homework-3-1

November 13, 2024

0.1 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

0.1.1 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)
```

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

0.1.2 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',
    '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)
```

```python
model.eval();

url = 'http://images.cocodataset.org/val2017/000000008211.jpg'
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)
```

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.

[ ]:
```python
# 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]
```

[ ]:
```python
# 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()
```

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

[ ]:
```python
# 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)
```

[ ]:
```python
# 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')
```

0.1.3 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 in DETR:

- Encoder Attention: The encoder in DETR uses self-attention to encode spatial information about the entire image. This means each pixel (or patch) in the feature map attends to every other pixel to learn global relationships.
- Decoder Attention: The decoder uses two types of attention: > - Self-attention: Similar to the encoder, but applied to the queries (object proposals) to learn relationships between them. > - Cross-attention: The decoder also uses cross-attention to attend to the encoder output. This allows each query to focus on specific parts of the image to predict an object.

Key Differences:

- Encoder Self-Attention: Focuses on encoding the entire image by allowing each pixel to attend to every other pixel. It helps in capturing global context and spatial relationships.
- Decoder Cross-Attention: Focuses on attending to specific regions of the encoder's output based on the queries. It helps each query to "look" at the relevant part of the image for detecting an object.

Analysis Based on Visualized Results:

- Encoder Attention > - Wide Attention Spread: The self-attention maps in the encoder (as shown in the last image) display how attention is spread across different regions of the input image. Each pixel or patch in the image attends to every other pixel, allowing the model to capture global context. > - Focus on Salient Features: In the visualizations, you can see that the encoder focuses on salient regions like the motorcycles and people. The bright areas in the attention maps indicate that the encoder gives more weight to parts of the image that contain objects or features that may be important for detection. > - Understanding Spatial Relationships: The encoder's attention helps establish a global understanding of the entire scene. This means that each pixel can attend to all other pixels, which is crucial for learning spatial relationships and providing a rich representation for the decoder.
- Decoder Query Attention > - Specific Object Focus: The decoder query attention maps (as shown in the second image) illustrate how each query attends to different parts of the image to predict a specific object. The visualizations clearly show that each query (such as "motorcycle," "person," or "chair") is attending to a localized area that corresponds to that object. > - Focused and Concentrated Attention: Unlike the encoder, the decoder attention is highly focused and concentrated. For each detected object, the decoder attends to specific regions, which allows it to precisely predict bounding boxes and labels. The attention maps highlight the model's ability to focus on relevant areas for each query, demonstrating that each query independently localizes and identifies an object. > - Query-Based Localization: Each

detected object is associated with a particular query id (e.g., "query id: 43" for a motorcycle). These visualizations show how individual queries map to specific areas in the image, allowing the model to locate and classify objects separately. The attention is more tightly grouped around the detected object, which contrasts with the encoder's broader attention.

Distinct Characteristics Between Encoder and Decoder Attention

- Scope of Attention: > - The encoder focuses on capturing a comprehensive understanding of the entire image by allowing all pixels to attend to each other. This wide attention helps in understanding contextual relationships and background information. > - The decoder focuses on specific parts of the image to detect and classify objects, making it more precise in terms of localization. This focused attention is key to differentiating individual objects.
- Role in Object Detection: > - The encoder's role is to create a global representation of the scene, ensuring that the features passed to the decoder carry information about all areas of the image. > - The decoder's role is to focus on individual objects using object queries, allowing it to generate predictions for the bounding boxes and classes of detected objects.
- Effectiveness in Localization: > - The encoder's attention maps are widespread, which helps in understanding general relationships, such as determining that the two motorcycles are part of a similar context. > - The decoder's attention maps, on the other hand, are concentrated on specific objects, showing how it zeroes in on objects like "motorcycle," "person," and "chair" in the image. The queries help the decoder effectively attend only to the regions of interest.