FCENet first predicts compact Fourier signatures of text instances, and then reconstructs text contours via IFT and NMS during test. Extensive experiments demonstrate that FCE is accurate and robust to fit contours of scene texts even with highly-curved shapes, and also validate the effectiveness and the good generalization of FCENet for arbitrary-shaped text detection. Furthermore, experimental results show that our FCENet is superior to the state-of-the-art (SOTA) methods on CTW1500 and Total-Text, especially on challenging highly-curved text subset.

13.3.2 Results and models

CTW1500

ICDAR2015

13.3.3 Citation

```
@InProceedings{zhu2021fourier,
      title={Fourier Contour Embedding for Arbitrary-Shaped Text Detection},
      author={Yiqin Zhu and Jianyong Chen and Lingyu Liang and Zhanghui Kuang and␣
↪Lianwen Jin and Wayne Zhang},
      year={2021},
      booktitle = {CVPR}
      }
```

13.4 Mask R-CNN

Mask R-CNN

13.4.1 Abstract

We present a conceptually simple, flexible, and general framework for object instance segmentation. Our approach efficiently detects objects in an image while simultaneously generating a high-quality segmentation mask for each instance. The method, called Mask R-CNN, extends Faster R-CNN by adding a branch for predicting an object mask in parallel with the existing branch for bounding box recognition. Mask R-CNN is simple to train and adds only a small overhead to Faster R-CNN, running at 5 fps. Moreover, Mask R-CNN is easy to generalize to other tasks, e.g., allowing us to estimate human poses in the same framework. We show top results in all three tracks of the COCO suite of challenges, including instance segmentation, bounding-box object detection, and person keypoint detection. Without bells and whistles, Mask R-CNN outperforms all existing, single-model entries on every task, including the COCO 2016 challenge winners. We hope our simple and effective approach will serve as a solid baseline and help ease future research in instance-level recognition.

13.4.2 Results and models

CTW1500

ICDAR2015

ICDAR2017

Note: We tuned parameters with the techniques in Pyramid Mask Text Detector

13.4.3 Citation

```
@INPROCEEDINGS{8237584,
  author={K. {He} and G. {Gkioxari} and P. {Dollár} and R. {Girshick}},
  booktitle={2017 IEEE International Conference on Computer Vision (ICCV)},
  title={Mask R-CNN},
  year={2017},
  pages={2980-2988},
  doi={10.1109/ICCV.2017.322}}
```

13.5 PANet

Efficient and Accurate Arbitrary-Shaped Text Detection with Pixel Aggregation Network

13.5.1 Abstract

Scene text detection, an important step of scene text reading systems, has witnessed rapid development with convolutional neural networks. Nonetheless, two main challenges still exist and hamper its deployment to real-world applications. The first problem is the trade-off between speed and accuracy. The second one is to model the arbitrary-shaped text instance. Recently, some methods have been proposed to tackle arbitrary-shaped text detection, but they rarely take the speed of the entire pipeline into consideration, which may fall short in practical this http URL this paper, we propose an efficient and accurate arbitrary-shaped text detector, termed Pixel Aggregation Network (PAN), which is equipped with a low computational-cost segmentation head and a learnable post-processing. More specifically, the segmentation head is made up of Feature Pyramid Enhancement Module (FPEM) and Feature Fusion Module (FFM). FPEM is a cascadable U-shaped module, which can introduce multi-level information to guide the better segmentation. FFM can gather the features given by the FPEMs of different depths into a final feature for segmentation. The learnable post-processing is implemented by Pixel Aggregation (PA), which can precisely aggregate text pixels by predicted similarity vectors. Experiments on several standard benchmarks validate the superiority of the proposed PAN. It is worth noting that our method can achieve a competitive F-measure of 79.9% at 84.2 FPS on CTW1500.

13.5.2 Results and models

CTW1500

ICDAR2015

Note: We've upgraded our IoU backend from `Polygon3` to `shapely`. There are some performance differences for some models due to the backends' different logics to handle invalid polygons (more info here). **New evaluation result is presented in brackets** and new logs will be uploaded soon.

13.5.3 Citation

```
@inproceedings{WangXSZWLYS19,
  author={Wenhai Wang and Enze Xie and Xiaoge Song and Yuhang Zang and Wenjia Wang and
↪Tong Lu and Gang Yu and Chunhua Shen},
  title={Efficient and Accurate Arbitrary-Shaped Text Detection With Pixel Aggregation
↪Network},
  booktitle={ICCV},
  pages={8439--8448},
  year={2019}
  }
```

13.6 PSENet

Shape robust text detection with progressive scale expansion network

13.6.1 Abstract

Scene text detection has witnessed rapid progress especially with the recent development of convolutional neural networks. However, there still exists two challenges which prevent the algorithm into industry applications. On the one hand, most of the state-of-art algorithms require quadrangle bounding box which is in-accurate to locate the texts with arbitrary shape. On the other hand, two text instances which are close to each other may lead to a false detection which covers both instances. Traditionally, the segmentation-based approach can relieve the first problem but usually fail to solve the second challenge. To address these two challenges, in this paper, we propose a novel Progressive Scale Expansion Network (PSENet), which can precisely detect text instances with arbitrary shapes. More specifically, PSENet generates the different scale of kernels for each text instance, and gradually expands the minimal scale kernel to the text instance with the complete shape. Due to the fact that there are large geometrical margins among the minimal scale kernels, our method is effective to split the close text instances, making it easier to use segmentation-based methods to detect arbitrary-shaped text instances. Extensive experiments on CTW1500, Total-Text, ICDAR 2015 and ICDAR 2017 MLT validate the effectiveness of PSENet. Notably, on CTW1500, a dataset full of long curve texts, PSENet achieves a F-measure of 74.3% at 27 FPS, and our best F-measure (82.2%) outperforms state-of-art algorithms by 6.6%. The code will be released in the future.

13.6.2 Results and models

CTW1500

ICDAR2015

Note: We've upgraded our IoU backend from `Polygon3` to `shapely`. There are some performance differences for some models due to the backends' different logics to handle invalid polygons (more info here). **New evaluation result is presented in brackets** and new logs will be uploaded soon.

13.6.3 Citation

```
@inproceedings{wang2019shape,
  title={Shape robust text detection with progressive scale expansion network},
  author={Wang, Wenhai and Xie, Enze and Li, Xiang and Hou, Wenbo and Lu, Tong and Yu,␣
↪Gang and Shao, Shuai},
  booktitle={Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern␣
↪Recognition},
  pages={9336--9345},
  year={2019}
}
```

13.7 Textsnake

TextSnake: A Flexible Representation for Detecting Text of Arbitrary Shapes

13.7.1 Abstract

Driven by deep neural networks and large scale datasets, scene text detection methods have progressed substantially over the past years, continuously refreshing the performance records on various standard benchmarks. However, limited by the representations (axis-aligned rectangles, rotated rectangles or quadrangles) adopted to describe text, existing methods may fall short when dealing with much more free-form text instances, such as curved text, which are actually very common in real-world scenarios. To tackle this problem, we propose a more flexible representation for scene text, termed as TextSnake, which is able to effectively represent text instances in horizontal, oriented and curved forms. In TextSnake, a text instance is described as a sequence of ordered, overlapping disks centered at symmetric axes, each of which is associated with potentially variable radius and orientation. Such geometry attributes are estimated via a Fully Convolutional Network (FCN) model. In experiments, the text detector based on TextSnake achieves state-of-the-art or comparable performance on Total-Text and SCUT-CTW1500, the two newly published benchmarks with special emphasis on curved text in natural images, as well as the widely-used datasets ICDAR 2015 and MSRA-TD500. Specifically, TextSnake outperforms the baseline on Total-Text by more than 40% in F-measure.

13.7.2 Results and models

CTW1500

13.7.3 Citation

```
@article{long2018textsnake,
  title={TextSnake: A Flexible Representation for Detecting Text of Arbitrary Shapes},
  author={Long, Shangbang and Ruan, Jiaqiang and Zhang, Wenjie and He, Xin and Wu, Wenhao and Yao, Cong},
  booktitle={ECCV},
  pages={20-36},
  year={2018}
}
```

CHAPTER

FOURTEEN

TEXT RECOGNITION MODELS

14.1 ABINet

Read Like Humans: Autonomous, Bidirectional and Iterative Language Modeling for Scene Text Recognition

14.1.1 Abstract

Linguistic knowledge is of great benefit to scene text recognition. However, how to effectively model linguistic rules in end-to-end deep networks remains a research challenge. In this paper, we argue that the limited capacity of language models comes from: 1) implicitly language modeling; 2) unidirectional feature representation; and 3) language model with noise input. Correspondingly, we propose an autonomous, bidirectional and iterative ABINet for scene text recognition. Firstly, the autonomous suggests to block gradient flow between vision and language models to enforce explicitly language modeling. Secondly, a novel bidirectional cloze network (BCN) as the language model is proposed based on bidirectional feature representation. Thirdly, we propose an execution manner of iterative correction for language model which can effectively alleviate the impact of noise input. Additionally, based on the ensemble of iterative predictions, we propose a self-training method which can learn from unlabeled images effectively. Extensive experiments indicate that ABINet has superiority on low-quality images and achieves state-of-the-art results on several mainstream benchmarks. Besides, the ABINet trained with ensemble self-training shows promising improvement in realizing human-level recognition.

14.1.2 Dataset

Train Dataset

Test Dataset

14.1.3 Results and models

Note:

1. ABINet allows its encoder to run and be trained without decoder and fuser. Its encoder is designed to recognize texts as a stand-alone model and therefore can work as an independent text recognizer. We release it as ABINet-Vision.
2. Facts about the pretrained model: MMOCR does not have a systematic pipeline to pretrain the language model (LM) yet, thus the weights of LM are converted from the official pretrained model. The weights of ABINet-Vision are directly used as the vision model of ABINet.

3. Due to some technical issues, the training process of ABINet was interrupted at the 13th epoch and we resumed it later. Both logs are released for full reference.
4. The model architecture in the logs looks slightly different from the final released version, since it was refactored afterward. However, both architectures are essentially equivalent.

14.1.4 Citation

```
@article{fang2021read,
  title={Read Like Humans: Autonomous, Bidirectional and Iterative Language Modeling for Scene Text Recognition},
  author={Fang, Shancheng and Xie, Hongtao and Wang, Yuxin and Mao, Zhendong and Zhang, Yongdong},
    booktitle={Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition},
  year={2021}
}
```

14.2 CRNN

An end-to-end trainable neural network for image-based sequence recognition and its application to scene text recognition

14.2.1 Abstract

Image-based sequence recognition has been a long-standing research topic in computer vision. In this paper, we investigate the problem of scene text recognition, which is among the most important and challenging tasks in image-based sequence recognition. A novel neural network architecture, which integrates feature extraction, sequence modeling and transcription into a unified framework, is proposed. Compared with previous systems for scene text recognition, the proposed architecture possesses four distinctive properties: (1) It is end-to-end trainable, in contrast to most of the existing algorithms whose components are separately trained and tuned. (2) It naturally handles sequences in arbitrary lengths, involving no character segmentation or horizontal scale normalization. (3) It is not confined to any predefined lexicon and achieves remarkable performances in both lexicon-free and lexicon-based scene text recognition tasks. (4) It generates an effective yet much smaller model, which is more practical for real-world application scenarios. The experiments on standard benchmarks, including the IIIT-5K, Street View Text and ICDAR datasets, demonstrate the superiority of the proposed algorithm over the prior arts. Moreover, the proposed algorithm performs well in the task of image-based music score recognition, which evidently verifies the generality of it.

14.2.2 Dataset

Train Dataset

Test Dataset

14.2.3 Results and models

14.2.4 Citation

```
@article{shi2016end,
  title={An end-to-end trainable neural network for image-based sequence recognition and its application to scene text recognition},
  author={Shi, Baoguang and Bai, Xiang and Yao, Cong},
  journal={IEEE transactions on pattern analysis and machine intelligence},
  year={2016}
}
```

14.3 NRTR

NRTR: A No-Recurrence Sequence-to-Sequence Model For Scene Text Recognition

14.3.1 Abstract

Scene text recognition has attracted a great many researches due to its importance to various applications. Existing methods mainly adopt recurrence or convolution based networks. Though have obtained good performance, these methods still suffer from two limitations: slow training speed due to the internal recurrence of RNNs, and high complexity due to stacked convolutional layers for long-term feature extraction. This paper, for the first time, proposes a no-recurrence sequence-to-sequence text recognizer, named NRTR, that dispenses with recurrences and convolutions entirely. NRTR follows the encoder-decoder paradigm, where the encoder uses stacked self-attention to extract image features, and the decoder applies stacked self-attention to recognize texts based on encoder output. NRTR relies solely on self-attention mechanism thus could be trained with more parallelization and less complexity. Considering scene image has large variation in text and background, we further design a modality-transform block to effectively transform 2D input images to 1D sequences, combined with the encoder to extract more discriminative features. NRTR achieves state-of-the-art or highly competitive performance on both regular and irregular benchmarks, while requires only a small fraction of training time compared to the best model from the literature (at least 8 times faster).

14.3.2 Dataset

Train Dataset

Test Dataset

14.3.3 Results and Models

Note:

- For backbone `R31-1/16-1/8`:
  - The output consists of 92 classes, including 26 lowercase letters, 26 uppercase letters, 28 symbols, 10 digital numbers, 1 unknown token and 1 end-of-sequence token.
  - The encoder-block number is 6.

  - `1/16-1/8` means the height of feature from backbone is 1/16 of input image, where 1/8 for width.

- For backbone `R31-1/8-1/4`:
  - The output consists of 92 classes, including 26 lowercase letters, 26 uppercase letters, 28 symbols, 10 digital numbers, 1 unknown token and 1 end-of-sequence token.
  - The encoder-block number is 6.
  - `1/8-1/4` means the height of feature from backbone is 1/8 of input image, where 1/4 for width.

14.3.4 Citation

```
@inproceedings{sheng2019nrtr,
  title={NRTR: A no-recurrence sequence-to-sequence model for scene text recognition},
  author={Sheng, Fenfen and Chen, Zhineng and Xu, Bo},
  booktitle={2019 International Conference on Document Analysis and Recognition (ICDAR)},
  pages={781--786},
  year={2019},
  organization={IEEE}
}
```

14.4 RobustScanner

RobustScanner: Dynamically Enhancing Positional Clues for Robust Text Recognition

14.4.1 Abstract

The attention-based encoder-decoder framework has recently achieved impressive results for scene text recognition, and many variants have emerged with improvements in recognition quality. However, it performs poorly on contextless texts (e.g., random character sequences) which is unacceptable in most of real application scenarios. In this paper, we first deeply investigate the decoding process of the decoder. We empirically find that a representative character-level sequence decoder utilizes not only context information but also positional information. Contextual information, which the existing approaches heavily rely on, causes the problem of attention drift. To suppress such side-effect, we propose a novel position enhancement branch, and dynamically fuse its outputs with those of the decoder attention module for scene text recognition. Specifically, it contains a position aware module to enable the encoder to output feature vectors encoding their own spatial positions, and an attention module to estimate glimpses using the positional clue (i.e., the current decoding time step) only. The dynamic fusion is conducted for more robust feature via an element-wise gate mechanism. Theoretically, our proposed method, dubbed \emph{RobustScanner}, decodes individual characters with dynamic ratio between context and positional clues, and utilizes more positional ones when the decoding sequences with scarce context, and thus is robust and practical. Empirically, it has achieved new state-of-the-art results on popular regular and irregular text recognition benchmarks while without much performance drop on contextless benchmarks, validating its robustness in both contextual and contextless application scenarios.

14.4.2 Dataset

Train Dataset

Test Dataset

14.4.3 Results and Models

14.4.4 References

[1] Li, Hui and Wang, Peng and Shen, Chunhua and Zhang, Guyu. Show, attend and read: A simple and strong baseline for irregular text recognition. In AAAI 2019.

14.4.5 Citation

```
@inproceedings{yue2020robustscanner,
  title={RobustScanner: Dynamically Enhancing Positional Clues for Robust Text␣
↪Recognition},
  author={Yue, Xiaoyu and Kuang, Zhanghui and Lin, Chenhao and Sun, Hongbin and Zhang,␣
↪Wayne},
  booktitle={European Conference on Computer Vision},
  year={2020}
}
```

14.5 SAR

Show, Attend and Read: A Simple and Strong Baseline for Irregular Text Recognition

14.5.1 Abstract

Recognizing irregular text in natural scene images is challenging due to the large variance in text appearance, such as curvature, orientation and distortion. Most existing approaches rely heavily on sophisticated model designs and/or extra fine-grained annotations, which, to some extent, increase the difficulty in algorithm implementation and data collection. In this work, we propose an easy-to-implement strong baseline for irregular scene text recognition, using off-the-shelf neural network components and only word-level annotations. It is composed of a 31-layer ResNet, an LSTM-based encoder-decoder framework and a 2-dimensional attention module. Despite its simplicity, the proposed method is robust and achieves state-of-the-art performance on both regular and irregular scene text recognition benchmarks.

14.5.2 Dataset

Train Dataset

Test Dataset

14.5.3 Results and Models

14.5.4 Chinese Dataset

14.5.5 Results and Models

Note:

- `R31-1/8-1/4` means the height of feature from backbone is 1/8 of input image, where 1/4 for width.
- We did not use beam search during decoding.
- We implemented two kinds of decoder. Namely, `ParallelSARDecoder` and `SequentialSARDecoder`.
  - `ParallelSARDecoder`: Parallel decoding during training with `LSTM` layer. It would be faster.
  - `SequentialSARDecoder`: Sequential Decoding during training with `LSTMCell`. It would be easier to understand.
- For train dataset.
  - We did not construct distinct data groups (20 groups in *[1]*) to train the model group-by-group since it would render model training too complicated.
  - Instead, we randomly selected `2.4m` patches from `Syn90k`, `2.4m` from `SynthText` and `1.2m` from `SynthAdd`, and grouped all data together. See config for details.
- We used 48 GPUs with `total_batch_size = 64 * 48` in the experiment above to speedup training, while keeping the `initial lr = 1e-3` unchanged.

14.5.6 Citation

```
@inproceedings{li2019show,
  title={Show, attend and read: A simple and strong baseline for irregular text␣
↪recognition},
  author={Li, Hui and Wang, Peng and Shen, Chunhua and Zhang, Guyu},
  booktitle={Proceedings of the AAAI Conference on Artificial Intelligence},
  volume={33},
  number={01},
  pages={8610--8617},
  year={2019}
}
```

14.6 SATRN

On Recognizing Texts of Arbitrary Shapes with 2D Self-Attention

14.6.1 Abstract

Scene text recognition (STR) is the task of recognizing character sequences in natural scenes. While there have been great advances in STR methods, current methods still fail to recognize texts in arbitrary shapes, such as heavily curved or rotated texts, which are abundant in daily life (e.g. restaurant signs, product labels, company logos, etc). This paper introduces a novel architecture to recognizing texts of arbitrary shapes, named Self-Attention Text Recognition Network (SATRN), which is inspired by the Transformer. SATRN utilizes the self-attention mechanism to describe two-dimensional (2D) spatial dependencies of characters in a scene text image. Exploiting the full-graph propagation of self-attention, SATRN can recognize texts with arbitrary arrangements and large inter-character spacing. As a result, SATRN outperforms existing STR models by a large margin of 5.7 pp on average in "irregular text" benchmarks. We provide empirical analyses that illustrate the inner mechanisms and the extent to which the model is applicable (e.g. rotated and multi-line text). We will open-source the code.

14.6.2 Dataset

Train Dataset

Test Dataset

14.6.3 Results and Models

14.6.4 Citation

```
@article{junyeop2019recognizing,
  title={On Recognizing Texts of Arbitrary Shapes with 2D Self-Attention},
  author={Junyeop Lee, Sungrae Park, Jeonghun Baek, Seong Joon Oh, Seonghyeon Kim,␣
↪Hwalsuk Lee},
  year={2019}
}
```

14.7 SegOCR

14.7.1 Abstract

Just a simple Seg-based baseline for text recognition tasks.

14.7.2 Dataset

Train Dataset

Test Dataset

14.7.3 Results and Models

Note:

- `R31-1/16` means the size (both height and width) of feature from backbone is 1/16 of input image.
- `1x` means the size (both height and width) of feature from head is the same with input image.

14.7.4 Citation

```
@unpublished{key,
  title={SegOCR Simple Baseline.},
  author={},
  note={Unpublished Manuscript},
  year={2021}
}
```

14.8 CRNN-STN

14.8.1 Abstract

Image-based sequence recognition has been a long-standing research topic in computer vision. In this paper, we investigate the problem of scene text recognition, which is among the most important and challenging tasks in image-based sequence recognition. A novel neural network architecture, which integrates feature extraction, sequence modeling and transcription into a unified framework, is proposed. Compared with previous systems for scene text recognition, the proposed architecture possesses four distinctive properties: (1) It is end-to-end trainable, in contrast to most of the existing algorithms whose components are separately trained and tuned. (2) It naturally handles sequences in arbitrary lengths, involving no character segmentation or horizontal scale normalization. (3) It is not confined to any predefined lexicon and achieves remarkable performances in both lexicon-free and lexicon-based scene text recognition tasks. (4) It generates an effective yet much smaller model, which is more practical for real-world application scenarios. The experiments on standard benchmarks, including the IIIT-5K, Street View Text and ICDAR datasets, demonstrate the superiority of the proposed algorithm over the prior arts. Moreover, the proposed algorithm performs well in the task of image-based music score recognition, which evidently verifies the generality of it.

Note: We use STN from this paper as the preprocessor and CRNN as the recognition network.

14.8.2 Dataset

Train Dataset

Test Dataset

14.8.3 Results and models

14.8.4 Citation

```
@article{shi2016robust,
  title={Robust Scene Text Recognition with Automatic Rectification},
  author={Shi, Baoguang and Wang, Xinggang and Lyu, Pengyuan and Yao,
  Cong and Bai, Xiang},
  year={2016}
}
```

CHAPTER

FIFTEEN

KEY INFORMATION EXTRACTION MODELS

15.1 SDMGR

Spatial Dual-Modality Graph Reasoning for Key Information Extraction

15.1.1 Abstract

Key information extraction from document images is of paramount importance in office automation. Conventional template matching based approaches fail to generalize well to document images of unseen templates, and are not robust against text recognition errors. In this paper, we propose an end-to-end Spatial Dual-Modality Graph Reasoning method (SDMG-R) to extract key information from unstructured document images. We model document images as dual-modality graphs, nodes of which encode both the visual and textual features of detected text regions, and edges of which represent the spatial relations between neighboring text regions. The key information extraction is solved by iteratively propagating messages along graph edges and reasoning the categories of graph nodes. In order to roundly evaluate our proposed method as well as boost the future research, we release a new dataset named WildReceipt, which is collected and annotated tailored for the evaluation of key information extraction from document images of unseen templates in the wild. It contains 25 key information categories, a total of about 69000 text boxes, and is about 2 times larger than the existing public datasets. Extensive experiments validate that all information including visual features, textual features and spatial relations can benefit key information extraction. It has been shown that SDMG-R can effectively extract key information from document images of unseen templates, and obtain new state-of-the-art results on the recent popular benchmark SROIE and our WildReceipt. Our code and dataset will be publicly released.

15.1.2 Results and models

WildReceipt

Note:

1. For `sdmgr_novisual`, images are not needed for training and testing. So fake `img_prefix` can be used in configs. As well, fake `file_name` can be used in annotation files.

WildReceiptOpenset

Note:

1. In the case of openset, the number of node categories is unknown or unfixed, and more node category can be added.
2. To show that our method can handle openset problem, we modify the ground truth of `WildReceipt` to `WildReceiptOpenset`. The `nodes` are just classified into 4 classes: `background, key, value, others`, while adding `edge` labels for each box.
3. The model is used to predict whether two nodes are a pair connecting by a valid edge.
4. You can learn more about the key differences between CloseSet and OpenSet annotations in our *tutorial*.

15.1.3 Citation

```
@misc{sun2021spatial,
      title={Spatial Dual-Modality Graph Reasoning for Key Information Extraction},
      author={Hongbin Sun and Zhanghui Kuang and Xiaoyu Yue and Chenhao Lin and Wayne␣
↪Zhang},
      year={2021},
      eprint={2103.14470},
      archivePrefix={arXiv},
      primaryClass={cs.CV}
}
```

CHAPTER

SIXTEEN

NAMED ENTITY RECOGNITION MODELS

16.1 Bert

Bert: Pre-training of deep bidirectional transformers for language understanding

16.1.1 Abstract

We introduce a new language representation model called BERT, which stands for Bidirectional Encoder Representations from Transformers. Unlike recent language representation models, BERT is designed to pre-train deep bidirectional representations from unlabeled text by jointly conditioning on both left and right context in all layers. As a result, the pre-trained BERT model can be fine-tuned with just one additional output layer to create state-of-the-art models for a wide range of tasks, such as question answering and language inference, without substantial task-specific architecture modifications. BERT is conceptually simple and empirically powerful. It obtains new state-of-the-art results on eleven natural language processing tasks, including pushing the GLUE score to 80.5% (7.7% point absolute improvement), MultiNLI accuracy to 86.7% (4.6% absolute improvement), SQuAD v1.1 question answering Test F1 to 93.2 (1.5 point absolute improvement) and SQuAD v2.0 Test F1 to 83.1 (5.1 point absolute improvement).

16.1.2 Dataset

Train Dataset

Test Dataset

16.1.3 Results and models

16.1.4 Citation

```
@article{devlin2018bert,
  title={Bert: Pre-training of deep bidirectional transformers for language␣
↪understanding},
  author={Devlin, Jacob and Chang, Ming-Wei and Lee, Kenton and Toutanova, Kristina},
  journal={arXiv preprint arXiv:1810.04805},
  year={2018}
}
```

CHAPTER

SEVENTEEN

TEXT DETECTION

17.1 Overview

The structure of the text detection dataset directory is organized as follows.

```
├── ctw1500
│   ├── annotations
│   ├── imgs
│   ├── instances_test.json
│   └── instances_training.json
├── icdar2015
│   ├── imgs
│   ├── instances_test.json
│   └── instances_training.json
├── icdar2017
│   ├── imgs
│   ├── instances_training.json
│   └── instances_val.json
├── synthtext
│   ├── imgs
│   └── instances_training.lmdb
│       ├── data.mdb
│       └── lock.mdb
├── textocr
│   ├── train
│   ├── instances_training.json
│   └── instances_val.json
├── totaltext
│   ├── imgs
│   ├── instances_test.json
│   └── instances_training.json
```

17.2 Important Note

Note: For users who want to train models on CTW1500, ICDAR 2015/2017, and Totaltext dataset, there might be some images containing orientation info in EXIF data. The default OpenCV backend used in MMCV would read them and apply the rotation on the images. However, their gold annotations are made on the raw pixels, and such inconsistency results in false examples in the training set. Therefore, users should use `dict(type='LoadImageFromFile', color_type='color_ignore_orientation')` in pipelines to change MMCV's default loading behaviour. (see DBNet's pipeline config for example)

17.3 Preparation Steps

17.3.1 ICDAR 2015

- Step0: Read *Important Note*
- Step1: Download `ch4_training_images.zip`, `ch4_test_images.zip`, `ch4_training_localization_transcription_gt.zip`, `Challenge4_Test_Task1_GT.zip` from homepage
- Step2:

```
mkdir icdar2015 && cd icdar2015
mkdir imgs && mkdir annotations
# For images,
mv ch4_training_images imgs/training
mv ch4_test_images imgs/test
# For annotations,
mv ch4_training_localization_transcription_gt annotations/training
mv Challenge4_Test_Task1_GT annotations/test
```

- Step3: Download instances_training.json and instances_test.json and move them to `icdar2015`
- Or, generate `instances_training.json` and `instances_test.json` with following command:

```
python tools/data/textdet/icdar_converter.py /path/to/icdar2015 -o /path/to/icdar2015 -d␣
↪icdar2015 --split-list training test
```

17.3.2 ICDAR 2017

- Follow similar steps as *ICDAR 2015*.

17.3.3 CTW1500

- Step0: Read *Important Note*
- Step1: Download `train_images.zip`, `test_images.zip`, `train_labels.zip`, `test_labels.zip` from github

```
mkdir ctw1500 && cd ctw1500
mkdir imgs && mkdir annotations

# For annotations
cd annotations
wget -O train_labels.zip https://universityofadelaide.box.com/shared/static/
↪jikuazluzyj4lq6umzei7m2ppmt3afyw.zip
wget -O test_labels.zip https://cloudstor.aarnet.edu.au/plus/s/uoeFl0pCN9BOCN5/download
unzip train_labels.zip && mv ctw1500_train_labels training
unzip test_labels.zip -d test
cd ..
# For images
cd imgs
wget -O train_images.zip https://universityofadelaide.box.com/shared/static/
↪py5uwlfyyytbb2pxzq9czvu6fuqbjdh8.zip
wget -O test_images.zip https://universityofadelaide.box.com/shared/static/
↪t4w48ofnqkdw7jyc4t11nsukoeqk9c3d.zip
unzip train_images.zip && mv train_images training
unzip test_images.zip && mv test_images test
```

- Step2: Generate `instances_training.json` and `instances_test.json` with following command:

```
python tools/data/textdet/ctw1500_converter.py /path/to/ctw1500 -o /path/to/ctw1500 --
↪split-list training test
```

17.3.4 SynthText

- Download data.mdb and lock.mdb to `synthtext/instances_training.lmdb/`.

17.3.5 TextOCR

- Step1: Download train_val_images.zip, TextOCR_0.1_train.json and TextOCR_0.1_val.json to `textocr/`.

```
mkdir textocr && cd textocr

# Download TextOCR dataset
wget https://dl.fbaipublicfiles.com/textvqa/images/train_val_images.zip
wget https://dl.fbaipublicfiles.com/textvqa/data/textocr/TextOCR_0.1_train.json
wget https://dl.fbaipublicfiles.com/textvqa/data/textocr/TextOCR_0.1_val.json

# For images
unzip -q train_val_images.zip
mv train_images train
```

- Step2: Generate `instances_training.json` and `instances_val.json` with the following command:

```
python tools/data/textdet/textocr_converter.py /path/to/textocr
```

17.3.6 Totaltext

- Step0: Read *Important Note*
- Step1: Download `totaltext.zip` from github dataset and `groundtruth_text.zip` from github Groundtruth (Our totaltext_converter.py supports groundtruth with both .mat and .txt format).

```
mkdir totaltext && cd totaltext
mkdir imgs && mkdir annotations

# For images
# in ./totaltext
unzip totaltext.zip
mv Images/Train imgs/training
mv Images/Test imgs/test

# For annotations
unzip groundtruth_text.zip
cd Groundtruth
mv Polygon/Train ../annotations/training
mv Polygon/Test ../annotations/test
```

- Step2: Generate `instances_training.json` and `instances_test.json` with the following command:

```
python tools/data/textdet/totaltext_converter.py /path/to/totaltext -o /path/to/
↪totaltext --split-list training test
```

CHAPTER

EIGHTEEN

TEXT RECOGNITION

18.1 Overview

The structure of the text recognition dataset directory is organized as follows.

```
├── mixture
│   ├── coco_text
│   │   ├── train_label.txt
│   │   ├── train_words
│   ├── icdar_2011
│   │   ├── training_label.txt
│   │   ├── Challenge1_Training_Task3_Images_GT
│   ├── icdar_2013
│   │   ├── train_label.txt
│   │   ├── test_label_1015.txt
│   │   ├── test_label_1095.txt
│   │   ├── Challenge2_Training_Task3_Images_GT
│   │   ├── Challenge2_Test_Task3_Images
│   ├── icdar_2015
│   │   ├── train_label.txt
│   │   ├── test_label.txt
│   │   ├── ch4_training_word_images_gt
│   │   ├── ch4_test_word_images_gt
│   ├── III5K
│   │   ├── train_label.txt
│   │   ├── test_label.txt
│   │   ├── train
│   │   ├── test
│   ├── ct80
│   │   ├── test_label.txt
│   │   ├── image
│   ├── svt
│   │   ├── test_label.txt
│   │   ├── image
│   ├── svtp
│   │   ├── test_label.txt
│   │   ├── image
│   ├── Syn90k
│   │   ├── shuffle_labels.txt
│   │   ├── label.txt
```

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```
|   |   ├── label.lmdb
|   |   ├── mnt
|   ├── SynthText
|   |   ├── alphanumeric_labels.txt
|   |   ├── shuffle_labels.txt
|   |   ├── instances_train.txt
|   |   ├── label.txt
|   |   ├── label.lmdb
|   |   ├── synthtext
|   ├── SynthAdd
|   |   ├── label.txt
|   |   ├── label.lmdb
|   |   ├── SynthText_Add
|   ├── TextOCR
|   |   ├── image
|   |   ├── train_label.txt
|   |   ├── val_label.txt
|   ├── Totaltext
|   |   ├── imgs
|   |   ├── annotations
|   |   ├── train_label.txt
|   |   ├── test_label.txt
|   ├── OpenVINO
|   |   ├── image_1
|   |   ├── image_2
|   |   ├── image_5
|   |   ├── image_f
|   |   ├── image_val
|   |   ├── train_1_label.txt
|   |   ├── train_2_label.txt
|   |   ├── train_5_label.txt
|   |   ├── train_f_label.txt
|   |   ├── val_label.txt
```

(*) Since the official homepage is unavailable now, we provide an alternative for quick reference. However, we do not guarantee the correctness of the dataset.

18.2 Preparation Steps

18.2.1 ICDAR 2013

- Step1: Download `Challenge2_Test_Task3_Images.zip` and `Challenge2_Training_Task3_Images_GT.zip` from homepage
- Step2: Download test_label_1015.txt and train_label.txt

18.2.2 ICDAR 2015

- Step1: Download `ch4_training_word_images_gt.zip` and `ch4_test_word_images_gt.zip` from homepage
- Step2: Download train_label.txt and test_label.txt

18.2.3 IIIT5K

- Step1: Download `IIIT5K-Word_V3.0.tar.gz` from homepage
- Step2: Download train_label.txt and test_label.txt

18.2.4 svt

- Step1: Download `svt.zip` form homepage
- Step2: Download test_label.txt
- Step3:

```
python tools/data/textrecog/svt_converter.py <download_svt_dir_path>
```

18.2.5 ct80

- Step1: Download test_label.txt

18.2.6 svtp

- Step1: Download test_label.txt

18.2.7 coco_text

- Step1: Download from homepage
- Step2: Download train_label.txt

18.2.8 MJSynth (Syn90k)

- Step1: Download `mjsynth.tar.gz` from homepage
- Step2: Download label.txt (8,919,273 annotations) and shuffle_labels.txt (2,400,000 randomly sampled annotations). **Please make sure you're using the right annotation to train the model by checking its dataset specs in Model Zoo.**
- Step3:

```
mkdir Syn90k && cd Syn90k

mv /path/to/mjsynth.tar.gz .
```

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```
tar -xzf mjsynth.tar.gz

mv /path/to/shuffle_labels.txt .
mv /path/to/label.txt .

# create soft link
cd /path/to/mmocr/data/mixture

ln -s /path/to/Syn90k Syn90k
```

18.2.9 SynthText (Synth800k)

- Step1: Download `SynthText.zip` from homepage
- Step2: According to your actual needs, download the most appropriate one from the following options: label.txt (7,266,686 annotations), shuffle_labels.txt (2,400,000 randomly sampled annotations), alphanumeric_labels.txt (7,239,272 annotations with alphanumeric characters only) and instances_train.txt (7,266,686 character-level annotations).

Warning: Please make sure you're using the right annotation to train the model by checking its dataset specs in Model Zoo.

- Step3:

```
mkdir SynthText && cd SynthText
mv /path/to/SynthText.zip .
unzip SynthText.zip
mv SynthText synthtext

mv /path/to/shuffle_labels.txt .
mv /path/to/label.txt .
mv /path/to/alphanumeric_labels.txt .
mv /path/to/instances_train.txt .

# create soft link
cd /path/to/mmocr/data/mixture
ln -s /path/to/SynthText SynthText
```

- Step4: Generate cropped images and labels:

```
cd /path/to/mmocr

python tools/data/textrecog/synthtext_converter.py data/mixture/SynthText/gt.mat data/
↪mixture/SynthText/ data/mixture/SynthText/synthtext/SynthText_patch_horizontal --n_
↪proc 8
```

18.2.10 SynthAdd

- Step1: Download `SynthText_Add.zip` from SynthAdd (code:627x))
- Step2: Download label.txt
- Step3:

```
mkdir SynthAdd && cd SynthAdd

mv /path/to/SynthText_Add.zip .

unzip SynthText_Add.zip

mv /path/to/label.txt .

# create soft link
cd /path/to/mmocr/data/mixture

ln -s /path/to/SynthAdd SynthAdd
```

Tip: To convert label file with `txt` format to `lmdb` format,

```
python tools/data/utils/txt2lmdb.py -i <txt_label_path> -o <lmdb_label_path>
```

For example,

```
python tools/data/utils/txt2lmdb.py -i data/mixture/Syn90k/label.txt -o data/mixture/
↪Syn90k/label.lmdb
```

18.2.11 TextOCR

- Step1: Download train_val_images.zip, TextOCR_0.1_train.json and TextOCR_0.1_val.json to `textocr/`.

```
mkdir textocr && cd textocr

# Download TextOCR dataset
wget https://dl.fbaipublicfiles.com/textvqa/images/train_val_images.zip
wget https://dl.fbaipublicfiles.com/textvqa/data/textocr/TextOCR_0.1_train.json
wget https://dl.fbaipublicfiles.com/textvqa/data/textocr/TextOCR_0.1_val.json

# For images
unzip -q train_val_images.zip
mv train_images train
```

- Step2: Generate `train_label.txt`, `val_label.txt` and crop images using 4 processes with the following command:

```
python tools/data/textrecog/textocr_converter.py /path/to/textocr 4
```

18.2.12 Totaltext

- Step1: Download `totaltext.zip` from github dataset and `groundtruth_text.zip` from github Groundtruth (Our totaltext_converter.py supports groundtruth with both .mat and .txt format).

```
mkdir totaltext && cd totaltext
mkdir imgs && mkdir annotations

# For images
# in ./totaltext
unzip totaltext.zip
mv Images/Train imgs/training
mv Images/Test imgs/test

# For annotations
unzip groundtruth_text.zip
cd Groundtruth
mv Polygon/Train ../annotations/training
mv Polygon/Test ../annotations/test
```

- Step2: Generate cropped images, `train_label.txt` and `test_label.txt` with the following command (the cropped images will be saved to `data/totaltext/dst_imgs/`):

```
python tools/data/textrecog/totaltext_converter.py /path/to/totaltext -o /path/to/
↪totaltext --split-list training test
```

18.2.13 OpenVINO

- Step0: Install awscli.
- Step1: Download Open Images subsets `train_1`, `train_2`, `train_5`, `train_f`, and `validation` to `openvino/`.

```
mkdir openvino && cd openvino

# Download Open Images subsets
for s in 1 2 5 f; do
  aws s3 --no-sign-request cp s3://open-images-dataset/tar/train_${s}.tar.gz .
done
aws s3 --no-sign-request cp s3://open-images-dataset/tar/validation.tar.gz .

# Download annotations
for s in 1 2 5 f; do
  wget https://storage.openvinotoolkit.org/repositories/openvino_training_extensions/
↪datasets/open_images_v5_text/text_spotting_openimages_v5_train_${s}.json
done
wget https://storage.openvinotoolkit.org/repositories/openvino_training_extensions/
↪datasets/open_images_v5_text/text_spotting_openimages_v5_validation.json

# Extract images
mkdir -p openimages_v5/val
for s in 1 2 5 f; do
  tar zxf train_${s}.tar.gz -C openimages_v5
```

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```
done
tar zxf validation.tar.gz -C openimages_v5/val
```

- Step2: Generate `train_{1,2,5,f}_label.txt`, `val_label.txt` and crop images using 4 processes with the following command:

```
python tools/data/textrecog/openvino_converter.py /path/to/openvino 4
```

CHAPTER

NINETEEN

KEY INFORMATION EXTRACTION

19.1 Overview

The structure of the key information extraction dataset directory is organized as follows.

```
└── wildreceipt
    ├── class_list.txt
    ├── dict.txt
    ├── image_files
    ├── openset_train.txt
    ├── openset_test.txt
    ├── test.txt
    └── train.txt
```

19.2 Preparation Steps

19.2.1 WildReceipt

- Just download and extract wildreceipt.tar.

19.2.2 WildReceiptOpenset

- Step0: have *WildReceipt* prepared.
- Step1: Convert annotation files to OpenSet format:

```
# You may find more available arguments by running
# python tools/data/kie/closeset_to_openset.py -h
python tools/data/kie/closeset_to_openset.py data/wildreceipt/train.txt data/wildreceipt/
↪openset_train.txt
python tools/data/kie/closeset_to_openset.py data/wildreceipt/test.txt data/wildreceipt/
↪openset_test.txt
```

Note: You can learn more about the key differences between CloseSet and OpenSet annotations in our *tutorial*.

CHAPTER

TWENTY

NAMED ENTITY RECOGNITION

20.1 Overview

The structure of the named entity recognition dataset directory is organized as follows.

```
└── cluener2020
    ├── cluener_predict.json
    ├── dev.json
    ├── README.md
    ├── test.json
    ├── train.json
    └── vocab.txt
```

20.2 Preparation Steps

20.2.1 CLUENER2020

- Download and extract cluener_public.zip to `cluener2020/`
- Download vocab.txt and move `vocab.txt` to `cluener2020/`

CHAPTER

TWENTYONE

USEFUL TOOLS

We provide some useful tools under `mmocr/tools` directory.

21.1 Publish a Model

Before you upload a model to AWS, you may want to (1) convert the 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. These functionalities could be achieved by `tools/publish_model.py`.

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

For example,

```
python tools/publish_model.py work_dirs/psenet/latest.pth psenet_r50_fpnf_sbn_1x_
↪20190801.pth
```

The final output filename will be `psenet_r50_fpnf_sbn_1x_20190801-{hash id}.pth`.

21.2 Convert txt annotation to lmdb format

Sometimes, loading a large txt annotation file with multiple workers can cause OOM (out of memory) error. You can convert the file into lmdb format using `tools/data/utils/txt2lmdb.py` and use LmdbLoader in your config to avoid this issue.

```
python tools/data/utils/txt2lmdb.py -i <txt_label_path> -o <lmdb_label_path>
```

For example,

```
python tools/data/utils/txt2lmdb.py -i data/mixture/Syn90k/label.txt -o data/mixture/
↪Syn90k/label.lmdb
```

CHAPTER

TWENTYTWO

CHANGELOG

22.1 v0.4.1 (27/01/2022)

22.1.1 Highlights

1. Visualizing edge weights in OpenSet KIE is now supported! https://github.com/open-mmlab/mmocr/pull/677
2. Some configurations have been optimized to significantly speed up the training and testing processes! Don't worry - you can still tune these parameters in case these modifications do not work. https://github.com/open-mmlab/mmocr/pull/757
3. Now you can use CPU to train/debug your model! https://github.com/open-mmlab/mmocr/pull/752
4. We have fixed a severe bug that causes users unable to call `mmocr.apis.test` with our pre-built wheels. https://github.com/open-mmlab/mmocr/pull/667

22.1.2 New Features & Enhancements

- Show edge score for openset kie by @cuhk-hbsun in https://github.com/open-mmlab/mmocr/pull/677
- Download flake8 from github as pre-commit hooks by @gaotongxiao in https://github.com/open-mmlab/mmocr/pull/695
- Deprecate the support for 'python setup.py test' by @Harold-lkk in https://github.com/open-mmlab/mmocr/pull/722
- Disable multi-processing feature of cv2 to speed up data loading by @gaotongxiao in https://github.com/open-mmlab/mmocr/pull/721
- Extend ctw1500 converter to support text fields by @Harold-lkk in https://github.com/open-mmlab/mmocr/pull/729
- Extend totaltext converter to support text fields by @Harold-lkk in https://github.com/open-mmlab/mmocr/pull/728
- Speed up training by @gaotongxiao in https://github.com/open-mmlab/mmocr/pull/739
- Add setup multi-processing both in train and test.py by @Harold-lkk in https://github.com/open-mmlab/mmocr/pull/757
- Support CPU training/testing by @gaotongxiao in https://github.com/open-mmlab/mmocr/pull/752
- Support specify gpu for testing and training with gpu-id instead of gpu-ids and gpus by @Harold-lkk in https://github.com/open-mmlab/mmocr/pull/756

- Remove unnecessary custom_import from test.py by @Harold-lkk in https://github.com/open-mmlab/mmocr/pull/758

22.1.3 Bug Fixes

- Fix satrn onnxruntime test by @AllentDan in https://github.com/open-mmlab/mmocr/pull/679
- Support both ConcatDataset and UniformConcatDataset by @cuhk-hbsun in https://github.com/open-mmlab/mmocr/pull/675
- Fix bugs of show_results in single_gpu_test by @cuhk-hbsun in https://github.com/open-mmlab/mmocr/pull/667
- Fix a bug for sar decoder when bi-rnn is used by @MhLiao in https://github.com/open-mmlab/mmocr/pull/690
- Fix opencv version to avoid some bugs by @gaotongxiao in https://github.com/open-mmlab/mmocr/pull/694
- Fix py39 ci error by @Harold-lkk in https://github.com/open-mmlab/mmocr/pull/707
- Update visualize.py by @TommyZihao in https://github.com/open-mmlab/mmocr/pull/715
- Fix link of config by @cuhk-hbsun in https://github.com/open-mmlab/mmocr/pull/726
- Use yaml.safe_load instead of load by @gaotongxiao in https://github.com/open-mmlab/mmocr/pull/753
- Add necessary keys to test_pipelines to enable test-time visualization by @gaotongxiao in https://github.com/open-mmlab/mmocr/pull/754

22.1.4 Docs

- Fix recog.md by @gaotongxiao in https://github.com/open-mmlab/mmocr/pull/674
- Add config tutorial by @gaotongxiao in https://github.com/open-mmlab/mmocr/pull/683
- Add MMSelfSup/MMRazor/MMDeploy in readme by @cuhk-hbsun in https://github.com/open-mmlab/mmocr/pull/692
- Add recog & det model summary by @gaotongxiao in https://github.com/open-mmlab/mmocr/pull/693
- Update docs link by @gaotongxiao in https://github.com/open-mmlab/mmocr/pull/710
- add pull request template.md by @Harold-lkk in https://github.com/open-mmlab/mmocr/pull/711
- Add website links to readme by @gaotongxiao in https://github.com/open-mmlab/mmocr/pull/731
- update readme according to standard by @Harold-lkk in https://github.com/open-mmlab/mmocr/pull/742

22.1.5 New Contributors

- @MhLiao made their first contribution in https://github.com/open-mmlab/mmocr/pull/690
- @TommyZihao made their first contribution in https://github.com/open-mmlab/mmocr/pull/715

Full Changelog: https://github.com/open-mmlab/mmocr/compare/v0.4.0...v0.4.1

22.2 v0.4.0 (15/12/2021)

22.2.1 Highlights

1. We release a new text recognition model - ABINet (CVPR 2021, Oral). With it dedicated model design and useful data augmentation transforms, ABINet can achieve the best performance on irregular text recognition tasks. Check it out!
2. We are also working hard to fulfill the requests from our community. OpenSet KIE is one of the achievement, which extends the application of SDMGR from text node classification to node-pair relation extraction. We also provide a demo script to convert WildReceipt to open set domain, though it cannot take the full advantage of OpenSet format. For more information, please read our tutorial.
3. APIs of models can be exposed through TorchServe. Docs

22.2.2 Breaking Changes & Migration Guide

Postprocessor

Some refactoring processes are still going on. For all text detection models, we unified their `decode` implementations into a new module category, `POSTPROCESSOR`, which is responsible for decoding different raw outputs into boundary instances. In all text detection configs, the `text_repr_type` argument in `bbox_head` is deprecated and will be removed in the future release.

Migration Guide: Find a similar line from detection model's config:

```
text_repr_type=xxx,
```

And replace it with

```
postprocessor=dict(type='{MODEL_NAME}Postprocessor', text_repr_type=xxx)),
```

Take a snippet of PANet's config as an example. Before the change, its config for `bbox_head` looks like:

```
    bbox_head=dict(
        type='PANHead',
        text_repr_type='poly',
        in_channels=[128, 128, 128, 128],
        out_channels=6,
        loss=dict(type='PANLoss')),
```

Afterwards:

```
    bbox_head=dict(
    type='PANHead',
    in_channels=[128, 128, 128, 128],
    out_channels=6,
    loss=dict(type='PANLoss'),
    postprocessor=dict(type='PANPostprocessor', text_repr_type='poly')),
```

There are other postprocessors and each takes different arguments. Interested users can find their interfaces or implementations in `mmocr/models/textdet/postprocess` or through our api docs.

New Config Structure

We reorganized the `configs/` directory by extracting reusable sections into `configs/_base_`. Now the directory tree of `configs/_base_` is organized as follows:

```
_base_
├── det_datasets
├── det_models
├── det_pipelines
├── recog_datasets
├── recog_models
├── recog_pipelines
└── schedules
```

Most of model configs are making full use of base configs now, which makes the overall structural clearer and facilitates fair comparison across models. Despite the seemingly significant hierarchical difference, **these changes would not break the backward compatibility** as the names of model configs remain the same.

22.2.3 New Features

- Support openset kie by @cuhk-hbsun in https://github.com/open-mmlab/mmocr/pull/498
- Add converter for the Open Images v5 text annotations by Krylov et al. by @baudm in https://github.com/open-mmlab/mmocr/pull/497
- Support Chinese for kie show result by @cuhk-hbsun in https://github.com/open-mmlab/mmocr/pull/464
- Add TorchServe support for text detection and recognition by @Harold-lkk in https://github.com/open-mmlab/mmocr/pull/522
- Save filename in text detection test results by @cuhk-hbsun in https://github.com/open-mmlab/mmocr/pull/570
- Add codespell pre-commit hook and fix typos by @gaotongxiao in https://github.com/open-mmlab/mmocr/pull/520
- Avoid duplicate placeholder docs in CN by @gaotongxiao in https://github.com/open-mmlab/mmocr/pull/582
- Save results to json file for kie. by @cuhk-hbsun in https://github.com/open-mmlab/mmocr/pull/589
- Add SAR_CN to ocr.py by @gaotongxiao in https://github.com/open-mmlab/mmocr/pull/579
- mim extension for windows by @gaotongxiao in https://github.com/open-mmlab/mmocr/pull/641
- Support muitiple pipelines for different datasets by @cuhk-hbsun in https://github.com/open-mmlab/mmocr/pull/657
- ABINet Framework by @gaotongxiao in https://github.com/open-mmlab/mmocr/pull/651

22.2.4 Refactoring

- Refactor textrecog config structure by @cuhk-hbsun in https://github.com/open-mmlab/mmocr/pull/617
- Refactor text detection config by @cuhk-hbsun in https://github.com/open-mmlab/mmocr/pull/626
- refactor transformer modules by @cuhk-hbsun in https://github.com/open-mmlab/mmocr/pull/618
- refactor textdet postprocess by @cuhk-hbsun in https://github.com/open-mmlab/mmocr/pull/640

22.2.5 Docs

- C++ example section by @apiaccess21 in https://github.com/open-mmlab/mmocr/pull/593
- install.md Chinese section by @A465539338 in https://github.com/open-mmlab/mmocr/pull/364
- Add Chinese Translation of deployment.md. by @fatfishZhao in https://github.com/open-mmlab/mmocr/pull/506
- Fix a model link and add the metafile for SATRN by @gaotongxiao in https://github.com/open-mmlab/mmocr/pull/473
- Improve docs style by @gaotongxiao in https://github.com/open-mmlab/mmocr/pull/474
- Enhancement & sync Chinese docs by @gaotongxiao in https://github.com/open-mmlab/mmocr/pull/492
- TorchServe docs by @gaotongxiao in https://github.com/open-mmlab/mmocr/pull/539
- Update docs menu by @gaotongxiao in https://github.com/open-mmlab/mmocr/pull/564
- Docs for KIE CloseSet & OpenSet by @gaotongxiao in https://github.com/open-mmlab/mmocr/pull/573
- Fix broken links by @gaotongxiao in https://github.com/open-mmlab/mmocr/pull/576
- Docstring for text recognition models by @gaotongxiao in https://github.com/open-mmlab/mmocr/pull/562
- Add MMFlow & MIM by @gaotongxiao in https://github.com/open-mmlab/mmocr/pull/597
- Add MMFewShot by @gaotongxiao in https://github.com/open-mmlab/mmocr/pull/621
- Update model readme by @gaotongxiao in https://github.com/open-mmlab/mmocr/pull/604
- Add input size check to model_inference by @mpena-vina in https://github.com/open-mmlab/mmocr/pull/633
- Docstring for textdet models by @gaotongxiao in https://github.com/open-mmlab/mmocr/pull/561
- Add MMHuman3D in readme by @gaotongxiao in https://github.com/open-mmlab/mmocr/pull/644
- Use shared menu from theme instead by @gaotongxiao in https://github.com/open-mmlab/mmocr/pull/655
- Refactor docs structure by @gaotongxiao in https://github.com/open-mmlab/mmocr/pull/662
- Docs fix by @gaotongxiao in https://github.com/open-mmlab/mmocr/pull/664

22.2.6 Enhancements

- Use bounding box around polygon instead of within polygon by @alexander-soare in https://github.com/open-mmlab/mmocr/pull/469
- Add CITATION.cff by @gaotongxiao in https://github.com/open-mmlab/mmocr/pull/476
- Add py3.9 CI by @gaotongxiao in https://github.com/open-mmlab/mmocr/pull/475
- update model-index.yml by @gaotongxiao in https://github.com/open-mmlab/mmocr/pull/484
- Use container in CI by @gaotongxiao in https://github.com/open-mmlab/mmocr/pull/502
- CircleCI Setup by @gaotongxiao in https://github.com/open-mmlab/mmocr/pull/611
- Remove unnecessary custom_import from train.py by @gaotongxiao in https://github.com/open-mmlab/mmocr/pull/603
- Change the upper version of mmcv to 1.5.0 by @zhouzaida in https://github.com/open-mmlab/mmocr/pull/628
- Update CircleCI by @gaotongxiao in https://github.com/open-mmlab/mmocr/pull/631
- Pass custom_hooks to MMCV by @gaotongxiao in https://github.com/open-mmlab/mmocr/pull/609

- Skip CI when some specific files were changed by @gaotongxiao in https://github.com/open-mmlab/mmocr/pull/642
- Add markdown linter in pre-commit hook by @gaotongxiao in https://github.com/open-mmlab/mmocr/pull/643
- Use shape from loaded image by @cuhk-hbsun in https://github.com/open-mmlab/mmocr/pull/652
- Cancel previous runs that are not completed by @Harold-lkk in https://github.com/open-mmlab/mmocr/pull/666

22.2.7 Bug Fixes

- Modify algorithm "sar" weights path in metafile by @ShoupingShan in https://github.com/open-mmlab/mmocr/pull/581
- Fix Cuda CI by @gaotongxiao in https://github.com/open-mmlab/mmocr/pull/472
- Fix image export in test.py for KIE models by @gaotongxiao in https://github.com/open-mmlab/mmocr/pull/486
- Allow invalid polygons in intersection and union by default by @gaotongxiao in https://github.com/open-mmlab/mmocr/pull/471
- Update checkpoints' links for SATRN by @gaotongxiao in https://github.com/open-mmlab/mmocr/pull/518
- Fix converting to onnx bug because of changing key from img_shape to resize_shape by @Harold-lkk in https://github.com/open-mmlab/mmocr/pull/523
- Fix PyTorch 1.6 incompatible checkpoints by @gaotongxiao in https://github.com/open-mmlab/mmocr/pull/540
- Fix paper field in metafiles by @gaotongxiao in https://github.com/open-mmlab/mmocr/pull/550
- Unify recognition task names in metafiles by @gaotongxiao in https://github.com/open-mmlab/mmocr/pull/548
- Fix py3.9 CI by @gaotongxiao in https://github.com/open-mmlab/mmocr/pull/563
- Always map location to cpu when loading checkpoint by @gaotongxiao in https://github.com/open-mmlab/mmocr/pull/567
- Fix wrong model builder in recog_test_imgs by @gaotongxiao in https://github.com/open-mmlab/mmocr/pull/574
- Improve dbnet r50 by fixing img std by @gaotongxiao in https://github.com/open-mmlab/mmocr/pull/578
- Fix resource warning: unclosed file by @cuhk-hbsun in https://github.com/open-mmlab/mmocr/pull/577
- Fix bug that same start_point for different texts in draw_texts_by_pil by @cuhk-hbsun in https://github.com/open-mmlab/mmocr/pull/587
- Keep original texts for kie by @cuhk-hbsun in https://github.com/open-mmlab/mmocr/pull/588
- Fix random seed by @gaotongxiao in https://github.com/open-mmlab/mmocr/pull/600
- Fix DBNet_r50 config by @gaotongxiao in https://github.com/open-mmlab/mmocr/pull/625
- Change SBC case to DBC case by @cuhk-hbsun in https://github.com/open-mmlab/mmocr/pull/632
- Fix kie demo by @innerlee in https://github.com/open-mmlab/mmocr/pull/610
- fix type check by @cuhk-hbsun in https://github.com/open-mmlab/mmocr/pull/650
- Remove depreciated image validator in totaltext converter by @gaotongxiao in https://github.com/open-mmlab/mmocr/pull/661
- Fix change locals() dict by @Fei-Wang in https://github.com/open-mmlab/mmocr/pull/663
- fix #614: textsnake targets by @HolyCrap96 in https://github.com/open-mmlab/mmocr/pull/660

22.2.8 New Contributors

- @alexander-soare made their first contribution in https://github.com/open-mmlab/mmocr/pull/469
- @A465539338 made their first contribution in https://github.com/open-mmlab/mmocr/pull/364
- @fatfishZhao made their first contribution in https://github.com/open-mmlab/mmocr/pull/506
- @baudm made their first contribution in https://github.com/open-mmlab/mmocr/pull/497
- @ShoupingShan made their first contribution in https://github.com/open-mmlab/mmocr/pull/581
- @apiaccess21 made their first contribution in https://github.com/open-mmlab/mmocr/pull/593
- @zhouzaida made their first contribution in https://github.com/open-mmlab/mmocr/pull/628
- @mpena-vina made their first contribution in https://github.com/open-mmlab/mmocr/pull/633
- @Fei-Wang made their first contribution in https://github.com/open-mmlab/mmocr/pull/663

Full Changelog: https://github.com/open-mmlab/mmocr/compare/v0.3.0...0.4.0

22.3 v0.3.0 (25/8/2021)

22.3.1 Highlights

1. We add a new text recognition model – SATRN! Its pretrained checkpoint achieves the best performance over other provided text recognition models. A lighter version of SATRN is also released which can obtain ~98% of the performance of the original model with only 45 MB in size. (@2793145003) #405
2. Improve the demo script, `ocr.py`, which supports applying end-to-end text detection, text recognition and key information extraction models on images with easy-to-use commands. Users can find its full documentation in the demo section. (@samayala22, @manjrekarom) #371, #386, #400, #374, #428
3. Our documentation is reorganized into a clearer structure. More useful contents are on the way! #409, #454
4. The requirement of `Polygon3` is removed since this project is no longer maintained or distributed. We unified all its references to equivalent substitutions in `shapely` instead. #448

22.3.2 Breaking Changes & Migration Guide

1. Upgrade version requirement of MMDetection to 2.14.0 to avoid bugs #382
2. MMOCR now has its own model and layer registries inherited from MMDetection's or MMCV's counterparts. (#436) The modified hierarchical structure of the model registries are now organized as follows.

```
mmcv.MODELS -> mmdet.BACKBONES -> BACKBONES
mmcv.MODELS -> mmdet.NECKS -> NECKS
mmcv.MODELS -> mmdet.ROI_EXTRACTORS -> ROI_EXTRACTORS
mmcv.MODELS -> mmdet.HEADS -> HEADS
mmcv.MODELS -> mmdet.LOSSES -> LOSSES
mmcv.MODELS -> mmdet.DETECTORS -> DETECTORS
mmcv.ACTIVATION_LAYERS -> ACTIVATION_LAYERS
mmcv.UPSAMPLE_LAYERS -> UPSAMPLE_LAYERS
```

To migrate your old implementation to our new backend, you need to change the import path of any registries and their corresponding builder functions (including `build_detectors`) from `mmdet.models.builder` to `mmocr.models.builder`. If you have referred to any model or layer of MMDetection or MMCV in your model config, you need to add `mmdet.` or `mmcv.` prefix to its name to inform the model builder of the right namespace to work on.

Interested users may check out MMCV's tutorial on Registry for in-depth explanations on its mechanism.

22.3.3 New Features

- Automatically replace SyncBN with BN for inference #420, #453
- Support batch inference for CRNN and SegOCR #407
- Support exporting documentation in pdf or epub format #406
- Support `persistent_workers` option in data loader #459

22.3.4 Bug Fixes

- Remove depreciated key in kie_test_imgs.py #381
- Fix dimension mismatch in batch testing/inference of DBNet #383
- Fix the problem of dice loss which stays at 1 with an empty target given #408
- Fix a wrong link in ocr.py (@naarkhoo) #417
- Fix undesired assignment to "pretrained" in test.py #418
- Fix a problem in polygon generation of DBNet #421, #443
- Skip invalid annotations in totaltext_converter #438
- Add zero division handler in poly utils, remove Polygon3 #448

22.3.5 Improvements

- Replace lanms-proper with lanms-neo to support installation on Windows (with special thanks to @gen-ko who has re-distributed this package!)
- Support MIM #394
- Add tests for PyTorch 1.9 in CI #401
- Enables fullscreen layout in readthedocs #413
- General documentation enhancement #395
- Update version checker #427
- Add copyright info #439
- Update citation information #440

22.3.6 Contributors

We thank @2793145003, @samayala22, @manjrekarom, @naarkhoo, @gen-ko, @duanjiaqi, @gaotongxiao, @cuhk-hbsun, @innerlee, @wdsd641417025 for their contribution to this release!

22.4 v0.2.1 (20/7/2021)

22.4.1 Highlights

1. Upgrade to use MMCV-full **>= 1.3.8** and MMDetection **>= 2.13.0** for latest features
2. Add ONNX and TensorRT export tool, supporting the deployment of DBNet, PSENet, PANet and CRNN (experimental) #278, #291, #300, #328
3. Unified parameter initialization method which uses init_cfg in config files #365

22.4.2 New Features

- Support TextOCR dataset #293
- Support Total-Text dataset #266, #273, #357
- Support grouping text detection box into lines #290, #304
- Add benchmark_processing script that benchmarks data loading process #261
- Add SynthText preprocessor for text recognition models #351, #361
- Support batch inference during testing #310
- Add user-friendly OCR inference script #366

22.4.3 Bug Fixes

- Fix improper class ignorance in SDMGR Loss #221
- Fix potential numerical zero division error in DRRG #224
- Fix installing requirements with pip and mim #242
- Fix dynamic input error of DBNet #269
- Fix space parsing error in LineStrParser #285
- Fix textsnake decode error #264
- Correct isort setup #288
- Fix a bug in SDMGR config #316
- Fix kie_test_img for KIE nonvisual #319
- Fix metafiles #342
- Fix different device problem in FCENet #334
- Ignore improper tailing empty characters in annotation files #358
- Docs fixes #247, #255, #265, #267, #268, #270, #276, #287, #330, #355, #367
- Fix NRTR config #356, #370

22.4.4 Improvements

- Add backend for resizeocr #244
- Skip image processing pipelines in SDMGR novisual #260
- Speedup DBNet #263
- Update mmcv installation method in workflow #323
- Add part of Chinese documentations #353, #362
- Add support for ConcatDataset with two workflows #348
- Add list_from_file and list_to_file utils #226
- Speed up sort_vertex #239
- Support distributed evaluation of KIE #234
- Add pretrained FCENet on IC15 #258
- Support CPU for OCR demo #227
- Avoid extra image pre-processing steps #375

22.5 v0.2.0 (18/5/2021)

22.5.1 Highlights

1. Add the NER approach Bert-softmax (NAACL'2019)
2. Add the text detection method DRRG (CVPR'2020)
3. Add the text detection method FCENet (CVPR'2021)
4. Increase the ease of use via adding text detection and recognition end-to-end demo, and colab online demo.
5. Simplify the installation.

22.5.2 New Features

- Add Bert-softmax for Ner task #148
- Add DRRG #189
- Add FCENet #133
- Add end-to-end demo #105
- Support batch inference #86 #87 #178
- Add TPS preprocessor for text recognition #117 #135
- Add demo documentation #151 #166 #168 #170 #171
- Add checkpoint for Chinese recognition #156
- Add metafile #175 #176 #177 #182 #183
- Add support for numpy array inference #74

22.5.3 Bug Fixes

- Fix the duplicated point bug due to transform for textsnake #130
- Fix CTC loss NaN #159
- Fix error raised if result is empty in demo #144
- Fix results missing if one image has a large number of boxes #98
- Fix package missing in dockerfile #109

22.5.4 Improvements

- Simplify installation procedure via removing compiling #188
- Speed up panet post processing so that it can detect dense texts #188
- Add zh-CN README #70 #95
- Support windows #89
- Add Colab #147 #199
- Add 1-step installation using conda environment #193 #194 #195

22.6 v0.1.0 (7/4/2021)

22.6.1 Highlights

- MMOCR is released.

22.6.2 Main Features

- Support text detection, text recognition and the corresponding downstream tasks such as key information extraction.
- For text detection, support both single-step (`PSENet`, `PANet`, `DBNet`, `TextSnake`) and two-step (`MaskRCNN`) methods.
- For text recognition, support CTC-loss based method `CRNN`; Encoder-decoder (with attention) based methods `SAR`, `Robustscanner`; Segmentation based method `SegOCR`; Transformer based method `NRTR`.
- For key information extraction, support GCN based method `SDMG-R`.
- Provide checkpoints and log files for all of the methods above.

CHAPTER

TWENTYTHREE

MMOCR.APIS

mmocr.apis.**disable_text_recog_aug_test**(*cfg*, *set_types=None*)
Remove aug_test from test pipeline for text recognition.

Parameters

- **cfg** (*mmcv.Config*) – Input config.
- **set_types** (*list[str]*) – Type of dataset source. Should be None or sublist of ['test', 'val'].

mmocr.apis.**init_detector**(*config*, *checkpoint=None*, *device='cuda:0'*, *cfg_options=None*)
Initialize a detector from config file.

Parameters

- **config** (str or mmcv.Config) – Config file path or the config object.
- **checkpoint** (*str, optional*) – Checkpoint path. If left as None, the model will not load any weights.
- **cfg_options** (*dict*) – Options to override some settings in the used config.

Returns The constructed detector.

Return type nn.Module

mmocr.apis.**init_random_seed**(*seed=None*, *device='cuda'*)
Initialize random seed. If the seed is None, it will be replaced by a random number, and then broadcasted to all processes.

Parameters

- **seed** (*int, Optional*) – The seed.
- **device** (*str*) – The device where the seed will be put on.

Returns Seed to be used.

Return type int

mmocr.apis.**model_inference**(*model*, *imgs*, *ann=None*, *batch_mode=False*, *return_data=False*)
Inference image(s) with the detector.

Parameters

- **model** (*nn.Module*) – The loaded detector.
- **imgs** (*str/ndarray or list[str/ndarray] or tuple[str/ndarray]*) – Either image files or loaded images.
- **batch_mode** (*bool*) – If True, use batch mode for inference.

- **ann** (*dict*) – Annotation info for key information extraction.
- **return_data** – Return postprocessed data.

Returns Predicted results.

Return type result (dict)

mmocr.apis.**replace_image_to_tensor**(*cfg*, *set_types=None*)
Replace 'ImageToTensor' to 'DefaultFormatBundle'.

mmocr.apis.**tensor2grayimgs**(*tensor*, *mean=(127)*, *std=(127)*, ***kwargs*)
Convert tensor to 1-channel gray images.

Parameters

- **tensor** (*torch.Tensor*) – Tensor that contains multiple images, shape (N, C, H, W).
- **mean** (*tuple[float], optional*) – Mean of images. Defaults to (127).
- **std** (*tuple[float], optional*) – Standard deviation of images. Defaults to (127).

Returns A list that contains multiple images.

Return type list[np.ndarray]

CHAPTER

TWENTYFOUR

MMOCR.CORE

24.1 evaluation

mmocr.core.evaluation.**compute_f1_score**(*preds*, *gts*, *ignores=[]*)

Compute the F1-score of prediction.

Parameters

- **preds** (*Tensor*) – The predicted probability NxC map with N and C being the sample number and class number respectively.
- **gts** (*Tensor*) – The ground truth vector of size N.
- **ignores** – The index set of classes that are ignored when reporting results. Note: all samples are participated in computing.

mmocr.core.evaluation.**eval_hmean**(*results*, *img_infos*, *ann_infos*, *metrics={'hmean-iou'}*, *score_thr=0.3*, *rank_list=None*, *logger=None*, ***kwargs*)

Evaluation in hmean metric.

Parameters

- **results** (*list[dict]*) – Each dict corresponds to one image, containing the following keys: boundary_result
- **img_infos** (*list[dict]*) – Each dict corresponds to one image, containing the following keys: filename, height, width
- **ann_infos** (*list[dict]*) – Each dict corresponds to one image, containing the following keys: masks, masks_ignore
- **score_thr** (*float*) – Score threshold of prediction map.
- **metrics** (*set{str}*) – Hmean metric set, should be one or all of {'hmean-iou', 'hmean-ic13'}

Returns float]

Return type dict[str

mmocr.core.evaluation.**eval_hmean_ic13**(*det_boxes*, *gt_boxes*, *gt_ignored_boxes*, *precision_thr=0.4*, *recall_thr=0.8*, *center_dist_thr=1.0*, *one2one_score=1.0*, *one2many_score=0.8*, *many2one_score=1.0*)

Evaluate hmean of text detection using the icdar2013 standard.

Parameters

- **det_boxes** (*list[list[list[float]]]*) – List of arrays of shape (n, 2k). Each element is the det_boxes for one img. k>=4.

- **gt_boxes** (*list[list[list[float]]]*) – List of arrays of shape (m, 2k). Each element is the gt_boxes for one img. k>=4.
- **gt_ignored_boxes** (*list[list[list[float]]]*) – List of arrays of (l, 2k). Each element is the ignored gt_boxes for one img. k>=4.
- **precision_thr** (*float*) – Precision threshold of the iou of one (gt_box, det_box) pair.
- **recall_thr** (*float*) – Recall threshold of the iou of one (gt_box, det_box) pair.
- **center_dist_thr** (*float*) – Distance threshold of one (gt_box, det_box) center point pair.
- **one2one_score** (*float*) – Reward when one gt matches one det_box.
- **one2many_score** (*float*) – Reward when one gt matches many det_boxes.
- **many2one_score** (*float*) – Reward when many gts match one det_box.

Returns Tuple of dicts which encodes the hmean for the dataset and all images.

Return type hmean (tuple[dict])

mmocr.core.evaluation.**eval_hmean_iou**(*pred_boxes*, *gt_boxes*, *gt_ignored_boxes*, *iou_thr=0.5*, *precision_thr=0.5*)

Evaluate hmean of text detection using IOU standard.

Parameters

- **pred_boxes** (*list[list[list[float]]]*) – Text boxes for an img list. Each box has 2k (>=8) values.
- **gt_boxes** (*list[list[list[float]]]*) – Ground truth text boxes for an img list. Each box has 2k (>=8) values.
- **gt_ignored_boxes** (*list[list[list[float]]]*) – Ignored ground truth text boxes for an img list. Each box has 2k (>=8) values.
- **iou_thr** (*float*) – Iou threshold when one (gt_box, det_box) pair is matched.
- **precision_thr** (*float*) – Precision threshold when one (gt_box, det_box) pair is matched.

Returns

Tuple of dicts indicates the hmean for the dataset and all images.

Return type hmean (tuple[dict])

mmocr.core.evaluation.**eval_ner_f1**(*results*, *gt_infos*)

Evaluate for ner task.

Parameters

- **results** (*list*) – Predict results of entities.
- **gt_infos** (*list[dict]*) – Ground-truth information which contains text and label.

Returns

precision,recall, f1-score of total and each catogory.

Return type class_info (dict)

mmocr.core.evaluation.**eval_ocr_metric**(*pred_texts*, *gt_texts*)

Evaluate the text recognition performance with metric: word accuracy and 1-N.E.D. See https://rrc.cvc.uab.es/?ch=14&com=tasks for details.

Parameters

- **pred_texts** (*list[str]*) – Text strings of prediction.
- **gt_texts** (*list[str]*) – Text strings of ground truth.

Returns

float]): Metric dict for text recognition, include:

- word_acc: Accuracy in word level.
- word_acc_ignore_case: Accuracy in word level, ignore letter case.
- **word_acc_ignore_case_symbol: Accuracy in word level, ignore** letter case and symbol. (default metric for academic evaluation)
- **char_recall: Recall in character level, ignore** letter case and symbol.
- **char_precision: Precision in character level, ignore** letter case and symbol.
- 1-N.E.D: 1 - normalized_edit_distance.

Return type eval_res (dict[str

CHAPTER

TWENTYFIVE

MMOCR.UTILS

class mmocr.utils.**Registry**(*name*, *build_func=None*, *parent=None*, *scope=None*)

A registry to map strings to classes.

Registered object could be built from registry.

Example

```
>>> MODELS = Registry('models')
>>> @MODELS.register_module()
>>> class ResNet:
>>>     pass
>>> resnet = MODELS.build(dict(type='ResNet'))
```

Please refer to https://mmcv.readthedocs.io/en/latest/understand_mmcv/registry.html for advanced usage.

Parameters

- **name** (*str*) – Registry name.
- **build_func** (*func, optional*) – Build function to construct instance from Registry, func:*build_from_cfg* is used if neither `parent` or `build_func` is specified. If `parent` is specified and `build_func` is not given, `build_func` will be inherited from `parent`. Default: None.
- **parent** (`Registry`, *optional*) – Parent registry. The class registered in children registry could be built from parent. Default: None.
- **scope** (*str, optional*) – The scope of registry. It is the key to search for children registry. If not specified, scope will be the name of the package where class is defined, e.g. mmdet, mmcls, mmseg. Default: None.

get(*key*)

Get the registry record.

Parameters **key** (*str*) – The class name in string format.

Returns The corresponding class.

Return type class

static infer_scope()

Infer the scope of registry.

The name of the package where registry is defined will be returned.

Example

```
>>> # in mmdet/models/backbone/resnet.py
>>> MODELS = Registry('models')
>>> @MODELS.register_module()
>>> class ResNet:
>>>     pass
The scope of ``ResNet`` will be ``mmdet``.
```

Returns The inferred scope name.

Return type str

register_module(*name=None*, *force=False*, *module=None*)

Register a module.

A record will be added to *self._module_dict*, whose key is the class name or the specified name, and value is the class itself. It can be used as a decorator or a normal function.

Example

```
>>> backbones = Registry('backbone')
>>> @backbones.register_module()
>>> class ResNet:
>>>     pass
```

```
>>> backbones = Registry('backbone')
>>> @backbones.register_module(name='mnet')
>>> class MobileNet:
>>>     pass
```

```
>>> backbones = Registry('backbone')
>>> class ResNet:
>>>     pass
>>> backbones.register_module(ResNet)
```

Parameters

- **name** (*str | None*) – The module name to be registered. If not specified, the class name will be used.
- **force** (*bool, optional*) – Whether to override an existing class with the same name. Default: False.
- **module** (*type*) – Module class to be registered.

static split_scope_key(*key*)

Split scope and key.

The first scope will be split from key.

Examples

```
>>> Registry.split_scope_key('mmdet.ResNet')
'mmdet', 'ResNet'
>>> Registry.split_scope_key('ResNet')
None, 'ResNet'
```

Returns The former element is the first scope of the key, which can be None. The latter is the remaining key.

Return type tuple[str | None, str]

class mmocr.utils.**StringStrip**(*strip=True*, *strip_pos='both'*, *strip_str=None*)

Removing the leading and/or the trailing characters based on the string argument passed.

Parameters

- **strip** (*bool*) – Whether remove characters from both left and right of the string. Default: True.
- **strip_pos** (*str*) – Which position for removing, can be one of ('both', 'left', 'right'), Default: 'both'.
- **strip_str** (*str|None*) – A string specifying the set of characters to be removed from the left and right part of the string. If None, all leading and trailing whitespaces are removed from the string. Default: None.

mmocr.utils.**bezier_to_polygon**(*bezier_points*, *num_sample=20*)

Sample points from the boundary of a polygon enclosed by two Bezier curves, which are controlled by bezier_points.

Parameters

- **bezier_points** (*ndarray*) – A $(2, 4, 2)$ array of 8 Bezeir points or its equalivance. The first 4 points control the curve at one side and the last four control the other side.
- **num_sample** (*int*) – The number of sample points at each Bezeir curve.

Returns A list of 2*num_sample points representing the polygon extracted from Bezier curves.

Return type list[ndarray]

Warning: The points are not guaranteed to be ordered. Please use *mmocr.utils.sort_points()* to sort points if necessary.

mmocr.utils.**build_from_cfg**(*cfg*, *registry*, *default_args=None*)

Build a module from config dict.

Parameters

- **cfg** (*dict*) – Config dict. It should at least contain the key "type".
- **registry** (*Registry*) – The registry to search the type from.
- **default_args** (*dict, optional*) – Default initialization arguments.

Returns The constructed object.

Return type object

mmocr.utils.**collect_env**()
Collect the information of the running environments.

mmocr.utils.**convert_annotations**(*image_infos*, *out_json_name*)
Convert the annotation into coco style.

Parameters

- **image_infos** (*list*) – The list of image information dicts
- **out_json_name** (*str*) – The output json filename

Returns The coco style dict

Return type out_json(dict)

mmocr.utils.**drop_orientation**(*img_file*)
Check if the image has orientation information. If yes, ignore it by converting the image format to png, and return new filename, otherwise return the original filename.

Parameters **img_file** (*str*) – The image path

Returns The converted image filename with proper postfix

mmocr.utils.**get_root_logger**(*log_file=None*, *log_level=20*)
Use *get_logger* method in mmcv to get the root logger.

The logger will be initialized if it has not been initialized. By default a StreamHandler will be added. If *log_file* is specified, a FileHandler will also be added. The name of the root logger is the top-level package name, e.g., "mmpose".

Parameters

- **log_file** (*str | None*) – The log filename. If specified, a FileHandler will be added to the root logger.
- **log_level** (*int*) – The root logger level. Note that only the process of rank 0 is affected, while other processes will set the level to "Error" and be silent most of the time.

Returns The root logger.

Return type logging.Logger

mmocr.utils.**is_2dlist**(*x*)
check x is 2d-list([[1], []]) or 1d empty list([]).

Notice: The reason that it contains 1d empty list is because some arguments from gt annotation file or model prediction may be empty, but usually, it should be 2d-list.

mmocr.utils.**is_3dlist**(*x*)
check x is 3d-list([[[1], []]]) or 2d empty list([[], []]) or 1d empty list([]).

Notice: The reason that it contains 1d or 2d empty list is because some arguments from gt annotation file or model prediction may be empty, but usually, it should be 3d-list.

mmocr.utils.**is_not_png**(*img_file*)
Check img_file is not png image.

Parameters **img_file** (*str*) – The input image file name

Returns The bool flag indicating whether it is not png

mmocr.utils.**is_on_same_line**(*box_a*, *box_b*, *min_y_overlap_ratio=0.8*)
Check if two boxes are on the same line by their y-axis coordinates.

Two boxes are on the same line if they overlap vertically, and the length of the overlapping line segment is greater than min_y_overlap_ratio * the height of either of the boxes.

Parameters

- **box_a** (*list), box_b (list*) – Two bounding boxes to be checked
- **min_y_overlap_ratio** (*float*) – The minimum vertical overlapping ratio allowed for boxes in the same line

Returns The bool flag indicating if they are on the same line

mmocr.utils.**list_from_file**(*filename*, *encoding='utf-8'*)

Load a text file and parse the content as a list of strings. The trailing "r" and "n" of each line will be removed.

Note: This will be replaced by mmcv's version after it supports encoding.

Parameters

- **filename** (*str*) – Filename.
- **encoding** (*str*) – Encoding used to open the file. Default utf-8.

Returns A list of strings.

Return type list[str]

mmocr.utils.**list_to_file**(*filename*, *lines*)

Write a list of strings to a text file.

Parameters

- **filename** (*str*) – The output filename. It will be created/overwritten.
- **lines** (*list(str)*) – Data to be written.

mmocr.utils.**revert_sync_batchnorm**(*module*)

Helper function to convert all *SyncBatchNorm* layers in the model to *BatchNormXd* layers.

Adapted from @kapily's work: (https://github.com/pytorch/pytorch/issues/41081#issuecomment-783961547)

Parameters **module** (*nn.Module*) – The module containing *SyncBatchNorm* layers.

Returns The converted module with *BatchNormXd* layers.

Return type module_output

mmocr.utils.**setup_multi_processes**(*cfg*)

Setup multi-processing environment variables.

mmocr.utils.**sort_points**(*points*)

Sort arbitory points in clockwise order. Reference: https://stackoverflow.com/a/6989383.

Parameters **points** (*list[ndarray] or ndarray or list[list]*) – A list of unsorted boundary points.

Returns A list of points sorted in clockwise order.

Return type list[ndarray]

mmocr.utils.**stitch_boxes_into_lines**(*boxes*, *max_x_dist=10*, *min_y_overlap_ratio=0.8*)

Stitch fragmented boxes of words into lines.

Note: part of its logic is inspired by @Johndirr (https://github.com/faustomorales/keras-ocr/issues/22)

Parameters

- **boxes** (*list*) – List of ocr results to be stitched
- **max_x_dist** (*int*) – The maximum horizontal distance between the closest edges of neighboring boxes in the same line
- **min_y_overlap_ratio** (*float*) – The minimum vertical overlapping ratio allowed for any pairs of neighboring boxes in the same line

Returns List of merged boxes and texts

Return type merged_boxes(list[dict])

CHAPTER

TWENTYSIX

MMOCR.MODELS

26.1 Common Backbones

class mmocr.models.common.backbones.**UNet**(*in_channels=3*, *base_channels=64*, *num_stages=5*, *strides=(1, 1, 1, 1, 1)*, *enc_num_convs=(2, 2, 2, 2, 2)*, *dec_num_convs=(2, 2, 2, 2)*, *downsamples=(True, True, True, True)*, *enc_dilations=(1, 1, 1, 1, 1)*, *dec_dilations=(1, 1, 1, 1)*, *with_cp=False*, *conv_cfg=None*, *norm_cfg={'type': 'BN'}*, *act_cfg={'type': 'ReLU'}*, *upsample_cfg={'type': 'InterpConv'}*, *norm_eval=False*, *dcn=None*, *plugins=None*, *init_cfg=[{'type': 'Kaiming', 'layer': 'Conv2d'}, {'type': 'Constant', 'layer': ['_BatchNorm', 'GroupNorm'], 'val': 1}]*)

UNet backbone. U-Net: Convolutional Networks for Biomedical Image Segmentation. https://arxiv.org/pdf/1505.04597.pdf

Parameters

- **in_channels** (*int*) – Number of input image channels. Default" 3.
- **base_channels** (*int*) – Number of base channels of each stage. The output channels of the first stage. Default: 64.
- **num_stages** (*int*) – Number of stages in encoder, normally 5. Default: 5.
- **strides** (*Sequence[int 1 | 2]*) – Strides of each stage in encoder. len(strides) is equal to num_stages. Normally the stride of the first stage in encoder is 1. If strides[i]=2, it uses stride convolution to downsample in the correspondence encoder stage. Default: (1, 1, 1, 1, 1).
- **enc_num_convs** (*Sequence[int]*) – Number of convolutional layers in the convolution block of the correspondence encoder stage. Default: (2, 2, 2, 2, 2).
- **dec_num_convs** (*Sequence[int]*) – Number of convolutional layers in the convolution block of the correspondence decoder stage. Default: (2, 2, 2, 2).
- **downsamples** (*Sequence[int]*) – Whether use MaxPool to downsample the feature map after the first stage of encoder (stages: [1, num_stages)). If the correspondence encoder stage use stride convolution (strides[i]=2), it will never use MaxPool to downsample, even downsamples[i-1]=True. Default: (True, True, True, True).
- **enc_dilations** (*Sequence[int]*) – Dilation rate of each stage in encoder. Default: (1, 1, 1, 1, 1).
- **dec_dilations** (*Sequence[int]*) – Dilation rate of each stage in decoder. Default: (1, 1, 1, 1).

- **with_cp** (*bool*) – Use checkpoint or not. Using checkpoint will save some memory while slowing down the training speed. Default: False.
- **conv_cfg** (*dict | None*) – Config dict for convolution layer. Default: None.
- **norm_cfg** (*dict | None*) – Config dict for normalization layer. Default: dict(type='BN').
- **act_cfg** (*dict | None*) – Config dict for activation layer in ConvModule. Default: dict(type='ReLU').
- **upsample_cfg** (*dict*) – The upsample config of the upsample module in decoder. Default: dict(type='InterpConv').
- **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.
- **dcn** (*bool*) – Use deformable convolution in convolutional layer or not. Default: None.
- **plugins** (*dict*) – plugins for convolutional layers. Default: None.

Notice: The input image size should be divisible by the whole downsample rate of the encoder. More detail of the whole downsample rate can be found in UNet._check_input_divisible.

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*)

Convert the model into training mode while keep normalization layer freezed.

class mmocr.models.common.losses.**DiceLoss**(*eps=1e-06*)

forward(*pred*, *target*, *mask=None*)

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 mmocr.models.common.losses.**FocalLoss**(*gamma=2*, *weight=None*, *ignore_index=- 100*)

Multi-class Focal loss implementation.

Parameters

- **gamma** (*float*) – The larger the gamma, the smaller the loss weight of easier samples.
- **weight** (*float*) – A manual rescaling weight given to each class.
- **ignore_index** (*int*) – Specifies a target value that is ignored and does not contribute to the input gradient.

forward(*input*, *target*)
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.

26.2 Text Detection Detectors

class mmocr.models.textdet.detectors.**DBNet**(*backbone*, *neck*, *bbox_head*, *train_cfg=None*, *test_cfg=None*, *pretrained=None*, *show_score=False*, *init_cfg=None*)
The class for implementing DBNet text detector: Real-time Scene Text Detection with Differentiable Binarization.

[https://arxiv.org/abs/1911.08947].

class mmocr.models.textdet.detectors.**DRRG**(*backbone*, *neck*, *bbox_head*, *train_cfg=None*, *test_cfg=None*, *pretrained=None*, *show_score=False*, *init_cfg=None*)
The class for implementing DRRG text detector. Deep Relational Reasoning Graph Network for Arbitrary Shape Text Detection.

[https://arxiv.org/abs/2003.07493]

forward_train(*img*, *img_metas*, ***kwargs*)

Parameters

- **img** (*Tensor*) – Input images of shape (N, C, H, W). Typically these should be mean centered and std scaled.
- **img_metas** (*list[dict]*) – A 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 of the values of these keys see `mmdet.datasets.pipelines.Collect`.

Returns A dictionary of loss components.

Return type dict[str, Tensor]

simple_test(*img*, *img_metas*, *rescale=False*)
Test function without test-time augmentation.

Parameters

- **img** (*torch.Tensor*) – Images with shape (N, C, H, W).
- **img_metas** (*list[dict]*) – List of image information.
- **rescale** (*bool, optional*) – Whether to rescale the results. Defaults to False.

Returns

BBox results of each image and classes. The outer list corresponds to each image. The inner list corresponds to each class.

Return type list[list[np.ndarray]]

class mmocr.models.textdet.detectors.**FCENet**(*backbone*, *neck*, *bbox_head*, *train_cfg=None*, *test_cfg=None*, *pretrained=None*, *show_score=False*, *init_cfg=None*)

The class for implementing FCENet text detector FCENet(CVPR2021): Fourier Contour Embedding for Arbitrary-shaped Text

Detection

[https://arxiv.org/abs/2104.10442]

simple_test(*img*, *img_metas*, *rescale=False*)

Test function without test-time augmentation.

Parameters

- **img** (*torch.Tensor*) – Images with shape (N, C, H, W).
- **img_metas** (*list[dict]*) – List of image information.
- **rescale** (*bool, optional*) – Whether to rescale the results. Defaults to False.

Returns

BBox results of each image and classes. The outer list corresponds to each image. The inner list corresponds to each class.

Return type list[list[np.ndarray]]

class mmocr.models.textdet.detectors.**OCRMaskRCNN**(*backbone*, *rpn_head*, *roi_head*, *train_cfg*, *test_cfg*, *neck=None*, *pretrained=None*, *text_repr_type='quad'*, *show_score=False*, *init_cfg=None*)

Mask RCNN tailored for OCR.

get_boundary(*results*)

Convert segmentation into text boundaries.

Parameters **results** (*tuple*) – The result tuple. The first element is segmentation while the second is its scores.

Returns A result dict containing 'boundary_result'.

Return type dict

simple_test(*img*, *img_metas*, *proposals=None*, *rescale=False*)

Test without augmentation.

class mmocr.models.textdet.detectors.**PANet**(*backbone*, *neck*, *bbox_head*, *train_cfg=None*, *test_cfg=None*, *pretrained=None*, *show_score=False*, *init_cfg=None*)

The class for implementing PANet text detector:

Efficient and Accurate Arbitrary-Shaped Text Detection with Pixel Aggregation Network [https://arxiv.org/abs/1908.05900].

class mmocr.models.textdet.detectors.**PSENet**(*backbone*, *neck*, *bbox_head*, *train_cfg=None*, *test_cfg=None*, *pretrained=None*, *show_score=False*, *init_cfg=None*)

The class for implementing PSENet text detector: Shape Robust Text Detection with Progressive Scale Expansion Network.

[https://arxiv.org/abs/1806.02559].

class mmocr.models.textdet.detectors.**SingleStageTextDetector**(*backbone*, *neck*, *bbox_head*, *train_cfg=None*, *test_cfg=None*, *pretrained=None*, *init_cfg=None*)

The class for implementing single stage text detector.

forward_train(*img*, *img_metas*, ***kwargs*)

Parameters

- **img** (*Tensor*) – Input images of shape (N, C, H, W). Typically these should be mean centered and std scaled.
- **img_metas** (*list[dict]*) – A 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.Collect.

Returns A dictionary of loss components.

Return type dict[str, Tensor]

simple_test(*img*, *img_metas*, *rescale=False*)

Test function without test-time augmentation.

Parameters

- **img** (*torch.Tensor*) – Images with shape (N, C, H, W).
- **img_metas** (*list[dict]*) – List of image information.
- **rescale** (*bool, optional*) – Whether to rescale the results. Defaults to False.

Returns

BBox results of each image and classes. The outer list corresponds to each image. The inner list corresponds to each class.

Return type list[list[np.ndarray]]

class mmocr.models.textdet.detectors.**TextDetectorMixin**(*show_score*)

Base class for text detector, only to show results.

Parameters **show_score** (*bool*) – Whether to show text instance score.

show_result(*img*, *result*, *score_thr=0.5*, *bbox_color='green'*, *text_color='green'*, *thickness=1*, *font_scale=0.5*, *win_name=''*, *show=False*, *wait_time=0*, *out_file=None*)

Draw *result* over *img*.

Parameters

- **img** (*str or Tensor*) – The image to be displayed.
- **result** (*dict*) – The results to draw over *img*.
- **score_thr** (*float, optional*) – Minimum score of bboxes to be shown. Default: 0.3.
- **bbox_color** (str or tuple or Color) – Color of bbox lines.
- **text_color** (str or tuple or Color) – Color of texts.
- **thickness** (*int*) – Thickness of lines.
- **font_scale** (*float*) – Font scales of texts.
- **win_name** (*str*) – The window name.

- **wait_time** (*int*) – Value of waitKey param. Default: 0.
- **show** (*bool*) – Whether to show the image. Default: False.
- **out_file** (*str or None*) – The filename to write the image. Default: None.imshow_pred_boundary`

class mmocr.models.textdet.detectors.**TextSnake**(*backbone*, *neck*, *bbox_head*, *train_cfg=None*, *test_cfg=None*, *pretrained=None*, *show_score=False*, *init_cfg=None*)

The class for implementing TextSnake text detector: TextSnake: A Flexible Representation for Detecting Text of Arbitrary Shapes.

[https://arxiv.org/abs/1807.01544]

26.3 Text Detection Heads

class mmocr.models.textdet.dense_heads.**DBHead**(*in_channels*, *with_bias=False*, *downsample_ratio=1.0*, *loss={'type': 'DBLoss'}*, *postprocessor={'text_repr_type': 'quad', 'type': 'DBPostprocessor'}*, *init_cfg=[{'type': 'Kaiming', 'layer': 'Conv'}, {'type': 'Constant', 'layer': 'BatchNorm', 'val': 1.0, 'bias': 0.0001}]*, *train_cfg=None*, *test_cfg=None*, ***kwargs*)

The class for DBNet head.

This was partially adapted from https://github.com/MhLiao/DB

Parameters

- **in_channels** (*int*) – The number of input channels of the db head.
- **with_bias** (*bool*) – Whether add bias in Conv2d layer.
- **downsample_ratio** (*float*) – The downsample ratio of ground truths.
- **loss** (*dict*) – Config of loss for dbnet.
- **postprocessor** (*dict*) – Config of postprocessor for dbnet.

forward(*inputs*)

Parameters **inputs** (*Tensor*) – Shape (batch_size, hidden_size, h, w).

Returns A tensor of the same shape as input.

Return type Tensor

class mmocr.models.textdet.dense_heads.**DRRGHead**(*in_channels*, *k_at_hops=(8, 4)*, *num_adjacent_linkages=3*, *node_geo_feat_len=120*, *pooling_scale=1.0*, *pooling_output_size=(4, 3)*, *nms_thr=0.3*, *min_width=8.0*, *max_width=24.0*, *comp_shrink_ratio=1.03*, *comp_ratio=0.4*, *comp_score_thr=0.3*, *text_region_thr=0.2*, *center_region_thr=0.2*, *center_region_area_thr=50*, *local_graph_thr=0.7*, *loss={'type': 'DRRGLoss'}*, *postprocessor={'link_thr': 0.85, 'type': 'DRRGPostprocessor'}*, *train_cfg=None*, *test_cfg=None*, *init_cfg={'mean': 0, 'override': {'name': 'out_conv'}, 'std': 0.01, 'type': 'Normal'}*, ***kwargs*)

The class for DRRG head: Deep Relational Reasoning Graph Network for Arbitrary Shape Text Detection.

Parameters

- **k_at_hops** (*tuple(int)*) – The number of i-hop neighbors, i = 1, 2.
- **num_adjacent_linkages** (*int*) – The number of linkages when constructing adjacent matrix.
- **node_geo_feat_len** (*int*) – The length of embedded geometric feature vector of a component.
- **pooling_scale** (*float*) – The spatial scale of rotated RoI-Align.
- **pooling_output_size** (*tuple(int)*) – The output size of RRoI-Aligning.
- **nms_thr** (*float*) – The locality-aware NMS threshold of text components.
- **min_width** (*float*) – The minimum width of text components.
- **max_width** (*float*) – The maximum width of text components.
- **comp_shrink_ratio** (*float*) – The shrink ratio of text components.
- **comp_ratio** (*float*) – The reciprocal of aspect ratio of text components.
- **comp_score_thr** (*float*) – The score threshold of text components.
- **text_region_thr** (*float*) – The threshold for text region probability map.
- **center_region_thr** (*float*) – The threshold for text center region probability map.
- **center_region_area_thr** (*int*) – The threshold for filtering small-sized text center region.
- **local_graph_thr** (*float*) – The threshold to filter identical local graphs.
- **loss** (*dict*) – The config of loss that DRRGHead uses..
- **postprocessor** (*dict*) – Config of postprocessor for Drrg.
- **init_cfg** (*dict or list[dict], optional*) – Initialization configs.

forward(*inputs*, *gt_comp_attribs*)

Parameters

- **inputs** (*Tensor*) – Shape of (N, C, H, W).
- **gt_comp_attribs** (*list[ndarray]*) – The padded text component attributes. Shape: (num_component, 8).

Returns

Returns (pred_maps, (gcn_pred, gt_labels)).

- pred_maps (Tensor): Prediction map with shape (N, C_{out}, H, W).
- gcn_pred (Tensor): Prediction from GCN module, with shape $(N, 2)$.
- gt_labels (Tensor): Ground-truth label with shape $(N, 8)$.

Return type tuple

get_boundary(*edges*, *scores*, *text_comps*, *img_metas*, *rescale*)

Compute text boundaries via post processing.

Parameters

- **edges** (*ndarray*) – The edge array of shape N * 2, each row is a pair of text component indices that makes up an edge in graph.
- **scores** (*ndarray*) – The edge score array.
- **text_comps** (*ndarray*) – The text components.
- **img_metas** (*list[dict]*) – The image meta infos.
- **rescale** (*bool*) – Rescale boundaries to the original image resolution.

Returns The result dict containing key *boundary_result*.

Return type dict

single_test(*feat_maps*)

Parameters **feat_maps** (*Tensor*) – Shape of (N, C, H, W).

Returns

Returns (edge, score, text_comps).

- edge (ndarray): The edge array of shape $(N, 2)$ where each row is a pair of text component indices that makes up an edge in graph.
- score (ndarray): The score array of shape $(N,)$, corresponding to the edge above.
- text_comps (ndarray): The text components of shape $(N, 9)$ where each row corresponds to one box and its score: (x1, y1, x2, y2, x3, y3, x4, y4, score).

Return type tuple

class mmocr.models.textdet.dense_heads.**FCEHead**(*in_channels*, *scales*, *fourier_degree=5*, *nms_thr=0.1*, *loss={'num_sample': 50, 'type': 'FCELoss'}*, *postprocessor={'alpha': 1.0, 'beta': 2.0, 'num_reconstr_points': 50, 'score_thr': 0.3, 'text_repr_type': 'poly', 'type': 'FCEPostprocessor'}*, *train_cfg=None*, *test_cfg=None*, *init_cfg={'mean': 0, 'override': [{'name': 'out_conv_cls'}, {'name': 'out_conv_reg'}], 'std': 0.01, 'type': 'Normal'}*, ***kwargs*)

The class for implementing FCENet head.

FCENet(CVPR2021): Fourier Contour Embedding for Arbitrary-shaped Text Detection

Parameters

- **in_channels** (*int*) – The number of input channels.

- **scales** (*list[int]*) – The scale of each layer.
- **fourier_degree** (*int*) – The maximum Fourier transform degree k.
- **nms_thr** (*float*) – The threshold of nms.
- **loss** (*dict*) – Config of loss for FCENet.
- **postprocessor** (*dict*) – Config of postprocessor for FCENet.

forward(*feats*)

Parameters **feats** (*list[Tensor]*) – Each tensor has the shape of (N, C_i, H_i, W_i).

Returns Each pair of tensors corresponds to the classification result and regression result computed from the input tensor with the same index. They have the shapes of $(N, C_{cls,i}, H_i, W_i)$ and $(N, C_{out,i}, H_i, W_i)$.

Return type list[[Tensor, Tensor]]

get_boundary(*score_maps*, *img_metas*, *rescale*)
Compute text boundaries via post processing.

Parameters

- **score_maps** (*Tensor*) – The text score map.
- **img_metas** (*dict*) – The image meta info.
- **rescale** (*bool*) – Rescale boundaries to the original image resolution if true, and keep the score_maps resolution if false.

Returns A dict where boundary results are stored in `boundary_result`.

Return type dict

class mmocr.models.textdet.dense_heads.**HeadMixin**(*loss*, *postprocessor*)
Base head class for text detection, including loss calcalation and postprocess.

Parameters

- **loss** (*dict*) – Config to build loss.
- **postprocessor** (*dict*) – Config to build postprocessor.

get_boundary(*score_maps*, *img_metas*, *rescale*)
Compute text boundaries via post processing.

Parameters

- **score_maps** (*Tensor*) – The text score map.
- **img_metas** (*dict*) – The image meta info.
- **rescale** (*bool*) – Rescale boundaries to the original image resolution if true, and keep the score_maps resolution if false.

Returns A dict where boundary results are stored in `boundary_result`.

Return type dict

loss(*pred_maps*, ***kwargs*)
Compute the loss for scene text detection.

Parameters **pred_maps** (*Tensor*) – The input score maps of shape $(NxCxHxW)$.

Returns The dict for losses.

Return type dict

resize_boundary(*boundaries*, *scale_factor*)

Rescale boundaries via scale_factor.

Parameters

- **boundaries** (*list[list[float]]*) – The boundary list. Each boundary has $2k + 1$ elements with $k >= 4$.
- **scale_factor** (*ndarray*) – The scale factor of size $(4,)$.

Returns The scaled boundaries.

Return type list[list[float]]

class mmocr.models.textdet.dense_heads.**PANHead**(*in_channels*, *out_channels*, *downsample_ratio=0.25*, *loss={'type': 'PANLoss'}*, *postprocessor={'text_repr_type': 'poly', 'type': 'PANPostprocessor'}*, *train_cfg=None*, *test_cfg=None*, *init_cfg={'mean': 0, 'override': {'name': 'out_conv'}, 'std': 0.01, 'type': 'Normal'}*, ***kwargs*)

The class for PANet head.

Parameters

- **in_channels** (*list[int]*) – A list of 4 numbers of input channels.
- **out_channels** (*int*) – Number of output channels.
- **downsample_ratio** (*float*) – Downsample ratio.
- **loss** (*dict*) – Configuration dictionary for loss type. Supported loss types are "PANLoss" and "PSELoss".
- **postprocessor** (*dict*) – Config of postprocessor for PANet.
- **train_cfg** (*dict*) – Depreciated.
- **test_cfg** (*dict*) – Depreciated.
- **init_cfg** (*dict or list[dict], optional*) – Initialization configs.

forward(*inputs*)

Parameters **inputs** (*list[Tensor] | Tensor*) – Each tensor has the shape of (N, C_i, W, H), where $\sum_i C_i = C_{in}$ and C_{in} is input_channels.

Returns A tensor of shape (N, C_{out}, W, H) where C_{out} is output_channels.

Return type Tensor

class mmocr.models.textdet.dense_heads.**PSEHead**(*in_channels*, *out_channels*, *downsample_ratio=0.25*, *loss={'type': 'PSELoss'}*, *postprocessor={'text_repr_type': 'poly', 'type': 'PSEPostprocessor'}*, *train_cfg=None*, *test_cfg=None*, *init_cfg=None*, ***kwargs*)

The class for PSENet head.

Parameters

- **in_channels** (*list[int]*) – A list of 4 numbers of input channels.
- **out_channels** (*int*) – Number of output channels.

- **downsample_ratio** (*float*) – Downsample ratio.
- **loss** (*dict*) – Configuration dictionary for loss type. Supported loss types are "PANLoss" and "PSELoss".
- **postprocessor** (*dict*) – Config of postprocessor for PSENet.
- **train_cfg** (*dict*) – Depreciated.
- **test_cfg** (*dict*) – Depreciated.
- **init_cfg** (*dict or list[dict], optional*) – Initialization configs.

class mmocr.models.textdet.dense_heads.**TextSnakeHead**(*in_channels*, *out_channels=5*, *downsample_ratio=1.0*, *loss={'type': 'TextSnakeLoss'}*, *postprocessor={'text_repr_type': 'poly', 'type': 'TextSnakePostprocessor'}*, *train_cfg=None*, *test_cfg=None*, *init_cfg={'mean': 0, 'override': {'name': 'out_conv'}, 'std': 0.01, 'type': 'Normal'}*, ***kwargs*)

The class for TextSnake head: TextSnake: A Flexible Representation for Detecting Text of Arbitrary Shapes.

TextSnake: A Flexible Representation for Detecting Text of Arbitrary Shapes.

Parameters

- **in_channels** (*int*) – Number of input channels.
- **out_channels** (*int*) – Number of output channels.
- **downsample_ratio** (*float*) – Downsample ratio.
- **loss** (*dict*) – Configuration dictionary for loss type.
- **postprocessor** (*dict*) – Config of postprocessor for TextSnake.
- **train_cfg** – Depreciated.
- **test_cfg** – Depreciated.
- **init_cfg** (*dict or list[dict], optional*) – Initialization configs.

forward(*inputs*)

Parameters **inputs** (*Tensor*) – Shape (N, C_{in}, H, W), where C_{in} is `in_channels`. H and W should be the same as the input of backbone.

Returns A tensor of shape $(N, 5, H, W)$.

Return type Tensor

26.4 Text Detection Necks

class mmocr.models.textdet.necks.**FPEM_FFM**(*in_channels*, *conv_out=128*, *fpem_repeat=2*, *align_corners=False*, *init_cfg={'distribution': 'uniform', 'layer': 'Conv2d', 'type': 'Xavier'}*)

This code is from https://github.com/WenmuZhou/PAN.pytorch.

Parameters

- **in_channels** (*list[int]*) – A list of 4 numbers of input channels.

- **conv_out** (*int*) – Number of output channels.
- **fpem_repeat** (*int*) – Number of FPEM layers before FFM operations.
- **align_corners** (*bool*) – The interpolation behaviour in FFM operation, used in `torch.nn.functional.interpolate()`.
- **init_cfg** (*dict or list[dict], optional*) – Initialization configs.

forward(*x*)

Parameters **x** (*list[Tensor]*) – A list of four tensors of shape (N, C_i, H_i, W_i), representing C2, C3, C4, C5 features respectively. C_i should matches the number in `in_channels`.

Returns Four tensors of shape (N, C_{out}, H_0, W_0) where C_{out} is `conv_out`.

Return type list[Tensor]

class mmocr.models.textdet.necks.**FPNC**(*in_channels*, *lateral_channels=256*, *out_channels=64*, *bias_on_lateral=False*, *bn_re_on_lateral=False*, *bias_on_smooth=False*, *bn_re_on_smooth=False*, *conv_after_concat=False*, *init_cfg=None*)

FPN-like fusion module in Real-time Scene Text Detection with Differentiable Binarization.

This was partially adapted from https://github.com/MhLiao/DB and https://github.com/WenmuZhou/DBNet.pytorch.

Parameters

- **in_channels** (*list[int]*) – A list of numbers of input channels.
- **lateral_channels** (*int*) – Number of channels for lateral layers.
- **out_channels** (*int*) – Number of output channels.
- **bias_on_lateral** (*bool*) – Whether to use bias on lateral convolutional layers.
- **bn_re_on_lateral** (*bool*) – Whether to use BatchNorm and ReLU on lateral convolutional layers.
- **bias_on_smooth** (*bool*) – Whether to use bias on smoothing layer.
- **bn_re_on_smooth** (*bool*) – Whether to use BatchNorm and ReLU on smoothing layer.
- **conv_after_concat** (*bool*) – Whether to add a convolution layer after the concatenation of predictions.
- **init_cfg** (*dict or list[dict], optional*) – Initialization configs.

forward(*inputs*)

Parameters **inputs** (*list[Tensor]*) – Each tensor has the shape of (N, C_i, H_i, W_i). It usually expects 4 tensors (C2-C5 features) from ResNet.

Returns A tensor of shape (N, C_{out}, H_0, W_0) where C_{out} is `out_channels`.

Return type Tensor

class mmocr.models.textdet.necks.**FPNF**(*in_channels=[256, 512, 1024, 2048]*, *out_channels=256*, *fusion_type='concat'*, *init_cfg={'distribution': 'uniform', 'layer': 'Conv2d', 'type': 'Xavier'}*)

FPN-like fusion module in Shape Robust Text Detection with Progressive Scale Expansion Network.

Parameters

- **in_channels** (*list[int]*) – A list of number of input channels.
- **out_channels** (*int*) – The number of output channels.
- **fusion_type** (*str*) – Type of the final feature fusion layer. Available options are "concat" and "add".
- **init_cfg** (*dict or list[dict], optional*) – Initialization configs.

forward(*inputs*)

Parameters **inputs** (*list[Tensor]*) – Each tensor has the shape of (N, C_i, H_i, W_i). It usually expects 4 tensors (C2-C5 features) from ResNet.

Returns A tensor of shape (N, C_{out}, H_0, W_0) where C_{out} is `out_channels`.

Return type Tensor

class mmocr.models.textdet.necks.**FPN_UNet**(*in_channels*, *out_channels*, *init_cfg={'distribution': 'uniform', 'layer': ['Conv2d', 'ConvTranspose2d'], 'type': 'Xavier'}*)

The class for implementing DRRG and TextSnake U-Net-like FPN.

DRRG: Deep Relational Reasoning Graph Network for Arbitrary Shape Text Detection.

TextSnake: A Flexible Representation for Detecting Text of Arbitrary Shapes.

Parameters

- **in_channels** (*list[int]*) – Number of input channels at each scale. The length of the list should be 4.
- **out_channels** (*int*) – The number of output channels.
- **init_cfg** (*dict or list[dict], optional*) – Initialization configs.

forward(*x*)

Parameters **x** (*list[Tensor] | tuple[Tensor]*) – A list of four tensors of shape (N, C_i, H_i, W_i), representing C2, C3, C4, C5 features respectively. C_i should matches the number in `in_channels`.

Returns Shape (N, C, H, W) where $H = 4H_0$ and $W = 4W_0$.

Return type Tensor

26.5 Text Detection Losses

class mmocr.models.textdet.losses.**DBLoss**(*alpha=1*, *beta=1*, *reduction='mean'*, *negative_ratio=3.0*, *eps=1e-06*, *bbce_loss=False*)

The class for implementing DBNet loss.

This is partially adapted from https://github.com/MhLiao/DB.

Parameters

- **alpha** (*float*) – The binary loss coef.
- **beta** (*float*) – The threshold loss coef.
- **reduction** (*str*) – The way to reduce the loss.
- **negative_ratio** (*float*) – The ratio of positives to negatives.

- **eps** (*float*) – Epsilon in the threshold loss function.
- **bbce_loss** (*bool*) – Whether to use balanced bce for probability loss. If False, dice loss will be used instead.

bitmasks2tensor(*bitmasks*, *target_sz*)
Convert Bitmasks to tensor.

Parameters

- **bitmasks** (*list[BitmapMasks]*) – The BitmapMasks list. Each item is for one img.
- **target_sz** (*tuple(int, int)*) – The target tensor of size (H, W).

Returns The list of kernel tensors. Each element stands for one kernel level.

Return type list[Tensor]

forward(*preds*, *downsample_ratio*, *gt_shrink*, *gt_shrink_mask*, *gt_thr*, *gt_thr_mask*)
Compute DBNet loss.

Parameters

- **preds** (*Tensor*) – The output tensor with size $(N, 3, H, W)$.
- **downsample_ratio** (*float*) – The downsample ratio for the ground truths.
- **gt_shrink** (*list[BitmapMasks]*) – The mask list with each element being the shrunk text mask for one img.
- **gt_shrink_mask** (*list[BitmapMasks]*) – The effective mask list with each element being the shrunk effective mask for one img.
- **gt_thr** (*list[BitmapMasks]*) – The mask list with each element being the threshold text mask for one img.
- **gt_thr_mask** (*list[BitmapMasks]*) – The effective mask list with each element being the threshold effective mask for one img.

Returns The dict for dbnet losses with "loss_prob", "loss_db" and "loss_thresh".

Return type dict

class mmocr.models.textdet.losses.**DRRGLoss**(*ohem_ratio=3.0*)
The class for implementing DRRG loss. This is partially adapted from https://github.com/GXYM/DRRG licensed under the MIT license.

DRRG: Deep Relational Reasoning Graph Network for Arbitrary Shape Text Detection.

Parameters **ohem_ratio** (*float*) – The negative/positive ratio in ohem.

balance_bce_loss(*pred*, *gt*, *mask*)
Balanced Binary-CrossEntropy Loss.

Parameters

- **pred** (*Tensor*) – Shape of $(1, H, W)$.
- **gt** (*Tensor*) – Shape of $(1, H, W)$.
- **mask** (*Tensor*) – Shape of $(1, H, W)$.

Returns Balanced bce loss.

Return type Tensor

bitmasks2tensor(*bitmasks*, *target_sz*)
Convert Bitmasks to tensor.

Parameters

- **bitmasks** (*list[BitmapMasks]*) – The BitmapMasks list. Each item is for one img.
- **target_sz** (*tuple(int, int)*) – The target tensor of size (H, W).

Returns The list of kernel tensors. Each element stands for one kernel level.

Return type list[Tensor]

forward(*preds*, *downsample_ratio*, *gt_text_mask*, *gt_center_region_mask*, *gt_mask*, *gt_top_height_map*, *gt_bot_height_map*, *gt_sin_map*, *gt_cos_map*)

Compute Drrg loss.

Parameters

- **preds** (*tuple(Tensor)*) – The first is the prediction map with shape (N, C_{out}, H, W). The second is prediction from GCN module, with shape $(N, 2)$. The third is ground-truth label with shape $(N, 8)$.
- **downsample_ratio** (*float*) – The downsample ratio.
- **gt_text_mask** (*list[BitmapMasks]*) – Text mask.
- **gt_center_region_mask** (*list[BitmapMasks]*) – Center region mask.
- **gt_mask** (*list[BitmapMasks]*) – Effective mask.
- **gt_top_height_map** (*list[BitmapMasks]*) – Top height map.
- **gt_bot_height_map** (*list[BitmapMasks]*) – Bottom height map.
- **gt_sin_map** (*list[BitmapMasks]*) – Sinusoid map.
- **gt_cos_map** (*list[BitmapMasks]*) – Cosine map.

Returns A loss dict with `loss_text`, `loss_center`, `loss_height`, `loss_sin`, `loss_cos`, and `loss_gcn`.

Return type dict

gcn_loss(*gcn_data*)

CrossEntropy Loss from gcn module.

Parameters **gcn_data** (*tuple(Tensor, Tensor)*) – The first is the prediction with shape $(N, 2)$ and the second is the gt label with shape (m, n) where $m * n = N$.

Returns CrossEntropy loss.

Return type Tensor

class mmocr.models.textdet.losses.**FCELoss**(*fourier_degree*, *num_sample*, *ohem_ratio=3.0*)

The class for implementing FCENet loss.

FCENet(CVPR2021): Fourier Contour Embedding for Arbitrary-shaped Text Detection

Parameters

- **fourier_degree** (*int*) – The maximum Fourier transform degree k.
- **num_sample** (*int*) – The sampling points number of regression loss. If it is too small, fcenet tends to be overfitting.
- **ohem_ratio** (*float*) – the negative/positive ratio in OHEM.

forward(*preds*, *_*, *p3_maps*, *p4_maps*, *p5_maps*)

Compute FCENet loss.

Parameters

- **preds** (*list[list[Tensor]]*) – The outer list indicates images in a batch, and the inner list indicates the classification prediction map (with shape (N, C, H, W)) and regression map (with shape (N, C, H, W)).
- **p3_maps** (*list[ndarray]*) – List of leval 3 ground truth target map with shape (C, H, W).
- **p4_maps** (*list[ndarray]*) – List of leval 4 ground truth target map with shape (C, H, W).
- **p5_maps** (*list[ndarray]*) – List of leval 5 ground truth target map with shape (C, H, W).

Returns A loss dict with `loss_text`, `loss_center`, `loss_reg_x` and `loss_reg_y`.

Return type dict

fourier2poly(*real_maps*, *imag_maps*)

Transform Fourier coefficient maps to polygon maps.

Parameters

- **real_maps** (*tensor*) – A map composed of the real parts of the Fourier coefficients, whose shape is (-1, 2k+1)
- **imag_maps** (*tensor*) – A map composed of the imag parts of the Fourier coefficients, whose shape is (-1, 2k+1)

Returns

x_maps (tensor): A map composed of the x value of the polygon represented by n sample points (xn, yn), whose shape is (-1, n)

y_maps (tensor): A map composed of the y value of the polygon represented by n sample points (xn, yn), whose shape is (-1, n)

class mmocr.models.textdet.losses.**PANLoss**(*alpha=0.5*, *beta=0.25*, *delta_aggregation=0.5*, *delta_discrimination=3*, *ohem_ratio=3*, *reduction='mean'*, *speedup_bbox_thr=- 1*)

The class for implementing PANet loss. This was partially adapted from https://github.com/WenmuZhou/PAN.pytorch.

PANet: Efficient and Accurate Arbitrary- Shaped Text Detection with Pixel Aggregation Network.

Parameters

- **alpha** (*float*) – The kernel loss coef.
- **beta** (*float*) – The aggregation and discriminative loss coef.
- **delta_aggregation** (*float*) – The constant for aggregation loss.
- **delta_discrimination** (*float*) – The constant for discriminative loss.
- **ohem_ratio** (*float*) – The negative/positive ratio in ohem.
- **reduction** (*str*) – The way to reduce the loss.
- **speedup_bbox_thr** (*int*) – Speed up if speedup_bbox_thr > 0 and < bbox num.

aggregation_discrimination_loss(*gt_texts*, *gt_kernels*, *inst_embeds*)

Compute the aggregation and discrimnative losses.

Parameters

- **gt_texts** (*Tensor*) – The ground truth text mask of size $(N, 1, H, W)$.
- **gt_kernels** (*Tensor*) – The ground truth text kernel mask of size $(N, 1, H, W)$.
- **inst_embeds** (*Tensor*) – The text instance embedding tensor of size $(N, 1, H, W)$.

Returns A tuple of aggregation loss and discriminative loss before reduction.

Return type (Tensor, Tensor)

bitmasks2tensor(*bitmasks*, *target_sz*)
Convert Bitmasks to tensor.

Parameters

- **bitmasks** (*list[BitmapMasks]*) – The BitmapMasks list. Each item is for one img.
- **target_sz** (*tuple(int, int)*) – The target tensor of size (H, W).

Returns The list of kernel tensors. Each element stands for one kernel level.

Return type list[Tensor]

forward(*preds*, *downsample_ratio*, *gt_kernels*, *gt_mask*)
Compute PANet loss.

Parameters

- **preds** (*Tensor*) – The output tensor of size $(N, 6, H, W)$.
- **downsample_ratio** (*float*) – The downsample ratio between preds and the input img.
- **gt_kernels** (*list[BitmapMasks]*) – The kernel list with each element being the text kernel mask for one img.
- **gt_mask** (*list[BitmapMasks]*) – The effective mask list with each element being the effective mask for one img.

Returns A loss dict with `loss_text`, `loss_kernel`, `loss_aggregation` and `loss_discrimination`.

Return type dict

ohem_batch(*text_scores*, *gt_texts*, *gt_mask*)
OHEM sampling for a batch of imgs.

Parameters

- **text_scores** (*Tensor*) – The text scores of size (H, W).
- **gt_texts** (*Tensor*) – The gt text masks of size (H, W).
- **gt_mask** (*Tensor*) – The gt effective mask of size (H, W).

Returns The sampled mask of size (H, W).

Return type Tensor

ohem_img(*text_score*, *gt_text*, *gt_mask*)
Sample the top-k maximal negative samples and all positive samples.

Parameters

- **text_score** (*Tensor*) – The text score of size (H, W).
- **gt_text** (*Tensor*) – The ground truth text mask of size (H, W).

- **gt_mask** (*Tensor*) – The effective region mask of size (H, W).

Returns The sampled pixel mask of size (H, W).

Return type Tensor

class mmocr.models.textdet.losses.**PSELoss**(*alpha=0.7*, *ohem_ratio=3*, *reduction='mean'*, *kernel_sample_type='adaptive'*)

The class for implementing PSENet loss. This is partially adapted from https://github.com/whai362/PSENet.

PSENet: Shape Robust Text Detection with Progressive Scale Expansion Network.

Parameters

- **alpha** (*float*) – Text loss coefficient, and $1 - \alpha$ is the kernel loss coefficient.
- **ohem_ratio** (*float*) – The negative/positive ratio in ohem.
- **reduction** (*str*) – The way to reduce the loss. Available options are "mean" and "sum".

forward(*score_maps*, *downsample_ratio*, *gt_kernels*, *gt_mask*)

Compute PSENet loss.

Parameters

- **score_maps** (*tensor*) – The output tensor with size of Nx6xHxW.
- **downsample_ratio** (*float*) – The downsample ratio between score_maps and the input img.
- **gt_kernels** (*list[BitmapMasks]*) – The kernel list with each element being the text kernel mask for one img.
- **gt_mask** (*list[BitmapMasks]*) – The effective mask list with each element being the effective mask for one img.

Returns A loss dict with `loss_text` and `loss_kernel`.

Return type dict

class mmocr.models.textdet.losses.**TextSnakeLoss**(*ohem_ratio=3.0*)

The class for implementing TextSnake loss. This is partially adapted from https://github.com/princewang1994/TextSnake.pytorch.

TextSnake: A Flexible Representation for Detecting Text of Arbitrary Shapes.

Parameters **ohem_ratio** (*float*) – The negative/positive ratio in ohem.

bitmasks2tensor(*bitmasks*, *target_sz*)

Convert Bitmasks to tensor.

Parameters

- **bitmasks** (*list[BitmapMasks]*) – The BitmapMasks list. Each item is for one img.
- **target_sz** (*tuple(int, int)*) – The target tensor of size (H, W).

Returns The list of kernel tensors. Each element stands for one kernel level.

Return type list[Tensor]

forward(*pred_maps*, *downsample_ratio*, *gt_text_mask*, *gt_center_region_mask*, *gt_mask*, *gt_radius_map*, *gt_sin_map*, *gt_cos_map*)

Parameters

- **pred_maps** (*Tensor*) – The prediction map of shape $(N, 5, H, W)$, where each dimension is the map of "text_region", "center_region", "sin_map", "cos_map", and "radius_map" respectively.
- **downsample_ratio** (*float*) – Downsample ratio.
- **gt_text_mask** (*list[BitmapMasks]*) – Gold text masks.
- **gt_center_region_mask** (*list[BitmapMasks]*) – Gold center region masks.
- **gt_mask** (*list[BitmapMasks]*) – Gold general masks.
- **gt_radius_map** (*list[BitmapMasks]*) – Gold radius maps.
- **gt_sin_map** (*list[BitmapMasks]*) – Gold sin maps.
- **gt_cos_map** (*list[BitmapMasks]*) – Gold cos maps.

Returns A loss dict with `loss_text`, `loss_center`, `loss_radius`, `loss_sin` and `loss_cos`.

Return type dict

26.6 Text Detection Postprocessors

class mmocr.models.textdet.postprocess.**DBPostprocessor**(*text_repr_type='poly'*, *mask_thr=0.3*, *min_text_score=0.3*, *min_text_width=5*, *unclip_ratio=1.5*, *max_candidates=3000*, ***kwargs*)

Decoding predictions of DbNet to instances. This is partially adapted from https://github.com/MhLiao/DB.

Parameters

- **text_repr_type** (*str*) – The boundary encoding type 'poly' or 'quad'.
- **mask_thr** (*float*) – The mask threshold value for binarization.
- **min_text_score** (*float*) – The threshold value for converting binary map to shrink text regions.
- **min_text_width** (*int*) – The minimum width of boundary polygon/box predicted.
- **unclip_ratio** (*float*) – The unclip ratio for text regions dilation.
- **max_candidates** (*int*) – The maximum candidate number.

class mmocr.models.textdet.postprocess.**DRRGPostprocessor**(*link_thr*, ***kwargs*)

Merge text components and construct boundaries of text instances.

Parameters **link_thr** (*float*) – The edge score threshold.

class mmocr.models.textdet.postprocess.**FCEPostprocessor**(*fourier_degree*, *num_reconstr_points*, *text_repr_type='poly'*, *alpha=1.0*, *beta=2.0*, *score_thr=0.3*, *nms_thr=0.1*, ***kwargs*)

Decoding predictions of FCENet to instances.

Parameters

- **fourier_degree** (*int*) – The maximum Fourier transform degree k.
- **num_reconstr_points** (*int*) – The points number of the polygon reconstructed from predicted Fourier coefficients.
- **text_repr_type** (*str*) – Boundary encoding type 'poly' or 'quad'.

- **scale** (*int*) – The down-sample scale of the prediction.
- **alpha** (*float*) – The parameter to calculate final scores. Score_{final} = (Score_{text region} ^ alpha) * (Score_{text center region}^ beta)
- **beta** (*float*) – The parameter to calculate final score.
- **score_thr** (*float*) – The threshold used to filter out the final candidates.
- **nms_thr** (*float*) – The threshold of nms.

class mmocr.models.textdet.postprocess.**PANPostprocessor**(*text_repr_type='poly'*, *min_text_confidence=0.5*, *min_kernel_confidence=0.5*, *min_text_avg_confidence=0.85*, *min_text_area=16*, ***kwargs*)

Convert scores to quadrangles via post processing in PANet. This is partially adapted from https://github.com/WenmuZhou/PAN.pytorch.

Parameters

- **text_repr_type** (*str*) – The boundary encoding type 'poly' or 'quad'.
- **min_text_confidence** (*float*) – The minimal text confidence.
- **min_kernel_confidence** (*float*) – The minimal kernel confidence.
- **min_text_avg_confidence** (*float*) – The minimal text average confidence.
- **min_text_area** (*int*) – The minimal text instance region area.

class mmocr.models.textdet.postprocess.**PSEPostprocessor**(*text_repr_type='poly'*, *min_kernel_confidence=0.5*, *min_text_avg_confidence=0.85*, *min_kernel_area=0*, *min_text_area=16*, ***kwargs*)

Decoding predictions of PSENet to instances. This is partially adapted from https://github.com/whai362/PSENet.

Parameters

- **text_repr_type** (*str*) – The boundary encoding type 'poly' or 'quad'.
- **min_kernel_confidence** (*float*) – The minimal kernel confidence.
- **min_text_avg_confidence** (*float*) – The minimal text average confidence.
- **min_kernel_area** (*int*) – The minimal text kernel area.
- **min_text_area** (*int*) – The minimal text instance region area.

class mmocr.models.textdet.postprocess.**TextSnakePostprocessor**(*text_repr_type='poly'*, *min_text_region_confidence=0.6*, *min_center_region_confidence=0.2*, *min_center_area=30*, *disk_overlap_thr=0.03*, *radius_shrink_ratio=1.03*, ***kwargs*)

Decoding predictions of TextSnake to instances. This was partially adapted from https://github.com/princewang1994/TextSnake.pytorch.

Parameters

- **text_repr_type** (*str*) – The boundary encoding type 'poly' or 'quad'.

- **min_text_region_confidence** (*float*) – The confidence threshold of text region in TextSnake.
- **min_center_region_confidence** (*float*) – The confidence threshold of text center region in TextSnake.
- **min_center_area** (*int*) – The minimal text center region area.
- **disk_overlap_thr** (*float*) – The radius overlap threshold for merging disks.
- **radius_shrink_ratio** (*float*) – The shrink ratio of ordered disks radii.

26.7 Text Recognition Recognizer

class mmocr.models.textrecog.recognizer.**ABINet**(*preprocessor=None*, *backbone=None*, *encoder=None*, *decoder=None*, *iter_size=1*, *fuser=None*, *loss=None*, *label_convertor=None*, *train_cfg=None*, *test_cfg=None*, *max_seq_len=40*, *pretrained=None*, *init_cfg=None*)

Implementation of `Read Like Humans: Autonomous, Bidirectional and Iterative LanguageModeling for Scene Text Recognition.

<https://arxiv.org/pdf/2103.06495.pdf>`_

forward_train(*img*, *img_metas*)

Parameters

- **img** (*tensor*) – Input images of shape (N, C, H, W). Typically these should be mean centered and std scaled.
- **img_metas** (*list[dict]*) – A list of image info dict where each dict contains: 'img_shape', 'filename', and may also contain 'ori_shape', and 'img_norm_cfg'. For details on the values of these keys see `mmdet.datasets.pipelines.Collect`.

Returns A dictionary of loss components.

Return type dict[str, tensor]

simple_test(*img*, *img_metas*, ***kwargs*)

Test function with test time augmentation.

Parameters

- **imgs** (*torch.Tensor*) – Image input tensor.
- **img_metas** (*list[dict]*) – List of image information.

Returns Text label result of each image.

Return type list[str]

class mmocr.models.textrecog.recognizer.**BaseRecognizer**(*init_cfg=None*)

Base class for text recognition.

abstract aug_test(*imgs*, *img_metas*, ***kwargs*)

Test function with test time augmentation.

Parameters

- **imgs** (*list[tensor]*) – Tensor should have shape NxCxHxW, which contains all images in the batch.

- **img_metas** (*list[list[dict]]*) – The metadata of images.

abstract extract_feat(*imgs*)
Extract features from images.

forward(*img*, *img_metas*, *return_loss=True*, ***kwargs*)
Calls either *forward_train()* or *forward_test()* depending on whether `return_loss` is `True`.

Note that img and img_meta are single-nested (i.e. tensor and list[dict]).

forward_test(*imgs*, *img_metas*, ***kwargs*)

Parameters

- **imgs** (*tensor | list[tensor]*) – Tensor should have shape NxCxHxW, which contains all images in the batch.
- **img_metas** (*list[dict] | list[list[dict]]*) – The outer list indicates images in a batch.

abstract forward_train(*imgs*, *img_metas*, ***kwargs*)

Parameters

- **img** (*tensor*) – tensors with shape (N, C, H, W). Typically should be mean centered and std scaled.
- **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 of the values of these keys, see `mmdet.datasets.pipelines.Collect`.
- **kwargs** (*keyword arguments*) – Specific to concrete implementation.

show_result(*img*, *result*, *gt_label=''*, *win_name=''*, *show=False*, *wait_time=0*, *out_file=None*, ***kwargs*)
Draw *result* on *img*.

Parameters

- **img** (*str or tensor*) – The image to be displayed.
- **result** (*dict*) – The results to draw on *img*.
- **gt_label** (*str*) – Ground truth label of img.
- **win_name** (*str*) – The window name.
- **wait_time** (*int*) – Value of waitKey param. Default: 0.
- **show** (*bool*) – Whether to show the image. Default: False.
- **out_file** (*str or None*) – The output filename. Default: None.

Returns Only if not *show* or *out_file*.

Return type img (tensor)

train_step(*data*, *optimizer*)
The iteration step during training.

This method defines an iteration step during training, except for the back propagation and optimizer update, which are done by an optimizer hook. Note that in some complicated cases or models (e.g. GAN), the whole process (including the back propagation and optimizer update) is also defined by this method.

Parameters

- **data** (*dict*) – The outputs of dataloader.
- **optimizer** (torch.optim.Optimizer | dict) – The optimizer of runner is passed to train_step(). This argument is unused and reserved.

Returns

It should contain at least 3 keys: loss, log_vars, num_samples.

- loss is a tensor for back propagation, which is a

weighted sum of multiple losses. - log_vars contains all the variables to be sent to the logger. - num_samples indicates the batch size used for averaging the logs (Note: for the DDP model, num_samples refers to the batch size for each GPU).

Return type dict

val_step(*data*, *optimizer*)
The iteration step during validation.

This method shares the same signature as *train_step()*, but is used during val epochs. Note that the evaluation after training epochs is not implemented by this method, but by an evaluation hook.

class mmocr.models.textrecog.recognizer.**CRNNNet**(*preprocessor=None*, *backbone=None*, *encoder=None*, *decoder=None*, *loss=None*, *label_convertor=None*, *train_cfg=None*, *test_cfg=None*, *max_seq_len=40*, *pretrained=None*, *init_cfg=None*)

CTC-loss based recognizer.

class mmocr.models.textrecog.recognizer.**EncodeDecodeRecognizer**(*preprocessor=None*, *backbone=None*, *encoder=None*, *decoder=None*, *loss=None*, *label_convertor=None*, *train_cfg=None*, *test_cfg=None*, *max_seq_len=40*, *pretrained=None*, *init_cfg=None*)

Base class for encode-decode recognizer.

aug_test(*imgs*, *img_metas*, ***kwargs*)
Test function as well as time augmentation.

Parameters

- **imgs** (*list[tensor]*) – Tensor should have shape NxCxHxW, which contains all images in the batch.
- **img_metas** (*list[list[dict]]*) – The metadata of images.

extract_feat(*img*)
Directly extract features from the backbone.

forward_train(*img*, *img_metas*)

Parameters

- **img** (*tensor*) – Input images of shape (N, C, H, W). Typically these should be mean centered and std scaled.
- **img_metas** (*list[dict]*) – A list of image info dict where each dict contains: 'img_shape', 'filename', and may also contain 'ori_shape', and 'img_norm_cfg'. For details on the values of these keys see mmdet.datasets.pipelines.Collect.

Returns A dictionary of loss components.

Return type dict[str, tensor]

simple_test(*img*, *img_metas*, ***kwargs*)
Test function with test time augmentation.

Parameters

- **imgs** (*torch.Tensor*) – Image input tensor.
- **img_metas** (*list[dict]*) – List of image information.

Returns Text label result of each image.

Return type list[str]

class mmocr.models.textrecog.recognizer.**NRTR**(*preprocessor=None*, *backbone=None*, *encoder=None*, *decoder=None*, *loss=None*, *label_convertor=None*, *train_cfg=None*, *test_cfg=None*, *max_seq_len=40*, *pretrained=None*, *init_cfg=None*)

Implementation of NRTR

class mmocr.models.textrecog.recognizer.**RobustScanner**(*preprocessor=None*, *backbone=None*, *encoder=None*, *decoder=None*, *loss=None*, *label_convertor=None*, *train_cfg=None*, *test_cfg=None*, *max_seq_len=40*, *pretrained=None*, *init_cfg=None*)

Implementation of `RobustScanner.

<https://arxiv.org/pdf/2007.07542.pdf>

class mmocr.models.textrecog.recognizer.**SARNet**(*preprocessor=None*, *backbone=None*, *encoder=None*, *decoder=None*, *loss=None*, *label_convertor=None*, *train_cfg=None*, *test_cfg=None*, *max_seq_len=40*, *pretrained=None*, *init_cfg=None*)

Implementation of SAR

class mmocr.models.textrecog.recognizer.**SATRN**(*preprocessor=None*, *backbone=None*, *encoder=None*, *decoder=None*, *loss=None*, *label_convertor=None*, *train_cfg=None*, *test_cfg=None*, *max_seq_len=40*, *pretrained=None*, *init_cfg=None*)

Implementation of SATRN

class mmocr.models.textrecog.recognizer.**SegRecognizer**(*preprocessor=None*, *backbone=None*, *neck=None*, *head=None*, *loss=None*, *label_convertor=None*, *train_cfg=None*, *test_cfg=None*, *pretrained=None*, *init_cfg=None*)

Base class for segmentation based recognizer.

aug_test(*imgs*, *img_metas*, ***kwargs*)
Test function with test time augmentation.

Parameters

- **imgs** (*list[tensor]*) – Tensor should have shape NxCxHxW, which contains all images in the batch.
- **img_metas** (*list[list[dict]]*) – The metadata of images.

extract_feat(*img*)
Directly extract features from the backbone.

forward_train(*img*, *img_metas*, *gt_kernels=None*)

Parameters

- **img** (*tensor*) – Input images of shape (N, C, H, W). Typically these should be mean centered and std scaled.
- **img_metas** (*list[dict]*) – A list of image info dict where each dict contains: 'img_shape', 'filename', and may also contain 'ori_shape', and 'img_norm_cfg'. For details on the values of these keys see `mmdet.datasets.pipelines.Collect`.

Returns A dictionary of loss components.

Return type dict[str, tensor]

simple_test(*img*, *img_metas*, ***kwargs*)

Test function without test time augmentation.

Parameters

- **imgs** (*torch.Tensor*) – Image input tensor.
- **img_metas** (*list[dict]*) – List of image information.

Returns Text label result of each image.

Return type list[str]

26.8 Text Recognition Backbones

class mmocr.models.textrecog.backbones.**NRTRModalityTransform**(*input_channels=3*, *init_cfg=[{'type': 'Kaiming', 'layer': 'Conv2d'}, {'type': 'Uniform', 'layer': 'BatchNorm2d'}]*)

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 mmocr.models.textrecog.backbones.**ResNet31OCR**(*base_channels=3*, *layers=[1, 2, 5, 3]*, *channels=[64, 128, 256, 256, 512, 512, 512]*, *out_indices=None*, *stage4_pool_cfg={'kernel_size': (2, 1), 'stride': (2, 1)}*, *last_stage_pool=False*, *init_cfg=[{'type': 'Kaiming', 'layer': 'Conv2d'}, {'type': 'Uniform', 'layer': 'BatchNorm2d'}]*)

Implement ResNet backbone for text recognition, modified from ResNet

Parameters

- **base_channels** (*int*) – Number of channels of input image tensor.

- **layers** (*list[int]*) – List of BasicBlock number for each stage.
- **channels** (*list[int]*) – List of out_channels of Conv2d layer.
- **out_indices** (*None | Sequence[int]*) – Indices of output stages.
- **stage4_pool_cfg** (*dict*) – Dictionary to construct and configure pooling layer in stage 4.
- **last_stage_pool** (*bool*) – If True, add *MaxPool2d* layer to last stage.

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 mmocr.models.textrecog.backbones.**ResNetABI**(*in_channels=3*, *stem_channels=32*, *base_channels=32*, *arch_settings=[3, 4, 6, 6, 3]*, *strides=[2, 1, 2, 1, 1]*, *out_indices=None*, *last_stage_pool=False*, *init_cfg=[{'type': 'Xavier', 'layer': 'Conv2d'}, {'type': 'Constant', 'val': 1, 'layer': 'BatchNorm2d'}]*)

Implement ResNet backbone for text recognition, modified from `ResNet.

<https://arxiv.org/pdf/1512.03385.pdf>`_ and https://github.com/FangShancheng/ABINet

Parameters

- **in_channels** (*int*) – Number of channels of input image tensor.
- **stem_channels** (*int*) – Number of stem channels.
- **base_channels** (*int*) – Number of base channels.
- **arch_settings** (*list[int]*) – List of BasicBlock number for each stage.
- **strides** (*Sequence[int]*) – Strides of the first block of each stage.
- **out_indices** (*None | Sequence[int]*) – Indices of output stages. If not specified, only the last stage will be returned.
- **last_stage_pool** (*bool*) – If True, add *MaxPool2d* layer to last stage.

forward(*x*)

Parameters **x** (*Tensor*) – Image tensor of shape $(N, 3, H, W)$.

Returns Feature tensor. Its shape depends on ResNetABI's config. It can be a list of feature outputs at specific layers if `out_indices` is specified.

Return type Tensor or list[Tensor]

class mmocr.models.textrecog.backbones.**ShallowCNN**(*input_channels=1*, *hidden_dim=512*, *init_cfg=[{'type': 'Kaiming', 'layer': 'Conv2d'}, {'type': 'Uniform', 'layer': 'BatchNorm2d'}]*)

Implement Shallow CNN block for SATRN.

SATRN: On Recognizing Texts of Arbitrary Shapes with 2D Self-Attention.

Parameters

- **base_channels** (*int*) – Number of channels of input image tensor D_i.
- **hidden_dim** (*int*) – Size of hidden layers of the model D_m.
- **init_cfg** (*dict or list[dict], optional*) – Initialization configs.

forward(*x*)

Parameters **x** (*Tensor*) – Input image feature (N, D_i, H, W).

Returns A tensor of shape $(N, D_m, H/4, W/4)$.

Return type Tensor

class mmocr.models.textrecog.backbones.**VeryDeepVgg**(*leaky_relu=True*, *input_channels=3*, *init_cfg=[{'type': 'Xavier', 'layer': 'Conv2d'}, {'type': 'Uniform', 'layer': 'BatchNorm2d'}]*)

Implement VGG-VeryDeep backbone for text recognition, modified from VGG-VeryDeep

Parameters

- **leaky_relu** (*bool*) – Use leakyRelu or not.
- **input_channels** (*int*) – Number of channels of input image tensor.

forward(*x*)

Parameters **x** (*Tensor*) – Images of shape (N, C, H, W).

Returns The feature Tensor of shape $(N, 512, H/32, (W/4 + 1))$.

Return type Tensor

26.9 Text Recognition Necks

class mmocr.models.textrecog.necks.**FPNOCR**(*in_channels*, *out_channels*, *last_stage_only=True*, *init_cfg=None*)

FPN-like Network for segmentation based text recognition.

Parameters

- **in_channels** (*list[int]*) – Number of input channels C_i for each scale.
- **out_channels** (*int*) – Number of output channels C_{out} for each scale.
- **last_stage_only** (*bool*) – If True, output last stage only.
- **init_cfg** (*dict or list[dict], optional*) – Initialization configs.

forward(*inputs*)

Parameters **inputs** (*list[Tensor]*) – A list of n tensors. Each tensor has the shape of (N, C_i, H_i, W_i). It usually expects 4 tensors (C2-C5 features) from ResNet.

Returns A tuple of n-1 tensors. Each has the of shape $(N, C_{out}, H_{n-2-i}, W_{n-2-i})$. If `last_stage_only=True` (default), the size of the tuple is 1 and only the last element will be returned.

Return type tuple(Tensor)

26.10 Text Recognition Heads

class mmocr.models.textrecog.heads.**SegHead**(*in_channels=128*, *num_classes=37*, *upsample_param=None*, *init_cfg=None*)

Head for segmentation based text recognition.

Parameters

- **in_channels** (*int*) – Number of input channels C.
- **num_classes** (*int*) – Number of output classes C_{out}.
- **upsample_param** (*dict | None*) – Config dict for interpolation layer. Default: `dict(scale_factor=1.0, mode='nearest')`
- **init_cfg** (*dict or list[dict], optional*) – Initialization configs.

forward(*out_neck*)

Parameters **out_neck** (*list[Tensor]*) – A list of tensor of shape (N, C_i, H_i, W_i). The network only uses the last one (`out_neck[-1]`).

Returns A tensor of shape (N, C_{out}, kH, kW) where k is determined by `upsample_param`.

Return type Tensor

26.11 Text Recognition Preprocessors

class mmocr.models.textrecog.preprocessor.**BasePreprocessor**(*init_cfg=None*)

Base Preprocessor class for text recognition.

forward(*x*, ***kwargs*)

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 mmocr.models.textrecog.preprocessor.**TPSPreprocessor**(*num_fiducial=20*, *img_size=(32, 100)*, *rectified_img_size=(32, 100)*, *num_img_channel=1*, *init_cfg=None*)

Rectification Network of RARE, namely TPS based STN in https://arxiv.org/pdf/1603.03915.pdf.

Parameters

- **num_fiducial** (*int*) – Number of fiducial points of TPS-STN.
- **img_size** (*tuple(int, int)*) – Size (H, W) of the input image.
- **rectified_img_size** (*tuple(int, int)*) – Size (H_r, W_r) of the rectified image.
- **num_img_channel** (*int*) – Number of channels of the input image.
- **init_cfg** (*dict or list[dict], optional*) – Initialization configs.

forward(*batch_img*)

Parameters **batch_img** (*Tensor*) – Images to be rectified with size (N, C, H, W).

Returns Rectified image with size (N, C, H_r, W_r).

Return type Tensor

26.12 Text Recognition Backbones

class mmocr.models.textrecog.backbones.**NRTRModalityTransform**(*input_channels=3*, *init_cfg=[{'type': 'Kaiming', 'layer': 'Conv2d'}, {'type': 'Uniform', 'layer': 'BatchNorm2d'}]*)

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 mmocr.models.textrecog.backbones.**ResNet31OCR**(*base_channels=3*, *layers=[1, 2, 5, 3]*, *channels=[64, 128, 256, 256, 512, 512, 512]*, *out_indices=None*, *stage4_pool_cfg={'kernel_size': (2, 1), 'stride': (2, 1)}*, *last_stage_pool=False*, *init_cfg=[{'type': 'Kaiming', 'layer': 'Conv2d'}, {'type': 'Uniform', 'layer': 'BatchNorm2d'}]*)

Implement ResNet backbone for text recognition, modified from ResNet

Parameters

- **base_channels** (*int*) – Number of channels of input image tensor.
- **layers** (*list[int]*) – List of BasicBlock number for each stage.
- **channels** (*list[int]*) – List of out_channels of Conv2d layer.
- **out_indices** (*None | Sequence[int]*) – Indices of output stages.
- **stage4_pool_cfg** (*dict*) – Dictionary to construct and configure pooling layer in stage 4.
- **last_stage_pool** (*bool*) – If True, add *MaxPool2d* layer to last stage.

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 mmocr.models.textrecog.backbones.**ResNetABI**(*in_channels=3*, *stem_channels=32*, *base_channels=32*, *arch_settings=[3, 4, 6, 6, 3]*, *strides=[2, 1, 2, 1, 1]*, *out_indices=None*, *last_stage_pool=False*, *init_cfg=[{'type': 'Xavier', 'layer': 'Conv2d'}, {'type': 'Constant', 'val': 1, 'layer': 'BatchNorm2d'}]*)

Implement ResNet backbone for text recognition, modified from `ResNet.

<https://arxiv.org/pdf/1512.03385.pdf>`_ and https://github.com/FangShancheng/ABINet

Parameters

- **in_channels** (*int*) – Number of channels of input image tensor.
- **stem_channels** (*int*) – Number of stem channels.
- **base_channels** (*int*) – Number of base channels.
- **arch_settings** (*list[int]*) – List of BasicBlock number for each stage.
- **strides** (*Sequence[int]*) – Strides of the first block of each stage.
- **out_indices** (*None | Sequence[int]*) – Indices of output stages. If not specified, only the last stage will be returned.
- **last_stage_pool** (*bool*) – If True, add *MaxPool2d* layer to last stage.

forward(*x*)

Parameters **x** (*Tensor*) – Image tensor of shape $(N, 3, H, W)$.

Returns Feature tensor. Its shape depends on ResNetABI's config. It can be a list of feature outputs at specific layers if `out_indices` is specified.

Return type Tensor or list[Tensor]

class mmocr.models.textrecog.backbones.**ShallowCNN**(*input_channels=1*, *hidden_dim=512*, *init_cfg=[{'type': 'Kaiming', 'layer': 'Conv2d'}, {'type': 'Uniform', 'layer': 'BatchNorm2d'}]*)

Implement Shallow CNN block for SATRN.

SATRN: On Recognizing Texts of Arbitrary Shapes with 2D Self-Attention.

Parameters

- **base_channels** (*int*) – Number of channels of input image tensor D_i.
- **hidden_dim** (*int*) – Size of hidden layers of the model D_m.
- **init_cfg** (*dict or list[dict], optional*) – Initialization configs.

forward(*x*)

Parameters **x** (*Tensor*) – Input image feature (N, D_i, H, W).

Returns A tensor of shape $(N, D_m, H/4, W/4)$.

Return type Tensor

class mmocr.models.textrecog.backbones.**VeryDeepVgg**(*leaky_relu=True*, *input_channels=3*, *init_cfg=[{'type': 'Xavier', 'layer': 'Conv2d'}, {'type': 'Uniform', 'layer': 'BatchNorm2d'}]*)

Implement VGG-VeryDeep backbone for text recognition, modified from VGG-VeryDeep

Parameters

- **leaky_relu** (*bool*) – Use leakyRelu or not.
- **input_channels** (*int*) – Number of channels of input image tensor.

forward(*x*)

Parameters **x** (*Tensor*) – Images of shape (N, C, H, W).

Returns The feature Tensor of shape $(N, 512, H/32, (W/4+1))$.

Return type Tensor

26.13 Text Recognition Layers

class mmocr.models.textrecog.layers.**Adaptive2DPositionalEncoding**(*d_hid=512*, *n_height=100*, *n_width=100*, *dropout=0.1*, *init_cfg=[{'type': 'Xavier', 'layer': 'Conv2d'}]*)

Implement Adaptive 2D positional encoder for SATRN, see SATRN Modified from https://github.com/Media-Smart/vedastr Licensed under the Apache License, Version 2.0 (the "License");

Parameters

- **d_hid** (*int*) – Dimensions of hidden layer.
- **n_height** (*int*) – Max height of the 2D feature output.
- **n_width** (*int*) – Max width of the 2D feature output.
- **dropout** (*int*) – Size of hidden layers of the model.

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 mmocr.models.textrecog.layers.**BasicBlock**(*inplanes*, *planes*, *stride=1*, *dilation=1*, *downsample=None*, *use_conv1x1=False*, *style='pytorch'*, *with_cp=False*)

class mmocr.models.textrecog.layers.**BidirectionalLSTM**(*nIn*, *nHidden*, *nOut*)

forward(*input*)
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 mmocr.models.textrecog.layers.**Bottleneck**(*inplanes*, *planes*, *stride=1*, *downsample=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 mmocr.models.textrecog.layers.**DotProductAttentionLayer**(*dim_model=None*)

forward(*query*, *key*, *value*, *mask=None*)
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 mmocr.models.textrecog.layers.**PositionAwareLayer**(*dim_model*, *rnn_layers=2*)

forward(*img_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 mmocr.models.textrecog.layers.**RobustScannerFusionLayer**(*dim_model*, *dim=- 1*, *init_cfg=None*)

forward(*x0*, *x1*)
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.

26.14 Text Recognition Convertors

class mmocr.models.textrecog.convertors.**ABIConvertor**(*dict_type='DICT90'*, *dict_file=None*, *dict_list=None*, *with_unknown=True*, *max_seq_len=40*, *lower=False*, *start_end_same=True*, ***kwargs*)

Convert between text, index and tensor for encoder-decoder based pipeline. Modified from AttnConvertor to get closer to ABINet's original implementation.

Parameters

- **dict_type** (*str*) – Type of dict, should be one of {'DICT36', 'DICT90'}.
- **dict_file** (*None|str*) – Character dict file path. If not none, higher priority than dict_type.
- **dict_list** (*None|list[str]*) – Character list. If not none, higher priority than dict_type, but lower than dict_file.
- **with_unknown** (*bool*) – If True, add *UKN* token to class.
- **max_seq_len** (*int*) – Maximum sequence length of label.
- **lower** (*bool*) – If True, convert original string to lower case.
- **start_end_same** (*bool*) – Whether use the same index for start and end token or not. Default: True.

str2tensor(*strings*)

Convert text-string into tensor. Different from *mmocr.models.textrecog.convertors.AttnConvertor*, the targets field returns target index no longer than max_seq_len (EOS token included).

Parameters **strings** (*list[str]*) – For instance, ['hello', 'world']

Returns

A dict with two tensors.

- targets (list[Tensor]): [torch.Tensor([1,2,3,3,4,8]), torch.Tensor([5,4,6,3,7,8])]
- padded_targets (Tensor): Tensor of shape (bsz * max_seq_len)).

Return type dict

class mmocr.models.textrecog.convertors.**AttnConvertor**(*dict_type='DICT90'*, *dict_file=None*, *dict_list=None*, *with_unknown=True*, *max_seq_len=40*, *lower=False*, *start_end_same=True*, ***kwargs*)

Convert between text, index and tensor for encoder-decoder based pipeline.

Parameters

- **dict_type** (*str*) – Type of dict, should be one of {'DICT36', 'DICT90'}.

- **dict_file** (*None|str*) – Character dict file path. If not none, higher priority than dict_type.
- **dict_list** (*None|list[str]*) – Character list. If not none, higher priority than dict_type, but lower than dict_file.
- **with_unknown** (*bool*) – If True, add *UKN* token to class.
- **max_seq_len** (*int*) – Maximum sequence length of label.
- **lower** (*bool*) – If True, convert original string to lower case.
- **start_end_same** (*bool*) – Whether use the same index for start and end token or not. Default: True.

str2tensor(*strings*)

Convert text-string into tensor. :param strings: [‘hello’, ‘world’] :type strings: list[str]

Returns

Tensor | list[tensor]):

tensors (list[Tensor]): [torch.Tensor([1,2,3,3,4]), torch.Tensor([5,4,6,3,7])]

padded_targets (Tensor(bsz * max_seq_len))

Return type dict (str

tensor2idx(*outputs*, *img_metas=None*)

Convert output tensor to text-index :param outputs: model outputs with size: N * T * C :type outputs: tensor :param img_metas: Each dict contains one image info. :type img_metas: list[dict]

Returns

[[1,2,3,3,4], [5,4,6,3,7]] scores (list[list[float]]): [[0.9,0.8,0.95,0.97,0.94],

[0.9,0.9,0.98,0.97,0.96]]

Return type indexes (list[list[int]])

class mmocr.models.textrecog.convertors.**BaseConvertor**(*dict_type='DICT90'*, *dict_file=None*, *dict_list=None*)

Convert between text, index and tensor for text recognize pipeline.

Parameters

- **dict_type** (*str*) – Type of dict, should be either ‘DICT36’ or ‘DICT90’.
- **dict_file** (*None|str*) – Character dict file path. If not none, the dict_file is of higher priority than dict_type.
- **dict_list** (*None|list[str]*) – Character list. If not none, the list is of higher priority than dict_type, but lower than dict_file.

idx2str(*indexes*)

Convert indexes to text strings.

Parameters **indexes** (*list[list[int]]*) – [[1,2,3,3,4], [5,4,6,3,7]].

Returns [‘hello’, ‘world’].

Return type strings (list[str])

num_classes()

Number of output classes.

str2idx(*strings*)
Convert strings to indexes.

Parameters **strings** (*list[str]*) – ['hello', 'world'].

Returns [[1,2,3,3,4], [5,4,6,3,7]].

Return type indexes (list[list[int]])

str2tensor(*strings*)
Convert text-string to input tensor.

Parameters **strings** (*list[str]*) – ['hello', 'world'].

Returns

[torch.Tensor([1,2,3,3,4]), torch.Tensor([5,4,6,3,7])].

Return type tensors (list[torch.Tensor])

tensor2idx(*output*)
Convert model output tensor to character indexes and scores. :param output: The model outputs with size: N * T * C :type output: tensor

Returns

[[1,2,3,3,4], [5,4,6,3,7]]. scores (list[list[float]]): [[0.9,0.8,0.95,0.97,0.94],

[0.9,0.9,0.98,0.97,0.96]].

Return type indexes (list[list[int]])

class mmocr.models.textrecog.convertors.**CTCConvertor**(*dict_type='DICT90'*, *dict_file=None*, *dict_list=None*, *with_unknown=True*, *lower=False*, ***kwargs*)
Convert between text, index and tensor for CTC loss-based pipeline.

Parameters

- **dict_type** (*str*) – Type of dict, should be either 'DICT36' or 'DICT90'.
- **dict_file** (*None|str*) – Character dict file path. If not none, the file is of higher priority than dict_type.
- **dict_list** (*None|list[str]*) – Character list. If not none, the list is of higher priority than dict_type, but lower than dict_file.
- **with_unknown** (*bool*) – If True, add *UKN* token to class.
- **lower** (*bool*) – If True, convert original string to lower case.

str2tensor(*strings*)
Convert text-string to ctc-loss input tensor.

Parameters **strings** (*list[str]*) – ['hello', 'world'].

Returns

tensor | list[tensor]):

tensors (list[tensor]): [torch.Tensor([1,2,3,3,4]), torch.Tensor([5,4,6,3,7])].

flatten_targets (tensor): torch.Tensor([1,2,3,3,4,5,4,6,3,7]). target_lengths (tensor): torch.IntTensot([5,5]).

Return type dict (str

tensor2idx(*output*, *img_metas*, *topk=1*, *return_topk=False*)
Convert model output tensor to index-list. :param output: The model outputs with size: N * T * C. :type output: tensor :param img_metas: Each dict contains one image info. :type img_metas: list[dict] :param topk: The highest k classes to be returned. :type topk: int :param return_topk: Whether to return topk or just top1. :type return_topk: bool

Returns

[[1,2,3,3,4], [5,4,6,3,7]]. scores (list[list[float]]): [[0.9,0.8,0.95,0.97,0.94],

[0.9,0.9,0.98,0.97,0.96]] (

indexes_topk (list[list[list[int]->len=topk]]): scores_topk (list[list[list[float]->len=topk]])

).

Return type indexes (list[list[int]])

class mmocr.models.textrecog.convertors.**SegConvertor**(*dict_type='DICT36'*, *dict_file=None*, *dict_list=None*, *with_unknown=True*, *lower=False*, ***kwargs*)
Convert between text, index and tensor for segmentation based pipeline.

Parameters

- **dict_type** (*str*) – Type of dict, should be either 'DICT36' or 'DICT90'.
- **dict_file** (*None|str*) – Character dict file path. If not none, the file is of higher priority than dict_type.
- **dict_list** (*None|list[str]*) – Character list. If not none, the list
- **of higher priority than dict_type** (*is*) –
- **lower than dict_file.** (*but*) –
- **with_unknown** (*bool*) – If True, add *UKN* token to class.
- **lower** (*bool*) – If True, convert original string to lower case.

tensor2str(*output*, *img_metas=None*)
Convert model output tensor to string labels. :param output: Model outputs with size: N * C * H * W :type output: tensor :param img_metas: Each dict contains one image info. :type img_metas: list[dict]

Returns Decoded text labels. scores (list[list[float]]): Decoded chars scores.

Return type texts (list[str])

26.15 Text Recognition Encoders

class mmocr.models.textrecog.encoders.**ABIVisionModel**(*encoder={'type': 'TransformerEncoder'}*, *decoder={'type': 'ABIVisionDecoder'}*, *init_cfg={'layer': 'Conv2d', 'type': 'Xavier'}*, ***kwargs*)
A wrapper of visual feature encoder and language token decoder that converts visual features into text tokens.

Implementation of VisionEncoder in ABINet.

Parameters

- **encoder** (*dict*) – Config for image feature encoder.

- **decoder** (*dict*) – Config for language token decoder.
- **init_cfg** (*dict*) – Specifies the initialization method for model layers.

forward(*feat*, *img_metas=None*)

Parameters **feat** (*Tensor*) – Images of shape (N, E, H, W).

Returns

A dict with keys `feature`, `logits` and `attn_scores`.

- feature (Tensor): Shape (N, T, E). Raw visual features for language decoder.
- logits (Tensor): Shape (N, T, C). The raw logits for characters. C is the number of characters.
- attn_scores (Tensor): Shape (N, T, H, W). Intermediate result for vision-language aligner.

Return type dict

class mmocr.models.textrecog.encoders.**BaseEncoder**(*init_cfg=None*)

Base Encoder class for text recognition.

forward(*feat*, ***kwargs*)

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 mmocr.models.textrecog.encoders.**ChannelReductionEncoder**(*in_channels*, *out_channels*, *init_cfg={'layer': 'Conv2d', 'type': 'Xavier'}*)

Change the channel number with a one by one convoluational layer.

Parameters

- **in_channels** (*int*) – Number of input channels.
- **out_channels** (*int*) – Number of output channels.
- **init_cfg** (*dict or list[dict], optional*) – Initialization configs.

forward(*feat*, *img_metas=None*)

Parameters

- **feat** (*Tensor*) – Image features with the shape of (N, C_{in}, H, W).
- **img_metas** (*None*) – Unused.

Returns A tensor of shape (N, C_{out}, H, W).

Return type Tensor

class mmocr.models.textrecog.encoders.**NRTREncoder**(*n_layers=6*, *n_head=8*, *d_k=64*, *d_v=64*, *d_model=512*, *d_inner=256*, *dropout=0.1*, *init_cfg=None*, ***kwargs*)

Transformer Encoder block with self attention mechanism.

Parameters

- **n_layers** (*int*) – The number of sub-encoder-layers in the encoder (default=6).
- **n_head** (*int*) – The number of heads in the multiheadattention models (default=8).
- **d_k** (*int*) – Total number of features in key.
- **d_v** (*int*) – Total number of features in value.
- **d_model** (*int*) – The number of expected features in the decoder inputs (default=512).
- **d_inner** (*int*) – The dimension of the feedforward network model (default=256).
- **dropout** (*float*) – Dropout layer on attn_output_weights.
- **init_cfg** (*dict or list[dict], optional*) – Initialization configs.

forward(*feat*, *img_metas=None*)

Parameters

- **feat** (*Tensor*) – Backbone output of shape (N, C, H, W).
- **img_metas** (*dict*) – A dict that contains meta information of input images. Preferably with the key `valid_ratio`.

Returns The encoder output tensor. Shape (N, T, C).

Return type Tensor

class mmocr.models.textrecog.encoders.**SAREncoder**(*enc_bi_rnn=False*, *enc_do_rnn=0.0*, *enc_gru=False*, *d_model=512*, *d_enc=512*, *mask=True*, *init_cfg=[{'type': 'Xavier', 'layer': 'Conv2d'}, {'type': 'Uniform', 'layer': 'BatchNorm2d'}]*, ***kwargs*)

Implementation of encoder module in `SAR.

<https://arxiv.org/abs/1811.00751>`_.

Parameters

- **enc_bi_rnn** (*bool*) – If True, use bidirectional RNN in encoder.
- **enc_do_rnn** (*float*) – Dropout probability of RNN layer in encoder.
- **enc_gru** (*bool*) – If True, use GRU, else LSTM in encoder.
- **d_model** (*int*) – Dim D_i of channels from backbone.
- **d_enc** (*int*) – Dim D_m of encoder RNN layer.
- **mask** (*bool*) – If True, mask padding in RNN sequence.
- **init_cfg** (*dict or list[dict], optional*) – Initialization configs.

forward(*feat*, *img_metas=None*)

Parameters

- **feat** (*Tensor*) – Tensor of shape (N, D_i, H, W).
- **img_metas** (*dict*) – A dict that contains meta information of input images. Preferably with the key `valid_ratio`.

Returns A tensor of shape (N, D_m).

Return type Tensor

class mmocr.models.textrecog.encoders.**SatrnEncoder**(*n_layers=12*, *n_head=8*, *d_k=64*, *d_v=64*, *d_model=512*, *n_position=100*, *d_inner=256*, *dropout=0.1*, *init_cfg=None*, ***kwargs*)

Implement encoder for SATRN, see `SATRN.

<https://arxiv.org/abs/1910.04396>`_.

Parameters

- **n_layers** (*int*) – Number of attention layers.
- **n_head** (*int*) – Number of parallel attention heads.
- **d_k** (*int*) – Dimension of the key vector.
- **d_v** (*int*) – Dimension of the value vector.
- **d_model** (*int*) – Dimension D_m of the input from previous model.
- **n_position** (*int*) – Length of the positional encoding vector. Must be greater than `max_seq_len`.
- **d_inner** (*int*) – Hidden dimension of feedforward layers.
- **dropout** (*float*) – Dropout rate.
- **init_cfg** (*dict or list[dict], optional*) – Initialization configs.

forward(*feat*, *img_metas=None*)

Parameters

- **feat** (*Tensor*) – Feature tensor of shape (N, D_m, H, W).
- **img_metas** (*dict*) – A dict that contains meta information of input images. Preferably with the key `valid_ratio`.

Returns A tensor of shape (N, T, D_m).

Return type Tensor

class mmocr.models.textrecog.encoders.**TransformerEncoder**(*n_layers=2*, *n_head=8*, *d_model=512*, *d_inner=2048*, *dropout=0.1*, *max_len=256*, *init_cfg=None*)

Implement transformer encoder for text recognition, modified from <*https://github.com/FangShancheng/ABINet*>.

Parameters

- **n_layers** (*int*) – Number of attention layers.
- **n_head** (*int*) – Number of parallel attention heads.
- **d_model** (*int*) – Dimension D_m of the input from previous model.
- **d_inner** (*int*) – Hidden dimension of feedforward layers.
- **dropout** (*float*) – Dropout rate.
- **max_len** (*int*) – Maximum output sequence length T.
- **init_cfg** (*dict or list[dict], optional*) – Initialization configs.

forward(*feature*)

Parameters **feature** (*Tensor*) – Feature tensor of shape (N, D_m, H, W).

Returns Features of shape (N, D_m, H, W).

Return type Tensor

26.16 Text Recognition Decoders

class mmocr.models.textrecog.decoders.**ABILanguageDecoder**(*d_model=512*, *n_head=8*, *d_inner=2048*, *n_layers=4*, *max_seq_len=40*, *dropout=0.1*, *detach_tokens=True*, *num_chars=90*, *use_self_attn=False*, *pad_idx=0*, *init_cfg=None*, ***kwargs*)

Transformer-based language model responsible for spell correction. Implementation of language model of ABINet.

Parameters

- **d_model** (*int*) – Hidden size of input.
- **n_head** (*int*) – Number of multi-attention heads.
- **d_inner** (*int*) – Hidden size of feedforward network model.
- **n_layers** (*int*) – The number of similar decoding layers.
- **max_seq_len** (*int*) – Maximum text sequence length T.
- **dropout** (*float*) – Dropout rate.
- **detach_tokens** (*bool*) – Whether to block the gradient flow at input tokens.
- **num_chars** (*int*) – Number of text characters C.
- **use_self_attn** (*bool*) – If True, use self attention in decoder layers, otherwise cross attention will be used.
- **pad_idx** (*bool*) – The index of the token indicating the end of output, which is used to compute the length of output. It is usually the index of *<EOS>* or *<PAD>* token.
- **init_cfg** (*dict*) – Specifies the initialization method for model layers.

forward_train(*feat*, *logits*, *targets_dict*, *img_metas*)

Parameters **logits** (*Tensor*) – Raw language logitis. Shape (N, T, C).

Returns

A dict with keys `feature` and `logits`. feature (Tensor): Shape (N, T, E). Raw textual features for vision

language aligner.

logits (Tensor): Shape (N, T, C). The raw logits for characters after spell correction.

class mmocr.models.textrecog.decoders.**ABIVisionDecoder**(*in_channels=512*, *num_channels=64*, *attn_height=8*, *attn_width=32*, *attn_mode='nearest'*, *max_seq_len=40*, *num_chars=90*, *init_cfg={'layer': 'Conv2d', 'type': 'Xavier'}*, ***kwargs*)

Converts visual features into text characters.

Implementation of VisionEncoder in ABINet.

Parameters

- **in_channels** (*int*) – Number of channels E of input vector.
- **num_channels** (*int*) – Number of channels of hidden vectors in mini U-Net.
- **h** (*int*) – Height H of input image features.
- **w** (*int*) – Width W of input image features.
- **in_channels** – Number of channels of input image features.
- **num_channels** – Number of channels of hidden vectors in mini U-Net.
- **attn_height** (*int*) – Height H of input image features.
- **attn_width** (*int*) – Width W of input image features.
- **attn_mode** (*str*) – Upsampling mode for `torch.nn.Upsample` in mini U-Net.
- **max_seq_len** (*int*) – Maximum text sequence length T.
- **num_chars** (*int*) – Number of text characters C.
- **init_cfg** (*dict*) – Specifies the initialization method for model layers.

forward_train(*feat*, *out_enc=None*, *targets_dict=None*, *img_metas=None*)

Parameters **feat** (*Tensor*) – Image features of shape (N, E, H, W).

Returns

A dict with keys `feature`, `logits` and `attn_scores`.

- feature (Tensor): Shape (N, T, E). Raw visual features for language decoder.
- logits (Tensor): Shape (N, T, C). The raw logits for characters.
- attn_scores (Tensor): Shape (N, T, H, W). Intermediate result for vision-language aligner.

Return type dict

class mmocr.models.textrecog.decoders.**BaseDecoder**(*init_cfg=None*, ***kwargs*)

Base decoder class for text recognition.

forward(*feat*, *out_enc*, *targets_dict=None*, *img_metas=None*, *train_mode=True*)

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 mmocr.models.textrecog.decoders.**CRNNDecoder**(*in_channels=None*, *num_classes=None*, *rnn_flag=False*, *init_cfg={'layer': 'Conv2d', 'type': 'Xavier'}*, ***kwargs*)

Decoder for CRNN.

Parameters

- **in_channels** (*int*) – Number of input channels.
- **num_classes** (*int*) – Number of output classes.
- **rnn_flag** (*bool*) – Use RNN or CNN as the decoder.
- **init_cfg** (*dict or list[dict], optional*) – Initialization configs.

forward_test(*feat*, *out_enc*, *img_metas*)

Parameters **feat** (*Tensor*) – A Tensor of shape $(N, H, 1, W)$.

Returns The raw logit tensor. Shape (N, W, C) where C is num_classes.

Return type Tensor

forward_train(*feat*, *out_enc*, *targets_dict*, *img_metas*)

Parameters **feat** (*Tensor*) – A Tensor of shape $(N, H, 1, W)$.

Returns The raw logit tensor. Shape (N, W, C) where C is num_classes.

Return type Tensor

class mmocr.models.textrecog.decoders.**NRTRDecoder**(*n_layers=6*, *d_embedding=512*, *n_head=8*, *d_k=64*, *d_v=64*, *d_model=512*, *d_inner=256*, *n_position=200*, *dropout=0.1*, *num_classes=93*, *max_seq_len=40*, *start_idx=1*, *padding_idx=92*, *init_cfg=None*, ***kwargs*)

Transformer Decoder block with self attention mechanism.

Parameters

- **n_layers** (*int*) – Number of attention layers.
- **d_embedding** (*int*) – Language embedding dimension.
- **n_head** (*int*) – Number of parallel attention heads.
- **d_k** (*int*) – Dimension of the key vector.
- **d_v** (*int*) – Dimension of the value vector.
- **d_model** (*int*) – Dimension D_m of the input from previous model.
- **d_inner** (*int*) – Hidden dimension of feedforward layers.
- **n_position** (*int*) – Length of the positional encoding vector. Must be greater than max_seq_len.
- **dropout** (*float*) – Dropout rate.
- **num_classes** (*int*) – Number of output classes C.
- **max_seq_len** (*int*) – Maximum output sequence length T.
- **start_idx** (*int*) – The index of <*SOS*>.
- **padding_idx** (*int*) – The index of <*PAD*>.

- **init_cfg** (*dict or list[dict], optional*) – Initialization configs.

Warning: This decoder will not predict the final class which is assumed to be <*PAD*>. Therefore, its output size is always $C - 1$. <*PAD*> is also ignored by loss as specified in *mmocr.models.textrecog.recognizer.EncodeDecodeRecognizer*.

forward_train(*feat*, *out_enc*, *targets_dict*, *img_metas*)

Parameters

- **feat** (*None*) – Unused.
- **out_enc** (*Tensor*) – Encoder output of shape (N, T, D_m) where D_m is `d_model`.
- **targets_dict** (*dict*) – A dict with the key `padded_targets`, a tensor of shape (N, T). Each element is the index of a character.
- **img_metas** (*dict*) – A dict that contains meta information of input images. Preferably with the key `valid_ratio`.

Returns The raw logit tensor. Shape (N, T, C).

Return type Tensor

static get_subsequent_mask(*seq*)

For masking out the subsequent info.

class mmocr.models.textrecog.decoders.**ParallelSARDecoder**(*num_classes=37*, *enc_bi_rnn=False*, *dec_bi_rnn=False*, *dec_do_rnn=0.0*, *dec_gru=False*, *d_model=512*, *d_enc=512*, *d_k=64*, *pred_dropout=0.0*, *max_seq_len=40*, *mask=True*, *start_idx=0*, *padding_idx=92*, *pred_concat=False*, *init_cfg=None*, ***kwargs*)

Implementation Parallel Decoder module in `SAR.

<https://arxiv.org/abs/1811.00751>`_.

Parameters

- **num_classes** (*int*) – Output class number C.
- **channels** (*list[int]*) – Network layer channels.
- **enc_bi_rnn** (*bool*) – If True, use bidirectional RNN in encoder.
- **dec_bi_rnn** (*bool*) – If True, use bidirectional RNN in decoder.
- **dec_do_rnn** (*float*) – Dropout of RNN layer in decoder.
- **dec_gru** (*bool*) – If True, use GRU, else LSTM in decoder.
- **d_model** (*int*) – Dim of channels from backbone D_i.
- **d_enc** (*int*) – Dim of encoder RNN layer D_m.
- **d_k** (*int*) – Dim of channels of attention module.
- **pred_dropout** (*float*) – Dropout probability of prediction layer.
- **max_seq_len** (*int*) – Maximum sequence length for decoding.

- **mask** (*bool*) – If True, mask padding in feature map.
- **start_idx** (*int*) – Index of start token.
- **padding_idx** (*int*) – Index of padding token.
- **pred_concat** (*bool*) – If True, concat glimpse feature from attention with holistic feature and hidden state.
- **init_cfg** (*dict or list[dict], optional*) – Initialization configs.

Warning: This decoder will not predict the final class which is assumed to be <*PAD*>. Therefore, its output size is always $C - 1$. <*PAD*> is also ignored by loss as specified in *mmocr.models.textrecog.recognizer.EncodeDecodeRecognizer*.

forward_test(*feat*, *out_enc*, *img_metas*)

Parameters

- **feat** (*Tensor*) – Tensor of shape (N, D_i, H, W).
- **out_enc** (*Tensor*) – Encoder output of shape (N, D_m, H, W).
- **img_metas** (*dict*) – A dict that contains meta information of input images. Preferably with the key `valid_ratio`.

Returns A raw logit tensor of shape $(N, T, C - 1)$.

Return type Tensor

forward_train(*feat*, *out_enc*, *targets_dict*, *img_metas*)

Parameters

- **feat** (*Tensor*) – Tensor of shape (N, D_i, H, W).
- **out_enc** (*Tensor*) – Encoder output of shape (N, D_m, H, W).
- **targets_dict** (*dict*) – A dict with the key `padded_targets`, a tensor of shape (N, T). Each element is the index of a character.
- **img_metas** (*dict*) – A dict that contains meta information of input images. Preferably with the key `valid_ratio`.

Returns A raw logit tensor of shape $(N, T, C - 1)$.

Return type Tensor

class mmocr.models.textrecog.decoders.**ParallelSARDecoderWithBS**(*beam_width=5*, *num_classes=37*, *enc_bi_rnn=False*, *dec_bi_rnn=False*, *dec_do_rnn=0*, *dec_gru=False*, *d_model=512*, *d_enc=512*, *d_k=64*, *pred_dropout=0.0*, *max_seq_len=40*, *mask=True*, *start_idx=0*, *padding_idx=0*, *pred_concat=False*, *init_cfg=None*, ***kwargs*)

Parallel Decoder module with beam-search in SAR.

Parameters **beam_width** (*int*) – Width for beam search.

forward_test(*feat*, *out_enc*, *img_metas*)

Parameters

- **feat** (*Tensor*) – Tensor of shape (N, D_i, H, W).
- **out_enc** (*Tensor*) – Encoder output of shape (N, D_m, H, W).
- **img_metas** (*dict*) – A dict that contains meta information of input images. Preferably with the key `valid_ratio`.

Returns A raw logit tensor of shape $(N, T, C-1)$.

Return type Tensor

class mmocr.models.textrecog.decoders.**PositionAttentionDecoder**(*num_classes=None*, *rnn_layers=2*, *dim_input=512*, *dim_model=128*, *max_seq_len=40*, *mask=True*, *return_feature=False*, *encode_value=False*, *init_cfg=None*)

Position attention decoder for RobustScanner.

RobustScanner: RobustScanner: Dynamically Enhancing Positional Clues for Robust Text Recognition

Parameters

- **num_classes** (*int*) – Number of output classes C.
- **rnn_layers** (*int*) – Number of RNN layers.
- **dim_input** (*int*) – Dimension D_i of input vector `feat`.
- **dim_model** (*int*) – Dimension D_m of the model. Should also be the same as encoder output vector `out_enc`.
- **max_seq_len** (*int*) – Maximum output sequence length T.
- **mask** (*bool*) – Whether to mask input features according to `img_meta['valid_ratio']`.
- **return_feature** (*bool*) – Return feature or logits as the result.
- **encode_value** (*bool*) – Whether to use the output of encoder `out_enc` as *value* of attention layer. If False, the original feature `feat` will be used.
- **init_cfg** (*dict or list[dict], optional*) – Initialization configs.

Warning: This decoder will not predict the final class which is assumed to be <*PAD*>. Therefore, its output size is always $C - 1$. <*PAD*> is also ignored by loss as specified in *mmocr.models.textrecog.recognizer.EncodeDecodeRecognizer*.

forward_test(*feat*, *out_enc*, *img_metas*)

Parameters

- **feat** (*Tensor*) – Tensor of shape (N, D_i, H, W).
- **out_enc** (*Tensor*) – Encoder output of shape (N, D_m, H, W).
- **img_metas** (*dict*) – A dict that contains meta information of input images. Preferably with the key `valid_ratio`.

Returns A raw logit tensor of shape $(N, T, C-1)$ if `return_feature=False`. Otherwise it would be the hidden feature before the prediction projection layer, whose shape is (N, T, D_m).

Return type Tensor

forward_train(*feat*, *out_enc*, *targets_dict*, *img_metas*)

Parameters

- **feat** (*Tensor*) – Tensor of shape (N, D_i, H, W).
- **out_enc** (*Tensor*) – Encoder output of shape (N, D_m, H, W).
- **targets_dict** (*dict*) – A dict with the key `padded_targets`, a tensor of shape (N, T). Each element is the index of a character.
- **img_metas** (*dict*) – A dict that contains meta information of input images. Preferably with the key `valid_ratio`.

Returns A raw logit tensor of shape $(N, T, C-1)$ if `return_feature=False`. Otherwise it will be the hidden feature before the prediction projection layer, whose shape is (N, T, D_m).

Return type Tensor

class mmocr.models.textrecog.decoders.**RobustScannerDecoder**(*num_classes=None*, *dim_input=512*, *dim_model=128*, *max_seq_len=40*, *start_idx=0*, *mask=True*, *padding_idx=None*, *encode_value=False*, *hybrid_decoder=None*, *position_decoder=None*, *init_cfg=None*)

Decoder for RobustScanner.

RobustScanner: RobustScanner: Dynamically Enhancing Positional Clues for Robust Text Recognition

Parameters

- **num_classes** (*int*) – Number of output classes C.
- **dim_input** (*int*) – Dimension D_i of input vector `feat`.
- **dim_model** (*int*) – Dimension D_m of the model. Should also be the same as encoder output vector `out_enc`.
- **max_seq_len** (*int*) – Maximum output sequence length T.
- **start_idx** (*int*) – The index of <*SOS*>.
- **mask** (*bool*) – Whether to mask input features according to `img_meta['valid_ratio']`.
- **padding_idx** (*int*) – The index of <*PAD*>.
- **encode_value** (*bool*) – Whether to use the output of encoder `out_enc` as *value* of attention layer. If False, the original feature `feat` will be used.
- **hybrid_decoder** (*dict*) – Configuration dict for hybrid decoder.
- **position_decoder** (*dict*) – Configuration dict for position decoder.
- **init_cfg** (*dict or list[dict], optional*) – Initialization configs.

Warning: This decoder will not predict the final class which is assumed to be <*PAD*>. Therefore, its output size is always $C - 1$. <*PAD*> is also ignored by loss as specified in *mmocr.models.textrecog.recognizer.EncodeDecodeRecognizer*.

forward_test(*feat*, *out_enc*, *img_metas*)

Parameters

- **feat** (*Tensor*) – Tensor of shape (N, D_i, H, W).
- **out_enc** (*Tensor*) – Encoder output of shape (N, D_m, H, W).
- **img_metas** (*dict*) – A dict that contains meta information of input images. Preferably with the key `valid_ratio`.

Returns The output logit sequence tensor of shape $(N, T, C - 1)$.

Return type Tensor

forward_train(*feat*, *out_enc*, *targets_dict*, *img_metas*)

Parameters

- **feat** (*Tensor*) – Tensor of shape (N, D_i, H, W).
- **out_enc** (*Tensor*) – Encoder output of shape (N, D_m, H, W).
- **targets_dict** (*dict*) – A dict with the key `padded_targets`, a tensor of shape (N, T). Each element is the index of a character.
- **img_metas** (*dict*) – A dict that contains meta information of input images. Preferably with the key `valid_ratio`.

Returns A raw logit tensor of shape $(N, T, C - 1)$.

Return type Tensor

class mmocr.models.textrecog.decoders.**SequenceAttentionDecoder**(*num_classes=None*, *rnn_layers=2*, *dim_input=512*, *dim_model=128*, *max_seq_len=40*, *start_idx=0*, *mask=True*, *padding_idx=None*, *dropout=0*, *return_feature=False*, *encode_value=False*, *init_cfg=None*)

Sequence attention decoder for RobustScanner.

RobustScanner: RobustScanner: Dynamically Enhancing Positional Clues for Robust Text Recognition

Parameters

- **num_classes** (*int*) – Number of output classes C.
- **rnn_layers** (*int*) – Number of RNN layers.
- **dim_input** (*int*) – Dimension D_i of input vector `feat`.
- **dim_model** (*int*) – Dimension D_m of the model. Should also be the same as encoder output vector `out_enc`.
- **max_seq_len** (*int*) – Maximum output sequence length T.

- **start_idx** (*int*) – The index of <*SOS*>.
- **mask** (*bool*) – Whether to mask input features according to `img_meta['valid_ratio']`.
- **padding_idx** (*int*) – The index of <*PAD*>.
- **dropout** (*float*) – Dropout rate.
- **return_feature** (*bool*) – Return feature or logits as the result.
- **encode_value** (*bool*) – Whether to use the output of encoder `out_enc` as *value* of attention layer. If False, the original feature `feat` will be used.
- **init_cfg** (*dict or list[dict], optional*) – Initialization configs.

Warning: This decoder will not predict the final class which is assumed to be <*PAD*>. Therefore, its output size is always $C - 1$. <*PAD*> is also ignored by loss as specified in *mmocr.models.textrecog.recognizer.EncodeDecodeRecognizer*.

forward_test(*feat*, *out_enc*, *img_metas*)

Parameters

- **feat** (*Tensor*) – Tensor of shape (N, D_i, H, W).
- **out_enc** (*Tensor*) – Encoder output of shape (N, D_m, H, W).
- **img_metas** (*dict*) – A dict that contains meta information of input images. Preferably with the key `valid_ratio`.

Returns The output logit sequence tensor of shape $(N, T, C - 1)$.

Return type Tensor

forward_test_step(*feat*, *out_enc*, *decode_sequence*, *current_step*, *img_metas*)

Parameters

- **feat** (*Tensor*) – Tensor of shape (N, D_i, H, W).
- **out_enc** (*Tensor*) – Encoder output of shape (N, D_m, H, W).
- **decode_sequence** (*Tensor*) – Shape (N, T). The tensor that stores history decoding result.
- **current_step** (*int*) – Current decoding step.
- **img_metas** (*dict*) – A dict that contains meta information of input images. Preferably with the key `valid_ratio`.

Returns Shape $(N, C - 1)$. The logit tensor of predicted tokens at current time step.

Return type Tensor

forward_train(*feat*, *out_enc*, *targets_dict*, *img_metas*)

Parameters

- **feat** (*Tensor*) – Tensor of shape (N, D_i, H, W).
- **out_enc** (*Tensor*) – Encoder output of shape (N, D_m, H, W).

- **targets_dict** (*dict*) – A dict with the key `padded_targets`, a tensor of shape (N, T). Each element is the index of a character.
- **img_metas** (*dict*) – A dict that contains meta information of input images. Preferably with the key `valid_ratio`.

Returns A raw logit tensor of shape $(N, T, C-1)$ if `return_feature=False`. Otherwise it would be the hidden feature before the prediction projection layer, whose shape is (N, T, D_m).

Return type Tensor

class mmocr.models.textrecog.decoders.**SequentialSARDecoder**(*num_classes=37*, *enc_bi_rnn=False*, *dec_bi_rnn=False*, *dec_gru=False*, *d_k=64*, *d_model=512*, *d_enc=512*, *pred_dropout=0.0*, *mask=True*, *max_seq_len=40*, *start_idx=0*, *padding_idx=92*, *pred_concat=False*, *init_cfg=None*, ***kwargs*)

Implementation Sequential Decoder module in `SAR.

<https://arxiv.org/abs/1811.00751>`_.

Parameters

- **num_classes** (*int*) – Output class number C.
- **enc_bi_rnn** (*bool*) – If True, use bidirectional RNN in encoder.
- **dec_bi_rnn** (*bool*) – If True, use bidirectional RNN in decoder.
- **dec_do_rnn** (*float*) – Dropout of RNN layer in decoder.
- **dec_gru** (*bool*) – If True, use GRU, else LSTM in decoder.
- **d_k** (*int*) – Dim of conv layers in attention module.
- **d_model** (*int*) – Dim of channels from backbone D_i.
- **d_enc** (*int*) – Dim of encoder RNN layer D_m.
- **pred_dropout** (*float*) – Dropout probability of prediction layer.
- **max_seq_len** (*int*) – Maximum sequence length during decoding.
- **mask** (*bool*) – If True, mask padding in feature map.
- **start_idx** (*int*) – Index of start token.
- **padding_idx** (*int*) – Index of padding token.
- **pred_concat** (*bool*) – If True, concat glimpse feature from attention with holistic feature and hidden state.

forward_test(*feat*, *out_enc*, *img_metas*)

Parameters

- **feat** (*Tensor*) – Tensor of shape (N, D_i, H, W).
- **out_enc** (*Tensor*) – Encoder output of shape (N, D_m, H, W).
- **img_metas** (*dict*) – A dict that contains meta information of input images. Preferably with the key `valid_ratio`.

Returns A raw logit tensor of shape $(N, T, C-1)$.

Return type Tensor

forward_train(*feat*, *out_enc*, *targets_dict*, *img_metas=None*)

Parameters

- **feat** (*Tensor*) – Tensor of shape (N, D_i, H, W).
- **out_enc** (*Tensor*) – Encoder output of shape (N, D_m, H, W).
- **targets_dict** (*dict*) – A dict with the key `padded_targets`, a tensor of shape (N, T). Each element is the index of a character.
- **img_metas** (*dict*) – A dict that contains meta information of input images. Preferably with the key `valid_ratio`.

Returns A raw logit tensor of shape $(N, T, C-1)$.

Return type Tensor

26.17 Text Recognition Fusers

class mmocr.models.textrecog.fusers.**ABIFuser**(*d_model=512*, *max_seq_len=40*, *num_chars=90*, *init_cfg=None*, ***kwargs*)

Mix and align visual feature and linguistic feature Implementation of language model of ABINet.

Parameters

- **d_model** (*int*) – Hidden size of input.
- **max_seq_len** (*int*) – Maximum text sequence length T.
- **num_chars** (*int*) – Number of text characters C.
- **init_cfg** (*dict*) – Specifies the initialization method for model layers.

forward(*l_feature*, *v_feature*)

Parameters

- **l_feature** – (N, T, E) where T is length, N is batch size and d is dim of model.
- **v_feature** – (N, T, E) shape the same as l_feature.

Returns

A dict with key `logits` The logits of shape (N, T, C) where N is batch size, T is length and C is the number of characters.

26.18 Text Recognition Losses

class mmocr.models.textrecog.losses.**ABILoss**(*enc_weight=1.0*, *dec_weight=1.0*, *fusion_weight=1.0*, *num_classes=37*, ***kwargs*)

Implementation of ABINet multiloss that allows mixing different types of losses with weights.

Parameters

- **enc_weight** (*float*) – The weight of encoder loss. Defaults to 1.0.
- **dec_weight** (*float*) – The weight of decoder loss. Defaults to 1.0.
- **fusion_weight** (*float*) – The weight of fuser (aligner) loss. Defaults to 1.0.
- **num_classes** (*int*) – Number of unique output language tokens.

Returns A dictionary whose key/value pairs are the losses of three modules.

forward(*outputs*, *targets_dict*, *img_metas=None*)

Parameters

- **outputs** (*dict*) – The output dictionary with at least one of `out_enc`, `out_dec` and `out_fusers` specified.
- **targets_dict** (*dict*) – The target dictionary containing the key `padded_targets`, which represents target sequences in shape (batch_size, sequence_length).

Returns A loss dictionary with `loss_visual`, `loss_lang` and `loss_fusion`. Each should either be the loss tensor or `0` if the output of its corresponding module is not given.

class mmocr.models.textrecog.losses.**CELoss**(*ignore_index=- 1*, *reduction='none'*, *ignore_first_char=False*)

Implementation of loss module for encoder-decoder based text recognition method with CrossEntropy loss.

Parameters

- **ignore_index** (*int*) – Specifies a target value that is ignored and does not contribute to the input gradient.
- **reduction** (*str*) – Specifies the reduction to apply to the output, should be one of the following: ('none', 'mean', 'sum').
- **ignore_first_char** (*bool*) – Whether to ignore the first token in target (usually the start token). If `True`, the last token of the output sequence will also be removed to be aligned with the target length.

forward(*outputs*, *targets_dict*, *img_metas=None*)

Parameters

- **outputs** (*Tensor*) – A raw logit tensor of shape (N, T, C).
- **targets_dict** (*dict*) – A dict with a key `padded_targets`, which is a tensor of shape (N, T). Each element is the index of a character.
- **img_metas** (*None*) – Unused.

Returns A loss dict with the key `loss_ce`.

Return type dict

class mmocr.models.textrecog.losses.**CTCLoss**(*flatten=True*, *blank=0*, *reduction='mean'*, *zero_infinity=False*, ***kwargs*)

Implementation of loss module for CTC-loss based text recognition.

Parameters

- **flatten** (*bool*) – If True, use flattened targets, else padded targets.
- **blank** (*int*) – Blank label. Default 0.
- **reduction** (*str*) – Specifies the reduction to apply to the output, should be one of the following: ('none', 'mean', 'sum').
- **zero_infinity** (*bool*) – Whether to zero infinite losses and the associated gradients. Default: False. Infinite losses mainly occur when the inputs are too short to be aligned to the targets.

forward(*outputs*, *targets_dict*, *img_metas=None*)

Parameters

- **outputs** (*Tensor*) – A raw logit tensor of shape (N, T, C).
- **targets_dict** (*dict*) – A dict with 3 keys `target_lengths`, `flatten_targets` and `targets`.
  - `target_lengths` (Tensor): A tensor of shape (N). Each item is the length of a word.
  - `flatten_targets` (Tensor): Used if `self.flatten=True` (default). A tensor of shape (sum(targets_dict['target_lengths'])). Each item is the index of a character.
  - `targets` (Tensor): Used if `self.flatten=False`. A tensor of (N, T). Empty slots are padded with `self.blank`.
- **img_metas** (*dict*) – A dict that contains meta information of input images. Preferably with the key `valid_ratio`.

Returns The loss dict with key `loss_ctc`.

Return type dict

class mmocr.models.textrecog.losses.**SARLoss**(*ignore_index=0*, *reduction='mean'*, ***kwargs*)

Implementation of loss module in `SAR.

<https://arxiv.org/abs/1811.00751>`_.

Parameters

- **ignore_index** (*int*) – Specifies a target value that is ignored and does not contribute to the input gradient.
- **reduction** (*str*) – Specifies the reduction to apply to the output, should be one of the following: ("none", "mean", "sum").

Warning: SARLoss assumes that the first input token is always <*SOS*>.

class mmocr.models.textrecog.losses.**SegLoss**(*seg_downsample_ratio=0.5*, *seg_with_loss_weight=True*, *ignore_index=255*, ***kwargs*)

Implementation of loss module for segmentation based text recognition method.

Parameters

- **seg_downsample_ratio** (*float*) – Downsample ratio of segmentation map.

- **seg_with_loss_weight** (*bool*) – If True, set weight for segmentation loss.
- **ignore_index** (*int*) – Specifies a target value that is ignored and does not contribute to the input gradient.

forward(*out_neck*, *out_head*, *gt_kernels*)

Parameters

- **out_neck** (*None*) – Unused.
- **out_head** (*Tensor*) – The output from head whose shape is (N, C, H, W).
- **gt_kernels** (*BitmapMasks*) – The ground truth masks.

Returns A loss dictionary with the key `loss_seg`.

Return type dict

class mmocr.models.textrecog.losses.**TFLoss**(*ignore_index=- 1*, *reduction='none'*, *flatten=True*, ***kwargs*)

Implementation of loss module for transformer.

Parameters

- **ignore_index** (*int, optional*) – The character index to be ignored in loss computation.
- **reduction** (*str*) – Type of reduction to apply to the output, should be one of the following: (“none”, “mean”, “sum”).
- **flatten** (*bool*) – Whether to flatten the vectors for loss computation.

Warning: TFLoss assumes that the first input token is always <*SOS*>.

26.19 KIE Extractors

class mmocr.models.kie.extractors.**SDMGR**(*backbone*, *neck=None*, *bbox_head=None*, *extractor={'featmap_strides': [1], 'roi_layer': {'output_size': 7, 'type': 'RoIAlign'}, 'type': 'mmdet.SingleRoIExtractor'}*, *visual_modality=False*, *train_cfg=None*, *test_cfg=None*, *class_list=None*, *init_cfg=None*, *openset=False*)

The implementation of the paper: Spatial Dual-Modality Graph Reasoning for Key Information Extraction. https://arxiv.org/abs/2103.14470.

Parameters

- **visual_modality** (*bool*) – Whether use the visual modality.
- **class_list** (*None | str*) – Mapping file of class index to class name. If None, class index will be shown in *show_results*, else class name.

extract_feat(*img*, *gt_bboxes*)

Directly extract features from the backbone+neck.

forward_test(*img*, *img_metas*, *relations*, *texts*, *gt_bboxes*, *rescale=False*)

Args: imgs (List[Tensor]): the outer list indicates test-time

augmentations and inner Tensor should have a shape NxCxHxW, which contains all images in the batch.

img_metas (List[List[dict]]): the outer list indicates test-time augs (multiscale, flip, etc.) and the inner list indicates images in a batch.

forward_train(*img*, *img_metas*, *relations*, *texts*, *gt_bboxes*, *gt_labels*)

Parameters

- **img** (*tensor*) – Input images of shape (N, C, H, W). Typically these should be mean centered and std scaled.
- **img_metas** (*list[dict]*) – A list of image info dict where each dict contains: 'img_shape', 'scale_factor', 'flip', and may also contain 'filename', 'ori_shape', 'pad_shape', and 'img_norm_cfg'. For details of the values of these keys, please see `mmdet.datasets.pipelines.Collect`.
- **relations** (*list[tensor]*) – Relations between bboxes.
- **texts** (*list[tensor]*) – Texts in bboxes.
- **gt_bboxes** (*list[tensor]*) – Each item is the truth boxes for each image in [tl_x, tl_y, br_x, br_y] format.
- **gt_labels** (*list[tensor]*) – Class indices corresponding to each box.

Returns A dictionary of loss components.

Return type dict[str, tensor]

show_result(*img*, *result*, *boxes*, *win_name=''*, *show=False*, *wait_time=0*, *out_file=None*, ***kwargs*)

Draw *result* on *img*.

Parameters

- **img** (*str or tensor*) – The image to be displayed.
- **result** (*dict*) – The results to draw on *img*.
- **boxes** (*list*) – Bbox of img.
- **win_name** (*str*) – The window name.
- **wait_time** (*int*) – Value of waitKey param. Default: 0.
- **show** (*bool*) – Whether to show the image. Default: False.
- **out_file** (*str or None*) – The output filename. Default: None.

Returns Only if not *show* or *out_file*.

Return type img (tensor)

26.20 KIE Heads

class mmocr.models.kie.heads.**SDMGRHead**(*num_chars=92*, *visual_dim=64*, *fusion_dim=1024*, *node_input=32*, *node_embed=256*, *edge_input=5*, *edge_embed=256*, *num_gnn=2*, *num_classes=26*, *loss={'type': 'SDMGRLoss'}*, *bidirectional=False*, *train_cfg=None*, *test_cfg=None*, *init_cfg={'mean': 0, 'override': {'name': 'edge_embed'}, 'std': 0.01, 'type': 'Normal'}*)

forward(*relations*, *texts*, *x=None*)

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.

26.21 KIE Losses

class mmocr.models.kie.losses.**SDMGRLoss**(*node_weight=1.0*, *edge_weight=1.0*, *ignore=- 100*)

The implementation the loss of key information extraction proposed in the paper: Spatial Dual-Modality Graph Reasoning for Key Information Extraction.

https://arxiv.org/abs/2103.14470.

forward(*node_preds*, *edge_preds*, *gts*)

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.

26.22 NER Encoders

class mmocr.models.ner.encoders.**BertEncoder**(*num_hidden_layers=12*, *initializer_range=0.02*, *vocab_size=21128*, *hidden_size=768*, *max_position_embeddings=128*, *type_vocab_size=2*, *layer_norm_eps=1e-12*, *hidden_dropout_prob=0.1*, *output_attentions=False*, *output_hidden_states=False*, *num_attention_heads=12*, *attention_probs_dropout_prob=0.1*, *intermediate_size=3072*, *hidden_act_cfg={'type': 'GeluNew'}*, *init_cfg=[{'type': 'Xavier', 'layer': 'Conv2d'}, {'type': 'Uniform', 'layer': 'BatchNorm2d'}]*)

Bert encoder :param num_hidden_layers: The number of hidden layers. :type num_hidden_layers: int :param ini-

tializer_range: :type initializer_range: float :param vocab_size: Number of words supported. :type vocab_size: int :param hidden_size: Hidden size. :type hidden_size: int :param max_position_embeddings: Max positions embedding size. :type max_position_embeddings: int :param type_vocab_size: The size of type_vocab. :type type_vocab_size: int :param layer_norm_eps: Epsilon of layer norm. :type layer_norm_eps: float :param hidden_dropout_prob: The dropout probability of hidden layer. :type hidden_dropout_prob: float :param output_attentions: Whether use the attentions in output. :type output_attentions: bool :param output_hidden_states: Whether use the hidden_states in output. :type output_hidden_states: bool :param num_attention_heads: The number of attention heads. :type num_attention_heads: int :param attention_probs_dropout_prob: The dropout probability

of attention.

Parameters

- **intermediate_size** (*int*) – The size of intermediate layer.
- **hidden_act_cfg** (*dict*) – Hidden layer activation.

forward(*results*)

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.

26.23 NER Decoders

class mmocr.models.ner.decoders.**FCDecoder**(*num_labels=None*, *hidden_dropout_prob=0.1*, *hidden_size=768*, *init_cfg=[{'type': 'Xavier', 'layer': 'Conv2d'}, {'type': 'Uniform', 'layer': 'BatchNorm2d'}]*)

FC Decoder class for Ner.

Parameters

- **num_labels** (*int*) – Number of categories mapped by entity label.
- **hidden_dropout_prob** (*float*) – The dropout probability of hidden layer.
- **hidden_size** (*int*) – Hidden layer output layer channels.

forward(*outputs*)

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.

26.24 NER Losses

class mmocr.models.ner.losses.**MaskedCrossEntropyLoss**(*num_labels=None*, *ignore_index=0*)
The implementation of masked cross entropy loss.

The mask has 1 for real tokens and 0 for padding tokens, which only keep active parts of the cross entropy loss.

Parameters

- **num_labels** (*int*) – Number of classes in labels.
- **ignore_index** (*int*) – Specifies a target value that is ignored and does not contribute to the input gradient.

forward(*logits*, *img_metas*)
Loss forword. :param logits: Model output with shape [N, C]. :param img_metas: A dict containing the following keys:

- img (list]): This parameter is reserved.
- **labels (list[int]): The labels for each word** of the sequence.
- texts (list): The words of the sequence.
- **input_ids (list): The ids for each word of** the sequence.
- **attention_mask (list): The mask for each word** of the sequence. The mask has 1 for real tokens and 0 for padding tokens. Only real tokens are attended to.
- **token_type_ids (list): The tokens for each word** of the sequence.

class mmocr.models.ner.losses.**MaskedFocalLoss**(*num_labels=None*, *ignore_index=0*)
The implementation of masked focal loss.

The mask has 1 for real tokens and 0 for padding tokens, which only keep active parts of the focal loss

Parameters

- **num_labels** (*int*) – Number of classes in labels.
- **ignore_index** (*int*) – Specifies a target value that is ignored and does not contribute to the input gradient.

forward(*logits*, *img_metas*)
Loss forword. :param logits: Model output with shape [N, C]. :param img_metas: A dict containing the following keys:

- img (list]): This parameter is reserved.
- **labels (list[int]): The labels for each word** of the sequence.
- texts (list): The words of the sequence.
- **input_ids (list): The ids for each word of** the sequence.
- **attention_mask (list): The mask for each word** of the sequence. The mask has 1 for real tokens and 0 for padding tokens. Only real tokens are attended to.
- **token_type_ids (list): The tokens for each word** of the sequence.

CHAPTER

TWENTYSEVEN

MMOCR.DATASETS

class mmocr.datasets.**BaseDataset**(*ann_file*, *loader*, *pipeline*, *img_prefix=''*, *test_mode=False*)

Custom dataset for text detection, text recognition, and their downstream tasks.

1. The text detection annotation format is as follows: The *annotations* field is optional for testing (this is one line of anno_file, with line-json-str

   converted to dict for visualizing only).

   { "file_name": "sample.jpg", "height": 1080, "width": 960, "annotations":

   [

   { "iscrowd": 0, "category_id": 1, "bbox": [357.0, 667.0, 804.0, 100.0], "segmentation": [[361, 667, 710, 670,

   72, 767, 357, 763]]

   }

   ]

   }

2. The two text recognition annotation formats are as follows: The *x1,y1,x2,y2,x3,y3,x4,y4* field is used for online crop augmentation during training.

   format1: sample.jpg hello format2: sample.jpg 20 20 100 20 100 40 20 40 hello

   Parameters

   - **ann_file** (*str*) – Annotation file path.
   - **pipeline** (*list[dict]*) – Processing pipeline.
   - **loader** (*dict*) – Dictionary to construct loader to load annotation infos.
   - **img_prefix** (*str, optional*) – Image prefix to generate full image path.
   - **test_mode** (*bool, optional*) – If set True, try...except will be turned off in __getitem__.

evaluate(*results*, *metric=None*, *logger=None*, ***kwargs*)

Evaluate the dataset.

Parameters

- **results** (*list*) – Testing results of the dataset.
- **metric** (*str | list[str]*) – Metrics to be evaluated.
- **logger** (*logging.Logger | str | None*) – Logger used for printing related information during evaluation. Default: None.

Returns float]

Return type dict[str

format_results(*results*, ***kwargs*)
Placeholder to format result to dataset-specific output.

pre_pipeline(*results*)
Prepare results dict for pipeline.

prepare_test_img(*img_info*)
Get testing data from pipeline.

Parameters **idx** (*int*) – Index of data.

Returns

Testing data after pipeline with new keys introduced by pipeline.

Return type dict

prepare_train_img(*index*)
Get training data and annotations from pipeline.

Parameters **index** (*int*) – Index of data.

Returns

Training data and annotation after pipeline with new keys introduced by pipeline.

Return type dict

class mmocr.datasets.**CustomFormatBundle**(*keys=[]*, *call_super=True*, *visualize={'boundary_key': None, 'flag': False}*)
Custom formatting bundle.

It formats common fields such as 'img' and 'proposals' as done in DefaultFormatBundle, while other fields such as 'gt_kernels' and 'gt_effective_region_mask' will be formatted to DC as follows:

- gt_kernels: to DataContainer (cpu_only=True)
- gt_effective_mask: to DataContainer (cpu_only=True)

Parameters

- **keys** (*list[str]*) – Fields to be formatted to DC only.
- **call_super** (*bool*) – If True, format common fields by DefaultFormatBundle, else format fields in keys above only.
- **visualize** (*dict*) – If flag=True, visualize gt mask for debugging.

class mmocr.datasets.**DBNetTargets**(*shrink_ratio=0.4*, *thr_min=0.3*, *thr_max=0.7*, *min_short_size=8*)
Generate gt shrunk text, gt threshold map, and their effective region masks to learn DBNet: Real-time Scene Text Detection with Differentiable Binarization [https://arxiv.org/abs/1911.08947]. This was partially adapted from https://github.com/MhLiao/DB.

Parameters

- **shrink_ratio** (*float*) – The area shrunk ratio between text kernels and their text masks.
- **thr_min** (*float*) – The minimum value of the threshold map.
- **thr_max** (*float*) – The maximum value of the threshold map.
- **min_short_size** (*int*) – The minimum size of polygon below which the polygon is invalid.

draw_border_map(*polygon*, *canvas*, *mask*)
Generate threshold map for one polygon.

Parameters

- **polygon** (*ndarray*) – The polygon boundary ndarray.
- **canvas** (*ndarray*) – The generated threshold map.
- **mask** (*ndarray*) – The generated threshold mask.

find_invalid(*results*)
Find invalid polygons.

Parameters **results** (*dict*) – The dict containing gt_mask.

Returns The indicators for ignoring polygons.

Return type ignore_tags (list[bool])

generate_targets(*results*)
Generate the gt targets for DBNet.

Parameters **results** (*dict*) – The input result dictionary.

Returns The output result dictionary.

Return type results (dict)

generate_thr_map(*img_size*, *polygons*)
Generate threshold map.

Parameters

- **img_size** (*tuple(int)*) – The image size (h,w)
- **polygons** (*list(ndarray)*) – The polygon list.

Returns The generated threshold map. thr_mask (ndarray): The effective mask of threshold map.

Return type thr_map (ndarray)

ignore_texts(*results*, *ignore_tags*)
Ignore gt masks and gt_labels while padding gt_masks_ignore in results given ignore_tags.

Parameters

- **results** (*dict*) – Result for one image.
- **ignore_tags** (*list[int]*) – Indicate whether to ignore its corresponding ground truth text.

Returns Results after filtering.

Return type results (dict)

invalid_polygon(*poly*)
Judge the input polygon is invalid or not. It is invalid if its area smaller than 1 or the shorter side of its minimum bounding box smaller than min_short_size.

Parameters **poly** (*ndarray*) – The polygon boundary point sequence.

Returns Whether the polygon is invalid.

Return type True/False (bool)

class mmocr.datasets.**FCENetTargets**(*fourier_degree=5*, *resample_step=4.0*, *center_region_shrink_ratio=0.3*, *level_size_divisors=(8, 16, 32)*, *level_proportion_range=((0, 0.4), (0.3, 0.7), (0.6, 1.0))*)

Generate the ground truth targets of FCENet: Fourier Contour Embedding for Arbitrary-Shaped Text Detection.

[https://arxiv.org/abs/2104.10442]

Parameters

- **fourier_degree** (*int*) – The maximum Fourier transform degree k.
- **resample_step** (*float*) – The step size for resampling the text center line (TCL). It's better not to exceed half of the minimum width.
- **center_region_shrink_ratio** (*float*) – The shrink ratio of text center region.
- **level_size_divisors** (*tuple(int)*) – The downsample ratio on each level.
- **level_proportion_range** (*tuple(tuple(int))*) – The range of text sizes assigned to each level.

cal_fourier_signature(*polygon*, *fourier_degree*)

Calculate Fourier signature from input polygon.

Parameters

- **polygon** (*ndarray*) – The input polygon.
- **fourier_degree** (*int*) – The maximum Fourier degree K.

Returns

An array shaped (2k+1, 2) containing real part and image part of 2k+1 Fourier coefficients.

Return type fourier_signature (ndarray)

clockwise(*c*, *fourier_degree*)

Make sure the polygon reconstructed from Fourier coefficients c in the clockwise direction.

Parameters **polygon** (*list[float]*) – The origin polygon.

Returns The polygon in clockwise point order.

Return type new_polygon (lost[float])

generate_center_region_mask(*img_size*, *text_polys*)

Generate text center region mask.

Parameters

- **img_size** (*tuple*) – The image size of (height, width).
- **text_polys** (*list[list[ndarray]]*) – The list of text polygons.

Returns The text center region mask.

Return type center_region_mask (ndarray)

generate_fourier_maps(*img_size*, *text_polys*)

Generate Fourier coefficient maps.

Parameters

- **img_size** (*tuple*) – The image size of (height, width).
- **text_polys** (*list[list[ndarray]]*) – The list of text polygons.

Returns

The Fourier coefficient real part maps. fourier_image_map (ndarray): The Fourier coefficient image part

maps.

Return type fourier_real_map (ndarray)

generate_level_targets(*img_size*, *text_polys*, *ignore_polys*)
Generate ground truth target on each level.

Parameters

- **img_size** (*list[int]*) – Shape of input image.
- **text_polys** (*list[list[ndarray]]*) – A list of ground truth polygons.
- **ignore_polys** (*list[list[ndarray]]*) – A list of ignored polygons.

Returns A list of ground target on each level.

Return type level_maps (list(ndarray))

generate_targets(*results*)
Generate the ground truth targets for FCENet.

Parameters **results** (*dict*) – The input result dictionary.

Returns The output result dictionary.

Return type results (dict)

normalize_polygon(*polygon*)
Normalize one polygon so that its start point is at right most.

Parameters **polygon** (*list[float]*) – The origin polygon.

Returns The polygon with start point at right.

Return type new_polygon (lost[float])

poly2fourier(*polygon*, *fourier_degree*)
Perform Fourier transformation to generate Fourier coefficients ck from polygon.

Parameters

- **polygon** (*ndarray*) – An input polygon.
- **fourier_degree** (*int*) – The maximum Fourier degree K.

Returns Fourier coefficients.

Return type c (ndarray(complex))

resample_polygon(*polygon*, *n=400*)
Resample one polygon with n points on its boundary.

Parameters

- **polygon** (*list[float]*) – The input polygon.
- **n** (*int*) – The number of resampled points.

Returns The resampled polygon.

Return type resampled_polygon (list[float])

class mmocr.datasets.**HardDiskLoader**(*ann_file*, *parser*, *repeat=1*)
Load annotation file from hard disk to RAM.

Parameters **ann_file** (*str*) – Annotation file path.

class mmocr.datasets.**IcdarDataset**(*ann_file*, *pipeline*, *classes=None*, *data_root=None*, *img_prefix=''*, *seg_prefix=None*, *proposal_file=None*, *test_mode=False*, *filter_empty_gt=True*, *select_first_k=-1*)

evaluate(*results*, *metric='hmean-iou'*, *logger=None*, *score_thr=0.3*, *rank_list=None*, ***kwargs*)
Evaluate the hmean metric.

Parameters

- **results** (*list[dict]*) – Testing results of the dataset.
- **metric** (*str | list[str]*) – Metrics to be evaluated.
- **logger** (*logging.Logger | str | None*) – Logger used for printing related information during evaluation. Default: None.
- **rank_list** (*str*) – json file used to save eval result of each image after ranking.

Returns float]]: The evaluation results.

Return type dict[dict[str

load_annotations(*ann_file*)
Load annotation from COCO style annotation file.

Parameters **ann_file** (*str*) – Path of annotation file.

Returns Annotation info from COCO api.

Return type list[dict]

class mmocr.datasets.**KIEDataset**(*ann_file=None*, *loader=None*, *dict_file=None*, *img_prefix=''*, *pipeline=None*, *norm=10.0*, *directed=False*, *test_mode=True*, ***kwargs*)

Parameters

- **ann_file** (*str*) – Annotation file path.
- **pipeline** (*list[dict]*) – Processing pipeline.
- **loader** (*dict*) – Dictionary to construct loader to load annotation infos.
- **img_prefix** (*str, optional*) – Image prefix to generate full image path.
- **test_mode** (*bool, optional*) – If True, try...except will be turned off in __getitem__.
- **dict_file** (*str*) – Character dict file path.
- **norm** (*float*) – Norm to map value from one range to another.

compute_relation(*boxes*)
Compute relation between every two boxes.

evaluate(*results*, *metric='macro_f1'*, *metric_options={'macro_f1': {'ignores': []}}*, ***kwargs*)
Evaluate the dataset.

Parameters

- **results** (*list*) – Testing results of the dataset.
- **metric** (*str | list[str]*) – Metrics to be evaluated.

- **logger** (*logging.Logger | str | None*) – Logger used for printing related information during evaluation. Default: None.

Returns float]

Return type dict[str

list_to_numpy(*ann_infos*)
Convert bboxes, relations, texts and labels to ndarray.

pad_text_indices(*text_inds*)
Pad text index to same length.

pre_pipeline(*results*)
Prepare results dict for pipeline.

prepare_train_img(*index*)
Get training data and annotations from pipeline.

Parameters **index** (*int*) – Index of data.

Returns

Training data and annotation after pipeline with new keys introduced by pipeline.

Return type dict

class mmocr.datasets.**LineJsonParser**(*keys=[]*)
Parse json-string of one line in annotation file to dict format.
Parameters **keys** (*list[str]*) – Keys in both json-string and result dict.

class mmocr.datasets.**LineStrParser**(*keys=['filename', 'text']*, *keys_idx=[0, 1]*, *separator=' '*, ***kwargs*)
Parse string of one line in annotation file to dict format.
Parameters

- **keys** (*list[str]*) – Keys in result dict.
- **keys_idx** (*list[int]*) – Value index in sub-string list for each key above.
- **separator** (*str*) – Separator to separate string to list of sub-string.

class mmocr.datasets.**LmdbLoader**(*ann_file*, *parser*, *repeat=1*)
Load annotation file with lmdb storage backend.

class mmocr.datasets.**NerDataset**(*ann_file*, *loader*, *pipeline*, *img_prefix=''*, *test_mode=False*)
Custom dataset for named entity recognition tasks.
Parameters

- **ann_file** (*txt*) – Annotation file path.
- **loader** (*dict*) – Dictionary to construct loader to load annotation infos.
- **pipeline** (*list[dict]*) – Processing pipeline.
- **test_mode** (*bool, optional*) – If True, try…except will be turned off in __getitem__.

evaluate(*results*, *metric=None*, *logger=None*, ***kwargs*)
Evaluate the dataset.

Parameters

- **results** (*list*) – Testing results of the dataset.
- **metric** (*str | list[str]*) – Metrics to be evaluated.

- **logger** (*logging.Logger | str | None*) – Logger used for printing related information during evaluation. Default: None.

Returns

A dict containing the following keys: 'acc', 'recall', 'f1-score'.

Return type info (dict)

prepare_train_img(*index*)
Get training data and annotations after pipeline.

Parameters **index** (*int*) – Index of data.

Returns Training data and annotation after pipeline with new keys introduced by pipeline.

Return type dict

class mmocr.datasets.**OCRDataset**(*ann_file*, *loader*, *pipeline*, *img_prefix=''*, *test_mode=False*)

evaluate(*results*, *metric='acc'*, *logger=None*, ***kwargs*)
Evaluate the dataset.

Parameters

- **results** (*list*) – Testing results of the dataset.
- **metric** (*str | list[str]*) – Metrics to be evaluated.
- **logger** (*logging.Logger | str | None*) – Logger used for printing related information during evaluation. Default: None.

Returns float]

Return type dict[str

pre_pipeline(*results*)
Prepare results dict for pipeline.

class mmocr.datasets.**OCRSegDataset**(*ann_file*, *loader*, *pipeline*, *img_prefix=''*, *test_mode=False*)

pre_pipeline(*results*)
Prepare results dict for pipeline.

prepare_train_img(*index*)
Get training data and annotations from pipeline.

Parameters **index** (*int*) – Index of data.

Returns

Training data and annotation after pipeline with new keys introduced by pipeline.

Return type dict

class mmocr.datasets.**OpensetKIEDataset**(*ann_file*, *loader*, *dict_file*, *img_prefix=''*, *pipeline=None*, *norm=10.0*, *link_type='one-to-one'*, *edge_thr=0.5*, *test_mode=True*, *key_node_idx=1*, *value_node_idx=2*, *node_classes=4*)
Openset KIE classifies the nodes (i.e. text boxes) into bg/key/value categories, and additionally learns key-value relationship among nodes.

Parameters

- **ann_file** (*str*) – Annotation file path.

- **loader** (*dict*) – Dictionary to construct loader to load annotation infos.
- **dict_file** (*str*) – Character dict file path.
- **img_prefix** (*str, optional*) – Image prefix to generate full image path.
- **pipeline** (*list[dict]*) – Processing pipeline.
- **norm** (*float*) – Norm to map value from one range to another.
- **link_type** (*str*) – `one-to-one|one-to-many|many-to-one|many-to-many`. For `many-to-many`, one key box can have many values and vice versa.
- **edge_thr** (*float*) – Score threshold for a valid edge.
- **test_mode** (*bool, optional*) – If True, try...except will be turned off in __getitem__.
- **key_node_idx** (*int*) – Index of key in node classes.
- **value_node_idx** (*int*) – Index of value in node classes.
- **node_classes** (*int*) – Number of node classes.

compute_openset_f1(*preds*, *gts*)

Compute openset macro-f1 and micro-f1 score.

Parameters

- **preds** – (list[dict]): List of prediction results, including keys: `filename`, `pairs`, etc.
- **gts** – (list[dict]): List of ground-truth infos, including keys: `filename`, `pairs`, etc.

Returns Evaluation result with keys: `node_openset_micro_f1`, `node_openset_macro_f1`, `edge_openset_f1`.

Return type dict

decode_gt(*filename*)

Decode ground truth.

Assemble boxes and labels into bboxes.

decode_pred(*result*)

Decode prediction.

Assemble boxes and predicted labels into bboxes, and convert edges into matrix.

evaluate(*results*, *metric='openset_f1'*, *metric_options=None*, ***kwargs*)

Evaluate the dataset.

Parameters

- **results** (*list*) – Testing results of the dataset.
- **metric** (*str | list[str]*) – Metrics to be evaluated.
- **logger** (*logging.Logger | str | None*) – Logger used for printing related information during evaluation. Default: None.

Returns float]

Return type dict[str

list_to_numpy(*ann_infos*)

Convert bboxes, relations, texts and labels to ndarray.

pre_pipeline(*results*)
Prepare results dict for pipeline.

class mmocr.datasets.**TextDetDataset**(*ann_file*, *loader*, *pipeline*, *img_prefix=''*, *test_mode=False*)

evaluate(*results*, *metric='hmean-iou'*, *score_thr=0.3*, *rank_list=None*, *logger=None*, ***kwargs*)
Evaluate the dataset.

Parameters

- **results** (*list*) – Testing results of the dataset.
- **metric** (*str | list[str]*) – Metrics to be evaluated.
- **score_thr** (*float*) – Score threshold for prediction map.
- **logger** (*logging.Logger | str | None*) – Logger used for printing related information during evaluation. Default: None.
- **rank_list** (*str*) – json file used to save eval result of each image after ranking.

Returns float]

Return type dict[str

prepare_train_img(*index*)
Get training data and annotations from pipeline.

Parameters **index** (*int*) – Index of data.

Returns

Training data and annotation after pipeline with new keys introduced by pipeline.

Return type dict

class mmocr.datasets.**UniformConcatDataset**(*datasets*, *separate_eval=True*, *pipeline=None*, *force_apply=False*, ***kwargs*)
A wrapper of ConcatDataset which support dataset pipeline assignment and replacement.

Parameters

- **datasets** (*list[dict] | list[list[dict]]*) – A list of datasets cfgs.
- **separate_eval** (*bool*) – Whether to evaluate the results separately if it is used as validation dataset. Defaults to True.
- **pipeline** (*None | list[dict] | list[list[dict]]*) – If None, each dataset in datasets use its own pipeline; If list[dict], it will be assigned to the dataset whose pipeline is None in datasets; If list[list[dict]], pipeline of dataset which is None in datasets will be replaced by the corresponding pipeline in the list.
- **force_apply** (*bool*) – If True, apply pipeline above to each dataset even if it have its own pipeline. Default: False.

mmocr.datasets.**build_dataloader**(*dataset*, *samples_per_gpu*, *workers_per_gpu*, *num_gpus=1*, *dist=True*, *shuffle=True*, *seed=None*, *runner_type='EpochBasedRunner'*, *persistent_workers=False*, ***kwargs*)
Build PyTorch DataLoader.

In distributed training, each GPU/process has a dataloader. In non-distributed training, there is only one dataloader for all GPUs.

Parameters

- **dataset** (*Dataset*) – A PyTorch dataset.

- **samples_per_gpu** (*int*) – Number of training samples on each GPU, i.e., batch size of each GPU.
- **workers_per_gpu** (*int*) – How many subprocesses to use for data loading for each GPU.
- **num_gpus** (*int*) – Number of GPUs. Only used in non-distributed training.
- **dist** (*bool*) – Distributed training/test or not. Default: True.
- **shuffle** (*bool*) – Whether to shuffle the data at every epoch. Default: True.
- **seed** (*int, Optional*) – Seed to be used. Default: None.
- **runner_type** (*str*) – Type of runner. Default: *EpochBasedRunner*
- **persistent_workers** (*bool*) – If True, the data loader will not shutdown the worker processes after a dataset has been consumed once. This allows to maintain the workers *Dataset* instances alive. This argument is only valid when PyTorch>=1.7.0. Default: False.
- **kwargs** – any keyword argument to be used to initialize DataLoader

Returns A PyTorch dataloader.

Return type DataLoader

27.1 datasets

class mmocr.datasets.base_dataset.**BaseDataset**(*ann_file*, *loader*, *pipeline*, *img_prefix=''*, *test_mode=False*)

Custom dataset for text detection, text recognition, and their downstream tasks.

1. The text detection annotation format is as follows: The *annotations* field is optional for testing (this is one line of anno_file, with line-json-str

   converted to dict for visualizing only).

   { “file_name”: “sample.jpg”, “height”: 1080, “width”: 960, “annotations”:

   [

   { “iscrowd”: 0, “category_id”: 1, “bbox”: [357.0, 667.0, 804.0, 100.0], “segmentation”: [[361, 667, 710, 670,

   72, 767, 357, 763]]

   }

   ]

   }
2. The two text recognition annotation formats are as follows: The *x1,y1,x2,y2,x3,y3,x4,y4* field is used for online crop augmentation during training.

   format1: sample.jpg hello format2: sample.jpg 20 20 100 20 100 40 20 40 hello

   Parameters

   - **ann_file** (*str*) – Annotation file path.
   - **pipeline** (*list[dict]*) – Processing pipeline.
   - **loader** (*dict*) – Dictionary to construct loader to load annotation infos.

- **img_prefix** (*str, optional*) – Image prefix to generate full image path.
- **test_mode** (*bool, optional*) – If set True, try...except will be turned off in __getitem__.

evaluate(*results*, *metric=None*, *logger=None*, ***kwargs*)
Evaluate the dataset.

Parameters

- **results** (*list*) – Testing results of the dataset.
- **metric** (*str | list[str]*) – Metrics to be evaluated.
- **logger** (*logging.Logger | str | None*) – Logger used for printing related information during evaluation. Default: None.

Returns float]

Return type dict[str

format_results(*results*, ***kwargs*)
Placeholder to format result to dataset-specific output.

pre_pipeline(*results*)
Prepare results dict for pipeline.

prepare_test_img(*img_info*)
Get testing data from pipeline.

Parameters **idx** (*int*) – Index of data.

Returns

Testing data after pipeline with new keys introduced by pipeline.

Return type dict

prepare_train_img(*index*)
Get training data and annotations from pipeline.

Parameters **index** (*int*) – Index of data.

Returns

Training data and annotation after pipeline with new keys introduced by pipeline.

Return type dict

class mmocr.datasets.icdar_dataset.**IcdarDataset**(*ann_file*, *pipeline*, *classes=None*, *data_root=None*, *img_prefix=''*, *seg_prefix=None*, *proposal_file=None*, *test_mode=False*, *filter_empty_gt=True*, *select_first_k=-1*)

evaluate(*results*, *metric='hmean-iou'*, *logger=None*, *score_thr=0.3*, *rank_list=None*, ***kwargs*)
Evaluate the hmean metric.

Parameters

- **results** (*list[dict]*) – Testing results of the dataset.
- **metric** (*str | list[str]*) – Metrics to be evaluated.
- **logger** (*logging.Logger | str | None*) – Logger used for printing related information during evaluation. Default: None.

- **rank_list** (*str*) – json file used to save eval result of each image after ranking.

Returns float]]: The evaluation results.

Return type dict[dict[str

load_annotations(*ann_file*)
Load annotation from COCO style annotation file.

Parameters **ann_file** (*str*) – Path of annotation file.

Returns Annotation info from COCO api.

Return type list[dict]

class mmocr.datasets.ocr_dataset.**OCRDataset**(*ann_file*, *loader*, *pipeline*, *img_prefix=''*, *test_mode=False*)

evaluate(*results*, *metric='acc'*, *logger=None*, ***kwargs*)
Evaluate the dataset.

Parameters

- **results** (*list*) – Testing results of the dataset.
- **metric** (*str | list[str]*) – Metrics to be evaluated.
- **logger** (*logging.Logger | str | None*) – Logger used for printing related information during evaluation. Default: None.

Returns float]

Return type dict[str

pre_pipeline(*results*)
Prepare results dict for pipeline.

class mmocr.datasets.ocr_seg_dataset.**OCRSegDataset**(*ann_file*, *loader*, *pipeline*, *img_prefix=''*, *test_mode=False*)

pre_pipeline(*results*)
Prepare results dict for pipeline.

prepare_train_img(*index*)
Get training data and annotations from pipeline.

Parameters **index** (*int*) – Index of data.

Returns

Training data and annotation after pipeline with new keys introduced by pipeline.

Return type dict

class mmocr.datasets.text_det_dataset.**TextDetDataset**(*ann_file*, *loader*, *pipeline*, *img_prefix=''*, *test_mode=False*)

evaluate(*results*, *metric='hmean-iou'*, *score_thr=0.3*, *rank_list=None*, *logger=None*, ***kwargs*)
Evaluate the dataset.

Parameters

- **results** (*list*) – Testing results of the dataset.
- **metric** (*str | list[str]*) – Metrics to be evaluated.

- **score_thr** (*float*) – Score threshold for prediction map.
- **logger** (*logging.Logger | str | None*) – Logger used for printing related information during evaluation. Default: None.
- **rank_list** (*str*) – json file used to save eval result of each image after ranking.

Returns float]

Return type dict[str

prepare_train_img(*index*)
Get training data and annotations from pipeline.

Parameters **index** (*int*) – Index of data.

Returns

Training data and annotation after pipeline with new keys introduced by pipeline.

Return type dict

class mmocr.datasets.kie_dataset.**KIEDataset**(*ann_file=None*, *loader=None*, *dict_file=None*, *img_prefix=''*, *pipeline=None*, *norm=10.0*, *directed=False*, *test_mode=True*, ***kwargs*)

Parameters

- **ann_file** (*str*) – Annotation file path.
- **pipeline** (*list[dict]*) – Processing pipeline.
- **loader** (*dict*) – Dictionary to construct loader to load annotation infos.
- **img_prefix** (*str, optional*) – Image prefix to generate full image path.
- **test_mode** (*bool, optional*) – If True, try...except will be turned off in __getitem__.
- **dict_file** (*str*) – Character dict file path.
- **norm** (*float*) – Norm to map value from one range to another.

compute_relation(*boxes*)
Compute relation between every two boxes.

evaluate(*results*, *metric='macro_f1'*, *metric_options={'macro_f1': {'ignores': []}}*, ***kwargs*)
Evaluate the dataset.

Parameters

- **results** (*list*) – Testing results of the dataset.
- **metric** (*str | list[str]*) – Metrics to be evaluated.
- **logger** (*logging.Logger | str | None*) – Logger used for printing related information during evaluation. Default: None.

Returns float]

Return type dict[str

list_to_numpy(*ann_infos*)
Convert bboxes, relations, texts and labels to ndarray.

pad_text_indices(*text_inds*)
Pad text index to same length.

pre_pipeline(*results*)
Prepare results dict for pipeline.

prepare_train_img(*index*)
Get training data and annotations from pipeline.

Parameters **index** (*int*) – Index of data.

Returns

Training data and annotation after pipeline with new keys introduced by pipeline.

Return type dict

27.2 pipelines

class mmocr.datasets.pipelines.**ColorJitter**(***kwargs*)
An interface for torch color jitter so that it can be invoked in mmdetection pipeline.

class mmocr.datasets.pipelines.**CustomFormatBundle**(*keys=[]*, *call_super=True*, *visualize={'boundary_key': None, 'flag': False}*)
Custom formatting bundle.

It formats common fields such as 'img' and 'proposals' as done in DefaultFormatBundle, while other fields such as 'gt_kernels' and 'gt_effective_region_mask' will be formatted to DC as follows:

- gt_kernels: to DataContainer (cpu_only=True)
- gt_effective_mask: to DataContainer (cpu_only=True)

Parameters

- **keys** (*list[str]*) – Fields to be formatted to DC only.
- **call_super** (*bool*) – If True, format common fields by DefaultFormatBundle, else format fields in keys above only.
- **visualize** (*dict*) – If flag=True, visualize gt mask for debugging.

class mmocr.datasets.pipelines.**DBNetTargets**(*shrink_ratio=0.4*, *thr_min=0.3*, *thr_max=0.7*, *min_short_size=8*)
Generate gt shrunk text, gt threshold map, and their effective region masks to learn DBNet: Real-time Scene Text Detection with Differentiable Binarization [https://arxiv.org/abs/1911.08947]. This was partially adapted from https://github.com/MhLiao/DB.

Parameters

- **shrink_ratio** (*float*) – The area shrunk ratio between text kernels and their text masks.
- **thr_min** (*float*) – The minimum value of the threshold map.
- **thr_max** (*float*) – The maximum value of the threshold map.
- **min_short_size** (*int*) – The minimum size of polygon below which the polygon is invalid.

draw_border_map(*polygon*, *canvas*, *mask*)
Generate threshold map for one polygon.

Parameters

- **polygon** (*ndarray*) – The polygon boundary ndarray.
- **canvas** (*ndarray*) – The generated threshold map.

- **mask** (*ndarray*) – The generated threshold mask.

find_invalid(*results*)
Find invalid polygons.

Parameters **results** (*dict*) – The dict containing gt_mask.

Returns The indicators for ignoring polygons.

Return type ignore_tags (list[bool])

generate_targets(*results*)
Generate the gt targets for DBNet.

Parameters **results** (*dict*) – The input result dictionary.

Returns The output result dictionary.

Return type results (dict)

generate_thr_map(*img_size*, *polygons*)
Generate threshold map.

Parameters

- **img_size** (*tuple(int)*) – The image size (h,w)
- **polygons** (*list(ndarray)*) – The polygon list.

Returns The generated threshold map. thr_mask (ndarray): The effective mask of threshold map.

Return type thr_map (ndarray)

ignore_texts(*results*, *ignore_tags*)
Ignore gt masks and gt_labels while padding gt_masks_ignore in results given ignore_tags.

Parameters

- **results** (*dict*) – Result for one image.
- **ignore_tags** (*list[int]*) – Indicate whether to ignore its corresponding ground truth text.

Returns Results after filtering.

Return type results (dict)

invalid_polygon(*poly*)
Judge the input polygon is invalid or not. It is invalid if its area smaller than 1 or the shorter side of its minimum bounding box smaller than min_short_size.

Parameters **poly** (*ndarray*) – The polygon boundary point sequence.

Returns Whether the polygon is invalid.

Return type True/False (bool)

class mmocr.datasets.pipelines.**FCENetTargets**(*fourier_degree=5*, *resample_step=4.0*, *center_region_shrink_ratio=0.3*, *level_size_divisors=(8, 16, 32)*, *level_proportion_range=((0, 0.4), (0.3, 0.7), (0.6, 1.0))*)
Generate the ground truth targets of FCENet: Fourier Contour Embedding for Arbitrary-Shaped Text Detection.

[https://arxiv.org/abs/2104.10442]
Parameters

- **fourier_degree** (*int*) – The maximum Fourier transform degree k.
- **resample_step** (*float*) – The step size for resampling the text center line (TCL). It's better not to exceed half of the minimum width.
- **center_region_shrink_ratio** (*float*) – The shrink ratio of text center region.
- **level_size_divisors** (*tuple(int)*) – The downsample ratio on each level.
- **level_proportion_range** (*tuple(tuple(int))*) – The range of text sizes assigned to each level.

cal_fourier_signature(*polygon*, *fourier_degree*)

Calculate Fourier signature from input polygon.

Parameters

- **polygon** (*ndarray*) – The input polygon.
- **fourier_degree** (*int*) – The maximum Fourier degree K.

Returns

An array shaped (2k+1, 2) containing real part and image part of 2k+1 Fourier coefficients.

Return type fourier_signature (ndarray)

clockwise(*c*, *fourier_degree*)

Make sure the polygon reconstructed from Fourier coefficients c in the clockwise direction.

Parameters **polygon** (*list[float]*) – The origin polygon.

Returns The polygon in clockwise point order.

Return type new_polygon (lost[float])

generate_center_region_mask(*img_size*, *text_polys*)

Generate text center region mask.

Parameters

- **img_size** (*tuple*) – The image size of (height, width).
- **text_polys** (*list[list[ndarray]]*) – The list of text polygons.

Returns The text center region mask.

Return type center_region_mask (ndarray)

generate_fourier_maps(*img_size*, *text_polys*)

Generate Fourier coefficient maps.

Parameters

- **img_size** (*tuple*) – The image size of (height, width).
- **text_polys** (*list[list[ndarray]]*) – The list of text polygons.

Returns

The Fourier coefficient real part maps. fourier_image_map (ndarray): The Fourier coefficient image part

maps.

Return type fourier_real_map (ndarray)

generate_level_targets(*img_size*, *text_polys*, *ignore_polys*)
Generate ground truth target on each level.

Parameters

- **img_size** (*list[int]*) – Shape of input image.
- **text_polys** (*list[list[ndarray]]*) – A list of ground truth polygons.
- **ignore_polys** (*list[list[ndarray]]*) – A list of ignored polygons.

Returns A list of ground target on each level.

Return type level_maps (list(ndarray))

generate_targets(*results*)
Generate the ground truth targets for FCENet.

Parameters **results** (*dict*) – The input result dictionary.

Returns The output result dictionary.

Return type results (dict)

normalize_polygon(*polygon*)
Normalize one polygon so that its start point is at right most.

Parameters **polygon** (*list[float]*) – The origin polygon.

Returns The polygon with start point at right.

Return type new_polygon (lost[float])

poly2fourier(*polygon*, *fourier_degree*)
Perform Fourier transformation to generate Fourier coefficients ck from polygon.

Parameters

- **polygon** (*ndarray*) – An input polygon.
- **fourier_degree** (*int*) – The maximum Fourier degree K.

Returns Fourier coefficients.

Return type c (ndarray(complex))

resample_polygon(*polygon*, *n=400*)
Resample one polygon with n points on its boundary.

Parameters

- **polygon** (*list[float]*) – The input polygon.
- **n** (*int*) – The number of resampled points.

Returns The resampled polygon.

Return type resampled_polygon (list[float])

class mmocr.datasets.pipelines.**FancyPCA**(*eig_vec=None*, *eig_val=None*)
Implementation of PCA based image augmentation, proposed in the paper `Imagenet Classification With Deep Convolutional Neural Networks`.

It alters the intensities of RGB values along the principal components of ImageNet dataset.

class mmocr.datasets.pipelines.**ImgAug**(*args=None*)
A wrapper to use imgaug https://github.com/aleju/imgaug.

Parameters **args** (*[list[list|dict]]*) – The argumentation list. For details, please refer to imgaug document. Take args=[['Fliplr', 0.5], dict(cls='Affine', rotate=[-10, 10]), ['Resize', [0.5, 3.0]]] as an example. The args horizontally flip images with probability 0.5, followed by random rotation with angles in range [-10, 10], and resize with an independent scale in range [0.5, 3.0] for each side of images.

class mmocr.datasets.pipelines.**KIEFormatBundle**(*img_to_float=True*, *pad_val={'img': 0, 'masks': 0, 'seg': 255}*)

Key information extraction formatting bundle.

Based on the DefaultFormatBundle, itt simplifies the pipeline of formatting common fields, including "img", "proposals", "gt_bboxes", "gt_labels", "gt_masks", "gt_semantic_seg", "relations" and "texts". These fields are formatted as follows.

- img: (1) transpose, (2) to tensor, (3) to DataContainer (stack=True)
- proposals: (1) to tensor, (2) to DataContainer
- gt_bboxes: (1) to tensor, (2) to DataContainer
- gt_bboxes_ignore: (1) to tensor, (2) to DataContainer
- gt_labels: (1) to tensor, (2) to DataContainer
- gt_masks: (1) to tensor, (2) to DataContainer (cpu_only=True)
- **gt_semantic_seg: (1) unsqueeze dim-0 (2) to tensor,**

  (3) to DataContainer (stack=True)
- relations: (1) scale, (2) to tensor, (3) to DataContainer
- texts: (1) to tensor, (2) to DataContainer

class mmocr.datasets.pipelines.**LoadImageFromNdarray**(*to_float32=False*, *color_type='color'*, *file_client_args={'backend': 'disk'}*)

Load an image from np.ndarray.

Similar with `LoadImageFromFile`, but the image read from `results['img']`, which is np.ndarray.

class mmocr.datasets.pipelines.**LoadTextAnnotations**(*with_bbox=True*, *with_label=True*, *with_mask=False*, *with_seg=False*, *poly2mask=True*, *use_img_shape=False*)

Load annotations for text detection.

Parameters

- **with_bbox** (*bool*) – Whether to parse and load the bbox annotation. Default: True.
- **with_label** (*bool*) – Whether to parse and load the label annotation. Default: True.
- **with_mask** (*bool*) – Whether to parse and load the mask annotation. Default: False.
- **with_seg** (*bool*) – Whether to parse and load the semantic segmentation annotation. Default: False.
- **poly2mask** (*bool*) – Whether to convert the instance masks from polygons to bitmaps. Default: True.
- **use_img_shape** (*bool*) – Use the shape of loaded image from previous pipeline `LoadImageFromFile` to generate mask.

process_polygons(*polygons*)

Convert polygons to list of ndarray and filter invalid polygons.

Parameters **polygons** (*list[list]*) – Polygons of one instance.

Returns Processed polygons.

Return type list[numpy.ndarray]

class mmocr.datasets.pipelines.**MultiRotateAugOCR**(*transforms*, *rotate_degrees=None*, *force_rotate=False*)

Test-time augmentation with multiple rotations in the case that img_height > img_width.

An example configuration is as follows:

```
rotate_degrees=[0, 90, 270],
transforms=[
    dict(
        type='ResizeOCR',
        height=32,
        min_width=32,
        max_width=160,
        keep_aspect_ratio=True),
    dict(type='ToTensorOCR'),
    dict(type='NormalizeOCR', **img_norm_cfg),
    dict(
        type='Collect',
        keys=['img'],
        meta_keys=[
            'filename', 'ori_shape', 'img_shape', 'valid_ratio'
        ]),
]
```

After MultiRotateAugOCR with above configuration, the results are wrapped into lists of the same length as follows:

```
dict(
    img=[...],
    img_shape=[...]
    ...
)
```

Parameters

- **transforms** (*list[dict]*) – Transformation applied for each augmentation.
- **rotate_degrees** (*list[int] | None*) – Degrees of anti-clockwise rotation.
- **force_rotate** (*bool*) – If True, rotate image by 'rotate_degrees' while ignore image aspect ratio.

class mmocr.datasets.pipelines.**NerTransform**(*label_convertor*, *max_len*)

Convert text to ID and entity in ground truth to label ID. The masks and tokens are generated at the same time. The four parameters will be used as input to the model.

Parameters

- **label_convertor** – Convert text to ID and entity
- **ground truth to label ID.** (*in*) –
- **max_len** (*int*) – Limited maximum input length.

class mmocr.datasets.pipelines.**NormalizeOCR**(*mean*, *std*)

Normalize a tensor image with mean and standard deviation.

class mmocr.datasets.pipelines.**OCRSegTargets**(*label_convertor=None*, *attn_shrink_ratio=0.5*, *seg_shrink_ratio=0.25*, *box_type='char_rects'*, *pad_val=255*)

Generate gt shrunk kernels for segmentation based OCR framework.

Parameters

- **label_convertor** (*dict*) – Dictionary to construct label_convertor to convert char to index.
- **attn_shrink_ratio** (*float*) – The area shrunk ratio between attention kernels and gt text masks.
- **seg_shrink_ratio** (*float*) – The area shrunk ratio between segmentation kernels and gt text masks.
- **box_type** (*str*) – Character box type, should be either 'char_rects' or 'char_quads', with 'char_rects' for rectangle with `xyxy` style and 'char_quads' for quadrangle with `x1y1x2y2x3y3x4y4` style.

generate_kernels(*resize_shape*, *pad_shape*, *char_boxes*, *char_inds*, *shrink_ratio=0.5*, *binary=True*)

Generate char instance kernels for one shrink ratio.

Parameters

- **resize_shape** (*tuple(int, int)*) – Image size (height, width) after resizing.
- **pad_shape** (*tuple(int, int)*) – Image size (height, width) after padding.
- **char_boxes** (*list[list[float]]*) – The list of char polygons.
- **char_inds** (*list[int]*) – List of char indexes.
- **shrink_ratio** (*float*) – The shrink ratio of kernel.
- **binary** (*bool*) – If True, return binary ndarray containing 0 & 1 only.

Returns The text kernel mask of (height, width).

Return type char_kernel (ndarray)

shrink_char_quad(*char_quad*, *shrink_ratio*)

Shrink char box in style of quadrangle.

Parameters

- **char_quad** (*list[float]*) – Char box with format [x1, y1, x2, y2, x3, y3, x4, y4].
- **shrink_ratio** (*float*) – The area shrunk ratio between gt kernels and gt text masks.

shrink_char_rect(*char_rect*, *shrink_ratio*)

Shrink char box in style of rectangle.

Parameters

- **char_rect** (*list[float]*) – Char box with format [x_min, y_min, x_max, y_max].
- **shrink_ratio** (*float*) – The area shrunk ratio between gt kernels and gt text masks.

class mmocr.datasets.pipelines.**OneOfWrapper**(*transforms*)

Randomly select and apply one of the transforms, each with the equal chance.

Warning: Different from albumentations, this wrapper only runs the selected transform, but doesn't guarantee the transform can always be applied to the input if the transform comes with a probability to run.

Parameters **transforms** (*list[dict|callable]*) – Candidate transforms to be applied.

class mmocr.datasets.pipelines.**OnlineCropOCR**(*box_keys=['x1', 'y1', 'x2', 'y2', 'x3', 'y3', 'x4', 'y4']*, *jitter_prob=0.5*, *max_jitter_ratio_x=0.05*, *max_jitter_ratio_y=0.02*)

Crop text areas from whole image with bounding box jitter. If no bbox is given, return directly.

Parameters

- **box_keys** (*list[str]*) – Keys in results which correspond to RoI bbox.
- **jitter_prob** (*float*) – The probability of box jitter.
- **max_jitter_ratio_x** (*float*) – Maximum horizontal jitter ratio relative to height.
- **max_jitter_ratio_y** (*float*) – Maximum vertical jitter ratio relative to height.

class mmocr.datasets.pipelines.**OpencvToPil**(***kwargs*)

Convert `numpy.ndarray` (bgr) to `PIL Image` (rgb).

class mmocr.datasets.pipelines.**PANetTargets**(*shrink_ratio=(1.0, 0.5)*, *max_shrink=20*)

Generate the ground truths for PANet: Efficient and Accurate Arbitrary- Shaped Text Detection with Pixel Aggregation Network.

[https://arxiv.org/abs/1908.05900]. This code is partially adapted from https://github.com/WenmuZhou/PAN.pytorch.

Parameters

- **shrink_ratio** (*tuple[float]*) – The ratios for shrinking text instances.
- **max_shrink** (*int*) – The maximum shrink distance.

generate_targets(*results*)

Generate the gt targets for PANet.

Parameters **results** (*dict*) – The input result dictionary.

Returns The output result dictionary.

Return type results (dict)

class mmocr.datasets.pipelines.**PilToOpencv**(***kwargs*)

Convert `PIL Image` (rgb) to `numpy.ndarray` (bgr).

class mmocr.datasets.pipelines.**PyramidRescale**(*factor=4*, *base_shape=(128, 512)*, *randomize_factor=True*)

Resize the image to the base shape, downsample it with gaussian pyramid, and rescale it back to original size.

Adapted from https://github.com/FangShancheng/ABINet.

Parameters

- **factor** (*int*) – The decay factor from base size, or the number of downsampling operations from the base layer.
- **base_shape** (*tuple(int)*) – The shape of the base layer of the pyramid.
- **randomize_factor** (*bool*) – If True, the final factor would be a random integer in [0, factor].

Required Keys

- `img` (ndarray): The input image.

Affected Keys

Modified

- `img` (ndarray): The modified image.

class mmocr.datasets.pipelines.**RandomCropInstances**(*target_size*, *instance_key*, *mask_type='inx0'*, *positive_sample_ratio=0.625*)

Randomly crop images and make sure to contain text instances.

Parameters

- **target_size** (*tuple or int*) – (height, width)
- **positive_sample_ratio** (*float*) – The probability of sampling regions that go through positive regions.

class mmocr.datasets.pipelines.**RandomCropPolyInstances**(*instance_key='gt_masks'*, *crop_ratio=0.625*, *min_side_ratio=0.4*)

Randomly crop images and make sure to contain at least one intact instance.

sample_crop_box(*img_size*, *results*)

Generate crop box and make sure not to crop the polygon instances.

Parameters

- **img_size** (*tuple(int)*) – The image size (h, w).
- **results** (*dict*) – The results dict.

class mmocr.datasets.pipelines.**RandomPaddingOCR**(*max_ratio=None*, *box_type=None*)

Pad the given image on all sides, as well as modify the coordinates of character bounding box in image.

Parameters

- **max_ratio** (*list[int]*) – [left, top, right, bottom].
- **box_type** (*None|str*) – Character box type. If not none, should be either 'char_rects' or 'char_quads', with 'char_rects' for rectangle with `xyxy` style and 'char_quads' for quadrangle with `x1y1x2y2x3y3x4y4` style.

class mmocr.datasets.pipelines.**RandomRotateImageBox**(*min_angle=- 10*, *max_angle=10*, *box_type='char_quads'*)

Rotate augmentation for segmentation based text recognition.

Parameters

- **min_angle** (*int*) – Minimum rotation angle for image and box.
- **max_angle** (*int*) – Maximum rotation angle for image and box.
- **box_type** (*str*) – Character box type, should be either 'char_rects' or 'char_quads', with 'char_rects' for rectangle with `xyxy` style and 'char_quads' for quadrangle with `x1y1x2y2x3y3x4y4` style.

class mmocr.datasets.pipelines.**RandomRotateTextDet**(*rotate_ratio=1.0*, *max_angle=10*)

Randomly rotate images.

class mmocr.datasets.pipelines.**RandomWrapper**(*transforms*, *p*)

Run a transform or a sequence of transforms with probability p.

Parameters

- **transforms** (*list[dict|callable]*) – Transform(s) to be applied.
- **p** (*int|float*) – Probability of running transform(s).

class mmocr.datasets.pipelines.**ResizeNoImg**(*img_scale*, *keep_ratio=True*)
Image resizing without img.

Used for KIE.

class mmocr.datasets.pipelines.**ResizeOCR**(*height*, *min_width=None*, *max_width=None*, *keep_aspect_ratio=True*, *img_pad_value=0*, *width_downsample_ratio=0.0625*, *backend=None*)
Image resizing and padding for OCR.

Parameters

- **height** (*int | tuple(int)*) – Image height after resizing.
- **min_width** (*none | int | tuple(int)*) – Image minimum width after resizing.
- **max_width** (*none | int | tuple(int)*) – Image maximum width after resizing.
- **keep_aspect_ratio** (*bool*) – Keep image aspect ratio if True during resizing, Otherwise resize to the size height * max_width.
- **img_pad_value** (*int*) – Scalar to fill padding area.
- **width_downsample_ratio** (*float*) – Downsample ratio in horizontal direction from input image to output feature.
- **backend** (*str | None*) – The image resize backend type. Options are *cv2*, *pillow*, *None*. If backend is None, the global imread_backend specified by `mmcv.use_backend()` will be used. Default: None.

class mmocr.datasets.pipelines.**ScaleAspectJitter**(*img_scale=None*, *multiscale_mode='range'*, *ratio_range=None*, *keep_ratio=False*, *resize_type='around_min_img_scale'*, *aspect_ratio_range=None*, *long_size_bound=None*, *short_size_bound=None*, *scale_range=None*)
Resize image and segmentation mask encoded by coordinates.

Allowed resize types are *around_min_img_scale*, *long_short_bound*, and *indep_sample_in_range*.

class mmocr.datasets.pipelines.**TextSnakeTargets**(*orientation_thr=2.0*, *resample_step=4.0*, *center_region_shrink_ratio=0.3*)
Generate the ground truth targets of TextSnake: TextSnake: A Flexible Representation for Detecting Text of Arbitrary Shapes.

[https://arxiv.org/abs/1807.01544]. This was partially adapted from https://github.com/princewang1994/TextSnake.pytorch.

Parameters **orientation_thr** (*float*) – The threshold for distinguishing between head edge and tail edge among the horizontal and vertical edges of a quadrangle.

cal_curve_length(*line*)
Calculate the length of each edge on the discrete curve and the sum.

Parameters **line** (*ndarray*) – The points composing a discrete curve.

Returns

Returns (edges_length, total_length).

- edge_length (ndarray): The length of each edge on the discrete curve.
- total_length (float): The total length of the discrete curve.

Return type tuple

draw_center_region_maps(*top_line*, *bot_line*, *center_line*, *center_region_mask*, *radius_map*, *sin_map*, *cos_map*, *region_shrink_ratio*)

Draw attributes on text center region.

Parameters

- **top_line** (*ndarray*) – The points composing top curved sideline of text polygon.
- **bot_line** (*ndarray*) – The points composing bottom curved sideline of text polygon.
- **center_line** (*ndarray*) – The points composing the center line of text instance.
- **center_region_mask** (*ndarray*) – The text center region mask.
- **radius_map** (*ndarray*) – The map where the distance from point to sidelines will be drawn on for each pixel in text center region.
- **sin_map** (*ndarray*) – The map where vector_sin(theta) will be drawn on text center regions. Theta is the angle between tangent line and vector (1, 0).
- **cos_map** (*ndarray*) – The map where vector_cos(theta) will be drawn on text center regions. Theta is the angle between tangent line and vector (1, 0).
- **region_shrink_ratio** (*float*) – The shrink ratio of text center.

find_head_tail(*points*, *orientation_thr*)

Find the head edge and tail edge of a text polygon.

Parameters

- **points** (*ndarray*) – The points composing a text polygon.
- **orientation_thr** (*float*) – The threshold for distinguishing between head edge and tail edge among the horizontal and vertical edges of a quadrangle.

Returns The indexes of two points composing head edge. tail_inds (list): The indexes of two points composing tail edge.

Return type head_inds (list)

generate_center_mask_attrib_maps(*img_size*, *text_polys*)

Generate text center region mask and geometric attribute maps.

Parameters

- **img_size** (*tuple*) – The image size of (height, width).
- **text_polys** (*list[list[ndarray]]*) – The list of text polygons.

Returns

The text center region mask. radius_map (ndarray): The distance map from each pixel in text

center region to top sideline.

sin_map (ndarray): The sin(theta) map where theta is the angle between vector (top point - bottom point) and vector (1, 0).

cos_map (ndarray): The cos(theta) map where theta is the angle between vector (top point - bottom point) and vector (1, 0).

Return type center_region_mask (ndarray)

generate_targets(*results*)
Generate the gt targets for TextSnake.

Parameters **results** (*dict*) – The input result dictionary.

Returns The output result dictionary.

Return type results (dict)

generate_text_region_mask(*img_size*, *text_polys*)
Generate text center region mask and geometry attribute maps.

Parameters

- **img_size** (*tuple*) – The image size (height, width).
- **text_polys** (*list[list[ndarray]]*) – The list of text polygons.

Returns The text region mask.

Return type text_region_mask (ndarray)

reorder_poly_edge(*points*)
Get the respective points composing head edge, tail edge, top sideline and bottom sideline.

Parameters **points** (*ndarray*) – The points composing a text polygon.

Returns

The two points composing the head edge of text polygon.

tail_edge (ndarray): The two points composing the tail edge of text polygon.

top_sideline (ndarray): The points composing top curved sideline of text polygon.

bot_sideline (ndarray): The points composing bottom curved sideline of text polygon.

Return type head_edge (ndarray)

resample_line(*line*, *n*)
Resample n points on a line.

Parameters

- **line** (*ndarray*) – The points composing a line.
- **n** (*int*) – The resampled points number.

Returns The points composing the resampled line.

Return type resampled_line (ndarray)

resample_sidelines(*sideline1*, *sideline2*, *resample_step*)
Resample two sidelines to be of the same points number according to step size.

Parameters

- **sideline1** (*ndarray*) – The points composing a sideline of a text polygon.
- **sideline2** (*ndarray*) – The points composing another sideline of a text polygon.
- **resample_step** (*float*) – The resampled step size.

Returns The resampled line 1. resampled_line2 (ndarray): The resampled line 2.

Return type resampled_line1 (ndarray)

class mmocr.datasets.pipelines.**ToTensorNER**
Convert data with `list` type to tensor.

class mmocr.datasets.pipelines.**ToTensorOCR**
Convert a `PIL Image` or `numpy.ndarray` to tensor.

class mmocr.datasets.pipelines.**TorchVisionWrapper**(*op*, ***kwargs*)
A wrapper of torchvision trasnforms. It applies specific transform to `img` and updates `img_shape` accordingly.

> **Warning:** This transform only affects the image but not its associated annotations, such as word bounding boxes and polygon masks. Therefore, it may only be applicable to text recognition tasks.

Parameters

- **op** (*str*) – The name of any transform class in `torchvision.transforms()`.
- ****kwargs** – Arguments that will be passed to initializer of torchvision transform.

Required Keys

- `img` (ndarray): The input image.

Affected Keys

Modified

- `img` (ndarray): The modified image.

Added

- `img_shape` (tuple(int)): Size of the modified image.

mmocr.datasets.pipelines.**sort_vertex**(*points_x*, *points_y*)
Sort box vertices in clockwise order from left-top first.

Parameters

- **points_x** (*list[float]*) – x of four vertices.
- **points_y** (*list[float]*) – y of four vertices.

Returns x of sorted four vertices. sorted_points_y (list[float]): y of sorted four vertices.

Return type sorted_points_x (list[float])

mmocr.datasets.pipelines.**sort_vertex8**(*points*)
Sort vertex with 8 points [x1 y1 x2 y2 x3 y3 x4 y4]

27.3 utils

class mmocr.datasets.utils.**HardDiskLoader**(*ann_file*, *parser*, *repeat=1*)
Load annotation file from hard disk to RAM.

Parameters **ann_file** (*str*) – Annotation file path.

class mmocr.datasets.utils.**LineJsonParser**(*keys=[]*)
Parse json-string of one line in annotation file to dict format.

Parameters **keys** (*list[str]*) – Keys in both json-string and result dict.

class mmocr.datasets.utils.**LineStrParser**(*keys=['filename', 'text']*, *keys_idx=[0, 1]*, *separator=' '*, ***kwargs*)
Parse string of one line in annotation file to dict format.

Parameters

- **keys** (*list[str]*) – Keys in result dict.
- **keys_idx** (*list[int]*) – Value index in sub-string list for each key above.
- **separator** (*str*) – Separator to separate string to list of sub-string.

class mmocr.datasets.utils.**LmdbLoader**(*ann_file*, *parser*, *repeat=1*)

Load annotation file with lmdb storage backend.

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