

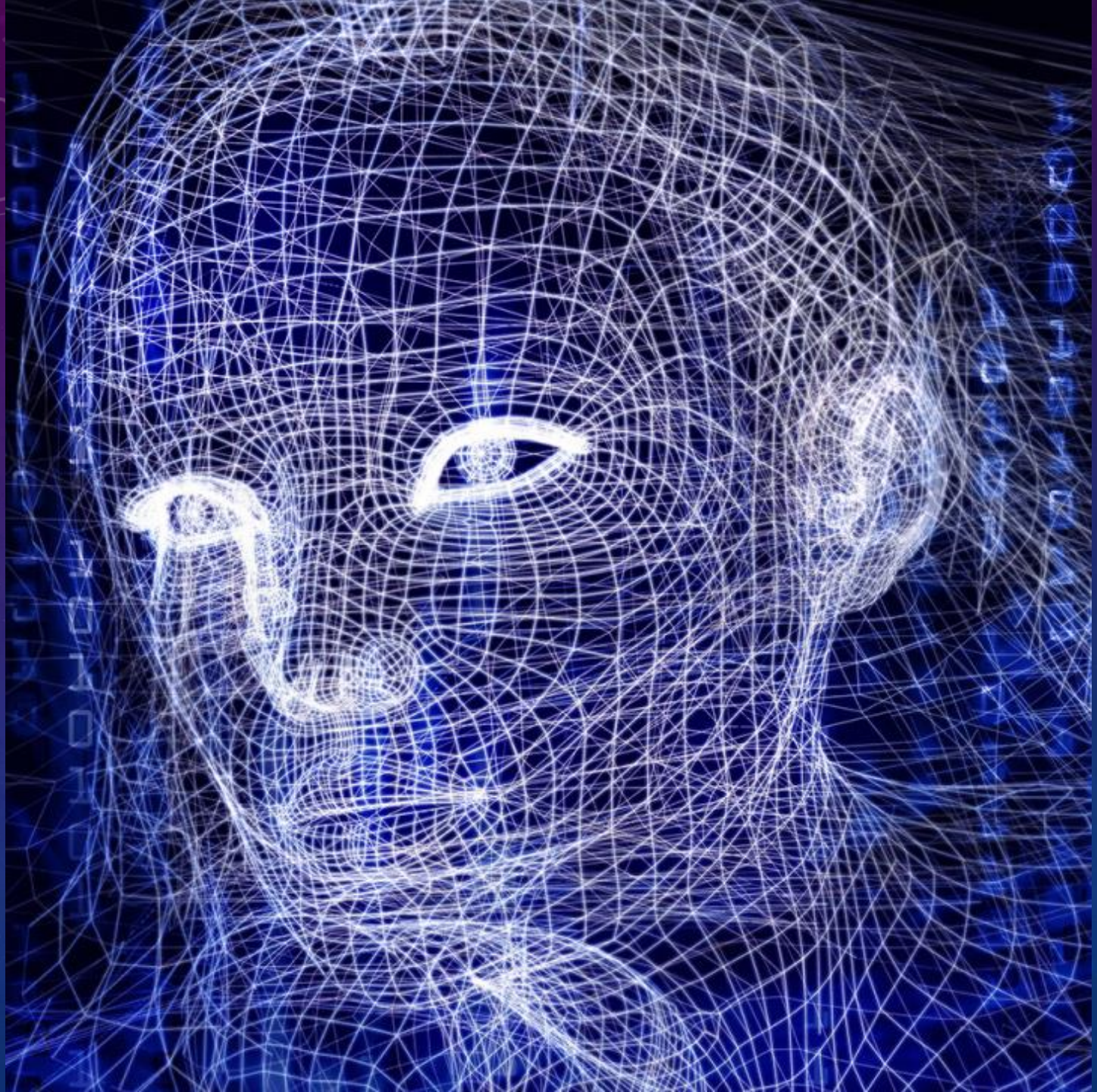
LECTURE SERIES FOR DIGITAL
SURVEILLANCE SYSTEMS AND APPLICATION

CH4
EXPERIMENT
FOR
OBJECT DETECTION

徐繼聖

Gee-Sern Jison Hsu

National Taiwan University of Science
and Technology

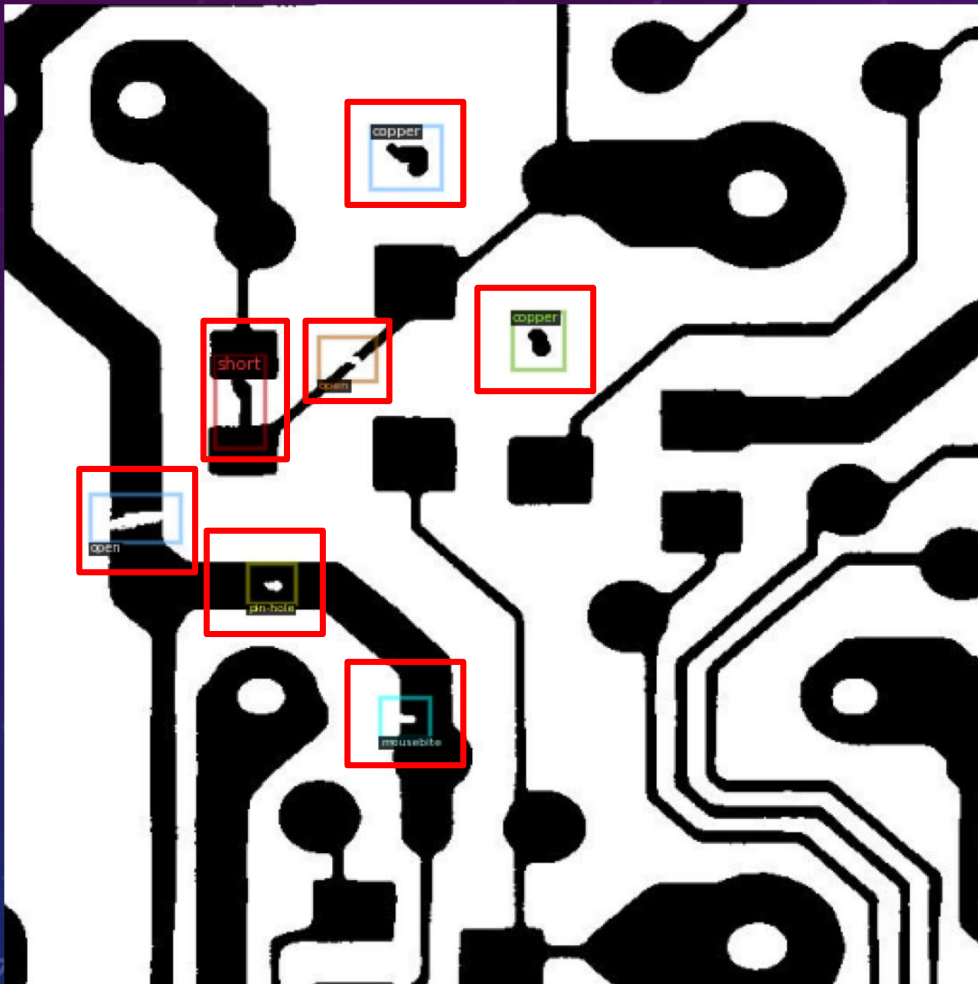


Example 4-1 – Faster RCNN

In this example, we want to use Faster RCNN to detect defects on a Printed Circuit Board (PCB). The problem is a classification of 6 different defect types. The defect types can be a short circuit or Pin-hole on the circuits for example. You can see an overview of all defect types in the following slide. We will use pretrained weights, which were trained on the COCO dataset and retrain on our own data.

Example 4-1 – Faster RCNN

PCB data sample:



Category Type Sample:



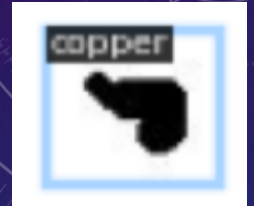
Open



Spur



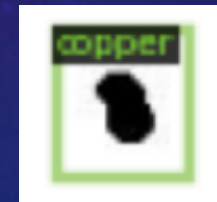
Short



Copper



Pin-hole



Copper



Mousebite

Training data :1000 images

Testing data : 500 images

Example 4-1 – Faster RCNN

Step 1 : Set up environment

```
!pip install -U torch==1.5 torchvision==0.6 -f https://download.pytorch.org/whl/cu101/torch_stable.html
!pip install cython pyyaml==5.1
!pip install -U 'git+https://github.com/cocodataset/cocoapi.git#subdirectory=PythonAPI'
import torch, torchvision
print(torch.__version__, torch.cuda.is_available())
!gcc --version
```

Result :

```
Successfully installed torch-1.5.0+cu101 torchvision-0.6.0+cu101
Requirement already satisfied: cython in /usr/local/lib/python3.6/dist-packages (0.29.20)
```

```
Successfully built pyyaml
```

```
Successfully installed pyyaml-5.1
```

```
Successfully installed pycocotools-2.0
```

Example 4-1 – Faster RCNN

Step 1 : Set up environment

```
!git clone https://github.com/tangsanli5201/DeepPCB
# install detectron2:
!pip install detectron2==0.1.3 -f https://dl.fbaipublicfiles.com/detectron2/wheels/cu101/torch1.5/index.html
```

Result :

```
Requirement already satisfied: pyasn1<0.5.0,>=0.4.6 in /usr/local/lib/python3.6/dist-packages (from pyasn1-modules>=0.2.1->google-auth<2,>=1.6.3->tensorflow)
Building wheels for collected packages: fvcare
  Building wheel for fvcare (setup.py) ... done
  Created wheel for fvcare: filename=fvcare-0.1.1.post20200630-cp36-none-any.whl size=41299 sha256=0973f00611a6330425c434401316cea811cc11c9d0ffe9159f9c
  Stored in directory: /root/.cache/pip/wheels/80/eb/49/83b9d20a804f1b4b163d1c1451c670a2067a00175662516f01
Successfully built fvcare
Installing collected packages: yacs, portalocker, fvcare, mock, detectron2
Successfully installed detectron2-0.1.3+cu101 fvcare-0.1.1.post20200630 mock-4.0.2 portalocker-1.7.0 yacs-0.1.7
```


Example 4-1 – Faster RCNN

Register PCB dataset

```
def get_PCB_dict(data_list):
    dataset_dicts = []

    for i, path in enumerate(data_list):
        filename = path[0]
        height, width = cv2.imread(filename).shape[:2]
        record = {}
        record['file_name'] = filename
        record['image_id'] = i
        record['height'] = height
        record['width'] = width

        objs = []
        with open(path[1]) as t:
            print(path[1])
            lines = t.readlines()
            print(lines)
            for line in lines:
```

The txt contains all the information in each image with all defect locations and types

Example 4-1 – Faster RCNN

We need to convert PCB-data into COCO format(.JSON) for training.
Here are some important information.

```
for line in lines:
    if line[-1]=="\n":
        box = line[:-1].split(' ')
    else:
        box = line.split(' ')
    print(box)
    boxes = list(map(float,[box[0],box[1],box[2],box[3]]))
    category = int(box[4])
    print(boxes)
    obj = {
        "bbox": boxes,
        "bbox_mode": BoxMode.XYXY_ABS,
        "#segmentation": [poly], To draw a line, along to ballon
        #you will need this for mask RCNN
        "category_id": category-1,
        "iscrowd": 0
    }
    print(obj)
    objs.append(obj)
    record["annotations"] = objs
    dataset_dicts.append(record)
return dataset_dicts #list of dicts
```

The location and type

The location(point from top left to bottom right) [x1,y1,x2,y2]

Type:0-open 1-short 2-mousebite 3-spur
4-copper 5-pin-hole

Example 4-1 – Faster RCNN

Take a photo and print the information

```
{'file_name': './DeepPCB/PCBData/group20085/20085/20085000_test.jpg', 'image_id': 0, 'height': 640, 'width': 640, 'annotations':
```

```
[{'bbox': [409.0, 394.0, 435.0, 422.0], 'bbox_mode': <BoxMode.XYXY_ABS: 0>, 'category_id': 2, 'iscrowd': 0},
```

```
{'bbox': [275.0, 383.0, 319.0, 417.0], 'bbox_mode': <BoxMode.XYXY_ABS: 0>, 'category_id': 2, 'iscrowd': 0},
```

```
{'bbox': [8.0, 163.0, 36.0, 191.0], 'bbox_mode': <BoxMode.XYXY_ABS: 0>, 'category_id': 3, 'iscrowd': 0},
```

```
{'bbox': [244.0, 151.0, 270.0, 182.0], 'bbox_mode': <BoxMode.XYXY_ABS: 0>, 'category_id': 4, 'iscrowd': 0},
```

```
{'bbox': [338.0, 519.0, 364.0, 543.0], 'bbox_mode': <BoxMode.XYXY_ABS: 0>, 'category_id': 5, 'iscrowd': 0},
```

```
{'bbox': [476.0, 460.0, 502.0, 481.0], 'bbox_mode': <BoxMode.XYXY_ABS: 0>, 'category_id': 3, 'iscrowd': 0}]]
```

bbox: Defect bounding box coordinates

Bbox_mode: Bbox format

Category: Defect category

Iscrowd: 0: An object

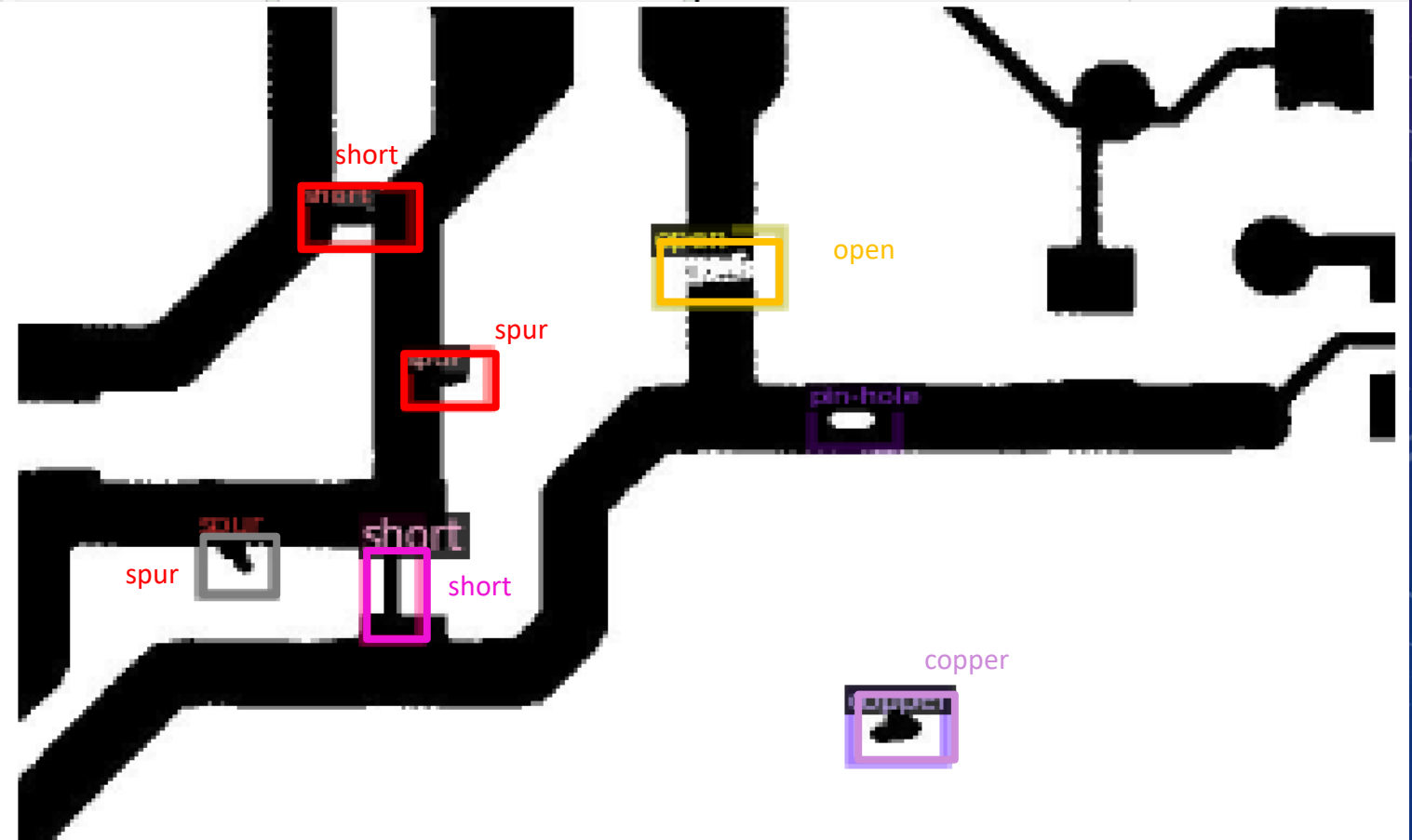
1: A set of objects

Example 4-1 – Faster RCNN

Visualizing the Train Dataset

Randomly select 2 pictures from the train folder of the dataset and check the appearance of the bounding box.

```
for d in random.sample(dataset_dicts, 2):  
    img = cv2.imread(d["file_name"])  
    visualizer = Visualizer(img[:, :, ::-1], metadata=PCB_metadata, scale=0.5)  
    vis = visualizer.draw_dataset_dict(d)  
    cv2.imshow(vis.get_image()[:, :, ::-1])
```



Example 4-1 – Faster RCNN

Define Hyper-parameter

In this part we select the faster_rcnn_R_50_FPN_3x pre-trained model in the model library. The model has been pre-trained on the COCO dataset.

```
from detectron2.engine import DefaultTrainer
from detectron2.config import get_cfg

cfg = get_cfg()
cfg.merge_from_file(model_zoo.get_config_file("COCO-Detection/faster_rcnn_R_50_FPN_3x.yaml"))
cfg.DATASETS.TRAIN = ("PCB_train",)
cfg.DATASETS.TEST = ()
cfg.DATALOADER.NUM_WORKERS = 0
cfg.MODEL.WEIGHTS = "detectron2://COCO-Detection/faster_rcnn_R_50_FPN_3x/137849458/model_final_280758.pkl" # Let training initialize from model zoo
cfg.SOLVER.IMS_PER_BATCH = 2
cfg.SOLVER.BASE_LR = 0.00025 # pick a good LR
cfg.SOLVER.MAX_ITER = 300 # 300 iterations seems good enough for this toy dataset; you may need to train longer for a practical dataset
cfg.MODEL.ROI_HEADS.BATCH_SIZE_PER_IMAGE = 4096 # faster, and good enough
cfg.MODEL.ROI_HEADS.NUM_CLASSES = 6

os.makedirs(cfg.OUTPUT_DIR, exist_ok=True)
trainer = DefaultTrainer(cfg)
trainer.resume_or_load(resume=False)
trainer.train()
```

Pretrained model

Define the max iterations of training

Set the trainer

Load last checkpoint or model.weights

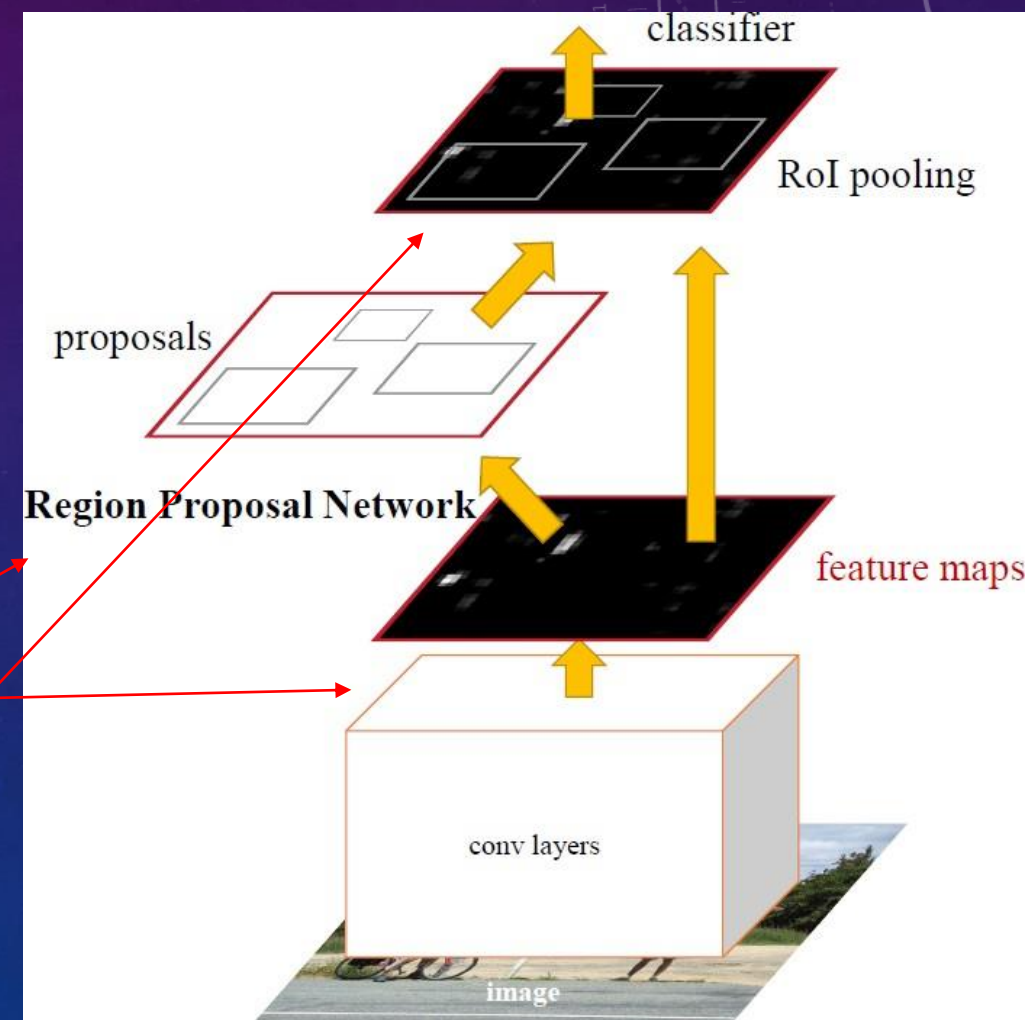
Start to train

Example 4-1 – Faster RCNN

This conv layers architecture uses FPN

```
class FPN(Backbone):  
    """  
    This module implements :paper:`FPN`.  
    It creates pyramid features built on top of some input feature maps.  
    """  
  
    def __init__(  
        self, bottom_up, in_features, out_channels, norm="", top_block=None, fuse_type="sum"  
    ):
```

```
features = self.backbone(images.tensors)  
if isinstance(features, torch.Tensor):  
    features = OrderedDict([('0', features)])  
proposals, proposal_losses = self.rpn(images, features, targets)  
detections, detector_losses = self.roi_heads(features, proposals, images.image_sizes, targets)  
detections = self.transform.postprocess(detections, images.image_sizes, original_image_sizes)
```



Example 4-1 – Faster RCNN

rpn.py

```
def forward(self, images, features, gt_instances=None):
    """
    Args:
        images (ImageList): input images of length `N`
        features (dict[str: Tensor]): input data as a mapping from feature
            map name to tensor. Axis 0 represents the number of images `N` in
            the input data; axes 1-3 are channels, height, and width, which may
            vary between feature maps (e.g., if a feature pyramid is used).
        gt_instances (list[Instances], optional): a length `N` list of `Instances`s.
            Each `Instances` stores ground-truth instances for the corresponding image.

    Returns:
        proposals: list[Instances]: contains fields "proposal_boxes", "objectness_logits"
        loss: dict[Tensor] or None
    """
    features = [features[f] for f in self.in_features]
    pred_objectness_logits, pred_anchor_deltas = self.rpn_head(features)
    anchors = self.anchor_generator(features)
```

Generate bounding box

Realize the core function of the RPN network, output the classification vector objectness, and realize the background classification. Store the four offsets of the candidate box in pred_anchor_deltas

```
with torch.no_grad():
    # Find the top proposals by applying NMS and removing boxes that
    # are too small. The proposals are treated as fixed for approximate
    # joint training with roi heads. This approach ignores the derivative
    # w.r.t. the proposal boxes' coordinates that are also network
    # responses, so is approximate.
    proposals = find_top_rpn_proposals(
        outputs.predict_proposals(),
        outputs.predict_objectness_logits(),
        images,
        self.nms_thresh,
        self.pre_nms_topk[self.training],
        self.post_nms_topk[self.training],
        self.min_box_side_len,
        self.training,
    )

return proposals, losses
```

Use NMS to pick bounding box

Example 4-1 – Faster RCNN

When starting to training , the colab will print the information for every 20 iterations

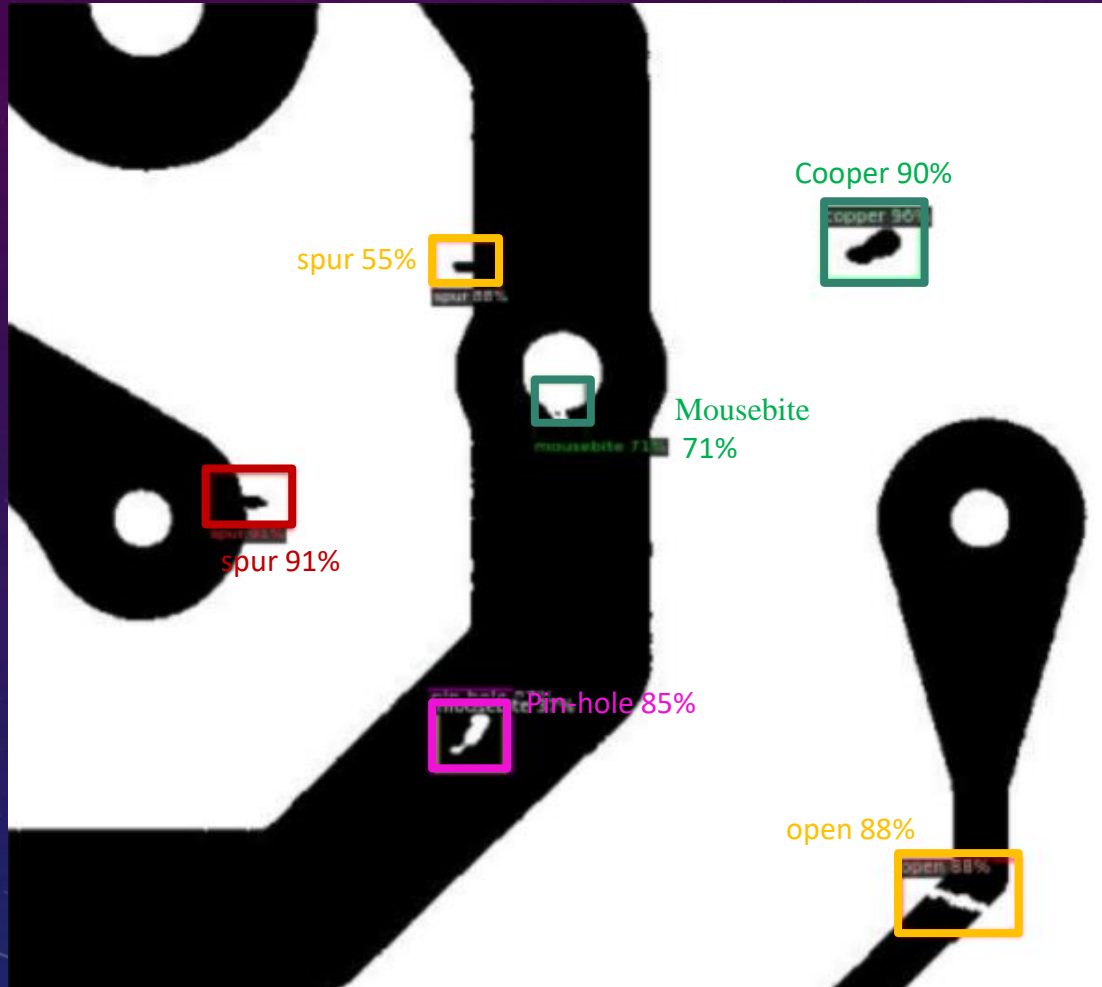
```
Adding parameter 'roi_heads.box_predictor.box_pred.bias' to the model due to incompatible shapes. (320,) in
08:57:18 d2.engine.train_loop]: Starting training from iteration 0
08:57:26 d2.utils.events]: eta: 0:18:07 iter: 19 total_loss: 2.585 loss_cls: 1.906 loss_box_reg: 0.042
08:57:33 d2.utils.events]: eta: 0:18:01 iter: 39 total_loss: 2.325 loss_cls: 1.703 loss_box_reg: 0.029
08:57:40 d2.utils.events]: eta: 0:17:50 iter: 59 total_loss: 1.812 loss_cls: 1.344 loss_box_reg: 0.034
08:57:48 d2.utils.events]: eta: 0:17:53 iter: 79 total_loss: 1.231 loss_cls: 0.869 loss_box_reg: 0.036
08:57:55 d2.utils.events]: eta: 0:17:50 iter: 99 total_loss: 0.912 loss_cls: 0.489 loss_box_reg: 0.038
08:58:03 d2.utils.events]: eta: 0:17:47 iter: 119 total_loss: 0.614 loss_cls: 0.247 loss_box_reg: 0.034
08:58:11 d2.utils.events]: eta: 0:17:48 iter: 139 total_loss: 0.466 loss_cls: 0.177 loss_box_reg: 0.068
08:58:18 d2.utils.events]: eta: 0:17:46 iter: 159 total_loss: 0.507 loss_cls: 0.176 loss_box_reg: 0.077
08:58:27 d2.utils.events]: eta: 0:17:47 iter: 179 total_loss: 0.521 loss_cls: 0.213 loss_box_reg: 0.098
```

the checkpoint but (24,) in the model. You might want to double check if this is expected.

```
loss_rpn_cls: 0.469 loss_rpn_loc: 0.154 time: 0.3619 data_time: 0.0438 lr: 0.000005 max_mem: 1826M
loss_rpn_cls: 0.416 loss_rpn_loc: 0.143 time: 0.3653 data_time: 0.0426 lr: 0.000010 max_mem: 1826M
loss_rpn_cls: 0.243 loss_rpn_loc: 0.135 time: 0.3647 data_time: 0.0437 lr: 0.000015 max_mem: 1826M
loss_rpn_cls: 0.162 loss_rpn_loc: 0.140 time: 0.3689 data_time: 0.0447 lr: 0.000020 max_mem: 1826M
loss_rpn_cls: 0.209 loss_rpn_loc: 0.122 time: 0.3682 data_time: 0.0422 lr: 0.000025 max_mem: 1826M
loss_rpn_cls: 0.185 loss_rpn_loc: 0.132 time: 0.3712 data_time: 0.0452 lr: 0.000030 max_mem: 1826M
loss_rpn_cls: 0.096 loss_rpn_loc: 0.119 time: 0.3742 data_time: 0.0428 lr: 0.000035 max_mem: 1826M
loss_rpn_cls: 0.098 loss_rpn_loc: 0.094 time: 0.3757 data_time: 0.0424 lr: 0.000040 max_mem: 1826M
loss_rpn_cls: 0.104 loss_rpn_loc: 0.084 time: 0.3790 data_time: 0.0440 lr: 0.000045 max_mem: 1826M
```

Example 4-1 – Faster RCNN

Visualizing the Testing Result



```
from detectron2.utils.visualizer import ColorMode
dataset_dicts = get_PCB_dict(test)

for d in random.sample(dataset_dicts, 10):
    im = cv2.imread(d["file_name"])
    outputs = predictor(im)
    v = Visualizer(im,
                   metadata=PCB_metadata,
                   scale=0.8,
                   instance_mode = ColorMode.IMAGE
    )



    # remove the colors of unsegmented pixels
    print(outputs['instances'].pred_classes)
    print(outputs["instances"].pred_boxes)

    v = v.draw_instance_predictions(outputs["instances"].to("cpu"))
    cv2.imshow(v.get_image())
```


Example 4-1 – Faster RCNN

- Formally we define confidence as $Pr(\text{Object}) * IOU(\text{pred}, \text{truth})$. If no object exists in that cell, the confidence score should be zero. Otherwise we want the confidence score to equal the intersection over union (IOU) between the predicted box and the ground truth.

- IOU

$$IoU = \frac{\text{Area of Overlap}}{\text{Area of Union}}$$


<http://blog.csdn.net/IAMoldpan>



Example 4-1 – Faster RCNN

```
if thresholds is None:
    step = 0.05
    thresholds = torch.arange(0.5, 0.95 + 1e-5, step, dtype=torch.float32)
recalls = torch.zeros_like(thresholds)
# compute recall for each iou threshold
for i, t in enumerate(thresholds):
    recalls[i] = (gt_overlaps >= t).float().sum() / float(num_pos)
# ar = 2 * np.trapz(recalls, thresholds)
ar = recalls.mean()
return {
    "ar": ar,
    "recalls": recalls,
    "thresholds": thresholds,
    "gt_overlaps": gt_overlaps,
    "num_pos": num_pos,
}
```

Compute recall for each IOU threshold

```
# Compute per-category AP
# from https://github.com/facebookresearch/Detectron/blob/a6a835f5b8208c45d0dce217
precisions = coco_eval.eval["precision"]
# precision has dims (iou, recall, cls, area range, max dets)
assert len(class_names) == precisions.shape[2]

results_per_category = []
for idx, name in enumerate(class_names):
    # area range index 0: all area ranges
    # max dets index -1: typically 100 per image
    precision = precisions[:, :, idx, 0, -1]
    precision = precision[precision > -1]
    ap = np.mean(precision) if precision.size else float("nan")
    results_per_category.append(("{} ".format(name), float(ap * 100)))
```

Compute per-category AP

Different IOU thresholds, from 0.5 to 0.95, step 0.05

Example 4-1 – Faster RCNN

Evaluate the trained model

```
from detectron2.evaluation import COCOEvaluator, inference_on_dataset, LVISEvaluator
from detectron2.data import build_detection_test_loader

evaluator = COCOEvaluator("PCB_test", cfg, False, output_dir="./output/")
val_loader = build_detection_test_loader(cfg, "PCB_test")
inference_on_dataset(trainer.model, val_loader, evaluator)
```

Area : target detection area

Small :

$\text{area} < 32 \times 32$

Medium :

$32 \times 32 < \text{area} < 96 \times 96$

Large :

$\text{area} > 96 \times 96$

Result:

Average Precision (AP) @[IoU=0.50:0.95 area= all maxDets=100]	= 0.555
Average Precision (AP) @[IoU=0.50 area= all maxDets=100]	= 0.862
Average Precision (AP) @[IoU=0.75 area= all maxDets=100]	= 0.623
Average Precision (AP) @[IoU=0.50:0.95 area= small maxDets=100]	= 0.531
Average Precision (AP) @[IoU=0.50:0.95 area=medium maxDets=100]	= 0.568
Average Precision (AP) @[IoU=0.50:0.95 area= large maxDets=100]	= 0.600
Average Recall (AR) @[IoU=0.50:0.95 area= all maxDets= 1]	= 0.508
Average Recall (AR) @[IoU=0.50:0.95 area= all maxDets= 10]	= 0.650
Average Recall (AR) @[IoU=0.50:0.95 area= all maxDets=100]	= 0.650
Average Recall (AR) @[IoU=0.50:0.95 area= small maxDets=100]	= 0.649
Average Recall (AR) @[IoU=0.50:0.95 area=medium maxDets=100]	= 0.645
Average Recall (AR) @[IoU=0.50:0.95 area= large maxDets=100]	= 0.600

[10/26 07:08:07 d2.evaluation.coco_evaluation]: Evaluation results for bbox:

AP	AP50	AP75	APs	APm	APl
55.525	86.206	62.343	53.122	56.825	60.000

[10/26 07:08:07 d2.evaluation.coco_evaluation]: Per category bbox AP

category	AP	category	AP	category	AP
open	45.682	short	30.675	mousebite	53.424
spur	56.391	copper	82.105	pin-hole	64.871

AP of each category

Exercise 4-1

- Please download the “PCBdata_fasterRCNN_colab.ipynb” from the Moodle and open by the Colab.
- Follow the Colab code and pip install packages for environments.
- Visualize the PCB data and define the hyper-parameter for training.
- Compare **different iterations** and comment on the results.

Please crop your results and code and paste to a MS Word, discuss the results, and then upload to the Moodles.

Example 4-2 – License Plate Detector

In this example, we want to use Faster RCNN to detect license plate. We have to learn how to label the license plate and we have to change the data into COCO data format. We will use pretrained weights, which were trained on the COCO dataset and retrain on our own data and test our own data.

Example 4-2 : License Plate - labelme

Install labelme

1. Python2 (Windows)

```
pip install pyqt  
pip install labelme
```

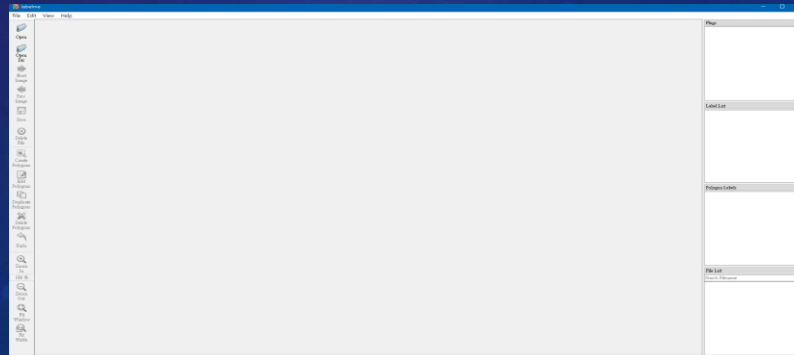
Python 3 (Windows)

```
pip install pyqt5  
pip install labelme
```

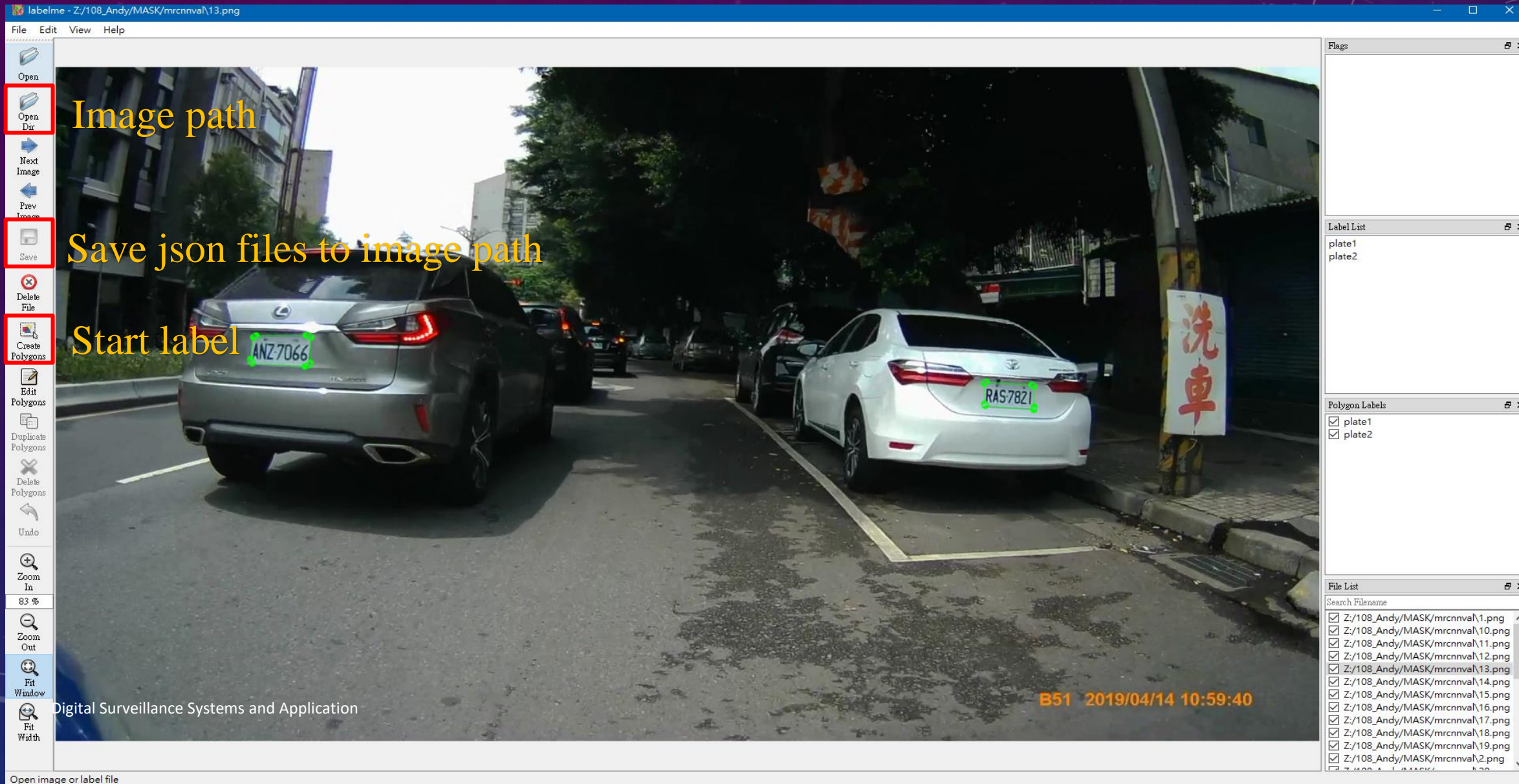
2. Cmd : labelme

```
(pythonGPU) C:\Users\andy>labelme
```

3. Start to label



Example 4-2 : Start to label License Plate



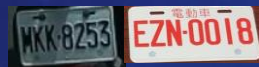
Example 4-2 : How to label License Plate

For example



Naming method:
(name+**order**)

Label list:



(normal class)plate**1** plate**2**

(yellow class)yellow_plate**1** yellow_plate**2**

(green class)green_plate**1** green_plate**2**

(red class)red_plate**1** red_plate**2**

Example 4-2 : Label Process

Step1:check the number of clear license plates in this image

We can get two samples from this image

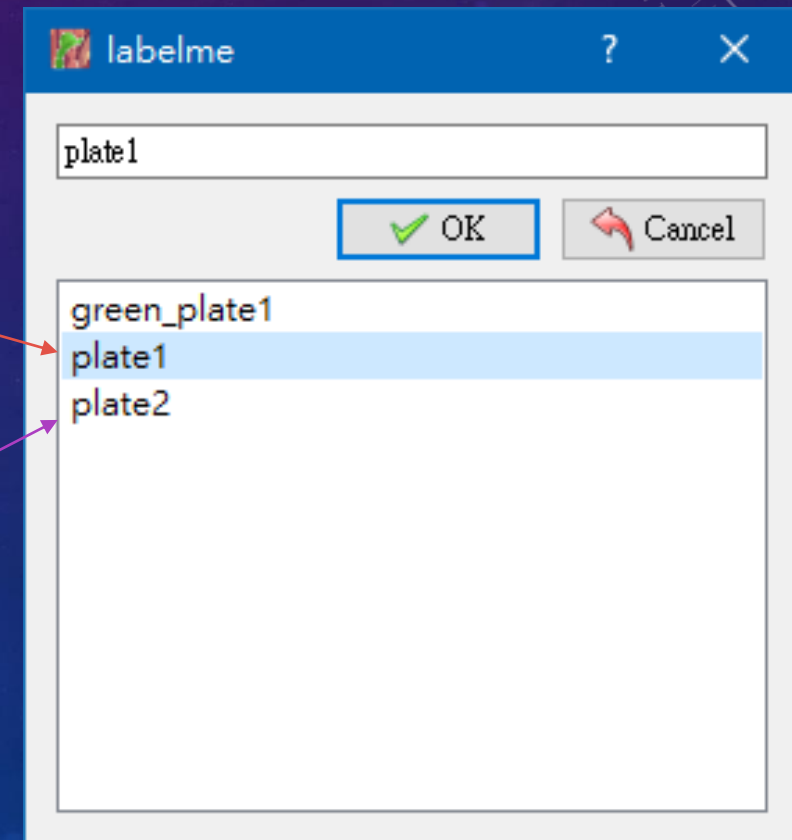
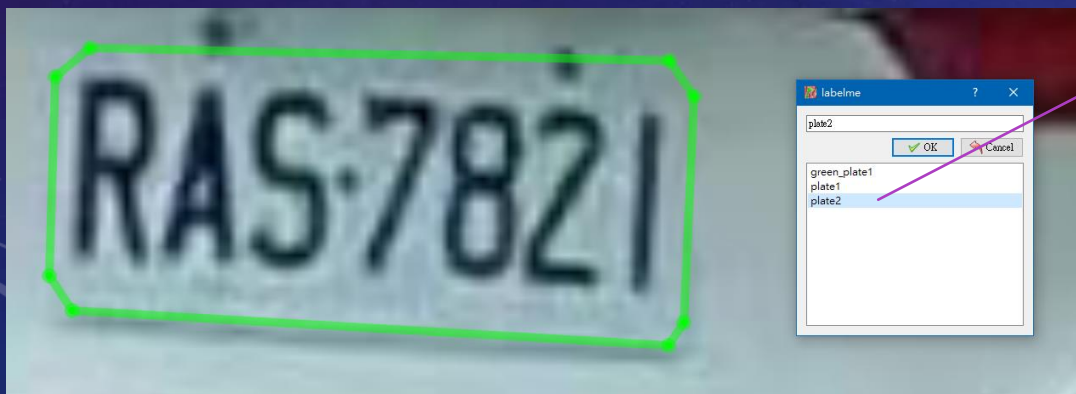
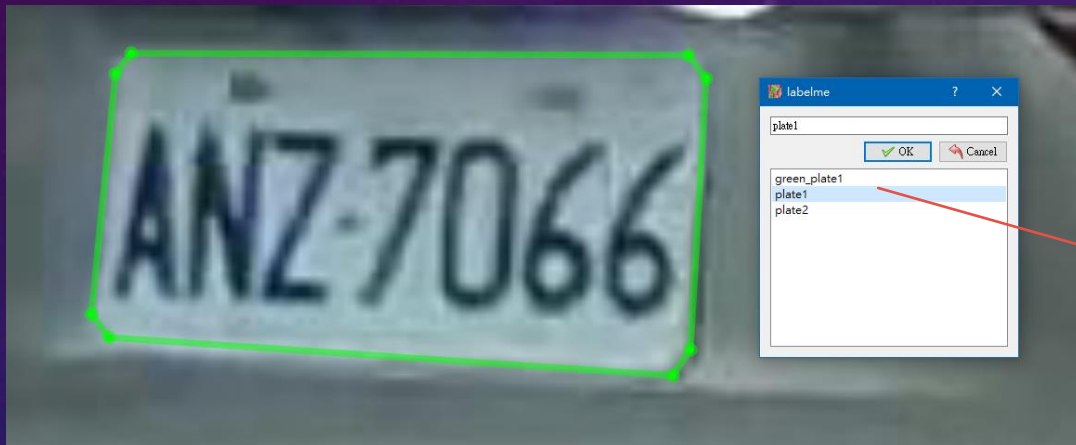
- There're two clear license plates
- All the license plate are normal class so we can named plate1 and plate 2



Example 4-2 : Label Process

Step2:Partial enlargement the license plate and use the dots to bound it

Step3:Give the license plate their name and order



Example 4-2 : Label Process

From the labelme we can get several json files that contain bounding boxes in the images (1 json/img). If you want to use multiple json files for combining multiple images, please consider using labelme2coco.py (given in the labelme2coco.7z from Moodle)

Step1: Put your image folder in the labelme2coco folder

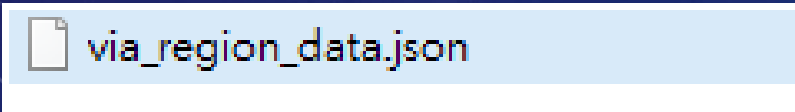
Step2: Make sure your json files and images are in the same folder

Step3: Open cmd and run **labelme2coco.py [folder name]**, as shown below

```
(C:\Users\Micky\Anaconda3\envs\Pytorch10) Y:\108_Andy\henry\labelme2coco-master>python labelme2coco.py images  
save coco json  
via_region_data.json
```

The images folder name

Result : The file via_region_data.json combines all json files with the associated images.

via_region_data.json

Example 4-2 : License Plate Detector

Step 1 : Set up environment

Install pytorch and detectron2

Step 2 : Prepare the “license plate dataset”

Download the dataset from <https://drive.google.com/file/d/14wXRkpow5vIVc2ROhHbWelEjwCJCx9b5/view?usp=sharing>

Step 3 : Write a function that loads the dataset into detectron2's standard format

Step 4 : Verify the data loading is correct

Step 5 : Fine-tune a pretrained model on the license plate dataset

Step 6 : Visualize the prediction results.

Example 4-2 : License Plate Detector

Step 1 : Set up environment

```
!pip install -U torch torchvision
!pip install git+https://github.com/facebookresearch/fvcore.git
import torch, torchvision
torch.__version__
```

Result :

```
Successfully built fvcore pyyaml
Installing collected packages: pyyaml, yacs, portalocker, fvcore
  Found existing installation: PyYAML 3.13
    Uninstalling PyYAML-3.13:
      Successfully uninstalled PyYAML-3.13
Successfully installed fvcore-0.1 portalocker-1.5.2 pyyaml-5.1.2 yacs-0.1.6
'1.3.1'
```

Example 4-2 : License Plate Detector

Step 1 : Set up environment

```
!git clone https://github.com/facebookresearch/detectron2 detectron2_repo  
!pip install -e detectron2_repo
```

Result :

```
Installing collected packages: Pillow, tqdm, detectron2  
Found existing installation: Pillow 4.3.0  
Uninstalling Pillow-4.3.0:  
Successfully uninstalled Pillow-4.3.0  
Found existing installation: tqdm 4.28.1  
Uninstalling tqdm-4.28.1:  
Successfully uninstalled tqdm-4.28.1  
Running setup.py develop for detectron2  
Successfully installed Pillow-6.2.1 detectron2 tqdm-4.39.0  
WARNING: The following packages were previously imported in this runtime:  
[PIL,tqdm]  
You must restart the runtime in order to use newly installed versions.
```

RESTART RUNTIME

If you have already installed the detectron2, you need to “restart runtime”.

Example 4-2 : License Plate Detector

Step 2 : Prepare the “license plate dataset”

Option 1 : run `!wget https://www.dropbox.com/s/rjra44iyszoh19te/plate.zip?dl=0 -O plate.zip`

Option 2 : Download the plate.zip from

<https://drive.google.com/file/d/14wXRkpow5vIVc2ROhHbWelEjwCJCx9b5/view?usp=sharing> and upload it

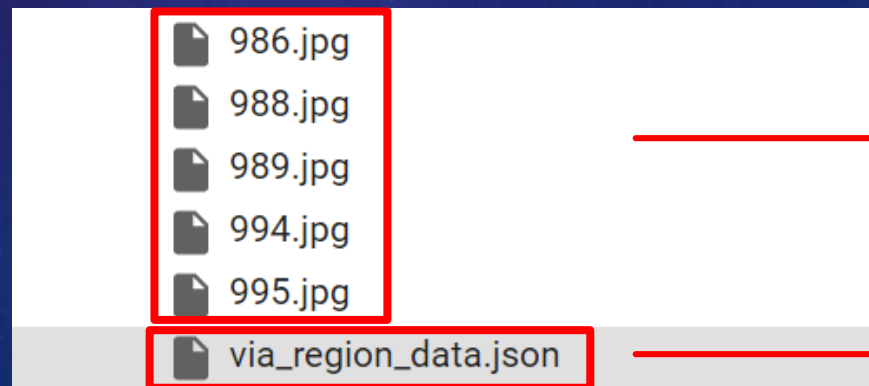
Unzip plate.zip.

`!unzip plate.zip`

Result :



In plate/train



Training data

Our label file

Example 4-2 : License Plate Detector

Step 3 : Write a function that loads the dataset into detectron2's standard format

```
def get_plate_dicts(img_dir):  
    json_file = os.path.join(img_dir, "via_region_data.json") # via_region_data.json  
    with open(json_file) as f:  
        imgs_anns = json.load(f)
```

Open the “via_region_data.json”

```
for i in range(len(filename_list)):  
    record = {}  
    filename = os.path.join(img_dir, filename_list[i]["file_name"])  
    height, width = cv2.imread(filename).shape[:2]  
    record["file_name"] = filename  
    record["image_id"] = i  
    record["height"] = 1080  
    record["width"] = 1920
```

In plate/train/via_region_data.json

```
"images": [  
    {  
        "height": 1080,  
        "width": 1920,  
        "id": 0,  
        "file_name": "10.jpg"  
    },  
    ...  
]
```

Example 4-2 : License Plate Detector

Step 3 : Write a function that loads the dataset into detectron2's standard format

In plate/train/via_region_data.json

```
for j in range(k, k+bbox_num[i]):
    if bbox_list[j]["image_id"] != record["image_id"]:
        assert False
    bbox = []
    bbox = [int(bbox_list[j]["bbox"][0]), int(bbox_list[j]["bbox"][1]),
            int(bbox_list[j]["bbox"][0]) + int(bbox_list[j]["bbox"][2]),
            int(bbox_list[j]["bbox"][1]) + int(bbox_list[j]["bbox"][3])]
    obj = {
        "bbox": bbox,
        "bbox_mode": BoxMode.XYXY_ABS,
        "segmentation": bbox_list[j]["segmentation"],
        "category_id": 0,
        "iscrowd": 0
    }
    objs.append(obj)
record["annotations"] = objs
k += bbox_num[i]
dataset_dicts.append(record)
```

```
"bbox": [
    710.0,
    283.0,
    128.0,
    81.0
],
```

The width and height
of plates

```
"segmentation": [
    732.9621380846324,
    283.5189309576837,
    723.8307349665924,
    283.2962138084632,
    710.467706013363,
    327.8396436525612,
    714.6993318485523,
    331.62583518930956,
    815.5902004454342,
    364.81069042316255,
    821.826280623608,
    361.2472160356347,
    838.3073496659242,
    316.9265033407572,
    835.1893095768373,
    312.6948775055679
]
```

Example 4-2 : License Plate Detector

Step 4 : Verify the data in the training folder

```
import random
dataset_dicts = get_plate_dicts("plate/train")
for d in random.sample(dataset_dicts, 3):  
    img = cv2.imread(d["file_name"])  
    visualizer = Visualizer(img[:, :, ::-1], metadata=plate_metadata, scale=0.5)  
    vis = visualizer.draw_dataset_dict(d)  
    cv2_imshow(vis.get_image()[:, :, ::-1])
```

Randomly select 3 samples to verify.

Result :



Example 4-2 : License Plate Detector

Step 5 : Fine-tune a pretrained model on the license plate dataset

```
from detectron2.engine import DefaultTrainer
from detectron2.config import get_cfg

cfg = get_cfg()
cfg.merge_from_file("../detectron2_repo/configs/COCO-InstanceSegmentation/mask_rcnn_R_50_FPN_3x.yaml")
cfg.DATASETS.TRAIN = ("plate_train",)
cfg.DATASETS.TEST = ()
cfg.DATALOADER.NUM_WORKERS = 5
cfg.MODEL.WEIGHTS = "detectron2://COCO-InstanceSegmentation/mask_rcnn_R_50_FPN_3x/137849600/model_final_f10217.pkl"
cfg.SOLVER.IMS_PER_BATCH = 2
cfg.SOLVER.BASE_LR = 0.00025
cfg.SOLVER.MAX_ITER = 2000
cfg.MODEL.ROI_HEADS.BATCH_SIZE_PER_IMAGE = 256
cfg.MODEL.ROI_HEADS.NUM_CLASSES = 1 # only has one class

os.makedirs(cfg.OUTPUT_DIR, exist_ok=True)
trainer = DefaultTrainer(cfg)
trainer.resume_or_load(resume=False)
trainer.train()
```

Define the max iterations of training

Pretrained model

Example 4-2 : License Plate Detector

Step 6 : Visualize the prediction results.

```
cfg.MODEL.WEIGHTS = os.path.join(cfg.OUTPUT_DIR, "model_final.pth")
cfg.MODEL.ROI_HEADS.SCORE_THRESH_TEST = 0.7 # set the testing threshold for this model
cfg.DATASETS.TEST = ("plate_val", )
predictor = DefaultPredictor(cfg)
```

Load trained model

```
from detectron2.utils.visualizer import ColorMode
dataset_dicts = get_plate_dicts("plate/val")
for d in random.sample(dataset_dicts, 10):
    im = cv2.imread(d["file_name"])
    outputs = predictor(im)
    v = Visualizer(im[:, :, ::-1],
                  metadata=plate_metadata,
                  scale=0.8,
                  instance_mode=ColorMode.IMAGE_BW
    )
    v = v.draw_instance_predictions(outputs["instances"].to("cpu"))
    cv2.imshow(v.get_image()[:, :, ::-1])
```

Randomly select 10 samples to test.

Example 4-2 : License Plate Detector

Result :



Exercise 4-2 : License Plate Detector

- Please download “Detectron2_license_plate.ipynb” and “test_plate.zip” and open “Detectron2_license_plate.ipynb” by Colab.
- Use labelme tool to label the 10 images by yourself and test it on trained model.
※Hint: If you want to test, you need to upload your images and json file into plate/val folder.
- Please write down result and your code in MS Word to Moodle

Example 4-3 – Detectron2 Tutorial

In this example, we will use detectron2 to fine-tune the balloon dataset, and then detect it. In addition, we will also test different pre-trained model, keypoint detection model, and try to run keypoint detection on a video.

Example 4-3 – Detectron2 Tutorial

Set up environment

```
▶ # install dependencies:  
!pip install pyyaml==5.1  
import torch, torchvision  
print(torch.__version__, torch.cuda.is_available())  
!gcc --version  
# opencv is pre-installed on colab
```

```
# install detectron2: (Colab has CUDA 10.1 + torch 1.7)  
# See https://detectron2.readthedocs.io/tutorials/install.html for instructions  
import torch  
assert torch.__version__.startswith("1.7")  
!pip install detectron2 -f https://dl.fbaipublicfiles.com/detectron2/wheels/cu101/torch1.7/index.html  
# exit(0) # After installation, you need to "restart runtime" in Colab. This line can also restart runtime
```

```
# Some basic setup:  
# Setup detectron2 logger  
import detectron2  
from detectron2.utils.logger import setup_logger  
setup_logger()  
  
# import some common libraries  
import numpy as np  
import os, json, cv2, random  
from google.colab.patches import cv2_imshow  
  
# import some common detectron2 utilities  
from detectron2 import model_zoo  
from detectron2.engine import DefaultPredictor  
from detectron2.config import get_cfg  
from detectron2.utils.visualizer import Visualizer  
from detectron2.data import MetadataCatalog, DatasetCatalog
```


Example 4-3 – Detectron2 Tutorial

Train on a custom dataset:

In this section, we show how to train an existing detectron2 model on a custom dataset in a new format.

We use the balloon segmentation dataset which only has one class: balloon. We'll train a balloon segmentation model from an existing model pre-trained on COCO dataset, available in detectron2's model zoo.

Prepare the dataset:

```
# download, decompress the data
!wget https://github.com/matterport/Mask_RCNN/releases/download/v2.1/balloon_dataset.zip
!unzip balloon_dataset.zip > /dev/null
```

Example 4-3 – Detectron2 Tutorial

Register the balloon dataset to detectron2:

```
from detectron2.structures import BoxMode

def get_balloon_dicts(img_dir):
    json_file = os.path.join(img_dir, "via_region_data.json")
    with open(json_file) as f:
        imgs_anns = json.load(f)

    dataset_dicts = []
    for idx, v in enumerate(imgs_anns.values()):
        record = {}

        filename = os.path.join(img_dir, v["filename"])
        height, width = cv2.imread(filename).shape[:2]

        record["file_name"] = filename
        record["image_id"] = idx
        record["height"] = height
        record["width"] = width

        annos = v["regions"]
        objs = []
        for _, anno in annos.items():
            assert not anno["region_attributes"]
            anno = anno["shape_attributes"]
            px = anno["all_points_x"]
            py = anno["all_points_y"]
            poly = [(x + 0.5, y + 0.5) for x, y in zip(px, py)]
            poly = [p for x in poly for p in x]
```

```
        obj = {
            "bbox": [np.min(px), np.min(py), np.max(px), np.max(py)],
            "bbox_mode": BoxMode.XYXY_ABS,
            "segmentation": [poly],
            "category_id": 0,
        }
        objs.append(obj)
        record["annotations"] = objs
        dataset_dicts.append(record)
    return dataset_dicts

for d in ["train", "val"]:
    DatasetCatalog.register("balloon_" + d, lambda d=d: get_balloon_dicts("balloon/" + d))
    MetadataCatalog.get("balloon_" + d).set(thing_classes=["balloon"])
balloon_metadata = MetadataCatalog.get("balloon_train")
```

Open "via_region_data.json" in the train and val folder

Example 4-3 – Detectron2 Tutorial

Verify the data in the training folder

```
import random
dataset_dicts = get_plate_dicts("balloon/train")
for d in random.sample(dataset_dicts, 3):  
    img = cv2.imread(d["file_name"])  
    visualizer = Visualizer(img[:, :, ::-1], metadata=plate_metadata, scale=0.5)  
    vis = visualizer.draw_dataset_dict(d)  
    cv2_imshow(vis.get_image()[:, :, ::-1])
```

Randomly select 3 samples to verify.

Result :



Example 4-3 – Detectron2 Tutorial

Fine-tune a pretrained model on the balloon dataset

```
from detectron2.engine import DefaultTrainer

cfg = get_cfg()
cfg.merge_from_file(model_zoo.get_config_file("COCO-InstanceSegmentation/mask_rcnn_R_50_FPN_3x.yaml"))
cfg.DATASETS.TRAIN = ("balloon_train",)
cfg.DATASETS.TEST = ()
cfg.DATALOADER.NUM_WORKERS = 2
cfg.MODEL.WEIGHTS = model_zoo.get_checkpoint_url("COCO-InstanceSegmentation/mask_rcnn_R_50_FPN_3x.yaml")
cfg.SOLVER.IMS_PER_BATCH = 2
cfg.SOLVER.BASE_LR = 0.00025 # pick a good LR
cfg.SOLVER.MAX_ITER = 300 # 300 iterations seems good enough for this toy dataset, you can increase it
cfg.MODEL.ROI_HEADS.BATCH_SIZE_PER_IMAGE = 128 # faster, and good enough for this toy dataset
cfg.MODEL.ROI_HEADS.NUM_CLASSES = 1 # only has one class (balloon). (see https://detectron2.readme.org/tutorials/setup/config.html)
cfg.MODEL.ANCHOR_GENERATOR.ASPECT RATIOS=[0.5, 1.0, 2.0]
cfg.MODEL.ANCHOR_GENERATOR.SIZES=[[[32], [64], [128], [256], [512]]]
print(cfg)
os.makedirs(cfg.OUTPUT_DIR, exist_ok=True)
trainer = DefaultTrainer(cfg)
trainer.resume_or_load(resume=False)
trainer.train()
```

Pretrained model

Define the max iterations of training

Only one class (balloon)

Define different anchor ratios

Define different anchor size

Example 4-3 – Detectron2 Tutorial

You can **print (cfg)** and find that you can adjust more different parameters for training.

```
CUDNN_BENCHMARK: False
DATALOADER:
  ASPECT_RATIO_GROUPING: True
  FILTER_EMPTY_ANNOTATIONS: True
  NUM_WORKERS: 2
  REPEAT_THRESHOLD: 0.0
  SAMPLER_TRAIN: TrainingSampler
DATASETS:
  PRECOMPUTED_PROPOSAL_TOPK_TEST: 1000
  PRECOMPUTED_PROPOSAL_TOPK_TRAIN: 2000
  PROPOSAL_FILES_TEST: ()
  PROPOSAL_FILES_TRAIN: ()
  TEST: ()
  TRAIN: ('balloon_train',)
GLOBAL:
  HACK: 1.0
INPUT:
  CROP:
    ENABLED: False
    SIZE: [0.9, 0.9]
    TYPE: relative_range
  FORMAT: BGR
  MASK_FORMAT: polygon
  MAX_SIZE_TEST: 1333
  MAX_SIZE_TRAIN: 1333
  MIN_SIZE_TEST: 800
  MIN_SIZE_TRAIN: (640, 672, 704, 736, 768, 800)
  MIN_SIZE_TRAIN_SAMPLING: choice
  RANDOM_FLIP: horizontal
MODEL:
  ANCHOR_GENERATOR:
    ANGLES: [[-90, 0, 90]]
    ASPECT RATIOS: [[0.5, 1.0, 2.0]]
    NAME: DefaultAnchorGenerator
    OFFSET: 0.0
    SIZES: [[32], [64], [128], [256], [512]]
```

`cfg.MODEL.ANCHOR_GENERATOR.ASPECT_RATIOS=[[0.5, 1.0, 2.0]]`

`cfg.MODEL.ANCHOR_GENERATOR.SIZES=[[32], [64], [128], [256], [512]]`

You can get 15 different anchor boxes(3*5)

Example 4-3 – Detectron2 Tutorial

Visualize the prediction results

Load trained model

```
# Inference should use the config with parameters that are used in training
# cfg now already contains everything we've set previously. We changed it a bit
cfg.MODEL.WEIGHTS = os.path.join(cfg.OUTPUT_DIR, "model_final.pth") # path to the
cfg.MODEL.ROI_HEADS.SCORE_THRESH_TEST = 0.7 # set a custom testing threshold
predictor = DefaultPredictor(cfg)
```

Set a testing threshold

```
from detectron2.utils.visualizer import ColorMode
dataset_dicts = get_balloon_dicts("balloon/val")
for d in random.sample(dataset_dicts, 3):
    im = cv2.imread(d["file_name"])
    outputs = predictor(im) # format is documented at https://detectron2.readthedocs.io/en/latest/tutorials/visualize.html
    v = Visualizer(im[:, :, ::-1],
                  metadata=balloon_metadata,
                  scale=0.5,
                  instance_mode=ColorMode.IMAGE_BW # remove the colors of unsegmented masks
    )
    out = v.draw_instance_predictions(outputs["instances"].to("cpu"))
    cv2.imshow(out.get_image()[:, :, ::-1])
```

Randomly select 3 samples to test.



Example 4-3 – Detectron2 Tutorial

Evaluate the trained model

```
from detectron2.evaluation import COCOEvaluator, inference_on_dataset
from detectron2.data import build_detection_test_loader
evaluator = COCOEvaluator("balloon_val", ("bbox", "segm"), False, output_dir="./output/")
val_loader = build_detection_test_loader(cfg, "balloon_val")
print(inference_on_dataset(trainer.model, val_loader, evaluator))
# another equivalent way to evaluate the model is to use `trainer.test`
```

Area : target detection area

Small :

$area < 32 \times 32$

Medium :

$32 \times 32 < area < 96 \times 96$

Large :

$area > 96 \times 96$

Result:

Average Precision	(AP) @[IoU=0.50:0.95	area= all	maxDets=100]	= 0.691
Average Precision	(AP) @[IoU=0.50	area= all	maxDets=100]	= 0.845
Average Precision	(AP) @[IoU=0.75	area= all	maxDets=100]	= 0.825
Average Precision	(AP) @[IoU=0.50:0.95	area= small	maxDets=100]	= 0.029
Average Precision	(AP) @[IoU=0.50:0.95	area= medium	maxDets=100]	= 0.550
Average Precision	(AP) @[IoU=0.50:0.95	area= large	maxDets=100]	= 0.837
Average Recall	(AR) @[IoU=0.50:0.95	area= all	maxDets= 1]	= 0.234
Average Recall	(AR) @[IoU=0.50:0.95	area= all	maxDets= 10]	= 0.730
Average Recall	(AR) @[IoU=0.50:0.95	area= all	maxDets=100]	= 0.766
Average Recall	(AR) @[IoU=0.50:0.95	area= small	maxDets=100]	= 0.233
Average Recall	(AR) @[IoU=0.50:0.95	area= medium	maxDets=100]	= 0.659
Average Recall	(AR) @[IoU=0.50:0.95	area= large	maxDets=100]	= 0.880

[11/20 15:14:37 d2.evaluation.coco_evaluation]: Evaluation results for bbox:

AP	AP50	AP75	APs	APm	APl
69.075	84.529	82.475	2.871	54.958	83.651

Average Precision	(AP) @[IoU=0.50:0.95	area= all	maxDets=100]	= 0.778
Average Precision	(AP) @[IoU=0.50	area= all	maxDets=100]	= 0.842
Average Precision	(AP) @[IoU=0.75	area= all	maxDets=100]	= 0.833
Average Precision	(AP) @[IoU=0.50:0.95	area= small	maxDets=100]	= 0.012
Average Precision	(AP) @[IoU=0.50:0.95	area= medium	maxDets=100]	= 0.581
Average Precision	(AP) @[IoU=0.50:0.95	area= large	maxDets=100]	= 0.957
Average Recall	(AR) @[IoU=0.50:0.95	area= all	maxDets= 1]	= 0.252
Average Recall	(AR) @[IoU=0.50:0.95	area= all	maxDets= 10]	= 0.792
Average Recall	(AR) @[IoU=0.50:0.95	area= all	maxDets=100]	= 0.824
Average Recall	(AR) @[IoU=0.50:0.95	area= small	maxDets=100]	= 0.200
Average Recall	(AR) @[IoU=0.50:0.95	area= medium	maxDets=100]	= 0.682
Average Recall	(AR) @[IoU=0.50:0.95	area= large	maxDets=100]	= 0.967

[11/20 15:14:37 d2.evaluation.coco_evaluation]: Evaluation results for segm:

AP	AP50	AP75	APs	APm	APl
77.839	84.201	83.293	1.238	58.077	95.700

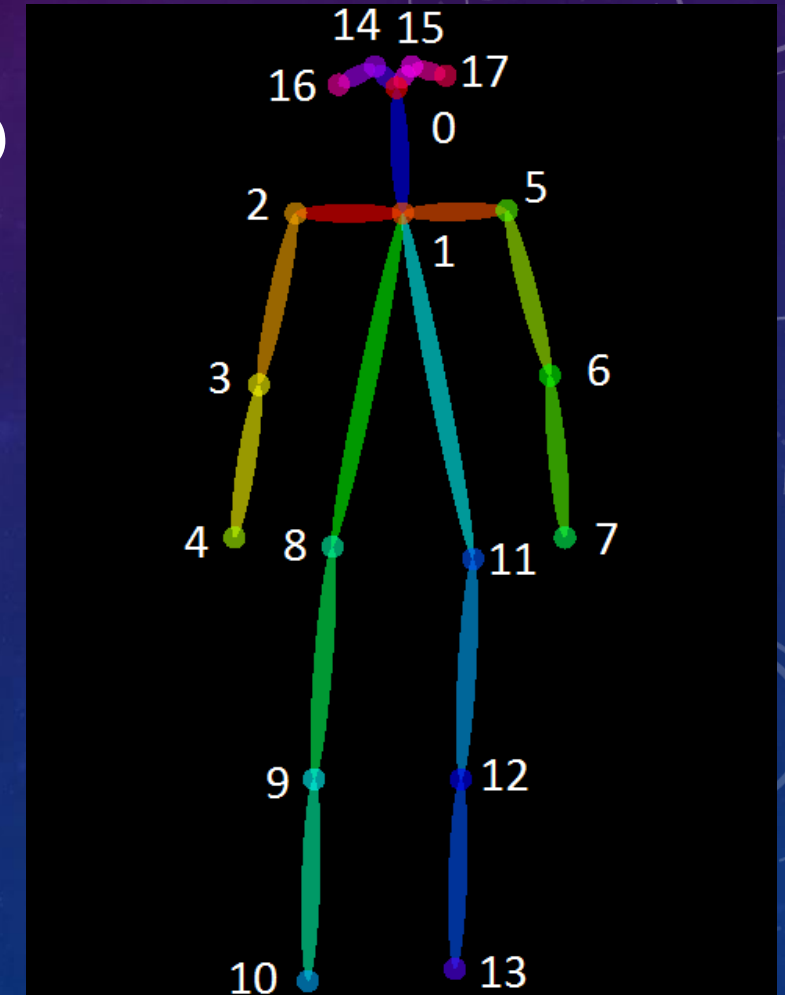
Example 4-3 – Detectron2 Tutorial

Keypoint detection model

- Train in COCO dataset (250,000 people with keypoints)
- 17 types of keypoints

Contains:

“nose”, “left_eye”, “right_eye”, “left_ear”, “right_ear”,
“left_shoulder”, “right_shoulder”, “left_elbow”,
“right_elbow”, “left_wrist”, “right_wrist”, “left_hip”,
“right_hip”, “left_knee”, “right_knee”, “left_ankle”,
“right_ankle”.



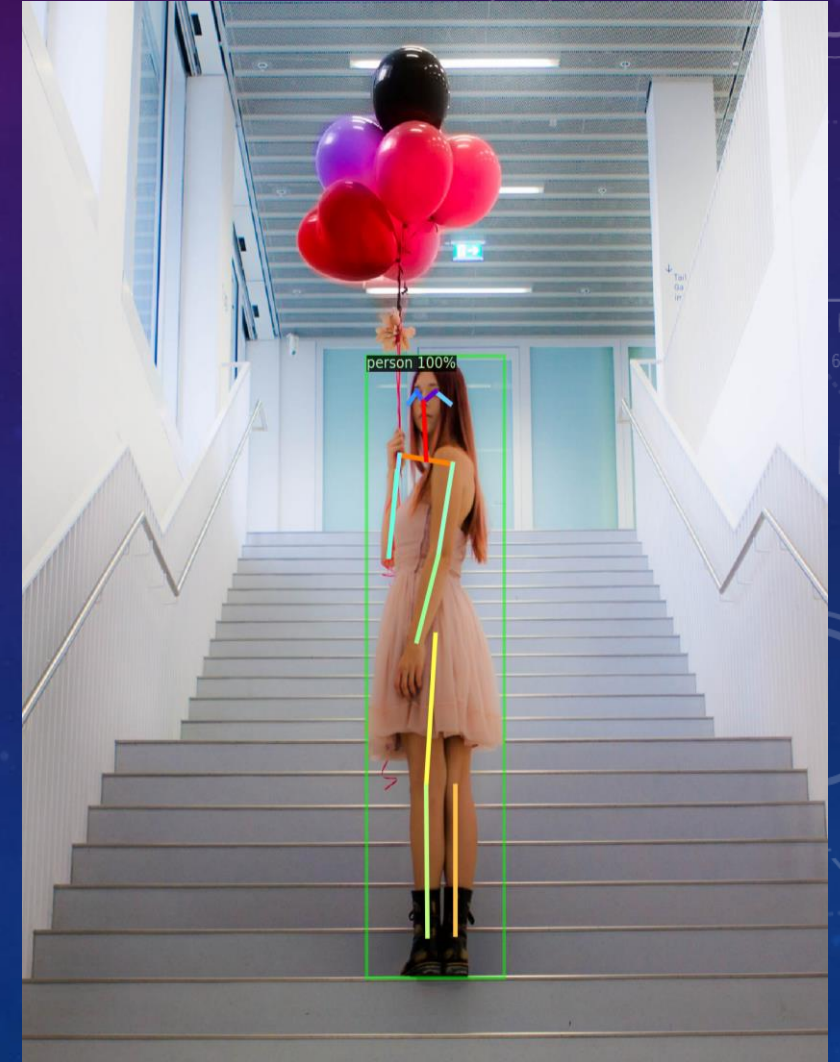
Example 4-3 – Detectron2 Tutorial

Other types of models- keypoint detection model

```
# Inference with a keypoint detection model
cfg = get_cfg()      # get a fresh new config
cfg.merge_from_file(model_zoo.get_config_file("COCO-Keypoints/keypoint_rcnn_R_50_FPN_3x.yaml"))
cfg.MODEL.ROI_HEADS.SCORE_THRESH_TEST = 0.7 # set threshold for this model
cfg.MODEL.WEIGHTS = model_zoo.get_checkpoint_url("COCO-Keypoints/keypoint_rcnn_R_50_FPN_3x.yaml")
predictor = DefaultPredictor(cfg)
outputs = predictor(im)
v = Visualizer(im[:,:,:-1], MetadataCatalog.get(cfg.DATASETS.TRAIN[0]), scale=1.2)
out = v.draw_instance_predictions(outputs["instances"].to("cpu"))
cv2.imshow(out.get_image()[:,:,:-1])
```

Set a testing threshold

Load pretrain model train on COCO



Example 4-3 – Detectron2 Tutorial

Run panoptic segmentation on a video:

Prepare the video URL

```
!pip install youtube-dl
!pip uninstall -y opencv-python-headless opencv-contrib-python
!apt install python3-opencv # the one pre-installed have some issues
!youtube-dl https://www.youtube.com/watch?v=ll8TgCZ0plk -f 22 -o video.mp4
!ffmpeg -i video.mp4 -t 00:00:06 -c v copy video-clip.mp4
```

Youtube URL

Use demo.py tool run frame-by-frame inference demo on this video

```
# Run frame-by-frame inference demo on this video (takes 3-4 minutes) with the "demo.py" tool we provided in the repo.
!git clone https://github.com/facebookresearch/detectron2
!python detectron2/demo/demo.py --config-file detectron2/configs/COCO-Keypoints/keypoint_rcnn_R_101_FPN_3x.yaml --video-input video-clip.mp4 --confidence-threshold 0.6
--opts MODEL.WEIGHTS detectron2://COCO-Keypoints/keypoint_rcnn_R_101_FPN_3x/138363331/model_final_997cc7.pkl
```

Download the results

```
from google.colab import files
files.download('video-output.mkv')
```

Model architecture

Model weight

Example 4-3 – Detectron2 Tutorial



Example 4-3 – Detectron2 Tutorial

Model_zoo.py

```
# COCO Detection with RetinaNet
"COCO-Detection/retinanet_R_50_FPN_1x.yaml": "190397773/model_final_bfca0b.pkl",
"COCO-Detection/retinanet_R_50_FPN_3x.yaml": "190397829/model_final_5bd44e.pkl",
"COCO-Detection/retinanet_R_101_FPN_3x.yaml": "190397697/model_final_971ab9.pkl",
# COCO Detection with RPN and Fast R-CNN
"COCO-Detection/rpn_R_50_C4_1x.yaml": "137258005/model_final_450694.pkl",
"COCO-Detection/rpn_R_50_FPN_1x.yaml": "137258492/model_final_02ce48.pkl",
"COCO-Detection/fast_rcnn_R_50_FPN_1x.yaml": "137635226/model_final_e5f7ce.pkl",
# COCO Instance Segmentation Baselines with Mask R-CNN
"COCO-InstanceSegmentation/mask_rcnn_R_50_C4_1x.yaml": "137259246/model_final_9243eb.pkl",
"COCO-InstanceSegmentation/mask_rcnn_R_50_DC5_1x.yaml": "137260150/model_final_4f86c3.pkl",
"COCO-InstanceSegmentation/mask_rcnn_R_50_FPN_1x.yaml": "137260431/model_final_a54504.pkl",
"COCO-InstanceSegmentation/mask_rcnn_R_50_C4_3x.yaml": "137849525/model_final_4ce675.pkl",
"COCO-InstanceSegmentation/mask_rcnn_R_50_DC5_3x.yaml": "137849551/model_final_84107b.pkl",
"COCO-InstanceSegmentation/mask_rcnn_R_50_FPN_3x.yaml": "137849600/model_final_f10217.pkl",
"COCO-InstanceSegmentation/mask_rcnn_R_101_C4_3x.yaml": "138363239/model_final_a2914c.pkl",
"COCO-InstanceSegmentation/mask_rcnn_R_101_DC5_3x.yaml": "138363294/model_final_0464b7.pkl",
"COCO-InstanceSegmentation/mask_rcnn_R_101_FPN_3x.yaml": "138205316/model_final_a3ec72.pkl",
"COCO-InstanceSegmentation/mask_rcnn_X_101_32x8d_FPN_3x.yaml": "139653917/model_final_2d9806.pkl", # noqa
# COCO Person Keypoint Detection Baselines with Keypoint R-CNN
"COCO-Keypoints/keypoint_rcnn_R_50_FPN_1x.yaml": "137261548/model_final_04e291.pkl",
"COCO-Keypoints/keypoint_rcnn_R_50_FPN_3x.yaml": "137849621/model_final_a6e10b.pkl",
"COCO-Keypoints/keypoint_rcnn_R_101_FPN_3x.yaml": "138363331/model_final_997cc7.pkl",
"COCO-Keypoints/keypoint_rcnn_X_101_32x8d_FPN_3x.yaml": "139686956/model_final_5ad38f.pkl",
# COCO Panoptic Segmentation Baselines with Panoptic FPN
"COCO-PanopticSegmentation/panoptic_fpn_R_50_1x.yaml": "139514544/model_final_dbfeb4.pkl",
"COCO-PanopticSegmentation/panoptic_fpn_R_50_3x.yaml": "139514569/model_final_c10459.pkl",
"COCO-PanopticSegmentation/panoptic_fpn_R_101_3x.yaml": "139514519/model_final_cafdb1.pkl",
# LVIS Instance Segmentation Baselines with Mask R-CNN
"LVISv0.5-InstanceSegmentation/mask_rcnn_R_50_FPN_1x.yaml": "144219072/model_final_571f7c.pkl", # noqa
"LVISv0.5-InstanceSegmentation/mask_rcnn_R_101_FPN_1x.yaml": "144219035/model_final_824ab5.pkl", # noqa
"LVISv0.5-InstanceSegmentation/mask_rcnn_X_101_32x8d_FPN_1x.yaml": "144219108/model_final_5e3439.pkl", # noqa
```

Model weight

Model architecture

Exercise 4-3 – Detectron2 Tutorial

- Please download “Detectron2_tutorial.ipynb” and open “Detectron2_tutorial.ipynb” by Colab.

1. Try to use **your own** pictures to test on keypoint detection models.

※ Hints: You must change random.sample to the specified picture.

2. Following the previous question change the `cfg.MODEL.ROI_HEADS.SCORE_THRESH_TEST` and compare the result.

3. Use different types of videos for key points model (8sec) .

4. Following the previous question choose different pretrain model to test.

※ Hints: Different weights and networks can be found at the following URL.

https://github.com/facebookresearch/detectron2/blob/master/detectron2/model_zoo/model_zoo.py

Exercise 4-3 – Detectron2 Tutorial

5. Retrain the model and change anchor box size and ratio then compare the result.
6. Following the previous question, retrain the new model on different cfg on the model and compare the influence on the model (In addition to the existing cfg, need 3 different cfg changes).
 - Please write down result and your code in MS Word to Moodle