MMOCR

Release 0.6.3

OpenMMLab

Apr 25, 2023

GETTING STARTED

You can switch between English and Chinese in the lower-left corner of the layout.

CHAPTER

ONE

INSTALLATION

1.1 Prerequisites

- Linux | Windows | macOS
- Python 3.7
- PyTorch 1.6 or higher
- torchvision 0.7.0
- CUDA 10.1
- NCCL 2
- GCC 5.4.0 or higher

1.2 Environment Setup

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

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

Step 1. Create a conda environment and activate it.

```
conda create --name openmmlab python=3.8 -y
conda activate openmmlab
```

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

On GPU platforms:

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

On CPU platforms:

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

1.3 Installation Steps

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

1.3.1 Best Practices

Step 0. Install MMCV using MIM.

```
pip install -U openmim
mim install mmcv-full
```

Step 1. Install MMDetection as a dependency.

```
pip install mmdet
```

Step 2. Install MMOCR.

Case A: If you wish to run and develop MMOCR directly, install it from source:

```
git clone https://github.com/open-mmlab/mmocr.git
cd mmocr
pip install -r requirements.txt
pip install -v -e .
# "-v" increases pip's verbosity.
# "-e" means installing the project in editable mode,
# That is, any local modifications on the code will take effect immediately.
```

Case B: If you use MMOCR as a dependency or third-party package, install it with pip:

```
pip install mmocr
```

Step 3. **(Optional)** If you wish to use any transform involving `albumentations` (For example, `Albu` in ABINet's pipeline), install the dependency using the following command:

```
# If MMOCR is installed from source
pip install -r requirements/albu.txt
# If MMOCR is installed via pip
pip install albumentations>=1.1.0 --no-binary qudida,albumentations
```

Note: We recommend checking the environment after installing `albumentations` to ensure that `opencv-python` and `opencv-python-headless` are not installed together, otherwise it might cause unexpected issues. If that's unfortunately the case, please uninstall `opencv-python-headless` to make sure MMOCR's visualization utilities can work.

Refer to 'albumentations`'s official documentation for more details.

1.3.2 Verify the installation

We provide two options to verify the installation via inference demo, depending on your installation method. You should be able to see a pop-up image and the inference result upon successful verification.

```
# Inference result
[{'filename': 'demo_text_det', 'text': ['ythеr', 'doyt', 'nan', 'heraies', '188790',
↪'cadets', 'army', 'ipioneered', 'and', 'icottages', 'land', 'hall', 'sgardens',
↪'established', 'ithis', 'preformer', 'social', 'octavial', 'hill', 'pm', 'ct', 'lof',
↪'aborought']}]
```

Case A - Installed from Source

Run the following in MMOCR's directory:

```
python mmocr/utils/ocr.py --det DB_r18 --recog CRNN demo/demo_text_det.jpg --imshow
```

Case B - Installed as a Package:

Step 1. We need to download configs, checkpoints and an image necessary for the verification.

```
mim download mmocr --config dbnet_r18_fpnc_1200e_icdar2015 --dest .
mim download mmocr --config crnn_academic_dataset --dest .
wget https://raw.githubusercontent.com/open-mmlab/mmocr/main/demo/demo_text_det.jpg
```

The downloading will take several seconds or more, depending on your network environment. The directory tree should look like the following once everything is done:

```
├── crnn_academic-a723a1c5.pth
├── crnn_academic_dataset.py
├── dbnet_r18_fpnc_1200e_icdar2015.py
├── dbnet_r18_fpnc_sbn_1200e_icdar2015_20210329-ba3ab597.pth
└── demo_text_det.jpg
```

Step 2. Run the following codes in your Python interpreter:

```
from mmocr.utils.ocr import MMOCR
ocr = MMOCR(recog='CRNN', recog_ckpt='crnn_academic-a723a1c5.pth', recog_config='crnn_
↪academic_dataset.py', det='DB_r18', det_ckpt='dbnet_r18_fpnc_sbn_1200e_icdar2015_
↪20210329-ba3ab597.pth', det_config='dbnet_r18_fpnc_1200e_icdar2015.py')
ocr.readtext('demo_text_det.jpg', imshow=True)
```

1.4 Customize Installation

1.4.1 CUDA versions

When installing PyTorch, you need to specify the version of CUDA. If you are not clear on which to choose, follow our recommendations:

- For Ampere-based NVIDIA GPUs, such as GeForce 30 series and NVIDIA A100, CUDA 11 is a must.
- For older NVIDIA GPUs, CUDA 11 is backward compatible, but CUDA 10.2 offers better compatibility and is more lightweight.

Please make sure the GPU driver satisfies the minimum version requirements. See this table for more information.

Note: Installing CUDA runtime libraries is enough if you follow our best practices, because no CUDA code will be compiled locally. However if you hope to compile MMCV from source or develop other CUDA operators, you need to install the complete CUDA toolkit from NVIDIA's website, and its version should match the CUDA version of PyTorch. i.e., the specified version of cudatoolkit in `conda install` command.

1.4.2 Install MMCV without MIM

MMCV contains C++ and CUDA extensions, thus depending on PyTorch in a complex way. MIM solves such dependencies automatically and makes the installation easier. However, it is not a must.

To install MMCV with pip instead of MIM, please follow MMCV installation guides. This requires manually specifying a find-url based on PyTorch version and its CUDA version.

For example, the following command install mmcv-full built for PyTorch 1.10.x and CUDA 11.3.

```
pip install mmcv-full -f https://download.openmmlab.com/mmcv/dist/cu113/torch1.10/index.
↪html
```

1.4.3 Install on CPU-only platforms

MMOCR can be built for CPU-only environment. In CPU mode you can train (requires MMCV version >= 1.4.4), test or inference a model.

However, some functionalities are gone in this mode:

- Deformable Convolution
- Modulated Deformable Convolution
- ROI pooling
- SyncBatchNorm

If you try to train/test/inference a model containing above ops, an error will be raised. The following table lists affected algorithms.

1.4.4 Using MMOCR with Docker

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 Dependency on MMCV & MMDetection

MMOCR has different version requirements on MMCV and MMDetection at each release to guarantee the implementation correctness. Please refer to the table below and ensure the package versions fit the requirement.

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/_base_/det_datasets/icdar2015.py` looks like the following:

```
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]
```

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. It exposes all the models in MMOCR to API as individual modules that can be called and chained together. Tesseract is integrated as a text detector and/or recognizer in the task pipeline.

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 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/', 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.
- MMOCR calls Tesseract's API via `tesserocr`

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 GPU

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

Here is the full usage of the script:

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

Note: By default, MMOCR prefers GPU to CPU. If you want to train a model on CPU, please empty `CUDA_VISIBLE_DEVICES` or set it to -1 to make GPU 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 GPUs

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 on Multiple Machines

You can launch a task on multiple machines connected to the same network.

```
NNODES=${NNODES} NODE_RANK=${NODE_RANK} PORT=${MASTER_PORT} MASTER_ADDR=${MASTER_ADDR} ./
↪tools/dist_train.sh ${CONFIG_FILE} ${WORK_DIR} ${GPU_NUM} [PY_ARGS]
```

Note: MMOCR relies on torch.distributed package for distributed training. Find more information at PyTorch's launch utility.

Say that you want to launch a job on two machines. On the first machine:

```
NNODES=2 NODE_RANK=0 PORT=${MASTER_PORT} MASTER_ADDR=${MASTER_ADDR} ./tools/dist_train.
↪sh ${CONFIG_FILE} ${WORK_DIR} ${GPU_NUM} [PY_ARGS]
```

On the second machine:

```
NNODES=2 NODE_RANK=1 PORT=${MASTER_PORT} MASTER_ADDR=${MASTER_ADDR} ./tools/dist_train.
↪sh ${CONFIG_FILE} ${WORK_DIR} ${GPU_NUM} [PY_ARGS]
```

Note: The speed of the network could be the bottleneck of training.

4.4 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
```

4.4.1 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}
```

4.5 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
# 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 on a 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 on 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 on Multiple Machines

You can launch a task on multiple machines connected to the same network.

```
NNODES=${NNODES} NODE_RANK=${NODE_RANK} PORT=${MASTER_PORT} MASTER_ADDR=${MASTER_ADDR} ./
↪tools/dist_test.sh ${CONFIG_FILE} ${CHECKPOINT_FILE} ${GPU_NUM} [PY_ARGS]
```

Note: MMOCR relies on torch.distributed package for distributed testing. Find more information at PyTorch's launch utility.

Say that you want to launch a job on two machines. On the first machine:

```
NNODES=2 NODE_RANK=0 PORT=${MASTER_PORT} MASTER_ADDR=${MASTER_ADDR} ./tools/dist_test.sh
↪${CONFIG_FILE} ${CHECKPOINT_FILE} ${GPU_NUM} [PY_ARGS]
```

On the second machine:

```
NNODES=2 NODE_RANK=1 PORT=${MASTER_PORT} MASTER_ADDR=${MASTER_ADDR} ./tools/dist_test.sh
↪${CONFIG_FILE} ${CHECKPOINT_FILE} ${GPU_NUM} [PY_ARGS]
```

Note: The speed of the network could be the bottleneck of testing.

5.4 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
```

5.5 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.properties`.

```
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_/default_runtime.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.

```
# The 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(  # Config to register logger hook
    interval=50,  # Interval to print the log
    hooks=[
        dict(type='TextLoggerHook', by_epoch=False),
        dict(type='TensorboardLoggerHook', by_epoch=False),
        dict(type='WandbLoggerHook', by_epoch=False, # The Wandb logger is also␣
↪supported, It requires `wandb` to be installed.
```

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```
            init_kwargs={
                        'project': "MMOCR", # Project name in WandB
                        }), # Check https://docs.wandb.ai/ref/python/init for more␣
↪init arguments.
        # ClearMLLoggerHook, DvcliveLoggerHook, MlflowLoggerHook, NeptuneLoggerHook,␣
↪PaviLoggerHook, SegmindLoggerHook are also supported based on MMCV implementation.
    ])

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}}

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 Dataset Wrapper

9.1.1 UniformConcatDataset

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

Applying a Pipeline on Multiple Datasets

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 applying 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`.

Getting Mean Evaluation Scores

Evaluating the model on multiple datasets is a common strategy in academia, and the mean score is therefore a critical indicator of the model's overall performance. By default, `UniformConcatDataset` reports mean scores in the form of `mean_{metric_name}` when more than 1 datasets are wrapped. You can customize the behavior by setting `show_mean_scores` in `data.val` and `data.test`. Choices are `'auto'`(default), `True` and `False`.

```
data = dict(
    ...
    val=dict(
        type='UniformConcatDataset',
        show_mean_scores=True,  # always show mean scores
        datasets=[train_list],
        pipeline=[train_pipeline)
    test=dict(
        type='UniformConcatDataset',
        show_mean_scores=False,  # do not show mean scores
        datasets=[train_list],
        pipeline=[train_pipeline))
```

9.2 Text Detection

9.2.1 IcdarDataset

Dataset with annotation file in coco-like json format

Example Configuration

```
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)
```

Annotation Format

You can check the content of the annotation file in `tests/data/toy_dataset/instances_test.json` for an example. It's compatible with any annotation file in COCO format defined in MMDetection:

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

Evaluation

`IcdarDataset` has implemented two evaluation metrics, `hmean-iou` and `hmean-ic13`, to evaluate the performance of text detection models, where `hmean-iou` is the most widely used metric which computes precision, recall and F-score based on IoU between ground truth and prediction.

In particular, filtering predictions with a reasonable score threshold greatly impacts the performance measurement. MMOCR alleviates such hyperparameter effect by sweeping through the hyperparameter space and returns the best performance every evaluation time. User can tune the searching scheme by passing `min_score_thr`, `max_score_thr` and `step` into the evaluation hook in the config.

For example, with the following configuration, you can evaluate the model's output on a list of boundary score thresholds [0.1, 0.2, 0.3, 0.4, 0.5] and get the best score from them **during training**.

```
evaluation = dict(
    interval=100,
    metric='hmean-iou',
    min_score_thr=0.1,
    max_score_thr=0.5,
    step=0.1)
```

During testing, you can change these parameter values by appending them to `--eval-options`.

```
python tools/test.py configs/textdet/dbnet/dbnet_r18_fpnc_1200e_icdar2015.py db_r18.pth --eval hmean-iou --eval-options min_score_thr=0.1 max_score_thr=0.6 step=0.1
```

Check out our API doc for further explanations on these parameters.

9.2.2 TextDetDataset

Dataset with annotation file in line-json txt format

We have designed new types of dataset consisting of **loader** , **backend**, and **parser** to load and parse different types of annotation files.

- **loader**: Load the annotation file. We now have a unified loader, `AnnFileLoader`, which can use different `backend` to load annotation from txt. The original `HardDiskLoader` and `LmdbLoader` will be deprecated.
- **backend**: Load annotation from different format and backend.
  - `LmdbAnnFileBackend`: Load annotation from lmdb dataset.
  - `HardDiskAnnFileBackend`: Load annotation file with raw hard disks storage backend. The annotation format can be either txt or lmdb.
  - `PetrelAnnFileBackend`: Load annotation file with petrel storage backend. The annotation format can be either txt or lmdb.
  - `HTTPAnnFileBackend`: Load annotation file with http storage backend. The annotation format can be either txt or lmdb.
- **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.).

Example Configuration

```
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='AnnFileLoader',
        repeat=4,
        parser=dict(
            type='LineJsonParser',
            keys=['file_name', 'height', 'width', 'annotations'])),
    pipeline=test_pipeline,
    test_mode=True)
```

Annotation Format

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]]}]}
```

Evaluation

`TextDetDataset` shares a similar implementation with `IcdarDataset`. Please refer to the evaluation section of *'IcdarDataset'*.

9.3 Text Recognition

9.3.1 OCRDataset

Dataset for encoder-decoder based recognizer

It shares a similar architecture with `TextDetDataset`. Check out the *introduction* for details.

Example Configuration

```
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='AnnFileLoader',
        repeat=10,
        parser=dict(
            type='LineStrParser',
            keys=['filename', 'text'],
            keys_idx=[0, 1],
            separator=' ')),
    pipeline=train_pipeline,
    test_mode=False)
```

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`.

Annotation Format

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'}`.

Loading LMDB Datasets

We have support for reading annotation files from the full lmdb dataset (with images and annotations). It is now possible to read lmdb datasets commonly used in academia. We have also implemented a new dataset conversion tool, recog2lmdb. It converts the recognition dataset to lmdb format. See PR982 for more details.

Here is an example configuration to load lmdb annotations:

```
lmdb_root = 'path to lmdb folder'
train = dict(
    type='OCRDataset',
    img_prefix=lmdb_root,
    ann_file=lmdb_root,
    loader=dict(
        type='AnnFileLoader',
        repeat=1,
        file_format='lmdb',
        parser=dict(
            type='LineJsonParser',
            keys=['filename', 'text']),
    pipeline=None,
    test_mode=False)
```

Evaluation

There are six evaluation metrics available for text recognition tasks: `word_acc`, `word_acc_ignore_case`, `word_acc_ignore_case_symbol`, `char_recall`, `char_precision` and `one_minus_ned`. See our API doc for explanations on metrics.

By default, `OCRDataset` generates full reports on all the metrics if its evaluation metric is `acc`. Here is an example case for **training**.

```
# Configuration
evaluation = dict(interval=1, metric='acc')
```

```
# Results
{'0_char_recall': 0.0484, '0_char_precision': 0.6, '0_word_acc': 0.0, '0_word_acc_ignore_
↪case': 0.0, '0_word_acc_ignore_case_symbol': 0.0, '0_1-N.E.D': 0.0525}
```

Note: '0_' prefixes result from `UniformConcatDataset`. It's kept here since MMOCR always wrap `UniformConcatDataset` around any datasets.

If you want to conduct the evaluation on a subset of evaluation metrics:

```
evaluation = dict(interval=1, metric=['word_acc_ignore_case', 'one_minus_ned'])
```

The result will look like:

```
{'0_word_acc_ignore_case': 0.0, '0_1-N.E.D': 0.0525}
```

During testing, you can specify the metrics to evaluate in the command line:

```
python tools/test.py configs/textrecog/crnn/crnn_toy_dataset.py crnn.pth --eval word_acc_
↪ignore_case one_minus_ned
```

9.3.2 OCRSegDataset

Dataset for segmentation-based recognizer

It shares a similar architecture with `TextDetDataset`. Check out the *introduction* for details.

Example Configuration

```
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='AnnFileLoader',
        repeat=10,
        parser=dict(
            type='LineJsonParser',
            keys=['file_name', 'annotations', 'text'])),
    pipeline=train_pipeline,
    test_mode=True)
```

Annotation Format

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

ENABLE BLANK SPACE RECOGNITION

It is noteworthy that the `LineStrParser` should **NOT** be used to parse the annotation files containing multiple blank spaces (in file name or recognition transcriptions). The users have to convert the `plain txt` annotations to `json lines` to enable space recognition. For example:

```
% A plain txt annotation file that contains blank spaces
test/img 1.jpg Hello World!
test/img 2.jpg Hello Open MMLab!
test/img 3.jpg Hello MMOCR!
```

The `LineStrParser` will split the above annotation line to pieces (e.g. ['test/img', '1.jpg', 'Hello', 'World!']) that cannot be matched to the `keys` (e.g. ['filename', 'text']). Therefore, we need to convert it to a json line format by `json.dumps` (check here to see how to dump `jsonl`), and then the annotation file will look like as follows:

```
% A json line annotation file that contains blank spaces
{"filename": "test/img 1.jpg", "text": "Hello World!"}
{"filename": "test/img 2.jpg", "text": "Hello Open MMLab!"}
{"filename": "test/img 3.jpg", "text": "Hello MMOCR!"}
```

After converting the annotation format, you just need to set the parser arguments as:

```
parser=dict(
    type='LineJsonParser',
    keys=['filename', 'text']))
```

Besides, you need to specify a dict that contains blank space to enable blank recognition. Particularly, MMOCR provides two built-in dicts `DICT37` and `DICT91` that contain blank space. For example, change the default `dict_type` in `configs/_base_/recog_models/crnn.py` to `DICT37`.

```
label_convertor = dict(
    type='CTCConvertor', dict_type='DICT37', with_unknown=False, lower=True) # ['DICT36',
↪'DICT37', 'DICT90', 'DICT91']
```

CHAPTER

TWELVE

STATISTICS

- Number of checkpoints: 33
- Number of configs: 26
- Number of papers: 19
  - ALGORITHM: 19

12.1 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

12.2 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

12.3 Text Detection Models

- Number of checkpoints: 15
- Number of configs: 11
- Number of papers: 8
  - [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 and Adaptive Scale Fusion
  - [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

12.4 Text Recognition Models

- Number of checkpoints: 14
- Number of configs: 11
- Number of papers: 9
  - [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
  - [ALGORITHM] {Master

CHAPTER

THIRTEEN

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.

13.1 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.

13.1.1 DBNet

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

13.1.2 DRRG

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

13.1.3 FCENet

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

13.1.4 Mask R-CNN

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

13.1.5 PANet

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

13.1.6 PSENet

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

13.1.7 Textsnake

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

13.2 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.

13.2.1 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.

13.2.2 CRNN

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

13.2.3 CRNN with TPS-based STN

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

13.2.4 MASTER

- Preprocessor: None
- Backbone: ResNet
- Encoder: None
- Decoder: MasterDecoder
- Loss: TFLoss
- Converter: AttnConvertor

13.2.5 NRTR

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

13.2.6 RobustScanner

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

13.2.7 SAR

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

13.2.8 SATRN

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

13.2.9 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.

13.3 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.

13.3.1 SDMGR

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

CHAPTER

FOURTEEN

TEXT DETECTION MODELS

14.1 DBNet

Real-time Scene Text Detection with Differentiable Binarization

14.1.1 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.

14.1.2 Results and models

ICDAR2015

14.1.3 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}}
```

14.2 DBNetpp

Real-Time Scene Text Detection with Differentiable Binarization and Adaptive Scale Fusion

14.2.1 Abstract

Recently, segmentation-based scene text detection methods have drawn extensive attention in the scene text detection field, because of their superiority in detecting the text instances of arbitrary shapes and extreme aspect ratios, profiting from the pixel-level descriptions. However, the vast majority of the existing segmentation-based approaches are limited to their complex post-processing algorithms and the scale robustness of their segmentation models, where the post-processing algorithms are not only isolated to the model optimization but also time-consuming and the scale robustness is usually strengthened by fusing multi-scale feature maps directly. In this paper, we propose a Differentiable Binarization (DB) module that integrates the binarization process, one of the most important steps in the post-processing procedure, into a segmentation network. Optimized along with the proposed DB module, the segmentation network can produce more accurate results, which enhances the accuracy of text detection with a simple pipeline. Furthermore, an efficient Adaptive Scale Fusion (ASF) module is proposed to improve the scale robustness by fusing features of different scales adaptively. By incorporating the proposed DB and ASF with the segmentation network, our proposed scene text detector consistently achieves state-of-the-art results, in terms of both detection accuracy and speed, on five standard benchmarks.

14.2.2 Results and models

ICDAR2015

14.2.3 Citation

```
@article{liao2022real,
    title={Real-Time Scene Text Detection with Differentiable Binarization and Adaptive
↪Scale Fusion},
    author={Liao, Minghui and Zou, Zhisheng and Wan, Zhaoyi and Yao, Cong and Bai, Xiang}
↪,
    journal={IEEE Transactions on Pattern Analysis and Machine Intelligence},
    year={2022},
    publisher={IEEE}
}
```

14.3 DRRG

Deep relational reasoning graph network for arbitrary shape text detection

14.3.1 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.

14.3.2 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.

14.3.3 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}
}
```

14.4 FCENet

Fourier Contour Embedding for Arbitrary-Shaped Text Detection

14.4.1 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.

14.4.2 Results and models

CTW1500

ICDAR2015

14.4.3 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}
      }
```

14.5 Mask R-CNN

Mask R-CNN

14.5.1 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.

14.5.2 Results and models

CTW1500

ICDAR2015

ICDAR2017

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

14.5.3 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}}
```

14.6 PANet

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

14.6.1 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.

14.6.2 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.

14.6.3 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}
  }
```

14.7 PSENet

Shape robust text detection with progressive scale expansion network

14.7.1 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.

14.7.2 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.

14.7.3 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}
}
```

14.8 Textsnake

TextSnake: A Flexible Representation for Detecting Text of Arbitrary Shapes

14.8.1 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.

14.8.2 Results and models

CTW1500

14.8.3 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

FIFTEEN

TEXT RECOGNITION MODELS

15.1 ABINet

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

15.1.1 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.

15.1.2 Dataset

Train Dataset

Test Dataset

15.1.3 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.

15.1.4 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}
}
```

15.2 CRNN

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

15.2.1 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.

15.2.2 Dataset

Train Dataset

Test Dataset

15.2.3 Results and models

15.2.4 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}
}
```

15.3 MASTER

MASTER: Multi-aspect non-local network for scene text recognition

15.3.1 Abstract

Attention-based scene text recognizers have gained huge success, which leverages a more compact intermediate representation to learn 1d- or 2d- attention by a RNN-based encoder-decoder architecture. However, such methods suffer from attention-drift problem because high similarity among encoded features leads to attention confusion under the RNN-based local attention mechanism. Moreover, RNN-based methods have low efficiency due to poor parallelization. To overcome these problems, we propose the MASTER, a self-attention based scene text recognizer that (1) not only encodes the input-output attention but also learns self-attention which encodes feature-feature and target-target relationships inside the encoder and decoder and (2) learns a more powerful and robust intermediate representation to spatial distortion, and (3) owns a great training efficiency because of high training parallelization and a high-speed inference because of an efficient memory-cache mechanism. Extensive experiments on various benchmarks demonstrate the superior performance of our MASTER on both regular and irregular scene text.

15.3.2 Dataset

Train Dataset

Test Dataset

15.3.3 Results and Models

15.3.4 Citation

```
@article{Lu2021MASTER,
  title={{MASTER}: Multi-Aspect Non-local Network for Scene Text Recognition},
  author={Ning Lu and Wenwen Yu and Xianbiao Qi and Yihao Chen and Ping Gong and Rong Xiao and Xiang Bai},
  journal={Pattern Recognition},
  year={2021}
}
```

15.4 NRTR

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

15.4.1 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).

15.4.2 Dataset

Train Dataset

Test Dataset

15.4.3 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.

15.4.4 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}
}
```

15.5 RobustScanner

RobustScanner: Dynamically Enhancing Positional Clues for Robust Text Recognition

15.5.1 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.

15.5.2 Dataset

Train Dataset

Test Dataset

15.5.3 Results and Models

15.5.4 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.

15.5.5 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}
}
```

15.6 SAR

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

15.6.1 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.

15.6.2 Dataset

Train Dataset

Test Dataset

15.6.3 Results and Models

15.6.4 Chinese Dataset

15.6.5 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.

15.6.6 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}
}
```

15.7 SATRN

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

15.7.1 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.

15.7.2 Dataset

Train Dataset

Test Dataset

15.7.3 Results and Models

15.7.4 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}
}
```

15.8 SegOCR

15.8.1 Abstract

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

15.8.2 Dataset

Train Dataset

Test Dataset

15.8.3 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.

15.8.4 Citation

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

15.9 CRNN-STN

15.9.1 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.

15.9.2 Dataset

Train Dataset

Test Dataset

15.9.3 Results and models

15.9.4 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

SIXTEEN

KEY INFORMATION EXTRACTION MODELS

16.1 SDMGR

Spatial Dual-Modality Graph Reasoning for Key Information Extraction

16.1.1 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.

16.1.2 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*.

16.1.3 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

SEVENTEEN

NAMED ENTITY RECOGNITION MODELS

17.1 Bert

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

17.1.1 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).

17.1.2 Dataset

Train Dataset

Test Dataset

17.1.3 Results and models

17.1.4 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

EIGHTEEN

TEXT DETECTION

18.1 Overview

18.1.1 Install AWS CLI (optional)

- Since there are some datasets that require the AWS CLI to be installed in advance, we provide a quick installation guide here:

```
curl "https://awscli.amazonaws.com/awscli-exe-linux-x86_64.zip" -o "awscliv2.zip"
unzip awscliv2.zip
sudo ./aws/install
./aws/install -i /usr/local/aws-cli -b /usr/local/bin
!aws configure
# this command will require you to input keys, you can skip them except
# for the Default region name
# AWS Access Key ID [None]:
# AWS Secret Access Key [None]:
# Default region name [None]: us-east-1
# Default output format [None]
```

18.2 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)

18.3 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
```

- The resulting directory structure looks like the following:

```
├── ctw1500
│   ├── imgs
│   ├── annotations
│   ├── instances_training.json
│   └── instances_val.json
```

18.4 ICDAR 2011 (Born-Digital Images)

- Step1: Download `Challenge1_Training_Task12_Images.zip`, `Challenge1_Training_Task1_GT.zip`, `Challenge1_Test_Task12_Images.zip`, and `Challenge1_Test_Task1_GT.zip` from homepage `Task 1. 1: Text Localization (2013 edition)`.

```
mkdir icdar2011 && cd icdar2011
mkdir imgs && mkdir annotations

# Download ICDAR 2011
wget https://rrc.cvc.uab.es/downloads/Challenge1_Training_Task12_Images.zip --no-
↪check-certificate
```

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```
wget https://rrc.cvc.uab.es/downloads/Challenge1_Training_Task1_GT.zip --no-check-
↪certificate
wget https://rrc.cvc.uab.es/downloads/Challenge1_Test_Task12_Images.zip --no-check-
↪certificate
wget https://rrc.cvc.uab.es/downloads/Challenge1_Test_Task1_GT.zip --no-check-
↪certificate

# For images
unzip -q Challenge1_Training_Task12_Images.zip -d imgs/training
unzip -q Challenge1_Test_Task12_Images.zip -d imgs/test
# For annotations
unzip -q Challenge1_Training_Task1_GT.zip -d annotations/training
unzip -q Challenge1_Test_Task1_GT.zip -d annotations/test

rm Challenge1_Training_Task12_Images.zip && rm Challenge1_Test_Task12_Images.zip &&␣
↪rm Challenge1_Training_Task1_GT.zip && rm Challenge1_Test_Task1_GT.zip
```

- Step 2: Generate `instances_training.json` and `instances_test.json` with the following command:

```
python tools/data/textdet/ic11_converter.py PATH/TO/icdar2011 --nproc 4
```

- After running the above codes, the directory structure should be as follows:

```
├── icdar2011
│   ├── imgs
│   ├── instances_test.json
│   └── instances_training.json
```

18.5 ICDAR 2013 (Focused Scene Text)

- Step1: Download `Challenge2_Training_Task12_Images.zip`, `Challenge2_Test_Task12_Images.zip`, `Challenge2_Training_Task1_GT.zip`, and `Challenge2_Test_Task1_GT.zip` from homepage `Task 2.1: Text Localization (2013 edition)`.

```
mkdir icdar2013 && cd icdar2013
mkdir imgs && mkdir annotations

# Download ICDAR 2013
wget https://rrc.cvc.uab.es/downloads/Challenge2_Training_Task12_Images.zip --no-
↪check-certificate
wget https://rrc.cvc.uab.es/downloads/Challenge2_Test_Task12_Images.zip --no-check-
↪certificate
wget https://rrc.cvc.uab.es/downloads/Challenge2_Training_Task1_GT.zip --no-check-
↪certificate
wget https://rrc.cvc.uab.es/downloads/Challenge2_Test_Task1_GT.zip --no-check-
↪certificate

# For images
unzip -q Challenge2_Training_Task12_Images.zip -d imgs/training
unzip -q Challenge2_Test_Task12_Images.zip -d imgs/test
```

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```
# For annotations
unzip -q Challenge2_Training_Task1_GT.zip -d annotations/training
unzip -q Challenge2_Test_Task1_GT.zip -d annotations/test

rm Challenge2_Training_Task12_Images.zip && rm Challenge2_Test_Task12_Images.zip &&␣
↪rm Challenge2_Training_Task1_GT.zip && rm Challenge2_Test_Task1_GT.zip
```

- Step 2: Generate `instances_training.json` and `instances_test.json` with the following command:

```
python tools/data/textdet/ic13_converter.py PATH/TO/icdar2013 --nproc 4
```

- After running the above codes, the directory structure should be as follows:

```
├── icdar2013
│   ├── imgs
│   ├── instances_test.json
│   └── instances_training.json
```

18.6 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 the following command:

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

- The resulting directory structure looks like the following:

```
├── icdar2015
│   ├── imgs
│   ├── annotations
│   ├── instances_test.json
│   └── instances_training.json
```

18.7 ICDAR 2017

- Follow similar steps as *ICDAR 2015*.
- The resulting directory structure looks like the following:

```
├── icdar2017
│   ├── imgs
│   ├── annotations
│   ├── instances_training.json
│   └── instances_val.json
```

18.8 SynthText

- Step1: Download SynthText.zip from [homepage](https://www.robots.ox.ac.uk/~vgg/data/scenetext/ and extract its content to `synthtext/img`.
- Step2: Download data.mdb and lock.mdb to `synthtext/instances_training.lmdb/`.
- The resulting directory structure looks like the following:

```
├── synthtext
│   ├── imgs
│   └── instances_training.lmdb
│       ├── data.mdb
│       └── lock.mdb
```

18.9 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
```

- The resulting directory structure looks like the following:

```
├── textocr
│   ├── train
```

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```
|   ├── instances_training.json
|   └── instances_val.json
```

18.10 Totaltext

- Step0: Read *Important Note*
- Step1: Download `totaltext.zip` from github dataset and `groundtruth_text.zip` or `TT_new_train_GT.zip` (if you prefer to use the latest version of training annotations) 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 legacy training and test annotations
unzip groundtruth_text.zip
mv Groundtruth/Polygon/Train annotations/training
mv Groundtruth/Polygon/Test annotations/test

# Using the latest training annotations
# WARNING: Delete legacy train annotations before running the following command.
unzip TT_new_train_GT.zip
mv Train annotations/training
```

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

```
python tools/data/textdet/totaltext_converter.py /path/to/totaltext
```

- The resulting directory structure looks like the following:

```
├── totaltext
|   ├── imgs
|   ├── annotations
|   ├── instances_test.json
|   └── instances_training.json
```

18.11 CurvedSynText150k

- Step1: Download syntext1.zip and syntext2.zip to `CurvedSynText150k/`.
- Step2:

```
unzip -q syntext1.zip
mv train.json train1.json
unzip images.zip
rm images.zip

unzip -q syntext2.zip
mv train.json train2.json
unzip images.zip
rm images.zip
```

- Step3: Download instances_training.json to `CurvedSynText150k/`
- Or, generate `instances_training.json` with following command:

```
python tools/data/common/curvedsyntext_converter.py PATH/TO/CurvedSynText150k --
↪nproc 4
```

- The resulting directory structure looks like the following:

```
├── CurvedSynText150k
│   ├── syntext_word_eng
│   ├── emcs_imgs
│   └── instances_training.json
```

18.12 FUNSD

- Step1: Download dataset.zip to `funsd/`.

```
mkdir funsd && cd funsd

# Download FUNSD dataset
wget https://guillaumejaume.github.io/FUNSD/dataset.zip
unzip -q dataset.zip

# For images
mv dataset/training_data/images imgs && mv dataset/testing_data/images/* imgs/

# For annotations
mkdir annotations
mv dataset/training_data/annotations annotations/training && mv dataset/testing_
↪data/annotations annotations/test

rm dataset.zip && rm -rf dataset
```

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

```
python tools/data/textdet/funsd_converter.py PATH/TO/funsd --nproc 4
```

- The resulting directory structure looks like the following:

```
├── funsd
│   ├── annotations
│   ├── imgs
│   ├── instances_test.json
│   └── instances_training.json
```

18.13 DeText

- Step1: Download `ch9_training_images.zip`, `ch9_training_localization_transcription_gt.zip`, `ch9_validation_images.zip`, and `ch9_validation_localization_transcription_gt.zip` from **Task 3: End to End** on the homepage.

```
mkdir detext && cd detext
mkdir imgs && mkdir annotations && mkdir imgs/training && mkdir imgs/val && mkdir␣
↪annotations/training && mkdir annotations/val

# Download DeText
wget https://rrc.cvc.uab.es/downloads/ch9_training_images.zip --no-check-certificate
wget https://rrc.cvc.uab.es/downloads/ch9_training_localization_transcription_gt.
↪zip --no-check-certificate
wget https://rrc.cvc.uab.es/downloads/ch9_validation_images.zip --no-check-
↪certificate
wget https://rrc.cvc.uab.es/downloads/ch9_validation_localization_transcription_gt.
↪zip --no-check-certificate

# Extract images and annotations
unzip -q ch9_training_images.zip -d imgs/training && unzip -q ch9_training_
↪localization_transcription_gt.zip -d annotations/training && unzip -q ch9_
↪validation_images.zip -d imgs/val && unzip -q ch9_validation_localization_
↪transcription_gt.zip -d annotations/val

# Remove zips
rm ch9_training_images.zip && rm ch9_training_localization_transcription_gt.zip &&␣
↪rm ch9_validation_images.zip && rm ch9_validation_localization_transcription_gt.
↪zip
```

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

```
python tools/data/textdet/detext_converter.py PATH/TO/detext --nproc 4
```

- After running the above codes, the directory structure should be as follows:

```
├── detext
│   ├── annotations
│   ├── imgs
│   ├── instances_test.json
│   └── instances_training.json
```

18.14 NAF

- Step1: Download labeled_images.tar.gz to `naf/`.

```
mkdir naf && cd naf

# Download NAF dataset
wget https://github.com/herobd/NAF_dataset/releases/download/v1.0/labeled_images.
↪tar.gz
tar -zxf labeled_images.tar.gz

# For images
mkdir annotations && mv labeled_images imgs

# For annotations
git clone https://github.com/herobd/NAF_dataset.git
mv NAF_dataset/train_valid_test_split.json annotations/ && mv NAF_dataset/groups␣
↪annotations/

rm -rf NAF_dataset && rm labeled_images.tar.gz
```

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

```
python tools/data/textdet/naf_converter.py PATH/TO/naf --nproc 4
```

- After running the above codes, the directory structure should be as follows:

```
├── naf
│   ├── annotations
│   ├── imgs
│   ├── instances_test.json
│   ├── instances_val.json
│   └── instances_training.json
```

18.15 SROIE

- Step1: Download `0325updated.task1train(626p).zip`, `task1&2_test(361p).zip`, and `text.task1&2-test361p).zip` from homepage to `sroie/`
- Step2:

```
mkdir sroie && cd sroie
mkdir imgs && mkdir annotations && mkdir imgs/training

# Warnninig: The zip files downloaded from Google Drive and BaiduYun Cloud may
# be different, the user should revise the following commands to the correct
# file name if encounter with errors while extracting and move the files.
unzip -q 0325updated.task1train\(626p\).zip && unzip -q task1\&2_test\(361p\).zip &&
↪ unzip -q text.task1\&2-test361p\).zip

# For images
```

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```
mv 0325updated.task1train\(626p\)/*.jpg imgs/training && mv fulltext_test\(361p\)␣
↪imgs/test

# For annotations
mv 0325updated.task1train\(626p\) annotations/training && mv text.task1\&2-test361p\
↪)/ annotations/test

rm 0325updated.task1train\(626p\).zip && rm task1\&2_test\(361p\).zip && rm text.
↪task1\&2-test361p\).zip
```

- Step3: Generate `instances_training.json` and `instances_test.json` with the following command:

```
python tools/data/textdet/sroie_converter.py PATH/TO/sroie --nproc 4
```

- After running the above codes, the directory structure should be as follows:

```
├── sroie
│   ├── annotations
│   ├── imgs
│   ├── instances_test.json
│   └── instances_training.json
```

18.16 Lecture Video DB

- Step1: Download IIIT-CVid.zip to `lv/`.

```
mkdir lv && cd lv

# Download LV dataset
wget http://cdn.iiit.ac.in/cdn/preon.iiit.ac.in/~kartik/IIIT-CVid.zip
unzip -q IIIT-CVid.zip

mv IIIT-CVid/Frames imgs

rm IIIT-CVid.zip
```

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

```
python tools/data/textdet/lv_converter.py PATH/TO/lv --nproc 4
```

- The resulting directory structure looks like the following:

```
├── lv
│   ├── imgs
│   ├── instances_test.json
│   ├── instances_training.json
│   └── instances_val.json
```

18.17 LSVT

- Step1: Download train_full_images_0.tar.gz, train_full_images_1.tar.gz, and train_full_labels.json to `lsvt/`.

```
mkdir lsvt && cd lsvt

# Download LSVT dataset
wget https://dataset-bj.cdn.bcebos.com/lsvt/train_full_images_0.tar.gz
wget https://dataset-bj.cdn.bcebos.com/lsvt/train_full_images_1.tar.gz
wget https://dataset-bj.cdn.bcebos.com/lsvt/train_full_labels.json

mkdir annotations
tar -xf train_full_images_0.tar.gz && tar -xf train_full_images_1.tar.gz
mv train_full_labels.json annotations/ && mv train_full_images_1/*.jpg train_full_
↪images_0/
mv train_full_images_0 imgs

rm train_full_images_0.tar.gz && rm train_full_images_1.tar.gz && rm -rf train_full_
↪images_1
```

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

```
# Annotations of LSVT test split is not publicly available, split a validation
# set by adding --val-ratio 0.2
python tools/data/textdet/lsvt_converter.py PATH/TO/lsvt
```

- After running the above codes, the directory structure should be as follows:

```
|— lsvt
|   ├— imgs
|   ├— instances_training.json
|   └— instances_val.json (optional)
```

18.18 IMGUR

- Step1: Run `download_imgur5k.py` to download images. You can merge PR#5 in your local repository to enable a **much faster** parallel execution of image download.

```
mkdir imgur && cd imgur

git clone https://github.com/facebookresearch/IMGUR5K-Handwriting-Dataset.git

# Download images from imgur.com. This may take SEVERAL HOURS!
python ./IMGUR5K-Handwriting-Dataset/download_imgur5k.py --dataset_info_dir ./
↪IMGUR5K-Handwriting-Dataset/dataset_info/ --output_dir ./imgs

# For annotations
mkdir annotations
mv ./IMGUR5K-Handwriting-Dataset/dataset_info/*.json annotations

rm -rf IMGUR5K-Handwriting-Dataset
```

- Step2: Generate `instances_train.json`, `instance_val.json` and `instances_test.json` with the following command:

```
python tools/data/textdet/imgur_converter.py PATH/TO/imgur
```

- After running the above codes, the directory structure should be as follows:

```
├── imgur
│   ├── annotations
│   ├── imgs
│   ├── instances_test.json
│   ├── instances_training.json
│   └── instances_val.json
```

18.19 KAIST

- Step1: Complete download KAIST_all.zip to `kaist/`.

```
mkdir kaist && cd kaist
mkdir imgs && mkdir annotations

# Download KAIST dataset
wget http://www.iapr-tc11.org/dataset/KAIST_SceneText/KAIST_all.zip
unzip -q KAIST_all.zip

rm KAIST_all.zip
```

- Step2: Extract zips:

```
python tools/data/common/extract_kaist.py PATH/TO/kaist
```

- Step3: Generate `instances_training.json` and `instances_val.json` (optional) with following command:

```
# Since KAIST does not provide an official split, you can split the dataset by␣
↪adding --val-ratio 0.2
python tools/data/textdet/kaist_converter.py PATH/TO/kaist --nproc 4
```

- After running the above codes, the directory structure should be as follows:

```
├── kaist
│   ├── annotations
│   ├── imgs
│   ├── instances_training.json
│   └── instances_val.json (optional)
```

18.20 MTWI

- Step1: Download `mtwi_2018_train.zip` from homepage.

```
mkdir mtwi && cd mtwi

unzip -q mtwi_2018_train.zip
mv image_train imgs && mv txt_train annotations

rm mtwi_2018_train.zip
```

- Step2: Generate `instances_training.json` and `instance_val.json` (optional) with the following command:

```
# Annotations of MTWI test split is not publicly available, split a validation
# set by adding --val-ratio 0.2
python tools/data/textdet/mtwi_converter.py PATH/TO/mtwi --nproc 4
```

- After running the above codes, the directory structure should be as follows:

```
├── mtwi
│   ├── annotations
│   ├── imgs
│   ├── instances_training.json
│   └── instances_val.json (optional)
```

18.21 COCO Text v2

- Step1: Download image train2014.zip and annotation cocotext.v2.zip to `coco_textv2/`.

```
mkdir coco_textv2 && cd coco_textv2
mkdir annotations

# Download COCO Text v2 dataset
wget http://images.cocodataset.org/zips/train2014.zip
wget https://github.com/bgshih/cocotext/releases/download/dl/cocotext.v2.zip
unzip -q train2014.zip && unzip -q cocotext.v2.zip

mv train2014 imgs && mv cocotext.v2.json annotations/

rm train2014.zip && rm -rf cocotext.v2.zip
```

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

```
python tools/data/textdet/cocotext_converter.py PATH/TO/coco_textv2
```

- After running the above codes, the directory structure should be as follows:

```
├── coco_textv2
│   ├── annotations
│   ├── imgs
```

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```
|   ├── instances_training.json
|   └── instances_val.json
```

18.22 ReCTS

- Step1: Download ReCTS.zip to `rects/` from the homepage.

```
mkdir rects && cd rects

# Download ReCTS dataset
# You can also find Google Drive link on the dataset homepage
wget https://datasets.cvc.uab.es/rrc/ReCTS.zip --no-check-certificate
unzip -q ReCTS.zip

mv img imgs && mv gt_unicode annotations

rm ReCTS.zip && rm -rf gt
```

- Step2: Generate `instances_training.json` and `instances_val.json` (optional) with following command:

```
# Annotations of ReCTS test split is not publicly available, split a validation
# set by adding --val-ratio 0.2
python tools/data/textdet/rects_converter.py PATH/TO/rects --nproc 4 --val-ratio 0.2
```

- After running the above codes, the directory structure should be as follows:

```
|── rects
|   ├── annotations
|   ├── imgs
|   ├── instances_val.json (optional)
|   └── instances_training.json
```

18.23 ILST

- Step1: Download `IIIT-ILST` from onedrive
- Step2: Run the following commands

```
unzip -q IIIT-ILST.zip && rm IIIT-ILST.zip
cd IIIT-ILST

# rename files
cd Devanagari && for i in `ls`; do mv -f $i `echo "devanagari_"$i`; done && cd ..
cd Malayalam && for i in `ls`; do mv -f $i `echo "malayalam_"$i`; done && cd ..
cd Telugu && for i in `ls`; do mv -f $i `echo "telugu_"$i`; done && cd ..

# transfer image path
mkdir imgs && mkdir annotations
mv Malayalam/{*jpg,*jpeg} imgs/ && mv Malayalam/*xml annotations/
```

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```
mv Devanagari/*jpg imgs/ && mv Devanagari/*xml annotations/
mv Telugu/*jpeg imgs/ && mv Telugu/*xml annotations/

# remove unnecessary files
rm -rf Devanagari && rm -rf Malayalam && rm -rf Telugu && rm -rf README.txt
```

- Step3: Generate `instances_training.json` and `instances_val.json` (optional). Since the original dataset doesn't have a validation set, you may specify `--val-ratio` to split the dataset. E.g., if val-ratio is 0.2, then 20% of the data are left out as the validation set in this example.

```
python tools/data/textdet/ilst_converter.py    PATH/TO/IIIT-ILST --nproc 4
```

- After running the above codes, the directory structure should be as follows:

```
├── IIIT-ILST
│   ├── annotations
│   ├── imgs
│   ├── instances_val.json (optional)
│   └── instances_training.json
```

18.24 VinText

- Step1: Download vintext.zip to `vintext`

```
mkdir vintext && cd vintext

# Download dataset from google drive
wget --load-cookies /tmp/cookies.txt "https://docs.google.com/uc?export=download&
↪confirm=$(wget --quiet --save-cookies /tmp/cookies.txt --keep-session-cookies --
↪no-check-certificate 'https://docs.google.com/uc?export=download&
↪id=1UUQhNvzgpZy7zXBFQp0Qox-BBjunZ0ml' -O- | sed -rn 's/.*confirm=([0-9A-Za-z_]+).
↪*/\1\n/p')&id=1UUQhNvzgpZy7zXBFQp0Qox-BBjunZ0ml" -O vintext.zip && rm -rf /tmp/
↪cookies.txt

# Extract images and annotations
unzip -q vintext.zip && rm vintext.zip
mv vietnamese/labels ./ && mv vietnamese/test_image ./ && mv vietnamese/train_
↪images ./ && mv vietnamese/unseen_test_images ./
rm -rf vietnamese

# Rename files
mv labels annotations && mv test_image test && mv train_images  training && mv␣
↪unseen_test_images  unseen_test
mkdir imgs
mv training imgs/ && mv test imgs/ && mv unseen_test imgs/
```

- Step2: Generate `instances_training.json`, `instances_test.json` and `instances_unseen_test.json`

```
python tools/data/textdet/vintext_converter.py PATH/TO/vintext --nproc 4
```

- After running the above codes, the directory structure should be as follows:

```
├── vintext
│   ├── annotations
│   ├── imgs
│   ├── instances_test.json
│   ├── instances_unseen_test.json
│   └── instances_training.json
```

18.25 BID

- Step1: Download BID Dataset.zip
- Step2: Run the following commands to preprocess the dataset

```
# Rename
mv BID\ Dataset.zip BID_Dataset.zip

# Unzip and Rename
unzip -q BID_Dataset.zip && rm BID_Dataset.zip
mv BID\ Dataset BID

# The BID dataset has a problem of permission, and you may
# add permission for this file
chmod -R 777 BID
cd BID
mkdir imgs && mkdir annotations

# For images and annotations
mv CNH_Aberta/*in.jpg imgs && mv CNH_Aberta/*txt annotations && rm -rf CNH_Aberta
mv CNH_Frente/*in.jpg imgs && mv CNH_Frente/*txt annotations && rm -rf CNH_Frente
mv CNH_Verso/*in.jpg imgs && mv CNH_Verso/*txt annotations && rm -rf CNH_Verso
mv CPF_Frente/*in.jpg imgs && mv CPF_Frente/*txt annotations && rm -rf CPF_Frente
mv CPF_Verso/*in.jpg imgs && mv CPF_Verso/*txt annotations && rm -rf CPF_Verso
mv RG_Aberto/*in.jpg imgs && mv RG_Aberto/*txt annotations && rm -rf RG_Aberto
mv RG_Frente/*in.jpg imgs && mv RG_Frente/*txt annotations && rm -rf RG_Frente
mv RG_Verso/*in.jpg imgs && mv RG_Verso/*txt annotations && rm -rf RG_Verso

# Remove unnecessary files
rm -rf desktop.ini
```

- Step3: - Step3: Generate `instances_training.json` and `instances_val.json` (optional). Since the original dataset doesn't have a validation set, you may specify `--val-ratio` to split the dataset. E.g., if val-ratio is 0.2, then 20% of the data are left out as the validation set in this example.

```
python tools/data/textdet/bid_converter.py PATH/TO/BID --nproc 4
```

- After running the above codes, the directory structure should be as follows:

```
├── BID
│   ├── annotations
│   ├── imgs
```

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```
    ├── instances_training.json
    └── instances_val.json (optional)
```

18.26 RCTW

- Step1: Download `train_images.zip.001`, `train_images.zip.002`, and `train_gts.zip` from the homepage, extract the zips to `rctw/imgs` and `rctw/annotations`, respectively.
- Step2: Generate `instances_training.json` and `instances_val.json` (optional). Since the test annotations are not publicly available, you may specify `--val-ratio` to split the dataset. E.g., if val-ratio is 0.2, then 20% of the data are left out as the validation set in this example.

```
# Annotations of RCTW test split is not publicly available, split a validation set␣
↪by adding --val-ratio 0.2
python tools/data/textdet/rctw_converter.py PATH/TO/rctw --nproc 4
```

- After running the above codes, the directory structure should be as follows:

```
── rctw
    ├── annotations
    ├── imgs
    ├── instances_training.json
    └── instances_val.json (optional)
```

18.27 HierText

- Step1 (optional): Install AWS CLI.
- Step2: Clone HierText repo to get annotations

```
mkdir HierText
git clone https://github.com/google-research-datasets/hiertext.git
```

- Step3: Download `train.tgz`, `validation.tgz` from aws

```
aws s3 --no-sign-request cp s3://open-images-dataset/ocr/train.tgz .
aws s3 --no-sign-request cp s3://open-images-dataset/ocr/validation.tgz .
```

- Step4: Process raw data

```
# process annotations
mv hiertext/gt ./
rm -rf hiertext
mv gt annotations
gzip -d annotations/train.jsonl.gz
gzip -d annotations/validation.jsonl.gz
# process images
mkdir imgs
mv train.tgz imgs/
mv validation.tgz imgs/
```

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```
tar -xzvf imgs/train.tgz
tar -xzvf imgs/validation.tgz
```

- Step5: Generate `instances_training.json` and `instance_val.json`. HierText includes different levels of annotation, from paragraph, line, to word. Check the original paper for details. E.g. set `--level paragraph` to get paragraph-level annotation. Set `--level line` to get line-level annotation. set `--level word` to get word-level annotation.

```
# Collect word annotation from HierText  --level word
python tools/data/textdet/hiertext_converter.py PATH/TO/HierText --level word --
↪nproc 4
```

- After running the above codes, the directory structure should be as follows:

```
├── HierText
    ├── annotations
    ├── imgs
    ├── instances_training.json
    └── instances_val.json
```

18.28 ArT

- Step1: Download `train_images.tar.gz`, and `train_labels.json` from the homepage to `art/`

```
mkdir art && cd art
mkdir annotations

# Download ArT dataset
wget https://dataset-bj.cdn.bcebos.com/art/train_images.tar.gz --no-check-
↪certificate
wget https://dataset-bj.cdn.bcebos.com/art/train_labels.json --no-check-certificate

# Extract
tar -xf train_images.tar.gz
mv train_images imgs
mv train_labels.json annotations/

# Remove unnecessary files
rm train_images.tar.gz
```

- Step2: Generate `instances_training.json` and `instances_val.json` (optional). Since the test annotations are not publicly available, you may specify `--val-ratio` to split the dataset. E.g., if val-ratio is 0.2, then 20% of the data are left out as the validation set in this example.

```
# Annotations of ArT test split is not publicly available, split a validation set␣
↪by adding --val-ratio 0.2
python tools/data/textdet/art_converter.py PATH/TO/art --nproc 4
```

- After running the above codes, the directory structure should be as follows:

```
├── art
│   ├── annotations
│   ├── imgs
│   ├── instances_training.json
│   └── instances_val.json (optional)
```

CHAPTER

NINETEEN

TEXT RECOGNITION

19.1 Overview

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

19.1.1 Install AWS CLI (optional)

- Since there are some datasets that require the AWS CLI to be installed in advance, we provide a quick installation guide here:

```
curl "https://awscli.amazonaws.com/awscli-exe-linux-x86_64.zip" -o "awscliv2.zip"
unzip awscliv2.zip
sudo ./aws/install
./aws/install -i /usr/local/aws-cli -b /usr/local/bin
!aws configure
# this command will require you to input keys, you can skip them except
# for the Default region name
# AWS Access Key ID [None]:
# AWS Secret Access Key [None]:
# Default region name [None]: us-east-1
# Default output format [None]
```

19.2 ICDAR 2011 (Born-Digital Images)

- Step1: Download `Challenge1_Training_Task3_Images_GT.zip`, `Challenge1_Test_Task3_Images.zip`, and `Challenge1_Test_Task3_GT.txt` from homepage `Task 1.3: Word Recognition (2013 edition)`.

```
mkdir icdar2011 && cd icdar2011
mkdir annotations

# Download ICDAR 2011
wget https://rrc.cvc.uab.es/downloads/Challenge1_Training_Task3_Images_GT.zip --no-
↪check-certificate
wget https://rrc.cvc.uab.es/downloads/Challenge1_Test_Task3_Images.zip --no-check-
↪certificate
wget https://rrc.cvc.uab.es/downloads/Challenge1_Test_Task3_GT.txt --no-check-
↪certificate
```

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```
# For images
mkdir crops
unzip -q Challenge1_Training_Task3_Images_GT.zip -d crops/train
unzip -q Challenge1_Test_Task3_Images.zip -d crops/test

# For annotations
mv Challenge1_Test_Task3_GT.txt annotations && mv train/gt.txt annotations/
↪Challenge1_Train_Task3_GT.txt
```

- Step2: Convert original annotations to `Train_label.jsonl` and `Test_label.jsonl` with the following command:

```
python tools/data/textrecog/ic11_converter.py PATH/TO/icdar2011
```

- After running the above codes, the directory structure should be as follows:

```
├── icdar2011
│   ├── crops
│   ├── train_label.jsonl
│   └── test_label.jsonl
```

19.3 ICDAR 2013 (Focused Scene Text)

- Step1: Download `Challenge2_Training_Task3_Images_GT.zip`, `Challenge2_Test_Task3_Images.zip`, and `Challenge2_Test_Task3_GT.txt` from homepage `Task 2.3: Word Recognition (2013 edition)`.

```
mkdir icdar2013 && cd icdar2013
mkdir annotations

# Download ICDAR 2013
wget https://rrc.cvc.uab.es/downloads/Challenge2_Training_Task3_Images_GT.zip --no-
↪check-certificate
wget https://rrc.cvc.uab.es/downloads/Challenge2_Test_Task3_Images.zip --no-check-
↪certificate
wget https://rrc.cvc.uab.es/downloads/Challenge2_Test_Task3_GT.txt --no-check-
↪certificate

# For images
mkdir crops
unzip -q Challenge2_Training_Task3_Images_GT.zip -d crops/train
unzip -q Challenge2_Test_Task3_Images.zip -d crops/test
# For annotations
mv Challenge2_Test_Task3_GT.txt annotations && mv crops/train/gt.txt annotations/
↪Challenge2_Train_Task3_GT.txt

rm Challenge2_Training_Task3_Images_GT.zip && rm Challenge2_Test_Task3_Images.zip
```

- Step 2: Generate `Train_label.jsonl` and `Test_label.jsonl` with the following command:

```
python tools/data/textrecog/ic13_converter.py PATH/TO/icdar2013
```

- After running the above codes, the directory structure should be as follows:

```
├── icdar2013
│   ├── crops
│   ├── train_label.jsonl
│   └── test_label.jsonl
```

19.4 ICDAR 2013 [Deprecated]

- 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
- After running the above codes, the directory structure should be as follows:

```
├── icdar_2013
│   ├── train_label.txt
│   ├── test_label_1015.txt
│   ├── test_label_1095.txt
│   ├── Challenge2_Training_Task3_Images_GT
│   └──  Challenge2_Test_Task3_Images
```

19.5 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
- After running the above codes, the directory structure should be as follows:

```
├── icdar_2015
│   ├── train_label.txt
│   ├── test_label.txt
│   ├── ch4_training_word_images_gt
│   └── ch4_test_word_images_gt
```

19.6 IIIT5K

- Step1: Download `IIIT5K-Word_V3.0.tar.gz` from homepage
- Step2: Download train_label.txt and test_label.txt
- After running the above codes, the directory structure should be as follows:

```
├── III5K
│   ├── train_label.txt
│   ├── test_label.txt
│   ├── train
│   └── test
```

19.7 svt

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

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

- After running the above codes, the directory structure should be as follows:

```
├── svt
│   ├── test_label.txt
│   └── image
```

19.8 ct80

- Step1: Download test_label.txt
- Step2: Download timage.tar.gz
- Step3:

```
mkdir ct80 && cd ct80
mv /path/to/test_label.txt .
mv /path/to/timage.tar.gz .
tar -xvf timage.tar.gz
# create soft link
cd /path/to/mmocr/data/mixture
ln -s /path/to/ct80 ct80
```

- After running the above codes, the directory structure should be as follows:

```
├── ct80
│   ├── test_label.txt
│   └── timage
```

19.9 svtp

- Step1: Download test_label.txt
- After running the above codes, the directory structure should be as follows:

```
├── svtp
│   ├── test_label.txt
│   └── image
```

19.10 coco_text

- Step1: Download from homepage
- Step2: Download train_label.txt
- After running the above codes, the directory structure should be as follows:

```
├── coco_text
│   ├── train_label.txt
│   └── train_words
```

19.11 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).

Note: 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 .

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

# Convert 'txt' format annos to 'lmdb' (optional)
```

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```
cd /path/to/mmocr
python tools/data/utils/lmdb_converter.py data/mixture/Syn90k/label.txt data/
↪mixture/Syn90k/label.lmdb --label-only
```

- After running the above codes, the directory structure should be as follows:

```
├── Syn90k
│   ├── shuffle_labels.txt
│   ├── label.txt
│   ├── label.lmdb (optional)
│   └── mnt
```

19.12 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

# Convert 'txt' format annos to 'lmdb' (optional)
```

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```
cd /path/to/mmocr
python tools/data/utils/lmdb_converter.py data/mixture/SynthText/label.txt data/
↪mixture/SynthText/label.lmdb --label-only
```

- After running the above codes, the directory structure should be as follows:

```
├── SynthText
│   ├── alphanumeric_labels.txt
│   ├── shuffle_labels.txt
│   ├── instances_train.txt
│   ├── label.txt
│   ├── label.lmdb (optional)
│   └── synthtext
```

19.13 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

# Convert 'txt' format annos to 'lmdb' (optional)
cd /path/to/mmocr
python tools/data/utils/lmdb_converter.py data/mixture/SynthAdd/label.txt data/
↪mixture/SynthAdd/label.lmdb --label-only
```

- After running the above codes, the directory structure should be as follows:

```
├── SynthAdd
│   ├── label.txt
│   ├── label.lmdb (optional)
│   └── SynthText_Add
```

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

```
python tools/data/utils/lmdb_converter.py <txt_label_path> <lmdb_label_path> --label-only
```

For example,

```
python tools/data/utils/lmdb_converter.py data/mixture/Syn90k/label.txt data/mixture/
↪Syn90k/label.lmdb --label-only
```

19.14 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
```

- After running the above codes, the directory structure should be as follows:

```
├── TextOCR
│   ├── image
│   ├── train_label.txt
│   └── val_label.txt
```

19.15 Totaltext

- Step1: Download `totaltext.zip` from github dataset and `groundtruth_text.zip` or `TT_new_train_GT.zip` (if you prefer to use the latest version of training annotations) 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 legacy training and test annotations
unzip groundtruth_text.zip
```

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```
mv Groundtruth/Polygon/Train annotations/training
mv Groundtruth/Polygon/Test annotations/test

# Using the latest training annotations
# WARNING: Delete legacy train annotations before running the following command.
unzip TT_new_train_GT.zip
mv Train annotations/training
```

- 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
```

- After running the above codes, the directory structure should be as follows:

```
├── totaltext
│   ├── dst_imgs
│   ├── train_label.txt
│   └── test_label.txt
```

19.16 OpenVINO

- Step1 (optional): Install AWS CLI.
- Step2: 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
done
tar zxf validation.tar.gz -C openimages_v5/val
```

- Step3: 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
```

- After running the above codes, the directory structure should be as follows:

```
├── 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
```

19.17 DeText

- Step1: Download `ch9_training_images.zip`, `ch9_training_localization_transcription_gt.zip`, `ch9_validation_images.zip`, and `ch9_validation_localization_transcription_gt.zip` from **Task 3: End to End** on the homepage.

```
mkdir detext && cd detext
mkdir imgs && mkdir annotations && mkdir imgs/training && mkdir imgs/val && mkdir␣
↪annotations/training && mkdir annotations/val

# Download DeText
wget https://rrc.cvc.uab.es/downloads/ch9_training_images.zip --no-check-certificate
wget https://rrc.cvc.uab.es/downloads/ch9_training_localization_transcription_gt.
↪zip --no-check-certificate
wget https://rrc.cvc.uab.es/downloads/ch9_validation_images.zip --no-check-
↪certificate
wget https://rrc.cvc.uab.es/downloads/ch9_validation_localization_transcription_gt.
↪zip --no-check-certificate

# Extract images and annotations
unzip -q ch9_training_images.zip -d imgs/training && unzip -q ch9_training_
↪localization_transcription_gt.zip -d annotations/training && unzip -q ch9_
↪validation_images.zip -d imgs/val && unzip -q ch9_validation_localization_
↪transcription_gt.zip -d annotations/val

# Remove zips
rm ch9_training_images.zip && rm ch9_training_localization_transcription_gt.zip &&␣
↪rm ch9_validation_images.zip && rm ch9_validation_localization_transcription_gt.
↪zip
```

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

```
# Add --preserve-vertical to preserve vertical texts for training, otherwise
# vertical images will be filtered and stored in PATH/TO/detext/ignores
python tools/data/textrecog/detext_converter.py PATH/TO/detext --nproc 4
```

- After running the above codes, the directory structure should be as follows:

```
├── detext
│   ├── crops
│   ├── ignores
│   ├── train_label.jsonl
│   └── test_label.jsonl
```

19.18 NAF

- Step1: Download labeled_images.tar.gz to `naf/`.

```
mkdir naf && cd naf

# Download NAF dataset
wget https://github.com/herobd/NAF_dataset/releases/download/v1.0/labeled_images.
↪tar.gz
tar -zxf labeled_images.tar.gz

# For images
mkdir annotations && mv labeled_images imgs

# For annotations
git clone https://github.com/herobd/NAF_dataset.git
mv NAF_dataset/train_valid_test_split.json annotations/ && mv NAF_dataset/groups␣
↪annotations/

rm -rf NAF_dataset && rm labeled_images.tar.gz
```

- Step2: Generate `train_label.txt`, `val_label.txt`, and `test_label.txt` with following command:

```
# Add --preserve-vertical to preserve vertical texts for training, otherwise
# vertical images will be filtered and stored in PATH/TO/naf/ignores
python tools/data/textrecog/naf_converter.py PATH/TO/naf --nproc 4
```

- After running the above codes, the directory structure should be as follows:

```
├── naf
│   ├── crops
│   ├── train_label.txt
│   ├── val_label.txt
│   └── test_label.txt
```

19.19 SROIE

- Step1: Step1: Download `0325updated.task1train(626p).zip`, `task1&2_test(361p).zip`, and `text.task1&2-test361p).zip` from homepage to `sroie/`
- Step2:

```
mkdir sroie && cd sroie
mkdir imgs && mkdir annotations && mkdir imgs/training

# Warnninig: The zip files downloaded from Google Drive and BaiduYun Cloud may
# be different, the user should revise the following commands to the correct
# file name if encounter with errors while extracting and move the files.
unzip -q 0325updated.task1train\(626p\).zip && unzip -q task1\&2_test\(361p\).zip &&
↪ unzip -q text.task1\&2-test361p\).zip

# For images
mv 0325updated.task1train\(626p\)/*.jpg imgs/training && mv fulltext_test\(361p\)␣
↪imgs/test

# For annotations
mv 0325updated.task1train\(626p\) annotations/training && mv text.task1\&2-test361p\
↪)/ annotations/test

rm 0325updated.task1train\(626p\).zip && rm task1\&2_test\(361p\).zip && rm text.
↪task1\&2-test361p\).zip
```

- Step3: Generate `train_label.jsonl` and `test_label.jsonl` and crop images using 4 processes with the following command:

```
python tools/data/textrecog/sroie_converter.py PATH/TO/sroie --nproc 4
```

- After running the above codes, the directory structure should be as follows:

```
├── sroie
│   ├── crops
│   ├── train_label.jsonl
│   └── test_label.jsonl
```

19.20 Lecture Video DB

Note: The LV dataset has already provided cropped images and the corresponding annotations

- Step1: Download IIIT-CVid.zip to `lv/`.

```
mkdir lv && cd lv

# Download LV dataset
wget http://cdn.iiit.ac.in/cdn/preon.iiit.ac.in/~kartik/IIIT-CVid.zip
unzip -q IIIT-CVid.zip
```

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```
# For image
mv IIIT-CVid/Crops ./

# For annotation
mv IIIT-CVid/train.txt train_label.txt && mv IIIT-CVid/val.txt val_label.txt && mv␣
↪IIIT-CVid/test.txt test_label.txt

rm IIIT-CVid.zip
```

- Step2: Generate `train_label.jsonl`, `val.jsonl`, and `test.jsonl` with following command:

```
python tools/data/textdreog/lv_converter.py PATH/TO/lv
```

- After running the above codes, the directory structure should be as follows:

```
├── lv
│   ├── Crops
│   ├── train_label.jsonl
│   └── test_label.jsonl
```

19.21 LSVT

- Step1: Download train_full_images_0.tar.gz, train_full_images_1.tar.gz, and train_full_labels.json to `lsvt/`.

```
mkdir lsvt && cd lsvt

# Download LSVT dataset
wget https://dataset-bj.cdn.bcebos.com/lsvt/train_full_images_0.tar.gz
wget https://dataset-bj.cdn.bcebos.com/lsvt/train_full_images_1.tar.gz
wget https://dataset-bj.cdn.bcebos.com/lsvt/train_full_labels.json

mkdir annotations
tar -xf train_full_images_0.tar.gz && tar -xf train_full_images_1.tar.gz
mv train_full_labels.json annotations/ && mv train_full_images_1/*.jpg train_full_
↪images_0/
mv train_full_images_0 imgs

rm train_full_images_0.tar.gz && rm train_full_images_1.tar.gz && rm -rf train_full_
↪images_1
```

- Step2: Generate `train_label.jsonl` and `val_label.jsonl` (optional) with the following command:

```
# Annotations of LSVT test split is not publicly available, split a validation
# set by adding --val-ratio 0.2
# Add --preserve-vertical to preserve vertical texts for training, otherwise
# vertical images will be filtered and stored in PATH/TO/lsvt/ignores
python tools/data/textdrecog/lsvt_converter.py PATH/TO/lsvt --nproc 4
```

- After running the above codes, the directory structure should be as follows:

```
├── lsvt
│   ├── crops
│   ├── ignores
│   ├── train_label.jsonl
│   └── val_label.jsonl (optional)
```

19.22 FUNSD

- Step1: Download dataset.zip to `funsd/`.

```
mkdir funsd && cd funsd

# Download FUNSD dataset
wget https://guillaumejaume.github.io/FUNSD/dataset.zip
unzip -q dataset.zip

# For images
mv dataset/training_data/images imgs && mv dataset/testing_data/images/* imgs/

# For annotations
mkdir annotations
mv dataset/training_data/annotations annotations/training && mv dataset/testing_
↪data/annotations annotations/test

rm dataset.zip && rm -rf dataset
```

- Step2: Generate `train_label.txt` and `test_label.txt` and crop images using 4 processes with following command (add `--preserve-vertical` if you wish to preserve the images containing vertical texts):

```
python tools/data/textrecog/funsd_converter.py PATH/TO/funsd --nproc 4
```

- After running the above codes, the directory structure should be as follows:

```
├── funsd
│   ├── imgs
│   ├── dst_imgs
│   ├── annotations
│   ├── train_label.txt
│   └── test_label.txt
```

19.23 IMGUR

- Step1: Run `download_imgur5k.py` to download images. You can merge PR#5 in your local repository to enable a **much faster** parallel execution of image download.

```
mkdir imgur && cd imgur

git clone https://github.com/facebookresearch/IMGUR5K-Handwriting-Dataset.git
```

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```
# Download images from imgur.com. This may take SEVERAL HOURS!
python ./IMGUR5K-Handwriting-Dataset/download_imgur5k.py --dataset_info_dir ./
↪IMGUR5K-Handwriting-Dataset/dataset_info/ --output_dir ./imgs

# For annotations
mkdir annotations
mv ./IMGUR5K-Handwriting-Dataset/dataset_info/*.json annotations

rm -rf IMGUR5K-Handwriting-Dataset
```

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

```
python tools/data/textrecog/imgur_converter.py PATH/TO/imgur
```

- After running the above codes, the directory structure should be as follows:

```
├── imgur
│   ├── crops
│   ├── train_label.jsonl
│   ├── test_label.jsonl
│   └── val_label.jsonl
```

19.24 KAIST

- Step1: Complete download KAIST_all.zip to `kaist/`.

```
mkdir kaist && cd kaist
mkdir imgs && mkdir annotations

# Download KAIST dataset
wget http://www.iapr-tc11.org/dataset/KAIST_SceneText/KAIST_all.zip
unzip -q KAIST_all.zip

rm KAIST_all.zip
```

- Step2: Extract zips:

```
python tools/data/common/extract_kaist.py PATH/TO/kaist
```

- Step3: Generate `train_label.jsonl` and `val_label.jsonl` (optional) with following command:

```
# Since KAIST does not provide an official split, you can split the dataset by␣
↪adding --val-ratio 0.2
# Add --preserve-vertical to preserve vertical texts for training, otherwise
# vertical images will be filtered and stored in PATH/TO/kaist/ignores
python tools/data/textrecog/kaist_converter.py PATH/TO/kaist --nproc 4
```

- After running the above codes, the directory structure should be as follows:

```
├── kaist
│   ├── crops
│   ├── ignores
│   ├── train_label.jsonl
│   └── val_label.jsonl (optional)
```

19.25 MTWI

- Step1: Download `mtwi_2018_train.zip` from homepage.

```
mkdir mtwi && cd mtwi

unzip -q mtwi_2018_train.zip
mv image_train imgs && mv txt_train annotations

rm mtwi_2018_train.zip
```

- Step2: Generate `train_label.jsonl` and `val_label.jsonl` (optional) with the following command:

```
# Annotations of MTWI test split is not publicly available, split a validation
# set by adding --val-ratio 0.2
# Add --preserve-vertical to preserve vertical texts for training, otherwise
# vertical images will be filtered and stored in PATH/TO/mtwi/ignores
python tools/data/textrecog/mtwi_converter.py PATH/TO/mtwi --nproc 4
```

- After running the above codes, the directory structure should be as follows:

```
├── mtwi
│   ├── crops
│   ├── train_label.jsonl
│   └── val_label.jsonl (optional)
```

19.26 COCO Text v2

- Step1: Download image train2014.zip and annotation cocotext.v2.zip to `coco_textv2/`.

```
mkdir coco_textv2 && cd coco_textv2
mkdir annotations

# Download COCO Text v2 dataset
wget http://images.cocodataset.org/zips/train2014.zip
wget https://github.com/bgshih/cocotext/releases/download/dl/cocotext.v2.zip
unzip -q train2014.zip && unzip -q cocotext.v2.zip

mv train2014 imgs && mv cocotext.v2.json annotations/

rm train2014.zip && rm -rf cocotext.v2.zip
```

- Step2: Generate `train_label.jsonl` and `val_label.jsonl` with the following command:

```
# Add --preserve-vertical to preserve vertical texts for training, otherwise
# vertical images will be filtered and stored in PATH/TO/mtwi/ignores
python tools/data/textrecog/cocotext_converter.py PATH/TO/coco_textv2 --nproc 4
```

- After running the above codes, the directory structure should be as follows:

```
├── coco_textv2
│   ├── crops
│   ├── ignores
│   ├── train_label.jsonl
│   └── val_label.jsonl
```

19.27 ReCTS

- Step1: Download ReCTS.zip to `rects/` from the homepage.

```
mkdir rects && cd rects

# Download ReCTS dataset
# You can also find Google Drive link on the dataset homepage
wget https://datasets.cvc.uab.es/rrc/ReCTS.zip --no-check-certificate
unzip -q ReCTS.zip

mv img imgs && mv gt_unicode annotations

rm ReCTS.zip -f && rm -rf gt
```

- Step2: Generate `train_label.jsonl` and `val_label.jsonl` (optional) with the following command:

```
# Annotations of ReCTS test split is not publicly available, split a validation
# set by adding --val-ratio 0.2
# Add --preserve-vertical to preserve vertical texts for training, otherwise
# vertical images will be filtered and stored in PATH/TO/rects/ignores
python tools/data/textrecog/rects_converter.py PATH/TO/rects --nproc 4
```

- After running the above codes, the directory structure should be as follows:

```
├── rects
│   ├── crops
│   ├── ignores
│   ├── train_label.jsonl
│   └── val_label.jsonl (optional)
```

19.28 ILST

- Step1: Download `IIIT-ILST.zip` from onedrive link
- Step2: Run the following commands

```
unzip -q IIIT-ILST.zip && rm IIIT-ILST.zip
cd IIIT-ILST

# rename files
cd Devanagari && for i in `ls`; do mv -f $i `echo "devanagari_"$i`; done && cd ..
cd Malayalam && for i in `ls`; do mv -f $i `echo "malayalam_"$i`; done && cd ..
cd Telugu && for i in `ls`; do mv -f $i `echo "telugu_"$i`; done && cd ..

# transfer image path
mkdir imgs && mkdir annotations
mv Malayalam/{*jpg,*jpeg} imgs/ && mv Malayalam/*xml annotations/
mv Devanagari/*jpg imgs/ && mv Devanagari/*xml annotations/
mv Telugu/*jpeg imgs/ && mv Telugu/*xml annotations/

# remove unnecessary files
rm -rf Devanagari && rm -rf Malayalam && rm -rf Telugu && rm -rf README.txt
```

- Step3: Generate `train_label.jsonl` and `val_label.jsonl` (optional) and crop images using 4 processes with the following command (add `--preserve-vertical` if you wish to preserve the images containing vertical texts). Since the original dataset doesn't have a validation set, you may specify `--val-ratio` to split the dataset. E.g., if val-ratio is 0.2, then 20% of the data are left out as the validation set in this example.

```
python tools/data/textrecog/ilst_converter.py PATH/TO/IIIT-ILST --nproc 4
```

- After running the above codes, the directory structure should be as follows:

```
├── IIIT-ILST
│   ├── crops
│   ├── ignores
│   ├── train_label.jsonl
│   └── val_label.jsonl (optional)
```

19.29 VinText

- Step1: Download vintext.zip to `vintext`

```
mkdir vintext && cd vintext

# Download dataset from google drive
wget --load-cookies /tmp/cookies.txt "https://docs.google.com/uc?export=download&
↪confirm=$(wget --quiet --save-cookies /tmp/cookies.txt --keep-session-cookies --
↪no-check-certificate 'https://docs.google.com/uc?export=download&
↪id=1UUQhNvzgpZy7zXBFQp0Qox-BBjunZ0ml' -O- | sed -rn 's/.*confirm=([0-9A-Za-z_]+).
↪*/\1\n/p')&id=1UUQhNvzgpZy7zXBFQp0Qox-BBjunZ0ml" -O vintext.zip && rm -rf /tmp/
↪cookies.txt
```

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```
# Extract images and annotations
unzip -q vintext.zip && rm vintext.zip
mv vietnamese/labels ./ && mv vietnamese/test_image ./ && mv vietnamese/train_
↪images ./ && mv vietnamese/unseen_test_images ./
rm -rf vietnamese

# Rename files
mv labels annotations && mv test_image test && mv train_images  training && mv␣
↪unseen_test_images  unseen_test
mkdir imgs
mv training imgs/ && mv test imgs/ && mv unseen_test imgs/
```

- Step2: Generate `train_label.jsonl`, `test_label.jsonl`, `unseen_test_label.jsonl`, and crop images using 4 processes with the following command (add `--preserve-vertical` if you wish to preserve the images containing vertical texts).

```
python tools/data/textrecog/vintext_converter.py PATH/TO/vietnamese --nproc 4
```

- After running the above codes, the directory structure should be as follows:

```
├── vintext
│   ├── crops
│   ├── ignores
│   ├── train_label.jsonl
│   ├── test_label.jsonl
│   └── unseen_test_label.jsonl
```

19.30 BID

- Step1: Download BID Dataset.zip
- Step2: Run the following commands to preprocess the dataset

```
# Rename
mv BID\ Dataset.zip BID_Dataset.zip

# Unzip and Rename
unzip -q BID_Dataset.zip && rm BID_Dataset.zip
mv BID\ Dataset BID

# The BID dataset has a problem of permission, and you may
# add permission for this file
chmod -R 777 BID
cd BID
mkdir imgs && mkdir annotations

# For images and annotations
mv CNH_Aberta/*in.jpg imgs && mv CNH_Aberta/*txt annotations && rm -rf CNH_Aberta
mv CNH_Frente/*in.jpg imgs && mv CNH_Frente/*txt annotations && rm -rf CNH_Frente
mv CNH_Verso/*in.jpg imgs && mv CNH_Verso/*txt annotations && rm -rf CNH_Verso
mv CPF_Frente/*in.jpg imgs && mv CPF_Frente/*txt annotations && rm -rf CPF_Frente
```

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```
mv CPF_Verso/*in.jpg imgs && mv CPF_Verso/*txt annotations && rm -rf CPF_Verso
mv RG_Aberto/*in.jpg imgs && mv RG_Aberto/*txt annotations && rm -rf RG_Aberto
mv RG_Frente/*in.jpg imgs && mv RG_Frente/*txt annotations && rm -rf RG_Frente
mv RG_Verso/*in.jpg imgs && mv RG_Verso/*txt annotations && rm -rf RG_Verso

# Remove unnecessary files
rm -rf desktop.ini
```

- Step3: Generate `train_label.jsonl` and `val_label.jsonl` (optional) and crop images using 4 processes with the following command (add `--preserve-vertical` if you wish to preserve the images containing vertical texts). Since the original dataset doesn't have a validation set, you may specify `--val-ratio` to split the dataset. E.g., if test-ratio is 0.2, then 20% of the data are left out as the validation set in this example.

```
python tools/data/textrecog/bid_converter.py dPATH/TO/BID --nproc 4
```

- After running the above codes, the directory structure should be as follows:

```
├── BID
│   ├── crops
│   ├── ignores
│   ├── train_label.jsonl
│   └── val_label.jsonl (optional)
```

19.31 RCTW

- Step1: Download `train_images.zip.001`, `train_images.zip.002`, and `train_gts.zip` from the homepage, extract the zips to `rctw/imgs` and `rctw/annotations`, respectively.
- Step2: Generate `train_label.jsonl` and `val_label.jsonl` (optional). Since the original dataset doesn't have a validation set, you may specify `--val-ratio` to split the dataset. E.g., if val-ratio is 0.2, then 20% of the data are left out as the validation set in this example.

```
# Annotations of RCTW test split is not publicly available, split a validation set␣
↪by adding --val-ratio 0.2
# Add --preserve-vertical to preserve vertical texts for training, otherwise␣
↪vertical images will be filtered and stored in PATH/TO/rctw/ignores
python tools/data/textrecog/rctw_converter.py PATH/TO/rctw --nproc 4
```

- After running the above codes, the directory structure should be as follows:

```
├── rctw
│   ├── crops
│   ├── ignores
│   ├── train_label.jsonl
│   └── val_label.jsonl (optional)
```

19.32 HierText

- Step1 (optional): Install AWS CLI.
- Step2: Clone HierText repo to get annotations

```
mkdir HierText
git clone https://github.com/google-research-datasets/hiertext.git
```

- Step3: Download `train.tgz`, `validation.tgz` from aws

```
aws s3 --no-sign-request cp s3://open-images-dataset/ocr/train.tgz .
aws s3 --no-sign-request cp s3://open-images-dataset/ocr/validation.tgz .
```

- Step4: Process raw data

```
# process annotations
mv hiertext/gt ./
rm -rf hiertext
mv gt annotations
gzip -d annotations/train.jsonl.gz
gzip -d annotations/validation.jsonl.gz
# process images
mkdir imgs
mv train.tgz imgs/
mv validation.tgz imgs/
tar -xzvf imgs/train.tgz
tar -xzvf imgs/validation.tgz
```

- Step5: Generate `train_label.jsonl` and `val_label.jsonl`. HierText includes different levels of annotation, including `paragraph`, `line`, and `word`. Check the original paper for details. E.g. set `--level paragraph` to get paragraph-level annotation. Set `--level line` to get line-level annotation. set `--level word` to get word-level annotation.

```
# Collect word annotation from HierText  --level word
# Add --preserve-vertical to preserve vertical texts for training, otherwise␣
↪vertical images will be filtered and stored in PATH/TO/HierText/ignores
python tools/data/textrecog/hiertext_converter.py PATH/TO/HierText --level word --
↪nproc 4
```

- After running the above codes, the directory structure should be as follows:

```
├── HierText
│   ├── crops
│   ├── ignores
│   ├── train_label.jsonl
│   └── val_label.jsonl
```

19.33 ArT

- Step1: Download `train_images.tar.gz`, and `train_labels.json` from the homepage to `art/`

```
mkdir art && cd art
mkdir annotations

# Download ArT dataset
wget https://dataset-bj.cdn.bcebos.com/art/train_task2_images.tar.gz
wget https://dataset-bj.cdn.bcebos.com/art/train_task2_labels.json

# Extract
tar -xf train_task2_images.tar.gz
mv train_task2_images crops
mv train_task2_labels.json annotations/

# Remove unnecessary files
rm train_images.tar.gz
```

- Step2: Generate `train_label.jsonl` and `val_label.jsonl` (optional). Since the test annotations are not publicly available, you may specify `--val-ratio` to split the dataset. E.g., if val-ratio is 0.2, then 20% of the data are left out as the validation set in this example.

```
# Annotations of ArT test split is not publicly available, split a validation set␣
↪by adding --val-ratio 0.2
python tools/data/textrecog/art_converter.py PATH/TO/art
```

- After running the above codes, the directory structure should be as follows:

```
├── art
│   ├── crops
│   ├── train_label.jsonl
│   └── val_label.jsonl (optional)
```

CHAPTER

TWENTY

KEY INFORMATION EXTRACTION

20.1 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
```

20.2 Preparation Steps

20.2.1 WildReceipt

- Just download and extract wildreceipt.tar.

20.2.2 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

TWENTYONE

NAMED ENTITY RECOGNITION

21.1 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
```

21.2 Preparation Steps

21.2.1 CLUENER2020

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

CHAPTER

TWENTYTWO

USEFUL TOOLS

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

22.1 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`.

22.2 Convert text recognition dataset to lmdb format

Reading images or labels from files can be slow when data are excessive, e.g. on a scale of millions. Besides, in academia, most of the scene text recognition datasets are stored in lmdb format, including images and labels. To get closer to the mainstream practice and enhance the data storage efficiency, MMOCR now provides `tools/data/utils/lmdb_converter.py` to convert text recognition datasets to lmdb format.

22.2.1 Examples

Generate a mixed lmdb file with label.txt and images in `imgs/`:

```
python tools/data/utils/lmdb_converter.py label.txt imgs.lmdb -i imgs
```

Generate a mixed lmdb file with label.jsonl and images in `imgs/`:

```
python tools/data/utils/lmdb_converter.py label.json imgs.lmdb -i imgs -f jsonl
```

Generate a label-only lmdb file with label.txt:

```
python tools/data/utils/lmdb_converter.py label.txt label.lmdb --label-only
```

Generate a label-only lmdb file with label.jsonl:

```
python tools/data/utils/lmdb_converter.py label.json label.lmdb --label-only -f jsonl
```

22.3 Convert annotations from Labelme

Labelme is a popular graphical image annotation tool. You can convert the labels generated by labelme to the MMOCR data format using `tools/data/common/labelme_converter.py`. Both detection and recognition tasks are supported.

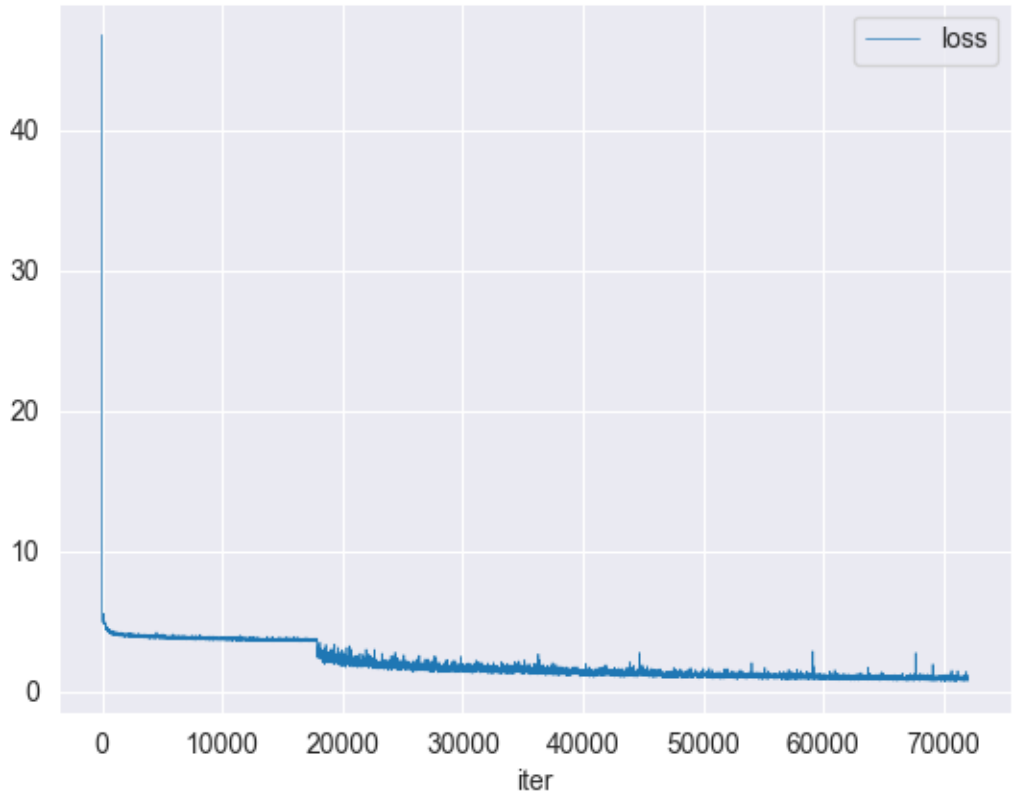
```
# tasks can be "det" or both "det", "recog"
python tools/data/common/labelme_converter.py <json_dir> <image_dir> <out_dir> --tasks
↪<tasks>
```

For example, converting the labelme format annotation in `tests/data/toy_dataset/labelme` to MMOCR detection labels `instances_training.txt` and cropping the image patches for recognition task to `tests/data/toy_dataset/crops` with the labels `train_label.jsonl`:

```
python tools/data/common/labelme_converter.py tests/data/toy_dataset/labelme tests/data/
↪toy_dataset/imgs tests/data/toy_dataset --tasks det recog
```

22.4 Log Analysis

You can use `tools/analyze_logs.py` to plot loss/hmean curves given a training log file. Run `pip install seaborn` first to install the dependency.




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

Examples:

Download the following DBNet and CRNN training logs to run demos.

```
wget https://download.openmmlab.com/mmocr/textdet/dbnet/dbnet_r18_fpnc_sbn_1200e_
↪icdar2015_20210329-ba3ab597.log.json -O DBNet_log.json

wget https://download.openmmlab.com/mmocr/textrecog/crnn/20210326_111035.log.json -O␣
↪CRNN_log.json
```

Please specify an output path if you are running the codes on systems without a GUI.

- Plot loss metric.

  ```
  python tools/analyze_logs.py plot_curve DBNet_log.json --keys loss --legend loss
  ```

- Plot hmean-iou:hmean metric of text detection.

  ```
  python tools/analyze_logs.py plot_curve DBNet_log.json --keys hmean-iou:hmean --
  ↪legend hmean-iou:hmean
  ```

- Plot 0_1-N.E.D metric of text recognition.

```
python tools/analyze_logs.py plot_curve CRNN_log.json --keys 0_1-N.E.D --legend 0_1-
↪N.E.D
```

- Compute the average training speed.

```
python tools/analyze_logs.py cal_train_time CRNN_log.json --include-outliers
```

The output is expected to be like the following.

```
-----Analyze train time of CRNN_log.json-----
slowest epoch 4, average time is 0.3464
fastest epoch 5, average time is 0.2365
time std over epochs is 0.0356
average iter time: 0.2906 s/iter
```

CHAPTER

TWENTYTHREE

CHANGELOG

23.1 0.6.3 (03/11/2022)

23.1.1 Highlights

This release enhances the inference script and fixes a bug that might cause failure on TorchServe.

Besides, a new backbone, oCLIP-ResNet, and a dataset preparation tool, Dataset Preparer, have been released in MMOCR 1.0.0rc3 (1.x branch). Check out the changelog for more information about the features, and maintenance plan for how we will maintain MMOCR in the future.

23.1.2 New Features & Enhancements

- Convert numpy.float32 type to python built-in float type by @JunYao1020 in https://github.com/open-mmlab/mmocr/pull/1462
- When '.' char not in output string, output is also considered to be a… by @JunYao1020 in https://github.com/open-mmlab/mmocr/pull/1457
- Refactor issue template by @Harold-lkk in https://github.com/open-mmlab/mmocr/pull/1449
- issue template by @Harold-lkk in https://github.com/open-mmlab/mmocr/pull/1489
- Update maintainers by @gaotongxiao in https://github.com/open-mmlab/mmocr/pull/1504
- Support MMCV < 1.8.0 by @gaotongxiao in https://github.com/open-mmlab/mmocr/pull/1508

23.1.3 Bug Fixes

- fix ci by @Harold-lkk in https://github.com/open-mmlab/mmocr/pull/1491
- [CI] Fix CI by @gaotongxiao in https://github.com/open-mmlab/mmocr/pull/1463

23.1.4 Docs

- [DOCs] Add MMYOLO in Readme. by @ysh329 in https://github.com/open-mmlab/mmocr/pull/1475
- [Docs] Update contributing.md by @gaotongxiao in https://github.com/open-mmlab/mmocr/pull/1490

23.1.5 New Contributors

- @ysh329 made their first contribution in https://github.com/open-mmlab/mmocr/pull/1475

Full Changelog: https://github.com/open-mmlab/mmocr/compare/v0.6.2...v0.6.3

23.2 0.6.2 (14/10/2022)

23.2.1 Highlights

It's now possible to train/test models through Python Interface. For example, you can train a model under mmocr/ directory in this way:

```
# an example of how to use such modifications is shown as the following:
from mmocr.tools.train import TrainArg, parse_args, run_train_cmd
args = TrainArg(config='/path/to/config.py')
args.add_arg('--work-dir', '/path/to/dir')
args = parse_args(args.arg_list)
run_train_cmd(args)
```

See PR #1138 for more details.

Besides, release candidates for MMOCR 1.0 with tons of new features are available at 1.x branch now! Check out the changelog for more information about the features, and maintenance plan for how we will maintain MMOCR in the future.

23.2.2 New Features

- Adding test & train API to be used directly in code by @wybryan in https://github.com/open-mmlab/mmocr/pull/1138
- Let ResizeOCR full support mmcv.impad's pad_val parameters by @hsiehpinghan in https://github.com/open-mmlab/mmocr/pull/1437

23.2.3 Bug Fixes

- Fix ABINet config by @gaotongxiao in https://github.com/open-mmlab/mmocr/pull/1256
- Fix Recognition Score Normalization Issue by @xinke-wang in https://github.com/open-mmlab/mmocr/pull/1333
- Remove max_seq_len inconsistency by @antoniolanza1996 in https://github.com/open-mmlab/mmocr/pull/1433
- box points ordering by @yjmm10 in https://github.com/open-mmlab/mmocr/pull/1205
- Correct spelling by misspelling 'preperties' to 'properties' by @JunYao1020 in https://github.com/open-mmlab/mmocr/pull/1446

23.2.4 Docs

- Demo, experiments and live inference API on Tiyaro by @Venkat2811 in https://github.com/open-mmlab/mmocr/pull/1272
- Update 1.x info by @Harold-lkk in https://github.com/open-mmlab/mmocr/pull/1369
- Add global notes to the docs and the version switcher menu by @gaotongxiao in https://github.com/open-mmlab/mmocr/pull/1406
- Logger Hook Config Updated to Add WandB by @Nourollah in https://github.com/open-mmlab/mmocr/pull/1345

23.2.5 New Contributors

- @Venkat2811 made their first contribution in https://github.com/open-mmlab/mmocr/pull/1272
- @wybryan made their first contribution in https://github.com/open-mmlab/mmocr/pull/1139
- @hsiehpinghan made their first contribution in https://github.com/open-mmlab/mmocr/pull/1437
- @yjmm10 made their first contribution in https://github.com/open-mmlab/mmocr/pull/1205
- @JunYao1020 made their first contribution in https://github.com/open-mmlab/mmocr/pull/1446
- @Nourollah made their first contribution in https://github.com/open-mmlab/mmocr/pull/1345

Full Changelog: https://github.com/open-mmlab/mmocr/compare/v0.6.1...v0.6.2

23.3 0.6.1 (04/08/2022)

23.3.1 Highlights

1. ArT dataset is available for text detection and recognition!
2. Fix several bugs that affects the correctness of the models.
3. Thanks to MIM, our installation is much simpler now! The docs has been renewed as well.

23.3.2 New Features & Enhancements

- Add ArT by @xinke-wang in https://github.com/open-mmlab/mmocr/pull/1006
- add ABINet_Vision api by @Abdelrahman350 in https://github.com/open-mmlab/mmocr/pull/1041
- add codespell ignore and use mdformat by @Harold-lkk in https://github.com/open-mmlab/mmocr/pull/1022
- Add mim to extras_requrie to setup.py, update mminstall... by @gaotongxiao in https://github.com/open-mmlab/mmocr/pull/1062
- Simplify normalized edit distance calculation by @maxbachmann in https://github.com/open-mmlab/mmocr/pull/1060
- Test mim in CI by @gaotongxiao in https://github.com/open-mmlab/mmocr/pull/1090
- Remove redundant steps by @gaotongxiao in https://github.com/open-mmlab/mmocr/pull/1091
- Update links to SDMGR links by @gaotongxiao in https://github.com/open-mmlab/mmocr/pull/1252

23.3.3 Bug Fixes

- Remove unnecessary requirements by @gaotongxiao in https://github.com/open-mmlab/mmocr/pull/1000
- Remove confusing img_scales in pipelines by @gaotongxiao in https://github.com/open-mmlab/mmocr/pull/1007
- inplace operator "+=" will cause RuntimeError when model backward by @garvan2021 in https://github.com/open-mmlab/mmocr/pull/1018
- Fix a typo problem in MASTER by @Mountchicken in https://github.com/open-mmlab/mmocr/pull/1031
- Fix config name of MASTER in ocr.py by @Mountchicken in https://github.com/open-mmlab/mmocr/pull/1044
- Relax OpenCV requirement by @gaotongxiao in https://github.com/open-mmlab/mmocr/pull/1061
- Restrict the minimum version of OpenCV to avoid potential vulnerability by @gaotongxiao in https://github.com/open-mmlab/mmocr/pull/1065
- typo by @tpoisonooo in https://github.com/open-mmlab/mmocr/pull/1024
- Fix a typo in setup.py by @gaotongxiao in https://github.com/open-mmlab/mmocr/pull/1095
- fix #1067: add torchserve DockerFile and fix bugs by @Hegelim in https://github.com/open-mmlab/mmocr/pull/1073
- Incorrect filename in labelme_converter.py by @xiefeifeihu in https://github.com/open-mmlab/mmocr/pull/1103
- Fix dataset configs by @Mountchicken in https://github.com/open-mmlab/mmocr/pull/1106
- Fix #1098: normalize text recognition scores by @Hegelim in https://github.com/open-mmlab/mmocr/pull/1119
- Update ST_SA_MJ_train.py by @MingyuLau in https://github.com/open-mmlab/mmocr/pull/1117
- PSENet metafile by @gaotongxiao in https://github.com/open-mmlab/mmocr/pull/1121
- Flexible ways of getting file name by @balandongiv in https://github.com/open-mmlab/mmocr/pull/1107
- Updating edge-embeddings after each GNN layer by @amitbcp in https://github.com/open-mmlab/mmocr/pull/1134
- links update by @TekayaNidham in https://github.com/open-mmlab/mmocr/pull/1141
- bug fix: access params by cfg.get by @doem97 in https://github.com/open-mmlab/mmocr/pull/1145
- Fix a bug in LmdbAnnFileBackend that cause breaking in Synthtext detection training by @Mountchicken in https://github.com/open-mmlab/mmocr/pull/1159
- Fix typo of –lmdb-map-size default value by @easilylazy in https://github.com/open-mmlab/mmocr/pull/1147
- Fixed docstring syntax error of line 19 & 21 by @APX103 in https://github.com/open-mmlab/mmocr/pull/1157
- Update lmdb_converter and ct80 cropped image source in document by @doem97 in https://github.com/open-mmlab/mmocr/pull/1164
- MMCV compatibility due to outdated MMDet by @gaotongxiao in https://github.com/open-mmlab/mmocr/pull/1192
- Update maximum version of mmcv by @xinke-wang in https://github.com/open-mmlab/mmocr/pull/1219
- Update ABINet links for main by @Mountchicken in https://github.com/open-mmlab/mmocr/pull/1221
- Update owners by @gaotongxiao in https://github.com/open-mmlab/mmocr/pull/1248
- Add back some missing fields in configs by @gaotongxiao in https://github.com/open-mmlab/mmocr/pull/1171

23.3.4 Docs

- Fix typos by @xinke-wang in https://github.com/open-mmlab/mmocr/pull/1001
- Configure Myst-parser to parse anchor tag by @gaotongxiao in https://github.com/open-mmlab/mmocr/pull/1012
- Fix a error in docs/en/tutorials/dataset_types.md by @Mountchicken in https://github.com/open-mmlab/mmocr/pull/1034
- Update readme according to the guideline by @gaotongxiao in https://github.com/open-mmlab/mmocr/pull/1047
- Limit markdown version by @gaotongxiao in https://github.com/open-mmlab/mmocr/pull/1172
- Limit extension versions by @Mountchicken in https://github.com/open-mmlab/mmocr/pull/1210
- Update installation guide by @gaotongxiao in https://github.com/open-mmlab/mmocr/pull/1254
- Update image link @gaotongxiao in https://github.com/open-mmlab/mmocr/pull/1255

23.3.5 New Contributors

- @tpoisonooo made their first contribution in https://github.com/open-mmlab/mmocr/pull/1024
- @Abdelrahman350 made their first contribution in https://github.com/open-mmlab/mmocr/pull/1041
- @Hegelim made their first contribution in https://github.com/open-mmlab/mmocr/pull/1073
- @xiefeifeihu made their first contribution in https://github.com/open-mmlab/mmocr/pull/1103
- @MingyuLau made their first contribution in https://github.com/open-mmlab/mmocr/pull/1117
- @balandongiv made their first contribution in https://github.com/open-mmlab/mmocr/pull/1107
- @amitbcp made their first contribution in https://github.com/open-mmlab/mmocr/pull/1134
- @TekayaNidham made their first contribution in https://github.com/open-mmlab/mmocr/pull/1141
- @easilylazy made their first contribution in https://github.com/open-mmlab/mmocr/pull/1147
- @APX103 made their first contribution in https://github.com/open-mmlab/mmocr/pull/1157

Full Changelog: https://github.com/open-mmlab/mmocr/compare/v0.6.0...v0.6.1

23.4 0.6.0 (05/05/2022)

23.4.1 Highlights

1. A new recognition algorithm MASTER has been added into MMOCR, which was the championship solution for the "ICDAR 2021 Competition on Scientific Table Image Recognition to Latex"! The model pre-trained on SynthText and MJSynth is available for testing! Credit to @JiaquanYe
2. DBNet++ has been released now! A new Adaptive Scale Fusion module has been equipped for feature enhancement. Benefiting from this, the new model achieved 2% better h-mean score than its predecessor on the ICDAR2015 dataset.
3. Three more dataset converters are added: LSVT, RCTW and HierText. Check the dataset zoo (Det & Recog) to explore further information.

4. To enhance the data storage efficiency, MMOCR now supports loading both images and labels from .lmdb format annotations for the text recognition task. To enable such a feature, the new lmdb_converter.py is ready for use to pack your cropped images and labels into an lmdb file. For a detailed tutorial, please refer to the following sections and the doc.
5. Testing models on multiple datasets is a widely used evaluation strategy. MMOCR now supports automatically reporting mean scores when there is more than one dataset to evaluate, which enables a more convenient comparison between checkpoints. Doc
6. Evaluation is more flexible and customizable now. For text detection tasks, you can set the score threshold range where the best results might come out. (Doc) If too many results are flooding your text recognition train log, you can trim it by specifying a subset of metrics in evaluation config. Check out the Evaluation section for details.
7. MMOCR provides a script to convert the .json labels obtained by the popular annotation toolkit **Labelme** to MMOCR-supported data format. @Y-M-Y contributed a log analysis tool that helps users gain a better understanding of the entire training process. Read tutorial docs to get started.

23.4.2 Lmdb Dataset

Reading images or labels from files can be slow when data are excessive, e.g. on a scale of millions. Besides, in academia, most of the scene text recognition datasets are stored in lmdb format, including images and labels. To get closer to the mainstream practice and enhance the data storage efficiency, MMOCR now officially supports loading images and labels from lmdb datasets via a new pipeline LoadImageFromLMDB. This section is intended to serve as a quick walkthrough for you to master this update and apply it to facilitate your research.

Specifications

To better align with the academic community, MMOCR now requires the following specifications for lmdb datasets:

- The parameter describing the data volume of the dataset is `num-samples` instead of `total_number` (deprecated).
- Images and labels are stored with keys in the form of `image-000000001` and `label-000000001`, respectively.

Usage

1. Use existing academic lmdb datasets if they meet the specifications; or the tool provided by MMOCR to pack images & annotations into a lmdb dataset.

- Previously, MMOCR had a function `txt2lmdb` (deprecated) that only supported converting labels to lmdb format. However, it is quite different from academic lmdb datasets, which usually contain both images and labels. Now MMOCR provides a new utility lmdb_converter to convert recognition datasets with both images and labels to lmdb format.
- Say that your recognition data in MMOCR's format are organized as follows. (See an example in ocr_toy_dataset).

```
# Directory structure

├──img_path
|       |-- img1.jpg
|       |-- img2.jpg
|       |-- ...
|--label.txt (or label.jsonl)
```

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```
# Annotation format

label.txt:  img1.jpg HELLO
            img2.jpg WORLD
            ...

label.jsonl:    {'filename':'img1.jpg', 'text':'HELLO'}
                {'filename':'img2.jpg', 'text':'WORLD'}
                ...
```

- Then pack these files up:

```
python tools/data/utils/lmdb_converter.py  {PATH_TO_LABEL} {OUTPUT_PATH} --i {PATH_
↪TO_IMAGES}
```

- Check out tools.md for more details.

2. The second step is to modify the configuration files. For example, to train CRNN on MJ and ST datasets:

- Set parser as `LineJsonParser` and `file_format` as 'lmdb' in dataset config

```
# configs/_base_/recog_datasets/ST_MJ_train.py
train1 = dict(
    type='OCRDataset',
    img_prefix=train_img_prefix1,
    ann_file=train_ann_file1,
    loader=dict(
        type='AnnFileLoader',
        repeat=1,
        file_format='lmdb',
        parser=dict(
            type='LineJsonParser',
            keys=['filename', 'text'],
        )),
    pipeline=None,
    test_mode=False)
```

- Use `LoadImageFromLMDB` in pipeline:

```
# configs/_base_/recog_pipelines/crnn_pipeline.py
train_pipeline = [
    dict(type='LoadImageFromLMDB', color_type='grayscale'),
    ...
```

3. You are good to go! Start training and MMOCR will load data from your lmdb dataset.

23.4.3 New Features & Enhancements

- Add analyze_logs in tools and its description in docs by @Y-M-Y in https://github.com/open-mmlab/mmocr/pull/899
- Add LSVT Data Converter by @xinke-wang in https://github.com/open-mmlab/mmocr/pull/896
- Add RCTW dataset converter by @xinke-wang in https://github.com/open-mmlab/mmocr/pull/914
- Support computing mean scores in UniformConcatDataset by @gaotongxiao in https://github.com/open-mmlab/mmocr/pull/981
- Support loading images and labels from lmdb file by @Mountchicken in https://github.com/open-mmlab/mmocr/pull/982
- Add recog2lmdb and new toy dataset files by @Mountchicken in https://github.com/open-mmlab/mmocr/pull/979
- Add labelme converter for textdet and textrecog by @cuhk-hbsun in https://github.com/open-mmlab/mmocr/pull/972
- Update CircleCI configs by @xinke-wang in https://github.com/open-mmlab/mmocr/pull/918
- Update Git Action by @xinke-wang in https://github.com/open-mmlab/mmocr/pull/930
- More customizable fields in dataloaders by @gaotongxiao in https://github.com/open-mmlab/mmocr/pull/933
- Skip CIs when docs are modified by @gaotongxiao in https://github.com/open-mmlab/mmocr/pull/941
- Rename Github tests, fix ignored paths by @gaotongxiao in https://github.com/open-mmlab/mmocr/pull/946
- Support latest MMCV by @gaotongxiao in https://github.com/open-mmlab/mmocr/pull/959
- Support dynamic threshold range in eval_hmean by @gaotongxiao in https://github.com/open-mmlab/mmocr/pull/962
- Update the version requirement of mmdet in docker by @Mountchicken in https://github.com/open-mmlab/mmocr/pull/966
- Replace `opencv-python-headless` with `open-python` by @gaotongxiao in https://github.com/open-mmlab/mmocr/pull/970
- Update Dataset Configs by @xinke-wang in https://github.com/open-mmlab/mmocr/pull/980
- Add SynthText dataset config by @xinke-wang in https://github.com/open-mmlab/mmocr/pull/983
- Automatically report mean scores when applicable by @gaotongxiao in https://github.com/open-mmlab/mmocr/pull/995
- Add DBNet++ by @xinke-wang in https://github.com/open-mmlab/mmocr/pull/973
- Add MASTER by @JiaquanYe in https://github.com/open-mmlab/mmocr/pull/807
- Allow choosing metrics to report in text recognition tasks by @gaotongxiao in https://github.com/open-mmlab/mmocr/pull/989
- Add HierText converter by @Mountchicken in https://github.com/open-mmlab/mmocr/pull/948
- Fix lint_only in CircleCI by @gaotongxiao in https://github.com/open-mmlab/mmocr/pull/998

23.4.4 Bug Fixes

- Fix CircleCi Main Branch Accidentally Run PR Stage Test by @xinke-wang in https://github.com/open-mmlab/mmocr/pull/927
- Fix a deprecate warning about mmdet.datasets.pipelines.formating by @Mountchicken in https://github.com/open-mmlab/mmocr/pull/944
- Fix a Bug in ResNet plugin by @Mountchicken in https://github.com/open-mmlab/mmocr/pull/967
- revert a wrong setting in db_r18 cfg by @gaotongxiao in https://github.com/open-mmlab/mmocr/pull/978
- Fix TotalText Anno version issue by @xinke-wang in https://github.com/open-mmlab/mmocr/pull/945
- Update installation step of `albumentations` by @gaotongxiao in https://github.com/open-mmlab/mmocr/pull/984
- Fix ImgAug transform by @gaotongxiao in https://github.com/open-mmlab/mmocr/pull/949
- Fix GPG key error in CI and docker by @gaotongxiao in https://github.com/open-mmlab/mmocr/pull/988
- update label.lmdb by @Mountchicken in https://github.com/open-mmlab/mmocr/pull/991
- correct meta key by @garvan2021 in https://github.com/open-mmlab/mmocr/pull/926
- Use new image by @gaotongxiao in https://github.com/open-mmlab/mmocr/pull/976
- Fix Data Converter Issues by @xinke-wang in https://github.com/open-mmlab/mmocr/pull/955

23.4.5 Docs

- Update CONTRIBUTING.md by @gaotongxiao in https://github.com/open-mmlab/mmocr/pull/905
- Fix the misleading description in test.py by @gaotongxiao in https://github.com/open-mmlab/mmocr/pull/908
- Update recog.md for lmdb Generation by @xinke-wang in https://github.com/open-mmlab/mmocr/pull/934
- Add MMCV by @gaotongxiao in https://github.com/open-mmlab/mmocr/pull/954
- Add wechat QR code to CN readme by @gaotongxiao in https://github.com/open-mmlab/mmocr/pull/960
- Update CONTRIBUTING.md by @gaotongxiao in https://github.com/open-mmlab/mmocr/pull/947
- Use QR codes from MMCV by @gaotongxiao in https://github.com/open-mmlab/mmocr/pull/971
- Renew dataset_types.md by @gaotongxiao in https://github.com/open-mmlab/mmocr/pull/997

23.4.6 New Contributors

- @Y-M-Y made their first contribution in https://github.com/open-mmlab/mmocr/pull/899

Full Changelog: https://github.com/open-mmlab/mmocr/compare/v0.5.0...v0.6.0

23.5 0.5.0 (31/03/2022)

23.5.1 Highlights

1. MMOCR now supports SPACE recognition! (What a prominent feature!) Users only need to convert the recognition annotations that contain spaces from a plain `.txt` file to JSON line format `.jsonl`, and then revise a few configurations to enable the `LineJsonParser`. For more information, please read our step-by-step tutorial.
2. Tesseract is now available in MMOCR! While MMOCR is more flexible to support various downstream tasks, users might sometimes not be satisfied with DL models and would like to turn to effective legacy solutions. Therefore, we offer this option in `mmocr.utils.ocr` by wrapping Tesseract as a detector and/or recognizer. Users can easily create an MMOCR object by `MMOCR(det='Tesseract', recog='Tesseract')`. Credit to @garvan2021
3. We release data converters for **16** widely used OCR datasets, including multiple scenarios such as document, handwritten, and scene text. Now it is more convenient to generate annotation files for these datasets. Check the dataset zoo (Det & Recog) to explore further information.
4. Special thanks to @EighteenSprings @BeyondYourself @yangrisheng, who had actively participated in documentation translation!

23.5.2 Migration Guide - ResNet

Some refactoring processes are still going on. For text recognition models, we unified the `ResNet-like` architectures which are used as backbones. By introducing stage-wise and block-wise plugins, the refactored ResNet is highly flexible to support existing models, like ResNet31 and ResNet45, and other future designs of ResNet variants.

Plugin

- `Plugin` is a module category inherited from MMCV's implementation of `PLUGIN_LAYERS`, which can be inserted between each stage of ResNet or into a basicblock. You can find a simple implementation of plugin at mmocr/models/textrecog/plugins/common.py, or click the button below.

```python
@PLUGIN_LAYERS.register_module()
class Maxpool2d(nn.Module):
    """A wrapper around nn.Maxpool2d().

    Args:
        kernel_size (int or tuple(int)): Kernel size for max pooling layer
        stride (int or tuple(int)): Stride for max pooling layer
        padding (int or tuple(int)): Padding for pooling layer
    """

    def __init__(self, kernel_size, stride, padding=0, **kwargs):
        super(Maxpool2d, self).__init__()
        self.model = nn.MaxPool2d(kernel_size, stride, padding)

    def forward(self, x):
        """
        Args:
            x (Tensor): Input feature map
```

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```
        Returns:
            Tensor: The tensor after Maxpooling layer.
        """
        return self.model(x)
```

Stage-wise Plugins

- ResNet is composed of stages, and each stage is composed of blocks. E.g., ResNet18 is composed of 4 stages, and each stage is composed of basicblocks. For each stage, we provide two ports to insert stage-wise plugins by giving `plugins` parameters in ResNet.

```
[port1: before stage] ---> [stage] ---> [port2: after stage]
```

- E.g. Using a ResNet with four stages as example. Suppose we want to insert an additional convolution layer before each stage, and an additional convolution layer at stage 1, 2, 4. Then you can define the special ResNet18 like this

```
resnet18_speical = ResNet(
        # for simplicity, some required
        # parameters are omitted
        plugins=[
            dict(
                cfg=dict(
                type='ConvModule',
                kernel_size=3,
                stride=1,
                padding=1,
                norm_cfg=dict(type='BN'),
                act_cfg=dict(type='ReLU')),
                stages=(True, True, True, True),
                position='before_stage')
            dict(
                cfg=dict(
                type='ConvModule',
                kernel_size=3,
                stride=1,
                padding=1,
                norm_cfg=dict(type='BN'),
                act_cfg=dict(type='ReLU')),
                stages=(True, True, False, True),
                position='after_stage')
        ])
```

- You can also insert more than one plugin in each port and those plugins will be executed in order. Let's take ResNet in MASTER as an example:
  - ResNet in Master is based on ResNet31. And after each stage, a module named `GCAModule` will be used. The `GCAModule` is inserted before the stage-wise convolution layer in ResNet31. In conlusion, there will be two plugins at `after_stage` port in the same time.

```
resnet_master = ResNet(
                # for simplicity, some required
```

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```
                # parameters are omitted
                plugins=[
                    dict(
                        cfg=dict(type='Maxpool2d', kernel_size=2, stride=(2,␣
↪2)),
                        stages=(True, True, False, False),
                        position='before_stage'),
                    dict(
                        cfg=dict(type='Maxpool2d', kernel_size=(2, 1),␣
↪stride=(2, 1)),
                        stages=(False, False, True, False),
                        position='before_stage'),
                    dict(
                        cfg=dict(type='GCAModule', kernel_size=3, stride=1,␣
↪padding=1),
                        stages=[True, True, True, True],
                        position='after_stage'),
                    dict(
                        cfg=dict(
                            type='ConvModule',
                            kernel_size=3,
                            stride=1,
                            padding=1,
                            norm_cfg=dict(type='BN'),
                            act_cfg=dict(type='ReLU')),
                        stages=(True, True, True, True),
                        position='after_stage')
                ])
```

  - In each plugin, we will pass two parameters (`in_channels`, `out_channels`) to support operations that need the information of current channels.

Block-wise Plugin (Experimental)

- We also refactored the `BasicBlock` used in ResNet. Now it can be customized with block-wise plugins. Check here for more details.
- BasicBlock is composed of two convolution layer in the main branch and a shortcut branch. We provide four ports to insert plugins.

```
    [port1: before_conv1] ---> [conv1] --->
    [port2: after_conv1] ---> [conv2] --->
    [port3: after_conv2] ---> +(shortcut) ---> [port4: after_shortcut]
```

- In each plugin, we will pass a parameter `in_channels` to support operations that need the information of current channels.
- E.g. Build a ResNet with customized BasicBlock with an additional convolution layer before conv1:

```
resnet_31 = ResNet(
        in_channels=3,
        stem_channels=[64, 128],
```

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```
        block_cfgs=dict(type='BasicBlock'),
        arch_layers=[1, 2, 5, 3],
        arch_channels=[256, 256, 512, 512],
        strides=[1, 1, 1, 1],
        plugins=[
            dict(
                cfg=dict(type='Maxpool2d',
                kernel_size=2,
                stride=(2, 2)),
                stages=(True, True, False, False),
                position='before_stage'),
            dict(
                cfg=dict(type='Maxpool2d',
                kernel_size=(2, 1),
                stride=(2, 1)),
                stages=(False, False, True, False),
                position='before_stage'),
            dict(
                cfg=dict(
                type='ConvModule',
                kernel_size=3,
                stride=1,
                padding=1,
                norm_cfg=dict(type='BN'),
                act_cfg=dict(type='ReLU')),
                stages=(True, True, True, True),
                position='after_stage')
        ])
```

Full Examples

- ResNet45 is used in ASTER and ABINet without any plugins.

```
resnet45_aster = ResNet(
    in_channels=3,
    stem_channels=[64, 128],
    block_cfgs=dict(type='BasicBlock', use_conv1x1='True'),
    arch_layers=[3, 4, 6, 6, 3],
    arch_channels=[32, 64, 128, 256, 512],
    strides=[(2, 2), (2, 2), (2, 1), (2, 1), (2, 1)])

resnet45_abi = ResNet(
    in_channels=3,
    stem_channels=32,
    block_cfgs=dict(type='BasicBlock', use_conv1x1='True'),
    arch_layers=[3, 4, 6, 6, 3],
    arch_channels=[32, 64, 128, 256, 512],
    strides=[2, 1, 2, 1, 1])
```

- ResNet31 is a typical architecture to use stage-wise plugins. Before the first three stages, Maxpooling layer is used. After each stage, a convolution layer with BN and ReLU is used.

```
resnet_31 = ResNet(
    in_channels=3,
    stem_channels=[64, 128],
    block_cfgs=dict(type='BasicBlock'),
    arch_layers=[1, 2, 5, 3],
    arch_channels=[256, 256, 512, 512],
    strides=[1, 1, 1, 1],
    plugins=[
        dict(
            cfg=dict(type='Maxpool2d',
            kernel_size=2,
            stride=(2, 2)),
            stages=(True, True, False, False),
            position='before_stage'),
        dict(
            cfg=dict(type='Maxpool2d',
            kernel_size=(2, 1),
            stride=(2, 1)),
            stages=(False, False, True, False),
            position='before_stage'),
        dict(
            cfg=dict(
            type='ConvModule',
            kernel_size=3,
            stride=1,
            padding=1,
            norm_cfg=dict(type='BN'),
            act_cfg=dict(type='ReLU')),
            stages=(True, True, True, True),
            position='after_stage')
    ])
```

23.5.3 Migration Guide - Dataset Annotation Loader

The annotation loaders, `LmdbLoader` and `HardDiskLoader`, are unified into `AnnFileLoader` for a more consistent design and wider support on different file formats and storage backends. `AnnFileLoader` can load the annotations from `disk`(default), `http` and `petrel` backend, and parse the annotation in `txt` or `lmdb` format. `LmdbLoader` and `HardDiskLoader` are deprecated, and users are recommended to modify their configs to use the new `AnnFileLoader`. Users can migrate their legacy loader `HardDiskLoader` referring to the following example:

```
# Legacy config
train = dict(
    type='OCRDataset',
    ...
    loader=dict(
        type='HardDiskLoader',
        ...))

# Suggested config
train = dict(
    type='OCRDataset',
```

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```
...
loader=dict(
    type='AnnFileLoader',
    file_storage_backend='disk',
    file_format='txt',
    ...))
```

Similarly, using `AnnFileLoader` with `file_format='lmdb'` instead of `LmdbLoader` is strongly recommended.

23.5.4 New Features & Enhancements

- Update mmcv install by @Harold-lkk in https://github.com/open-mmlab/mmocr/pull/775
- Upgrade isort by @gaotongxiao in https://github.com/open-mmlab/mmocr/pull/771
- Automatically infer device for inference if not speicifed by @gaotongxiao in https://github.com/open-mmlab/mmocr/pull/781
- Add open-mmlab precommit hooks by @gaotongxiao in https://github.com/open-mmlab/mmocr/pull/787
- Add windows CI by @gaotongxiao in https://github.com/open-mmlab/mmocr/pull/790
- Add CurvedSyntext150k Converter by @gaotongxiao in https://github.com/open-mmlab/mmocr/pull/719
- Add FUNSD Converter by @xinke-wang in https://github.com/open-mmlab/mmocr/pull/808
- Support loading annotation file with petrel/http backend by @cuhk-hbsun in https://github.com/open-mmlab/mmocr/pull/793
- Support different seeds on different ranks by @gaotongxiao in https://github.com/open-mmlab/mmocr/pull/820
- Support json in recognition converter by @Mountchicken in https://github.com/open-mmlab/mmocr/pull/844
- Add args and docs for multi-machine training/testing by @gaotongxiao in https://github.com/open-mmlab/mmocr/pull/849
- Add warning info for LineStrParser by @xinke-wang in https://github.com/open-mmlab/mmocr/pull/850
- Deploy openmmlab-bot by @gaotongxiao in https://github.com/open-mmlab/mmocr/pull/876
- Add Tesserocr Inference by @garvan2021 in https://github.com/open-mmlab/mmocr/pull/814
- Add LV Dataset Converter by @xinke-wang in https://github.com/open-mmlab/mmocr/pull/871
- Add SROIE Converter by @xinke-wang in https://github.com/open-mmlab/mmocr/pull/810
- Add NAF Converter by @xinke-wang in https://github.com/open-mmlab/mmocr/pull/815
- Add DeText Converter by @xinke-wang in https://github.com/open-mmlab/mmocr/pull/818
- Add IMGUR Converter by @xinke-wang in https://github.com/open-mmlab/mmocr/pull/825
- Add ILST Converter by @Mountchicken in https://github.com/open-mmlab/mmocr/pull/833
- Add KAIST Converter by @xinke-wang in https://github.com/open-mmlab/mmocr/pull/835
- Add IC11 (Born-digital Images) Data Converter by @xinke-wang in https://github.com/open-mmlab/mmocr/pull/857
- Add IC13 (Focused Scene Text) Data Converter by @xinke-wang in https://github.com/open-mmlab/mmocr/pull/861
- Add BID Converter by @Mountchicken in https://github.com/open-mmlab/mmocr/pull/862

- Add Vintext Converter by @Mountchicken in https://github.com/open-mmlab/mmocr/pull/864
- Add MTWI Data Converter by @xinke-wang in https://github.com/open-mmlab/mmocr/pull/867
- Add COCO Text v2 Data Converter by @xinke-wang in https://github.com/open-mmlab/mmocr/pull/872
- Add ReCTS Data Converter by @xinke-wang in https://github.com/open-mmlab/mmocr/pull/892
- Refactor ResNets by @Mountchicken in https://github.com/open-mmlab/mmocr/pull/809

23.5.5 Bug Fixes

- Bump mmdet version to 2.20.0 in Dockerfile by @GPhilo in https://github.com/open-mmlab/mmocr/pull/763
- Update mmdet version limit by @cuhk-hbsun in https://github.com/open-mmlab/mmocr/pull/773
- Minimum version requirement of albumentations by @gaotongxiao in https://github.com/open-mmlab/mmocr/pull/769
- Disable worker in the dataloader of gpu unit test by @gaotongxiao in https://github.com/open-mmlab/mmocr/pull/780
- Standardize the type of torch.device in ocr.py by @gaotongxiao in https://github.com/open-mmlab/mmocr/pull/800
- Use RECOGNIZER instead of DETECTORS by @cuhk-hbsun in https://github.com/open-mmlab/mmocr/pull/685
- Add num_classes to configs of ABINet by @gaotongxiao in https://github.com/open-mmlab/mmocr/pull/805
- Support loading space character from dict file by @gaotongxiao in https://github.com/open-mmlab/mmocr/pull/854
- Description in tools/data/utils/txt2lmdb.py by @Mountchicken in https://github.com/open-mmlab/mmocr/pull/870
- ignore_index in SARLoss by @Mountchicken in https://github.com/open-mmlab/mmocr/pull/869
- Fix a bug that may cause inplace operation error by @Mountchicken in https://github.com/open-mmlab/mmocr/pull/884
- Use hyphen instead of underscores in script args by @gaotongxiao in https://github.com/open-mmlab/mmocr/pull/890

23.5.6 Docs

- Add deprecation message for deploy tools by @xinke-wang in https://github.com/open-mmlab/mmocr/pull/801
- Reorganizing OpenMMLab projects in readme by @xinke-wang in https://github.com/open-mmlab/mmocr/pull/806
- Add demo/README_zh.md by @EighteenSprings in https://github.com/open-mmlab/mmocr/pull/802
- Add detailed version requirement table by @gaotongxiao in https://github.com/open-mmlab/mmocr/pull/778
- Correct misleading section title in training.md by @gaotongxiao in https://github.com/open-mmlab/mmocr/pull/819
- Update README_zh-CN document URL by @BeyondYourself in https://github.com/open-mmlab/mmocr/pull/823
- translate testing.md. by @yangrisheng in https://github.com/open-mmlab/mmocr/pull/822

- Fix confused description for load-from and resume-from by @xinke-wang in https://github.com/open-mmlab/mmocr/pull/842
- Add documents getting_started in docs/zh by @BeyondYourself in https://github.com/open-mmlab/mmocr/pull/841
- Add the model serving translation document by @BeyondYourself in https://github.com/open-mmlab/mmocr/pull/845
- Update docs about installation on Windows by @Mountchicken in https://github.com/open-mmlab/mmocr/pull/852
- Update tutorial notebook by @gaotongxiao in https://github.com/open-mmlab/mmocr/pull/853
- Update Instructions for New Data Converters by @xinke-wang in https://github.com/open-mmlab/mmocr/pull/900
- Brief installation instruction in README by @Harold-lkk in https://github.com/open-mmlab/mmocr/pull/897
- update doc for ILST, VinText, BID by @Mountchicken in https://github.com/open-mmlab/mmocr/pull/902
- Fix typos in readme by @gaotongxiao in https://github.com/open-mmlab/mmocr/pull/903
- Recog dataset doc by @Harold-lkk in https://github.com/open-mmlab/mmocr/pull/893
- Reorganize the directory structure section in det.md by @gaotongxiao in https://github.com/open-mmlab/mmocr/pull/894

23.6 New Contributors

- @GPhilo made their first contribution in https://github.com/open-mmlab/mmocr/pull/763
- @xinke-wang made their first contribution in https://github.com/open-mmlab/mmocr/pull/801
- @EighteenSprings made their first contribution in https://github.com/open-mmlab/mmocr/pull/802
- @BeyondYourself made their first contribution in https://github.com/open-mmlab/mmocr/pull/823
- @yangrisheng made their first contribution in https://github.com/open-mmlab/mmocr/pull/822
- @Mountchicken made their first contribution in https://github.com/open-mmlab/mmocr/pull/844
- @garvan2021 made their first contribution in https://github.com/open-mmlab/mmocr/pull/814

Full Changelog: https://github.com/open-mmlab/mmocr/compare/v0.4.1...v0.5.0

23.7 v0.4.1 (27/01/2022)

23.7.1 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

23.7.2 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

23.7.3 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

23.7.4 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

23.7.5 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

23.8 v0.4.0 (15/12/2021)

23.8.1 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

23.8.2 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.

23.8.3 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

23.8.4 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

23.8.5 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

23.8.6 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

23.8.7 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

23.8.8 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

23.9 v0.3.0 (25/8/2021)

23.9.1 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

23.9.2 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.

23.9.3 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

23.9.4 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

23.9.5 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

23.9.6 Contributors

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

23.10 v0.2.1 (20/7/2021)

23.10.1 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

23.10.2 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

23.10.3 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

23.10.4 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

23.11 v0.2.0 (18/5/2021)

23.11.1 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.

23.11.2 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

23.11.3 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

23.11.4 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

23.12 v0.1.0 (7/4/2021)

23.12.1 Highlights

- MMOCR is released.

23.12.2 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.

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WELCOME TO THE OPENMMLAB COMMUNITY

Scan the QR code below to follow the OpenMMLab team's **Zhihu Official Account** and join the OpenMMLab team's **QQ Group**, or join the official communication WeChat group by adding the WeChat, or join our **Slack**

We will provide you with the OpenMMLab community

- share the latest core technologies of AI frameworks
- Explaining PyTorch common module source Code
- News related to the release of OpenMMLab
- Introduction of cutting-edge algorithms developed by OpenMMLab Get the more efficient answer and feedback
- Provide a platform for communication with developers from all walks of life

The OpenMMLab community looks forward to your participation!

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