DETR

End-to-End Object Detection with Transformers (2020) 4k

end-to-end: remove non-maximum suppression (nms, select a single bounding box out of many overlapping ones) or anchor generation, reduce many hyperparameters

view object detection as a direct set prediction problem; 1. a set-based global loss that forces unique predictions via bipartite matching, 2. a transformer encoder-decoder architecture

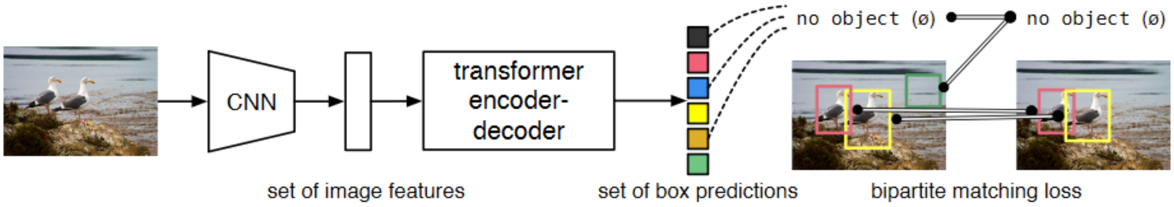

Fig. 1: DETR directly predicts (in parallel) the final set of detections by combining a common CNN with a transformer architecture. During training, bipartite matching uniquely assigns predictions with ground truth boxes. Prediction with no match should yield a "`no object`" (∅) class prediction.

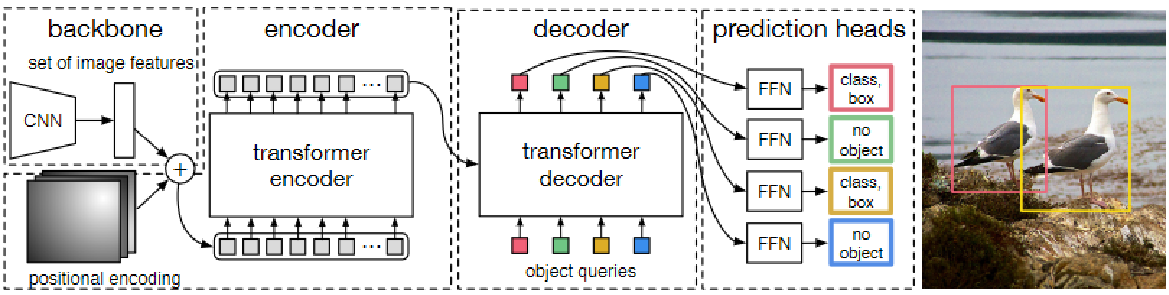

Fig. 2: DETR uses a conventional CNN backbone to learn a 2D representation of an input image. The model flattens it and supplements it with a positional encoding before passing it into a transformer encoder. A transformer decoder then takes as input a small fixed number of learned positional embeddings, which we call *object queries*, and additionally attends to the encoder output. We pass each output embedding of the decoder to a shared feed forward network (FFN) that predicts either a detection (class and bounding box) or a "`no object`" class.

for each image, predict 100 boxes including no object (∅)

during training: match some of them to ground truth boxes

during inference: output boxes with confidence >0.7

Object detection set prediction loss

Backbone using CNN → Transformer encoder → Transformer decoder → Prediction feed-forward networks (FFN) using MLP

```python
import torch
from torch import nn
from torchvision.models import resnet50

class DETR(nn.Module):

    def __init__(self, num_classes, hidden_dim, nheads,
                 num_encoder_layers, num_decoder_layers):
        super().__init__()
        # We take only convolutional layers from ResNet-50 model
        self.backbone = nn.Sequential(*list(resnet50(pretrained=True).children())[:-2])
        self.conv = nn.Conv2d(2048, hidden_dim, 1)
        self.transformer = nn.Transformer(hidden_dim, nheads,
                                          num_encoder_layers, num_decoder_layers)
        self.linear_class = nn.Linear(hidden_dim, num_classes + 1)
        self.linear_bbox = nn.Linear(hidden_dim, 4)
        self.query_pos = nn.Parameter(torch.rand(100, hidden_dim))
        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):
        x = self.backbone(inputs)
        h = self.conv(x)
        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)
        h = self.transformer(pos + h.flatten(2).permute(2, 0, 1),
                             self.query_pos.unsqueeze(1))
        return self.linear_class(h), self.linear_bbox(h).sigmoid()

detr = DETR(num_classes=91, hidden_dim=256, nheads=8, num_encoder_layers=6, num_decoder_layers=6)
detr.eval()
inputs = torch.randn(1, 3, 800, 1200)
logits, bboxes = detr(inputs)
```

Similar performance to Faster R-CNN, better performance on large objects

Later work: *Deformable DETR* faster, improved performance on small objects