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.

In [29]:

```
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) # no object
        self.linear_bbox = nn.Linear(hidden_dim, 4)

        # output positional encodings (object queries)
        self.query_pos = nn.Parameter(torch.rand(100, hidden_dim))

        # 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.

In [110…

```
import math

from PIL import Image
import requests
```

```python
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',
    '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.

In [111…

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

url = 'https://www.shutterstock.com/image-photo/woman-dog-standing-traffic-light
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)

# propagate through the model
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# keep only predictions with 0.7+ confidence
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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)
```
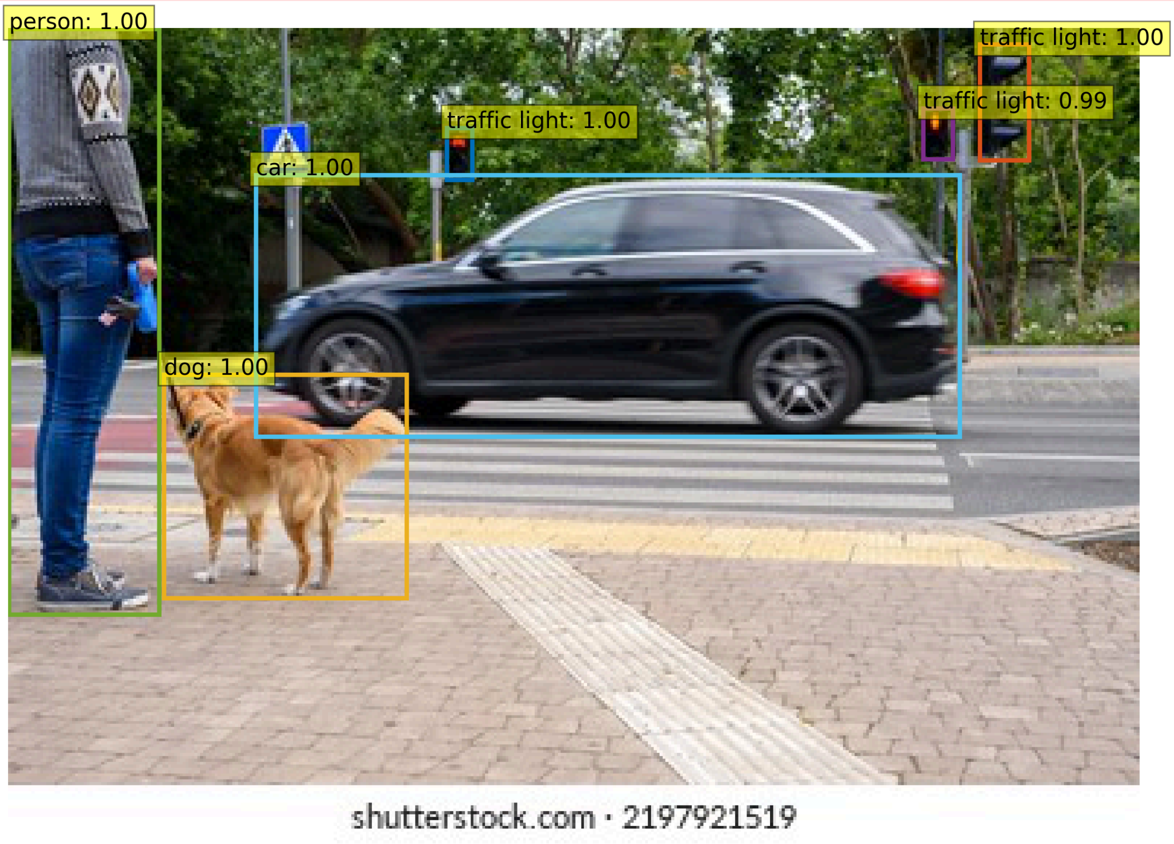

```
plot_results(im, probas[keep], bboxes_scaled)
```

```
Using cache found in /home/eainx/.cache/torch/hub/facebookresearch_detr_main
```



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.

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```
# use lists to store the outputs via up-values
# store the outputs from convolutional features, encoder attention weights, and
conv_features, enc_attn_weights, dec_attn_weights = [], [], []

# hook: Register a forward hook on the module.
# modify the input inplace but it will not have effect on forward since this is
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
```

```
# Each list is assumed to have captured exactly one batch of data
conv_features = conv_features[0]
enc_attn_weights = enc_attn_weights[0]
dec_attn_weights = dec_attn_weights[0]
```

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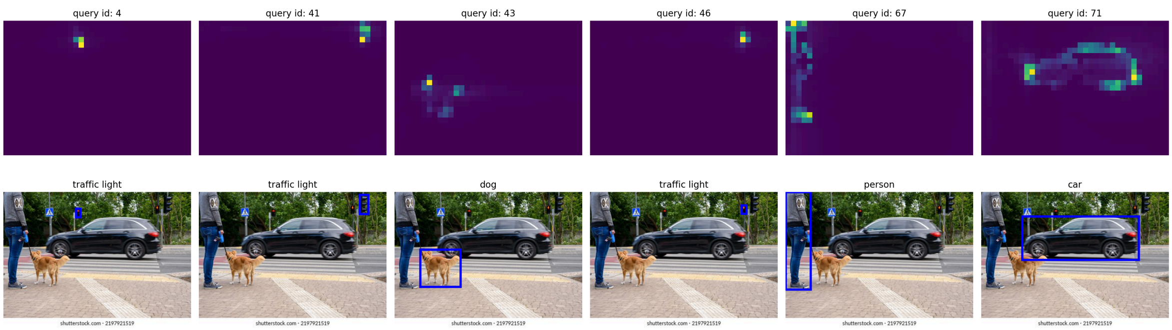
```
# get the feature map shape
# This extracts the height (h) and width (w) of the tensor from the first elemen
h, w = conv_features['0'].tensors.shape[-2:]

# Two rows for each detected bounding box
fig, axs = plt.subplots(ncols=len(bboxes_scaled), nrows=2, figsize=(22, 7))
colors = COLORS * 100
centers = []

for idx, ax_i, (xmin, ymin, xmax, ymax) in zip(keep.nonzero(), axs.T, bboxes_sca
    # first row
    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()}')
    # second row
    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()])

    # calculate bb center
    xcen = float((xmin + xmax) / 2)
    ycen = float((ymin + ymax) / 2)
    centers.append((xcen, ycen))

fig.tight_layout()
```



In [117…

```
# output of the CNN
f_map = conv_features['0']
print("Encoder attention:      ", enc_attn_weights[0].shape) # 25 * 35
print("Feature map:            ", f_map.tensors.shape)
print(centers)
```

```
Encoder attention:       torch.Size([875, 875])
Feature map:             torch.Size([1, 2048, 25, 35])
[(154.80862426757812, 42.781211853027344), (342.1312561035156, 25.0757236480712
9), (94.89056396484375, 156.98123168945312), (319.3326416015625, 35.8328132629394
5), (25.69803237915039, 100.36334991455078), (205.71519470214844, 94.913566589355
47)]
```

In [118…

```
# 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, 35, 25, 35])
```

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```
# 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 = [(int(x * 3), int(y * 3)) for y, x in centers[-4:]]

# 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
# 인코딩 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')

# 같은 객체 내에 포함되는 픽셀들 사이에 attention score이 높다.
```

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.

Types of attention & Difference

- **Encoder attention**: multi-head self attention.
- **Decoder attention**: multi-head self attention + multi-head attention.
- **Difference**: Encoder의 attention은 feature map에서 픽셀 간의 관계를 추출하여 "객체의 존재 여부와 형태"를 파악하는 것을 목적으로 하며, Decoder의 attention은 encoder가 추출한 관계 정보를 사용하여 이것을 object query를 통해 "어떤 객체인지" 파악하는 것을 목적으로 한다.

Characteristics

- **Encoder attention**:
  - Each token (pixel-level feature from the CNN backbone) attends to every other token across the entire input sequence. (전체 이미지 내에서 pixel 사이의 관계를 추출하여 이것을 attention score에 반영)
  - spatial positional encoding이 더해진다.
- **Decoder attention**:
  - input의 순서와 무관하게 같은 결과를 도출하는 permutation-invariant한 연산이므로, N개의 input이 서로 다른 객체 탐지 결과(class 및 bounding box)를 도출하려면 input 자체가 서로 다른 embedding 벡터로 구성되어야 한다. 이러한 N개의 decoder input을 object query라고 한다.
  - object query를 입력받아 multi-head self attention layer를 거친 후 ,
  - Encoder memory (출력값)를 받아 multi-head attention을 수행한다.