Homework 3

Instructions

- This homework focuses on understanding and applying DETR for object detection and attention visualization. It consists of **three questions** designed to assess both theoretical understanding and practical application.
- Please organize your answers and results for the questions below and submit this jupyter notebook as **a .pdf file**.
- **Deadline: 11/14 (Thur) 23:59**

Reference

- End-to-End Object Detection with Transformers (DETR): https://github.com/facebookresearch/detr

Q1. Understanding DETR model

- Fill-in-the-blank exercise to test your understanding of critical parts of the DETR model workflow.

```
from torch import nn
class DETR(nn.Module):
    def __init__(self, num_classes, hidden_dim=256, nheads=8,
                 num_encoder_layers=6, num_decoder_layers=6,
num_queries=100):
        super().__init__()

        # create ResNet-50 backbone
        self.backbone = resnet50()
        del self.backbone.fc

        # create conversion layer
        self.conv = nn.Conv2d(2048, hidden_dim, 1)

        # create a default PyTorch transformer
        self.transformer = nn.Transformer(hidden_dim, nheads,
num_encoder_layers, num_decoder_layers)


        # prediction heads, one extra class for predicting non-empty
slots
        # note that in baseline DETR linear_bbox layer is 3-layer MLP
        self.linear_class = nn.Linear(hidden_dim, num_classes + 1)
        self.linear_bbox = nn.Linear(hidden_dim, 4)

        # output positional encodings (object queries)
        self.query_pos = nn.Parameter(torch.rand(num_queries,
hidden_dim))
```

```python
        # spatial positional encodings
        # note that in baseline DETR we use sine positional encodings
        self.row_embed = nn.Parameter(torch.rand(50, hidden_dim // 2))
        self.col_embed = nn.Parameter(torch.rand(50, hidden_dim // 2))

    def forward(self, inputs):
        # propagate inputs through ResNet-50 up to avg-pool layer
        x = self.backbone.conv1(inputs)
        x = self.backbone.bn1(x)
        x = self.backbone.relu(x)
        x = self.backbone.maxpool(x)

        x = self.backbone.layer1(x)
        x = self.backbone.layer2(x)
        x = self.backbone.layer3(x)
        x = self.backbone.layer4(x)

        # convert from 2048 to 256 feature planes for the transformer
        h = self.conv(x)

        # construct positional encodings
        H, W = h.shape[-2:]
        pos = torch.cat([
            self.col_embed[:W].unsqueeze(0).repeat(H, 1, 1),
            self.row_embed[:H].unsqueeze(1).repeat(1, W, 1),
        ], dim=-1).flatten(0, 1).unsqueeze(1)

        # propagate through the transformer
        h = self.transformer(pos + 0.1 * h.flatten(2).permute(2, 0,
1), self.query_pos.unsqueeze(1)).transpose(0, 1)

        # finally project transformer outputs to class labels and
bounding boxes
        pred_logits = self.linear_class(h)
        pred_boxes = self.linear_bbox(h).sigmoid()

        return {'pred_logits': pred_logits,
                'pred_boxes': pred_boxes}
```

Q2. Custom Image Detection and Attention Visualization

In this task, you will upload an **image of your choice** (different from the provided sample) and follow the steps below:

- Object Detection using DETR
- Use the DETR model to detect objects in your uploaded image.
- Attention Visualization in Encoder

- Visualize the regions of the image where the encoder focuses the most.
- Decoder Query Attention in Decoder
- Visualize how the decoder's query attends to specific areas corresponding to the detected objects.

```
import math

from PIL import Image
import requests
import matplotlib.pyplot as plt
%config InlineBackend.figure_format = 'retina'

import ipywidgets as widgets
from IPython.display import display, clear_output

import torch
from torch import nn


from torchvision.models import resnet50
import torchvision.transforms as T
torch.set_grad_enabled(False);

# COCO classes
CLASSES = [
    'N/A', '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', 'cow', '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',
```

```python
    'book', 'clock', 'vase', 'scissors', 'teddy bear', 'hair drier',
    'toothbrush'
]

# colors for visualization
COLORS = [[0.000, 0.447, 0.741], [0.850, 0.325, 0.098], [0.929, 0.694,
0.125],
          [0.494, 0.184, 0.556], [0.466, 0.674, 0.188], [0.301, 0.745,
0.933]]
# standard PyTorch mean-std input image normalization
transform = T.Compose([
    T.Resize(800),
    T.ToTensor(),
    T.Normalize([0.485, 0.456, 0.406], [0.229, 0.224, 0.225])
])

# for output bounding box post-processing
def box_cxcywh_to_xyxy(x):
    x_c, y_c, w, h = x.unbind(1)
    b = [(x_c - 0.5 * w), (y_c - 0.5 * h),
         (x_c + 0.5 * w), (y_c + 0.5 * h)]
    return torch.stack(b, dim=1)

def rescale_bboxes(out_bbox, size):
    img_w, img_h = size
    b = box_cxcywh_to_xyxy(out_bbox)
    b = b * torch.tensor([img_w, img_h, img_w, img_h],
dtype=torch.float32)
    return b

def plot_results(pil_img, prob, boxes):
    plt.figure(figsize=(16,10))
    plt.imshow(pil_img)
    ax = plt.gca()
    colors = COLORS * 100
    for p, (xmin, ymin, xmax, ymax), c in zip(prob, boxes.tolist(),
colors):
        ax.add_patch(plt.Rectangle((xmin, ymin), xmax - xmin, ymax -
ymin,
                                   fill=False, color=c, linewidth=3))
        cl = p.argmax()
        text = f'{CLASSES[cl]}: {p[cl]:0.2f}'
        ax.text(xmin, ymin, text, fontsize=15,
                bbox=dict(facecolor='yellow', alpha=0.5))
    plt.axis('off')
    plt.show()
```

In this section, we show-case how to load a model from hub, run it on a custom image, and print the result. Here we load the simplest model (DETR-R50) for fast inference. You can swap it with any other model from the model zoo.

```
model = torch.hub.load('facebookresearch/detr', 'detr_resnet50', pretrained=True)

model.eval();

# url = 'http://images.cocodataset.org/val2017/000000039769.jpg'
url = 'https://encrypted-tbn0.gstatic.com/images?q=tbn:ANd9GcSLwAX54YLWzfVJVnDhWiKGduBSySs2iNN-DapaOgdElnEhC9M4S19O57QfH39yvt7M2RM&usqp=CAU'

im = Image.open(requests.get(url, stream=True).raw) # put your own image

# mean-std normalize the input image (batch-size: 1)
img = transform(im).unsqueeze(0)

# propagate through the model
outputs = model(img)

# keep only predictions with 0.7+ confidence
probas = outputs['pred_logits'].softmax(-1)[0, :, :-1]
keep = probas.max(-1).values > 0.9

# convert boxes from [0; 1] to image scales
bboxes_scaled = rescale_bboxes(outputs['pred_boxes'][0, keep], im.size)

# mean-std normalize the input image (batch-size: 1)
img = transform(im).unsqueeze(0)

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# convert boxes from [0; 1] to image scales
bboxes_scaled = rescale_bboxes(outputs['pred_boxes'][0, keep],
im.size)

plot_results(im, probas[keep], bboxes_scaled)
```
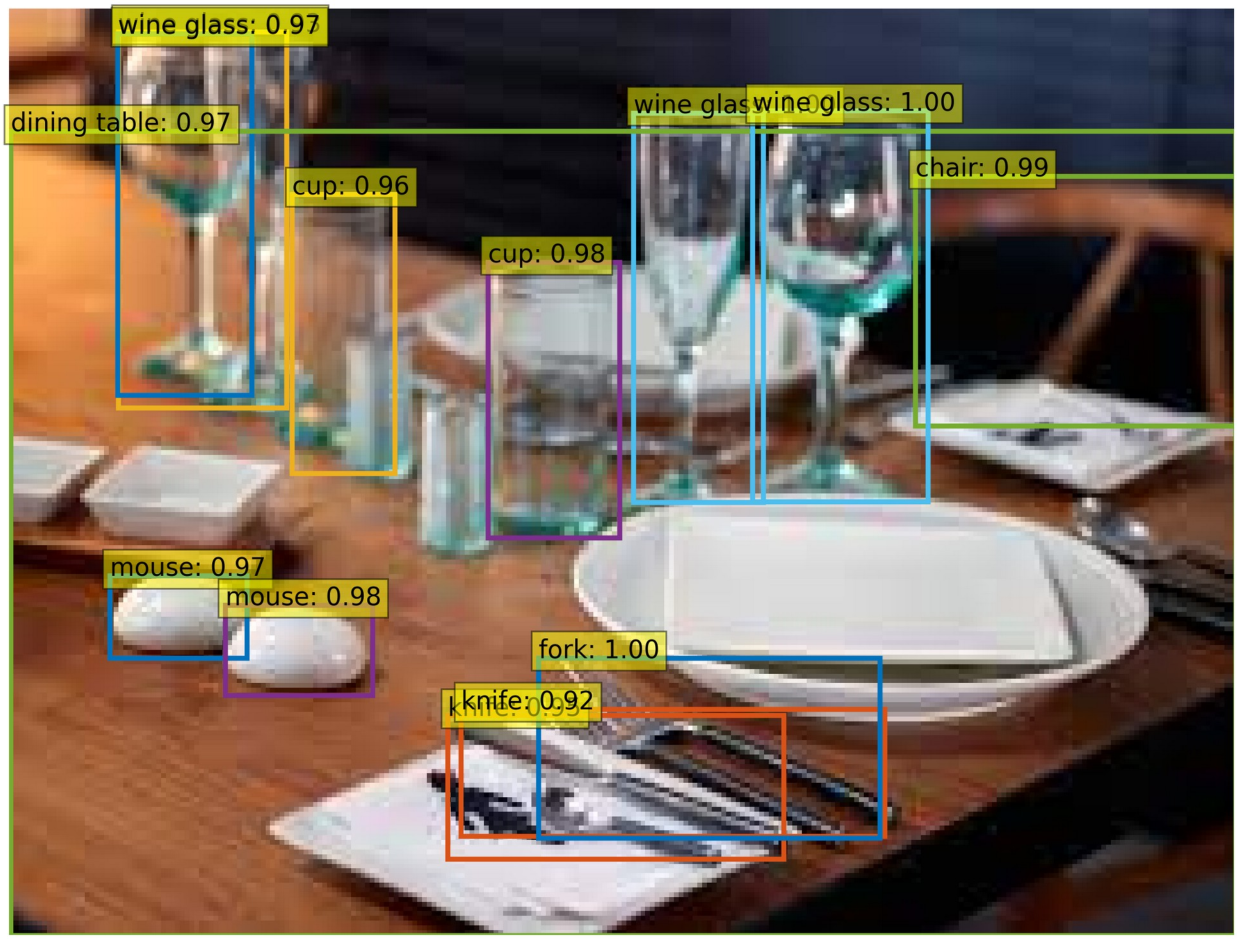
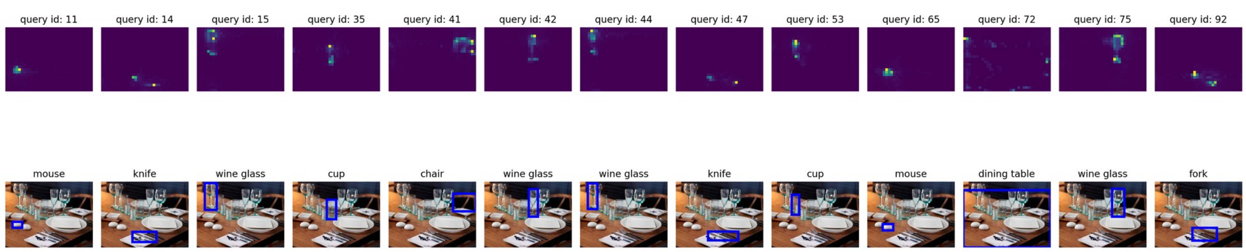

```
Downloading: "https://github.com/facebookresearch/detr/zipball/main"
to /root/.cache/torch/hub/main.zip
/usr/local/lib/python3.10/dist-packages/torchvision/models/_utils.py:2
08: UserWarning: The parameter 'pretrained' is deprecated since 0.13
and may be removed in the future, please use 'weights' instead.
  warnings.warn(
/usr/local/lib/python3.10/dist-packages/torchvision/models/_utils.py:2
23: UserWarning: Arguments other than a weight enum or `None` for
'weights' are deprecated since 0.13 and may be removed in the future.
The current behavior is equivalent to passing
`weights=ResNet50_Weights.IMAGENET1K_V1`. You can also use
`weights=ResNet50_Weights.DEFAULT` to get the most up-to-date weights.
  warnings.warn(msg)
Downloading: "https://download.pytorch.org/models/resnet50-
0676ba61.pth" to /root/.cache/torch/hub/checkpoints/resnet50-
0676ba61.pth
100%|██████████| 97.8M/97.8M [00:00<00:00, 120MB/s]
Downloading: "https://dl.fbaipublicfiles.com/detr/detr-r50-
e632da11.pth" to /root/.cache/torch/hub/checkpoints/detr-r50-
e632da11.pth
100%|██████████| 159M/159M [00:01<00:00, 121MB/s]
```



Here we visualize attention weights of the last decoder layer. This corresponds to visualizing, for each detected objects, which part of the image the model was looking at to predict this specific bounding box and class.

```
# use lists to store the outputs via up-values
conv_features, enc_attn_weights, dec_attn_weights = [], [], []

hooks = [
    model.backbone[-2].register_forward_hook(
        lambda self, input, output: conv_features.append(output)
    ),
    model.transformer.encoder.layers[-
1].self_attn.register_forward_hook(
        lambda self, input, output: enc_attn_weights.append(output[1])
    ),
    model.transformer.decoder.layers[-
1].multihead_attn.register_forward_hook(
        lambda self, input, output: dec_attn_weights.append(output[1])
    ),
]
```

```
# propagate through the model
outputs = model(img) # put your own image

for hook in hooks:
    hook.remove()

# don't need the list anymore
conv_features = conv_features[0]
enc_attn_weights = enc_attn_weights[0]
dec_attn_weights = dec_attn_weights[0]

# get the feature map shape
h, w = conv_features['0'].tensors.shape[-2:]

fig, axs = plt.subplots(ncols=len(bboxes_scaled), nrows=2,
figsize=(22, 7))
colors = COLORS * 100
for idx, ax_i, (xmin, ymin, xmax, ymax) in zip(keep.nonzero(), axs.T,
bboxes_scaled):
    ax = ax_i[0]
    ax.imshow(dec_attn_weights[0, idx].view(h, w))
    ax.axis('off')
    ax.set_title(f'query id: {idx.item()}')
    ax = ax_i[1]
    ax.imshow(im)
    ax.add_patch(plt.Rectangle((xmin, ymin), xmax - xmin, ymax - ymin,
                               fill=False, color='blue', linewidth=3))
    ax.axis('off')
    ax.set_title(CLASSES[probas[idx].argmax()])
fig.tight_layout()
```




```
# output of the CNN
f_map = conv_features['0']
print("Encoder attention:      ", enc_attn_weights[0].shape)
print("Feature map:            ", f_map.tensors.shape)
```

```
Encoder attention:       torch.Size([850, 850])
Feature map:             torch.Size([1, 2048, 25, 34])
```

```
# get the HxW shape of the feature maps of the CNN
shape = f_map.tensors.shape[-2:]
# and reshape the self-attention to a more interpretable shape
```

```
sattn = enc_attn_weights[0].reshape(shape + shape)
print("Reshaped self-attention:", sattn.shape)
```

```
Reshaped self-attention: torch.Size([25, 34, 25, 34])
```

```
# downsampling factor for the CNN, is 32 for DETR and 16 for DETR DC5
fact = 32

# let's select 4 reference points for visualization
idxs = [(200, 200), (280, 400), (200, 600), (440, 800),]

# here we create the canvas
fig = plt.figure(constrained_layout=True, figsize=(25 * 0.7, 8.5 *
0.7))
# and we add one plot per reference point
gs = fig.add_gridspec(2, 4)
axs = [
    fig.add_subplot(gs[0, 0]),
    fig.add_subplot(gs[1, 0]),
    fig.add_subplot(gs[0, -1]),
    fig.add_subplot(gs[1, -1]),
]

# for each one of the reference points, let's plot the self-attention
# for that point
for idx_o, ax in zip(idxs, axs):
    idx = (idx_o[0] // fact, idx_o[1] // fact)
    ax.imshow(sattn[..., idx[0], idx[1]], cmap='cividis',
interpolation='nearest')
    ax.axis('off')
    ax.set_title(f'self-attention{idx_o}')

# and now let's add the central image, with the reference points as
red circles
fcenter_ax = fig.add_subplot(gs[:, 1:-1])
fcenter_ax.imshow(im)
for (y, x) in idxs:
    scale = im.height / img.shape[-2]
    x = ((x // fact) + 0.5) * fact
    y = ((y // fact) + 0.5) * fact
    fcenter_ax.add_patch(plt.Circle((x * scale, y * scale), fact // 2,
color='r'))
    fcenter_ax.axis('off')
```

Q3. Understanding Attention Mechanisms

In this task, you focus on understanding the attention mechanisms present in the encoder and decoder of DETR.

- Briefly describe the types of attention used in the encoder and decoder, and explain the key differences between them.
- Based on the visualized results from Q2, provide an analysis of the distinct characteristics of each attention mechanism in the encoder and decoder. Feel free to express your insights.

DETR leverages self-attention in encoder and cross-attention in decoder. Self-attention enables each position in the input sequence to attend to all other positions. This allows the model to capture long-range dependencies and contextual information within the image features. Cross-attention is used to connect the object queries with the encoded image features. This mechanism helps the decoder focus on relevant parts of the image while generating object predictions. The key difference is in input because self-attention operates on a single sequence of image features, while cross-attention involves two sequences, the object queries and encoded image features. Also self-attention helps the model understand the relationships within the image itself but cross-attention guides the decoder to attend to specific regions of the image that are relevant to the object queries.

From the first image output we can see only certain areas of the image such as edges (dinner table, wine classes) or objects with high contrast (mouse, knife) that are likely to draw attention to themselves but attending to the whole image ensuring that all contextual information is captured which helps the model understand the overall structure of the image before making any object-specific predictions. Given that self-attention operates on the entire feature map after convolutional layers, it integrates information across different spatial scales whicn in turn provides a rich high-level understanding of object relationships, backgrounds, and scene context like the dinner table and chair. Moving on to the last two images they clearly display the object localization and classification mechanisms of the cross-attention in decoder. We can see how each query representing an object attends to specific regions in the image guided by bounding boxes. Also the attention heatmap highlights the exact area of the image corresponding to the predicted object. For instance the picture shows the two queries corresponding to "wine glass" , a quary to "cup" and another to "dinner table" attenting to the exact area of the image where these objects are located, clearly linking the objects to their position. The specific regions highlighted by decoder queries directly correspond to the locations of the objects, making the decoder's attention more "localized" compared to the encoder’s.