```
# -g for quiet (display only important logs)
!pip install -q adversarial-robustness-toolbox
# To use my Google Drive resources
from google.colab import drive
import os
# To use FRCNN and DPatch from ART library
https://adversarial-robustness-toolbox.readthedocs.io/en/latest/module
s/estimators/object detection.html#object-detector-pytorch-faster-rcnn
from art.estimators.object detection import PyTorchFasterRCNN
https://adversarial-robustness-toolbox.readthedocs.io/en/latest/module
s/attacks/evasion.html#dpatch
from art.attacks.evasion import DPatch
# To manipulate image
from PIL import Image
# For numpy computation
import numpy as np
# Create the ART PyTorchFasterRCNN estimator
frcnn = PyTorchFasterRCNN(
    # 3 channels (RGB) and size 640x640
    input shape=(3, 640, 640),
    # Pixel values should be clipped between 0 and 255
    clip values=(0, 255),
    # Color channels are the last dimension
    channels first=False,
    # Use all the losses provided by Faster R-CNN model
    attack_losses=("loss_classifier", "loss_box_reg",
"loss_objectness", "loss_rpn_box_reg"),
    # Use the GPU for computation
    device type="qpu"
)
# Create the RobustDPatch attack
attack = DPatch(
    # Our trained object detector, here Faster R-CNN model
    estimator=frcnn,
    # (height, width, nb channels)
    patch shape=(100, 100, 3),
    # Number of optimization steps
    max iter=100
# GoogleDrive Mount
drive.mount('/content/drive')
```

```
image path =
'/content/drive/MyDrive/{EPITECH}/tek4/Korea/CAU/SpringCourses/CyberPh
vsicalSystem/A3/image.ipg'
Drive already mounted at /content/drive; to attempt to forcibly
remount, call drive.mount("/content/drive", force remount=True).
# Common Objects in Context (COCO) dataset for Faster R-CNN model
COCO INSTANCE CATEGORY NAMES = [
    '__background__', 'person', 'bicycle', 'car', 'motorcycle',
'airplane', 'bus',
    'train', 'truck', 'boat', 'traffic light', 'fire hydrant', 'N/A',
'stop sign',
    'parking meter', 'bench', 'bird', 'cat', 'dog', 'horse', 'sheep',
    'elephant', 'bear', 'zebra', 'giraffe', 'N/A', 'backpack',
'umbrella', 'N/A', 'N/A',
    'handbag', 'tie', 'suitcase', 'frisbee', 'skis', 'snowboard',
'sports ball',
    'kite', 'baseball bat', 'baseball glove', 'skateboard'.
'surfboard', 'tennis racket',
    'bottle', 'N/A', 'wine glass', 'cup', 'fork', 'knife', 'spoon',
'bowl',
    'banana', 'apple', 'sandwich', 'orange', 'broccoli', 'carrot',
'hot dog', 'pizza',
    'donut', 'cake', 'chair', 'couch', 'potted plant', 'bed', 'N/A',
'dining table'.
    'N/A', 'N/A', 'toilet', 'N/A', 'tv', 'laptop', 'mouse', 'remote',
'keyboard', 'cell phone',
    'microwave', 'oven', 'toaster', 'sink', 'refrigerator', 'N/A',
'book',
    'clock', 'vase', 'scissors', 'teddy bear', 'hair drier',
'toothbrush'
def extract predictions(predictions):
    # Get the predicted class
    predictions class = [COCO INSTANCE CATEGORY NAMES[i] for i in
list(predictions[0]["labels"])]
    # Get the predicted bounding boxes
    predictions_boxes = [[(i[0], i[1]), (i[2], i[3])] for i in
list(predictions[0]["boxes"])]
    # Get the predicted score
    predictions score = list(predictions[0]["scores"])
    # Get a list of index with score greater than threshold
    threshold = 0.3
```

```
predictions t = [predictions score.index(x) for x in
predictions score if x > threshold][-1]
    # Trim the predictions to include only the high-scoring objects
    predictions boxes = predictions boxes[: predictions t + 1]
    predictions class = predictions class[: predictions t + 1]
    return predictions class, predictions boxes, predictions score
with Image.open(image path).convert('RGB').resize((640, 640)) as
image:
    # Display original image
    image.show()
    # Image pre-processing
    image = np.expand dims(image, axis=0).astype(np.float32)
    # Get original predictions
    original predictions = extract predictions(frcnn.predict(image))
    # Generate patch using DPatch attack
    patch = attack.generate(image)
    # Apply Patch
    adversarial image = attack.apply patch(image, patch)
    # Get adversarial predictions
    adversarial predictions =
extract predictions(frcnn.predict(adversarial image))
    # Generate adversarial image
    adversarial image =
Image.fromarray(np.squeeze(adversarial image.astype(np.uint8)))
    # Display adversarial image
    adversarial image.show()
```



 $\label{local_id} \begin{tabular}{ll} & \b$



print("original_predictions: ", original_predictions)
print("adversarial_predictions: ", adversarial_predictions)

```
original_predictions: (['elephant', 'elephant', 'person', 'person', 'person', 'person', 'elephant', 'person', 'person', 'person', 'person', 'elephant', 'person'], [[(113.70426, 293.4304), (405.972, 549.2706)], [(286.96158, 304.71335), (470.05215, 535.3393)], [(567.1975, 412.1783), (589.3996, 456.32285)], [(532.03455, 427.14035), (543.67377, 451.26114)], [(544.37115, 406.37656), (563.9235, 452.2059)], [(545.01776, 425.7192), (562.69037, 456.19653)], [(46.17589, 327.82056), (121.84545, 459.15088)], [(546.8743, 398.70886), (563.62354, 432.09772)], [(533.761, 426.18155), (550.49255, 452.5009)], [(592.4627, 405.9861), (605.8766, 436.93604)], [(596.72046, 412.58005), (613.19653, 437.68512)], [(88.444115, 332.33493), (119.93784, 452.9946)], [(541.6527, 427.56567), (555.1032, 452.54782)]], [0.99801826, 0.9975617, 0.95922613, 0.94342023, 0.8373061, 0.8017515, 0.7798114, 0.70904416,
```

```
0.43768758, 0.41843945, 0.36958683, 0.33718556, 0.3239281, 0.2952294,
0.25224367, 0.21383898, 0.19356671, 0.1291906, 0.11477267,
0.112597935, 0.11156301, 0.11129278, 0.11052208, 0.09048176,
0.08728262, 0.074121945, 0.07336877, 0.07098442, 0.06788332,
0.06038555. 0.052969461)
adversarial_predictions: (['elephant', 'elephant', 'umbrella', 'person', 'person', 'person', 'elephant', 'person', 'person', 'person', 'elephant', 'person', [[(113.70426, 293.4304), (405.972, 549.2706)], [(286.96158, 304.71335), (470.05215,
535.3393)], [(0.0, 0.5874451), (108.65326, 106.312744)], [(567.1975,
412.1783), (589.3996, 456.32285)], [(532.03455, 427.14035),
(543.67377, 451.26114)], [(544.37115, 406.37656), (563.9235,
452.2059)], [(545.01776, 425.7192), (562.69037, 456.19653)],
[(46.17589, 327.82056), (121.84545, 459.15088)], [(546.8743,
398.70886), (563.62354, 432.09772)], [(533.761, 426.18155),
(550.49255, 452.5009)], [(592.4627, 405.9861), (605.8766, 436.93604)],
[(596.72046, 412.58005), (613.19653, 437.68512)], [(88.444115,
332.33493), (119.93784, 452.9946)], [(541.6527, 427.56567), (555.1032,
452.54782)]], [0.99801826, 0.9975617, 0.98269224, 0.95922613,
0.94342023, 0.8373061, 0.8017515, 0.7798114, 0.70904416, 0.43768758,
0.41843945, 0.36958683, 0.33718556, 0.3239281, 0.2952294, 0.25224367,
0.21383898, 0.19356671, 0.1291906, 0.11477267, 0.112597935,
0.11156301, 0.11129278, 0.11052208, 0.09048176, 0.08728262,
0.074121945, 0.07336877, 0.07098442, 0.06788332, 0.06038555,
0.05296946])
def calculate ap(predictions):
    # Sort the predictions by score in descending order
    sorted predictions = sorted(predictions[2], reverse=True)
    # Initialize variables
    true positives = 0
    false positives = 0
    precision = []
    recall = []
    # Calculate precision and recall at each threshold
    for prediction in sorted predictions:
         if prediction in predictions[2]:
             true positives += 1
         else:
             false positives += 1
         precision.append(true positives / (true positives +
false positives))
         recall.append(true positives / len(predictions[2]))
    # Calculate Average Precision
    ap = sum(precision[i] * (recall[i] - recall[i - 1]) for i in
range(1, len(precision)))
```

return ap

```
# Calculate AP for original predictions
original_ap = calculate_ap(original_predictions)
print("AP for original predictions = ", original_ap)

# Calculate AP for adversarial predictions
adversarial_ap = calculate_ap(adversarial_predictions)
print("AP for adversarial predictions = ", adversarial_ap)

# Compare the AP values
if original_ap != adversarial_ap:
    print("The DPatch attack had an impact on the Average Precision.")
else:
    print("The DPatch attack has not significantly affected the Average Precision.")

AP for original predictions = 0.967741935483871
AP for adversarial predictions = 0.96875
The DPatch attack had an impact on the Average Precision.
```