Visual Recognitionusing Deep Learning

Lab3 report

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My github

1. https://github.com/Potato-TW/visual_dl/tree/main

Introduction

In this lab, we implement Mask RCNN with different pretrain weights to solve instance segmentation task.
We train our model on medical cell images of 4 classes.
Evaluate prediction by COCO evaluation to reach highest average precision.

Method

We basically implement on detectron2 that is developed, maintained by Facebook.
And we refer to official tutorial of detectron2.

Dataset

We first register training data, and validation data.
In this lab, we use $\frac{1}{5}$ of the whole dataset to be validation data.

```
def register_dataset(name: str, suffix: str):
    if name in DatasetCatalog.list():
        return

    DatasetCatalog.register(name, lambda s=suffix: get_dict(s))
    MetadataCatalog.get(name).set(
        thing_classes=[f'class{i}' for i in range(1, NUM_CLASSES+1)],
        mask_format="bitmask",
    )
def get_dict(suffix: str) -> List[Dict]:
    dirs = list((DATA_ROOT / "train").iterdir())
    random.Random(SEED).shuffle(dirs)
    end = int(len(dirs) * (1 - VAL_RATIO))
    splited_dir = dirs[:end] if suffix == "train" else dirs[end:]
    return [get_item(dir, i) for i, dir in enumerate(splited_dir)]
```

Then we first make dataset into COCO format.
We load in image infomation, and the importance is annotation that we use segmentation with RLE format.
For each mask file, there are several unique value representing the same class.
Then encode binary mask into bounding box.

```python
def get_item(dir_path: Path, img_id: int) -> Dict:
    img_path = dir_path / "image.tif"
    img = cv2.imread(str(img_path))
    h, w = img.shape[0], img.shape[1]
    record = {
        "file_name": str(img_path),
        "image_id": img_id,
        "height": h,
        "width": w,
    }

    annos = []
    for mask_path in dir_path.glob("class*.tif"):
        m = re.search(r"class(\d+)\.tif", mask_path.name)
        class_ = int(m.group(1)) - 1
        mask = cv2.imread(str(mask_path), cv2.IMREAD_UNCHANGED)
        if mask.ndim > 2:
            mask = mask[..., 0]
        for inst_id in np.unique(mask):
            if inst_id == 0:
                continue
            bin_mask = (mask == inst_id).astype(np.uint8).copy()
            ys, xs = np.where(bin_mask)
            x0, y0, x1, y1 = xs.min(), ys.min(), xs.max(), ys.max() # xyxy
            rle = encode_mask(bin_mask)
            annos.append(
                {
                    "bbox": [int(x0), int(y0), int(x1), int(y1)],
                    "bbox_mode": BoxMode.XYXY_ABS,
                    "segmentation": rle,
                    "category_id": class_,
                    "iscrowd": 0,
                }
            )

    record["annotations"] = annos
    return record
```

Train

In training step, load in model file, and set training configure.
Most of the settings is default settings, which use WarmupMultiStepLR and 0.0004 as initial learning rate.
For 1000 iterations, evaluate the result by coco evaluator.

```python
class Trainer(DefaultTrainer):
    @classmethod
    def build_evaluator(cls, cfg, dataset_name, output_folder=None):
        if output_folder is None:
            output_folder = os.path.join(cfg.OUTPUT_DIR, 'coco')
        return COCOEvaluator(dataset_name, cfg, output_dir=output_folder)
```

```python
def setup(args):
    cfg=get_cfg()
    cfg.merge_from_file(model_zoo.get_config_file(MODEL_YAML))
    cfg.MODEL.WEIGHTS=model_zoo.get_checkpoint_url(MODEL_YAML)
    cfg.INPUT.MASK_FORMAT="bitmask"

    cfg.DATASETS.TRAIN=(f'{DATASET_NAME}_train',)
    cfg.DATASETS.TEST=(f'{DATASET_NAME}_val',)
    cfg.DATALOADER.NUM_WORKERS=NUM_WORKERS

    cfg.MODEL.ROI_HEADS.NUM_CLASSES=NUM_CLASSES

    cfg.SOLVER.IMS_PER_BATCH=1
    cfg.SOLVER.BASE_LR=4e-4
    cfg.SOLVER.MAX_ITER=TOTAL_ITER
    cfg.SOLVER.STEPS=(5000,)
    cfg.SOLVER.CHECKPOINT_PERIOD=1000

    cfg.INPUT.MIN_SIZE_TRAIN=(512,)
    cfg.INPUT.MAX_SIZE_TRAIN=1024
    cfg.INPUT.MIN_SIZE_TEST=0
    cfg.INPUT.MAX_SIZE_TEST=1024

    cfg.TEST.EVAL_PERIOD=1000

    cfg.OUTPUT_DIR=str(OUTPUT_DIR.resolve())
    os.makedirs(cfg.OUTPUT_DIR, exist_ok=True)

    cfg.freeze()
    default_setup(cfg, args)

    return cfg
```

Inference

For inference and validation, we load in original size of images.
And export to coco format with xyxy of bbox.

```python
def setup():
    cfg=get_cfg()
    cfg.merge_from_file(model_zoo.get_config_file(MODEL_YAML))
    cfg.MODEL.WEIGHTS='log/model_final.pth'
    cfg.MODEL.ROI_HEADS.NUM_CLASSES=NUM_CLASSES
    cfg.INPUT.MIN_SIZE_TEST=0
    # cfg.INPUT.MAX_SIZE_TEST=1024
    cfg.freeze()
    return cfg
```

```
if __name__=='__main__':
    predictor=DefaultPredictor(setup())

    test_file_name_id = {}
    with open(DATA_ROOT/'test_image_name_to_ids.json') as f:
        for img_info in json.load(f):
            name = img_info['file_name']
            id = img_info['id']
            test_file_name_id[name] = id


    results=[]
    for img_path in list((DATA_ROOT/'test_release').glob('*.tif')):
        img = cv2.imread(str(img_path))

        output = predictor(img)['instances'].to('cpu')
        for box, mask, class_, score in
zip(output.pred_boxes.tensor.numpy(),
                                            output.pred_masks.numpy(),
                                            output.pred_classes.numpy(),
                                            output.scores.numpy()):
            rle = encode_mask(mask)
            results.append({
                'image_id': int(test_file_name_id[img_path.name]),
                'bbox': box.tolist(),
                'score': float(score),
                'category_id': int(class_ + 1),
                'segmentation': rle
            })

    json_path = './test-results.json'
    with open(json_path, 'w') as f:
        json.dump(results, f)
```

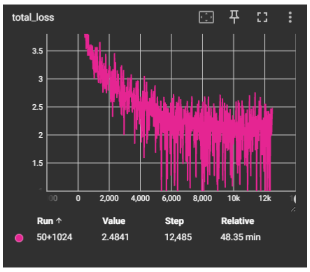
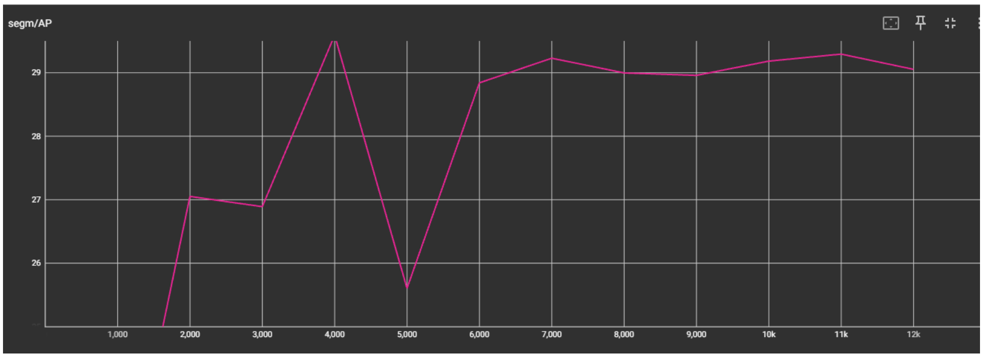
Hyperparameter

- Learning rate: 0.0004
- LR scheduler: WarmupMultiStepLR
- Gamma: 0.1
- Weight decay: 0.0001
- Momentum: 0.9
- Model: cascade_mask_rcnn_R_50_FPN_3x

Results

In validation with resizing images to 512 (min size), we can get around 30 AP score.
And in test, we can get around 41 AP score showing in Codebench.

Total training loss	Segmentation AP

Total training loss	Segmentation AP
	

References

Detectron2 official github

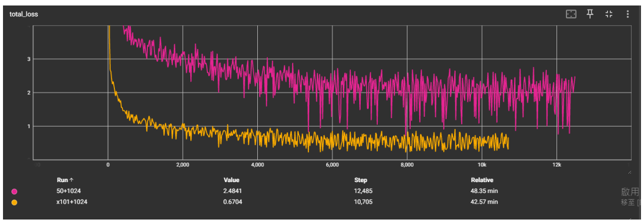
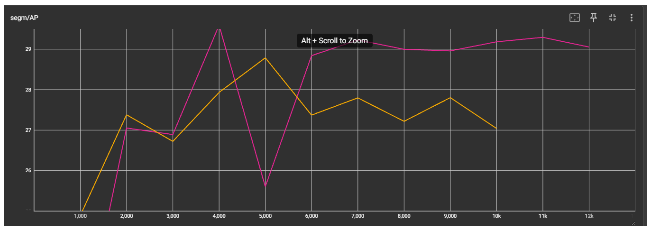
Detectron2 Colab tutorial

Additional experiments

Different models

- Red line: cascade_mask_rcnn_R_50_FPN_3x
- Yellow line: mask_rcnn_X_101_32x8d_FPN_3x

In original resnet comparision, resXnet101 is much better than resnet50.
But in with cascade on mask rcnn with backbone resnet50, though 101 gets better loss, cascade resnet50 performs much better in AP on test data.
Even they have similar parameter size.

Total training loss	AP
	

Different Max size of images

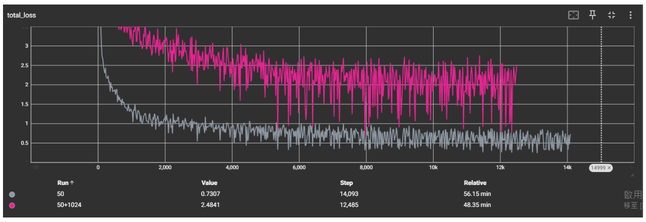
Both are cascade_mask_rcnn_R_50_FPN_3x

- Red: With max size of 1024
- Gray: With max size of 1333 (default)

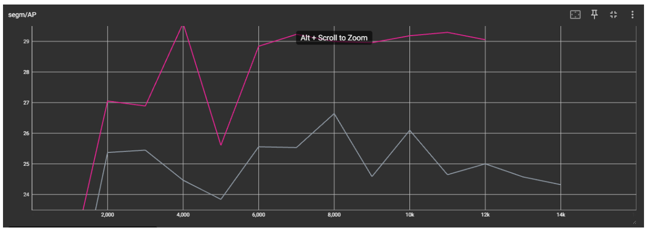
Originally, I think larger images are better for model to recognize the mask. Thus we resize bigger to feed in.
For both groups, we can see max size of images affects a lot on performance of loss and AP.
Max size is used in Detectron2.transform.ResizeShortestEdge that resize images according to the

proportion of shortest edges.
In conclusion, smaller max size is better for this model.

Total training loss

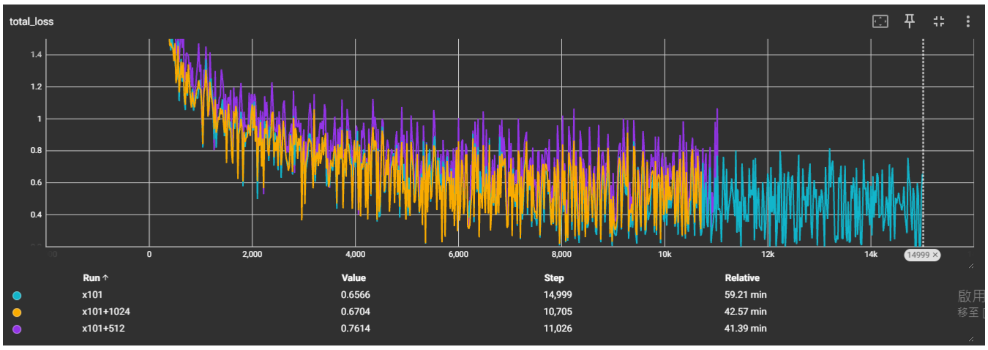


AP



It also shows in another model that for sure the smaller max size is better for model.

Total training loss



AP