Detectron2 Beginner's Tutorial

Welcome to detectron2! In this tutorial, we will go through some basics usage of detectron2, including the following:

- Run inference on images or videos, with an existing detectron2 model
- Train a detectron2 model on a new dataset

You can make a copy of this tutorial or use "File -> Open in playground mode" to play with it yourself.

Install detectron2

```
# install dependencies
!pip install -U torch torchvision cython fvcore Pillow==6.2.2
!pip install -U 'git+https://github.com/cocodataset/cocoapi.git#subdirectory=PythonAPI'
import torch, torchvision
torch.__version__
```

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

```
# You may need to restart your runtime prior to this, to let your installation take effect
# 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 cv2
import 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
```

Run a pre-trained detectron2 model

We first download a random image from the COCO dataset:

```
!wget http://images.cocodataset.org/val2017/000000439715.jpg -O input.jpg
im = cv2.imread("./input.jpg")
cv2_imshow(im)
```

```
—2019-12-26 06:45:01—  http://images.cocodataset.org/val2017/000000439715.jpg
Resolving images.cocodataset.org (images.cocodataset.org)... 52.217.42.132
Connecting to images.cocodataset.org (images.cocodataset.org)|52.217.42.132|:80... connected.
HTTP request sent, awaiting response... 200 OK
Length: 209222 (204K) [image/jpeg]
Saving to: 'input.jpg'

input.jpg           100%[==================>] 204.32K  1.08MB/s    in 0.2s

2019-12-26 06:45:01 (1.08 MB/s) - 'input.jpg' saved [209222/209222]
```

Then, we create a detectron2 config and a detectron2 `DefaultPredictor` to run inference on this image.

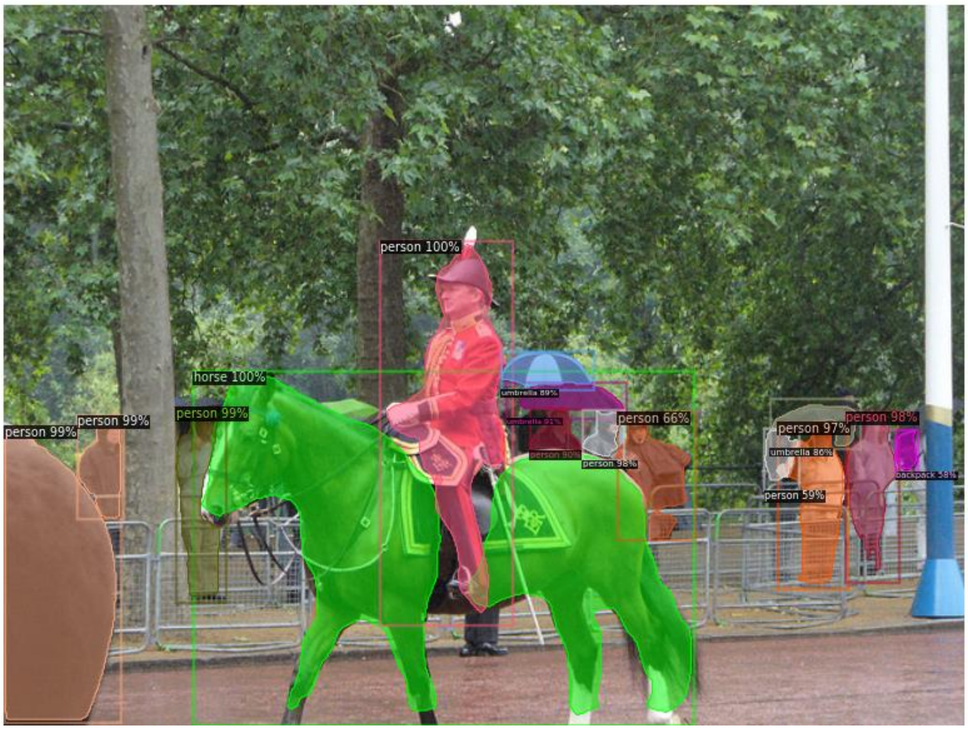
```
[ ]  cfg = get_cfg()
     # add project-specific config (e.g., TensorMask) here if you're not running a model in detectron2's core library
     cfg.merge_from_file(model_zoo.get_config_file("COCO-InstanceSegmentation/mask_rcnn_R_50_FPN_3x.yaml"))
     cfg.MODEL.ROI_HEADS.SCORE_THRESH_TEST = 0.5  # set threshold for this model
     # Find a model from detectron2's model zoo. You can either use the https://dl.fbaipublicfiles.... url, or use the detectron2://
     cfg.MODEL.WEIGHTS = "detectron2://COCO-InstanceSegmentation/mask_rcnn_R_50_FPN_3x/137849600/model_final_f10217.pkl"
     predictor = DefaultPredictor(cfg)
     outputs = predictor(im)
```

```
WARNING [12/26 06:45:43 d2.config.compat]: Config '/content/detectron2_repo/detectron2/model_zoo/configs/COCO-InstanceSegmentatio
model_final_f10217.pkl: 178MB [00:02, 63.7MB/s]
```

```
[ ]  # look at the outputs. See https://detectron2.readthedocs.io/tutorials/models.html#model-output-format for specification
     outputs["instances"].pred_classes
     outputs["instances"].pred_boxes
```

```
Boxes(tensor([[126.6035, 244.8977, 459.8291, 480.0000],
        [251.1083, 157.8127, 338.9731, 413.6379],
        [114.8496, 268.6864, 148.2352, 398.8111],
        [  0.8217, 281.0327,  78.6072, 478.4210],
        [ 49.3954, 274.1229,  80.1545, 342.9808],
        [561.2248, 271.5816, 596.2755, 385.2552],
        [385.9072, 270.3125, 413.7130, 304.0397],
        [515.9295, 278.3744, 562.2792, 389.3802],
        [335.2409, 251.9167, 414.7491, 275.9375],
        [350.9300, 269.2060, 386.0984, 297.9081],
        [331.6292, 230.9996, 393.2759, 257.2009],
        [510.7349, 263.2656, 570.9865, 295.9194],
        [409.0841, 271.8646, 460.5582, 356.8722],
        [506.8767, 283.3257, 529.9403, 324.0392],
        [594.5663, 283.4820, 609.0577, 311.4124]], device='cuda:0'))
```

```
[ ]  # We can use `Visualizer` to draw the predictions on the image.
     v = Visualizer(im[:, :, ::-1], MetadataCatalog.get(cfg.DATASETS.TRAIN[0]), scale=1.2)
     v = v.draw_instance_predictions(outputs["instances"].to("cpu"))
     cv2_imshow(v.get_image()[:, :, ::-1])
```



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.

Note that COCO dataset does not have the "balloon" category. We'll be able to recognize this new class in a few minutes.

Prepare the dataset

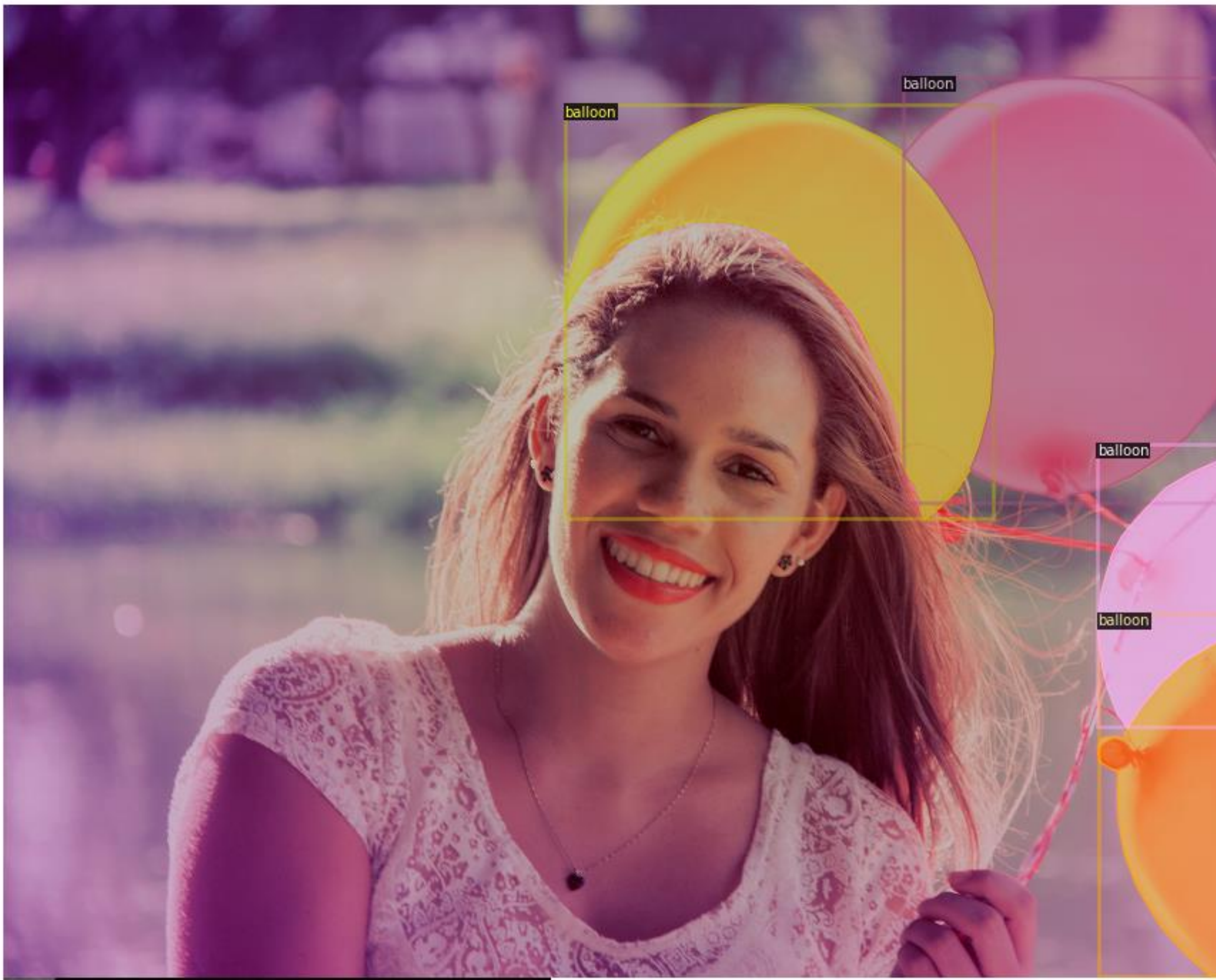
```
[ ] # download, decompress the data
    !wget https://github.com/matterport/Mask_RCNN/releases/download/v2.1/balloon_dataset.zip
    !unzip balloon_dataset.zip > /dev/null
```

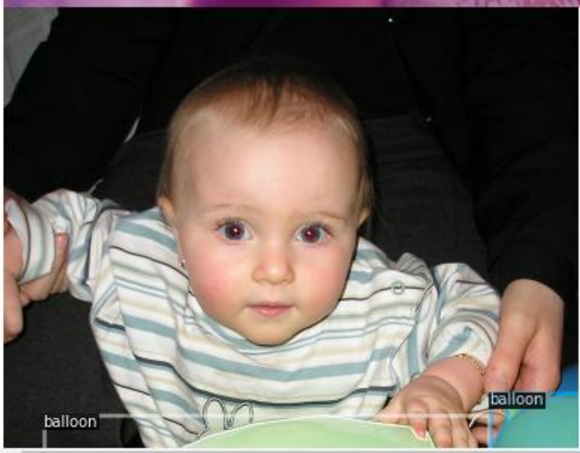
Register the balloon dataset to detectron2, following the detectron2 custom dataset tutorial. Here, the dataset is in its custom format, therefore we write a function to parse it and prepare it into detectron2's standard format. See the tutorial for more details.

```
[ ] import os
    import numpy as np
    import json
    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,
                    "iscrowd": 0
                }
                objs.append(obj)
            record["annotations"] = objs
            dataset_dicts.append(record)
        return dataset_dicts

    from detectron2.data import DatasetCatalog, MetadataCatalog
    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")
```

To verify the data loading is correct, let's visualize the annotations of randomly selected samples in the training set:

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





Train!

Now, let's fine-tune a coco-pretrained R50-FPN Mask R-CNN model on the balloon dataset. It takes ~6 minutes to train 300 iteration on Colab's K80 GPU, or ~2 minutes on a P100 GPU.

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

    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 = "detectron2://COCO-InstanceSegmentation/mask_rcnn_R_50_FPN_3x/137849600/model_final_f10217.pkl"  # Let tra
    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 pract
    cfg.MODEL.ROI_HEADS.BATCH_SIZE_PER_IMAGE = 128   # faster, and good enough for this toy dataset (default: 512)
    cfg.MODEL.ROI_HEADS.NUM_CLASSES = 1  # only has one class (ballon)

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

```
WARNING [11/15 04:10:08 d2.config.compat]: Config './detectron2_repo/configs/COCO-InstanceSegmentation/mask_rcnn_R_50_FPN_3x.ya
[11/15 04:10:08 d2.engine.defaults]: Model:
GeneralizedRCNN(
  (backbone): FPN(
    (fpn_lateral2): Conv2d(256, 256, kernel_size=(1, 1), stride=(1, 1))
    (fpn_output2): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (fpn_lateral3): Conv2d(512, 256, kernel_size=(1, 1), stride=(1, 1))
    (fpn_output3): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (fpn_lateral4): Conv2d(1024, 256, kernel_size=(1, 1), stride=(1, 1))
    (fpn_output4): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (fpn_lateral5): Conv2d(2048, 256, kernel_size=(1, 1), stride=(1, 1))
    (fpn_output5): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (top_block): LastLevelMaxPool()
    (bottom_up): ResNet(
      (stem): BasicStem(
        (conv1): Conv2d(
          3, 64, kernel_size=(7, 7), stride=(2, 2), padding=(3, 3), bias=False
          (norm): FrozenBatchNorm2d(num_features=64, eps=1e-05)
        )
      )
      (res2): Sequential(
        (0): BottleneckBlock(
          (shortcut): Conv2d(
            64, 256, kernel_size=(1, 1), stride=(1, 1), bias=False
            (norm): FrozenBatchNorm2d(num_features=256, eps=1e-05)
          )
          (conv1): Conv2d(
            64, 64, kernel_size=(1, 1), stride=(1, 1), bias=False
            (norm): FrozenBatchNorm2d(num_features=64, eps=1e-05)
          )
          (conv2): Conv2d(
            64, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False
            (norm): FrozenBatchNorm2d(num_features=64, eps=1e-05)
          )
          (conv3): Conv2d(
            64, 256, kernel_size=(1, 1), stride=(1, 1), bias=False
            (norm): FrozenBatchNorm2d(num_features=256, eps=1e-05)
          )
        )
        (1): BottleneckBlock(
          (conv1): Conv2d(
            256, 64, kernel_size=(1, 1), stride=(1, 1), bias=False
            (norm): FrozenBatchNorm2d(num_features=64, eps=1e-05)
          )
          (conv2): Conv2d(
            64, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False
            (norm): FrozenBatchNorm2d(num_features=64, eps=1e-05)
          )
          (conv3): Conv2d(
            64, 256, kernel_size=(1, 1), stride=(1, 1), bias=False
            (norm): FrozenBatchNorm2d(num_features=256, eps=1e-05)
          )
        )
        (2): BottleneckBlock(
```

```
[ ] # Look at training curves in tensorboard:
    %load_ext tensorboard
    %tensorboard --logdir output
```

Inference & evaluation using the trained model

Now, let's run inference with the trained model on the balloon validation dataset. First, let's create a predictor using the mod trained:

```
[ ] 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 = ("balloon_val", )
    predictor = DefaultPredictor(cfg)
```

Then, we randomly select several samples to visualize the prediction results.

```
[ ] 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)
        v = Visualizer(im[:, :, ::-1],
                       metadata=balloon_metadata,
                       scale=0.8,
                       instance_mode=ColorMode.IMAGE_BW   # remove the colors of unsegmented pixels
        )
        v = v.draw_instance_predictions(outputs["instances"].to("cpu"))
        cv2_imshow(v.get_image()[:, :, ::-1])
```

We can also evaluate its performance using AP metric implemented in COCO API. This gives an AP of ~70%. Not bad!

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

Other types of builtin models

```
[ ] # Inference with a keypoint detection model
    cfg = get_cfg()
    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 = "detectron2://COCO-Keypoints/keypoint_rcnn_R_50_FPN_3x/137849621/model_final_a6e10b.pkl"
    predictor = DefaultPredictor(cfg)
    outputs = predictor(im)
    v = Visualizer(im[:, :, ::-1], MetadataCatalog.get(cfg.DATASETS.TRAIN[0]), scale=1.2)
    v = v.draw_instance_predictions(outputs["instances"].to("cpu"))
    cv2_imshow(v.get_image()[:, :, ::-1])
```

```
WARNING [10/15 06:33:32 d2.config.compat]: Config './detectron2_repo/configs/COCO-Keyp _FPN_3x.yaml' has n
```

```
[ ] # Inference with a panoptic segmentation model
    cfg = get_cfg()
    cfg.merge_from_file(model_zoo.get_config_file("COCO-PanopticSegmentation/panoptic_fpn_R_101_3x.yaml"))
    cfg.MODEL.WEIGHTS = "detectron2://COCO-PanopticSegmentation/panoptic_fpn_R_101_3x/139514519/model_final_cafdb1.pkl"
    predictor = DefaultPredictor(cfg)
    panoptic_seg, segments_info = predictor(im)["panoptic_seg"]
    v = Visualizer(im[:, :, ::-1], MetadataCatalog.get(cfg.DATASETS.TRAIN[0]), scale=1.2)
    v = v.draw_panoptic_seg_predictions(panoptic_seg.to("cpu"), segments_info)
    cv2_imshow(v.get_image()[:, :, ::-1])
```

```
WARNING [10/15 06:33:37 d2.config.compat]: Config './detectron2_repo/configs/COCO-PanopticSegmentation/panoptic_fpn_R_101_3x.yaml
```

Run panoptic segmentation on a video

```
# This is the video we're going to process
from IPython.display import YouTubeVideo, display
video = YouTubeVideo("ll8TgCZ0plk", width=500)
display(video)
```


```
# Install dependencies, download the video, and crop 5 seconds for processing
!pip install youtube-dl
!pip uninstall -y opencv-python opencv-contrib-python
!apt install python3-opencv
!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
```

```
# Run frame-by-frame inference demo on this video (takes 3-4 minutes)
# Using a model trained on COCO dataset
!cd detectron2_repo && python demo/demo.py --config-file configs/COCO-PanopticSegmentation/panoptic_fpn_R_101_3x.yaml --video-in
  --opts MODEL.WEIGHTS detectron2://COCO-PanopticSegmentation/panoptic_fpn_R_101_3x/139514519/model_final_cafdb1.pkl
```

```
# Download the results
from google.colab import files
files.download('video-output.mkv')
```