COSE474-2024F: Deep Learning HW3

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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.

[7]:
```
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(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.

[8]:
```
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',
    '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.

[9]:
```
model = torch.hub.load('facebookresearch/detr', 'detr_resnet50',␣
 ↪pretrained=True)
model.eval();

url = 'https://delhi4cats.wordpress.com/wp-content/uploads/2009/07/
 ↪4-cute-puppies-wallpaper-640x480.jpg'
```

```python
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 = 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)
```
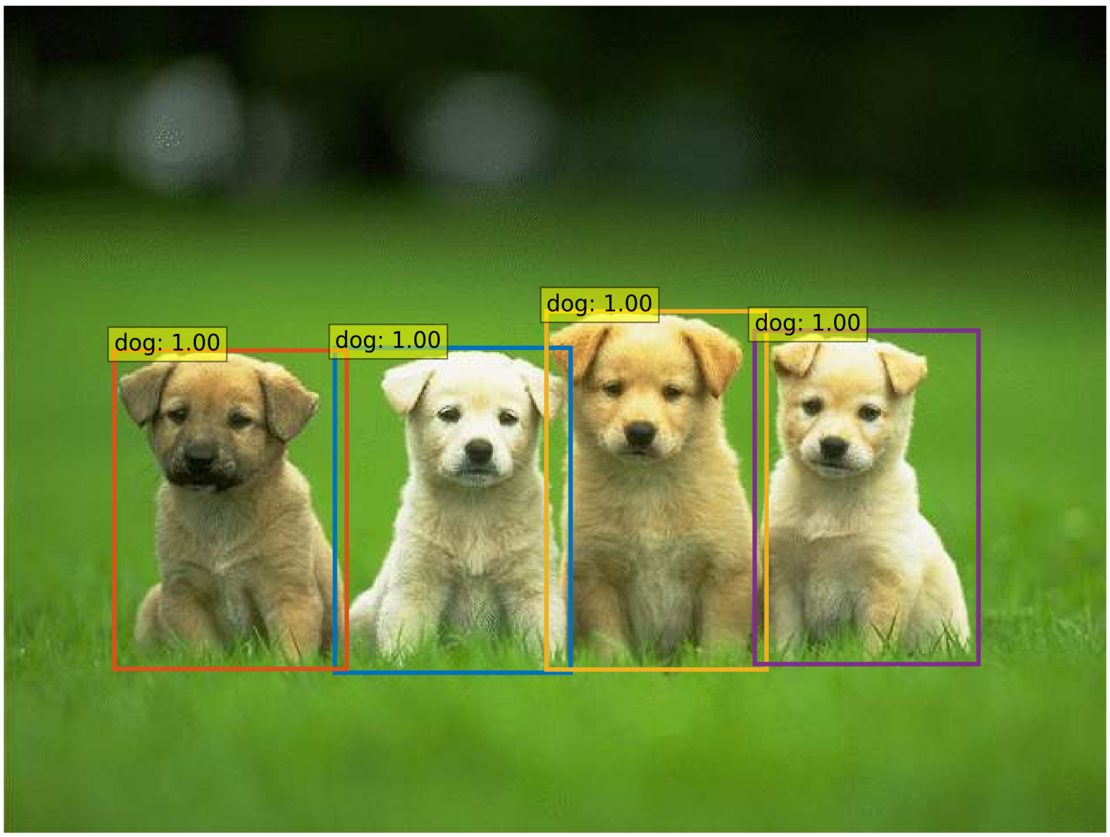

```
Using cache found in
/Users/hanjaehoon/.cache/torch/hub/facebookresearch_detr_main
/Users/hanjaehoon/Library/Mobile Documents/com~apple~CloudDocs/Korea Univ./2024
Fall/Deep Learning/20242R0136COSE47402/hw3/.venv/lib/python3.10/site-
packages/torchvision/models/_utils.py:208: UserWarning: The parameter
```

```
'pretrained' is deprecated since 0.13 and may be removed in the future, please
use 'weights' instead.
  warnings.warn(
/Users/hanjaehoon/Library/Mobile Documents/com~apple~CloudDocs/Korea Univ./2024
Fall/Deep Learning/20242R0136COSE47402/hw3/.venv/lib/python3.10/site-
packages/torchvision/models/_utils.py:223: 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)
```

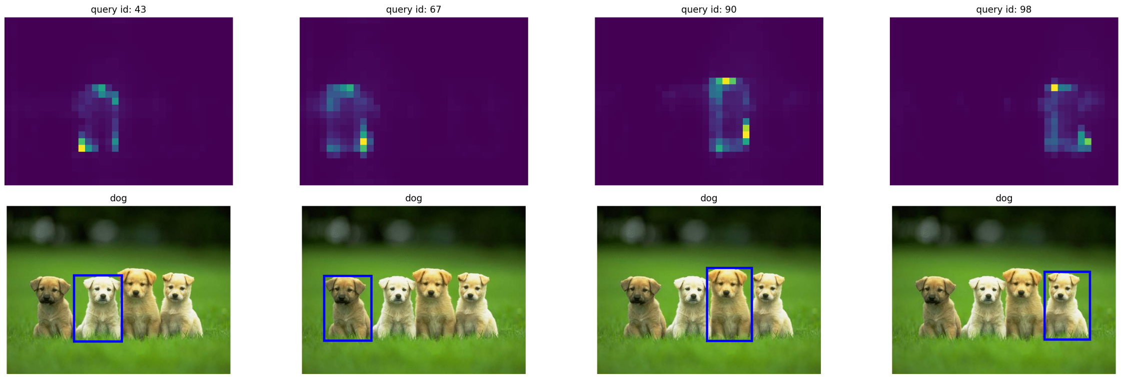


Here we visualize attention weights of the last decoder layer. This corresponds to visualizing, for each detected objects, which part of the image the model was looking at to predict this specific bounding box and class.

[10]:
```
# 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]
```

[11]:
```
# 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()
```



[12]:
```
# output of the CNN
f_map = conv_features['0']
print("Encoder attention:      ", enc_attn_weights[0].shape)
print("Feature map:            ", f_map.tensors.shape)
```

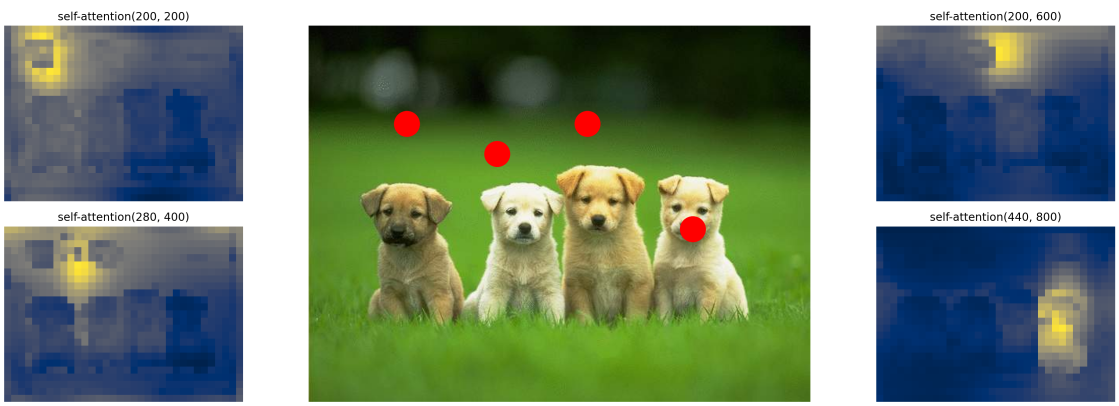
```
Encoder attention:       torch.Size([850, 850])
Feature map:             torch.Size([1, 2048, 25, 34])
```

[13]:
```
# 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])
```

[14]:
```
# 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
```

```python
# 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.**
  - **Encoder's Self-Attention**
    - Learns relationships among input image features.
      - Considers the relationships between each pixel and all other pixels in the encoder to capture the boundaries between objects and background in the image.
      - Focuses on capturing the overall characteristics of the entire image rather than the details of individual objects.
  - **Decoder's Cross-Attention**

        * Cross-attention focuses on specific queries by referencing the encoder's output.
            · Each query focuses on the location and type of each object.
            · The decoder predicts appropriate bounding boxes and labels for each object.

- **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.**
    - The encoder's self-attention captures the overall context of the image, while the decoder's cross-attention focuses on specific queries to learn detailed features.
    - According to the visualized results from Q2, the encoder's attention covers the entire image in a general manner, while the decoder's attention shows a more focused attention on specific object locations with finer detail.