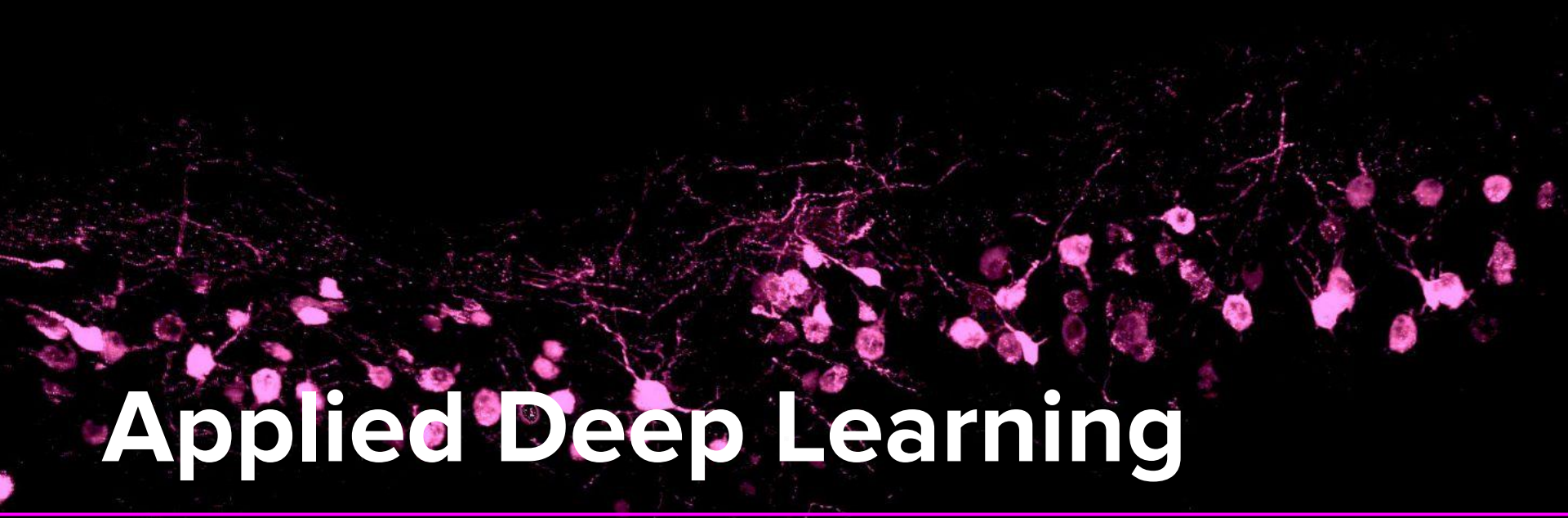


Applied Deep Learning

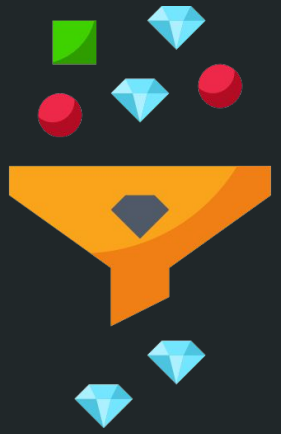
Transformers

Alexander Pacha - TU Wien

Recap

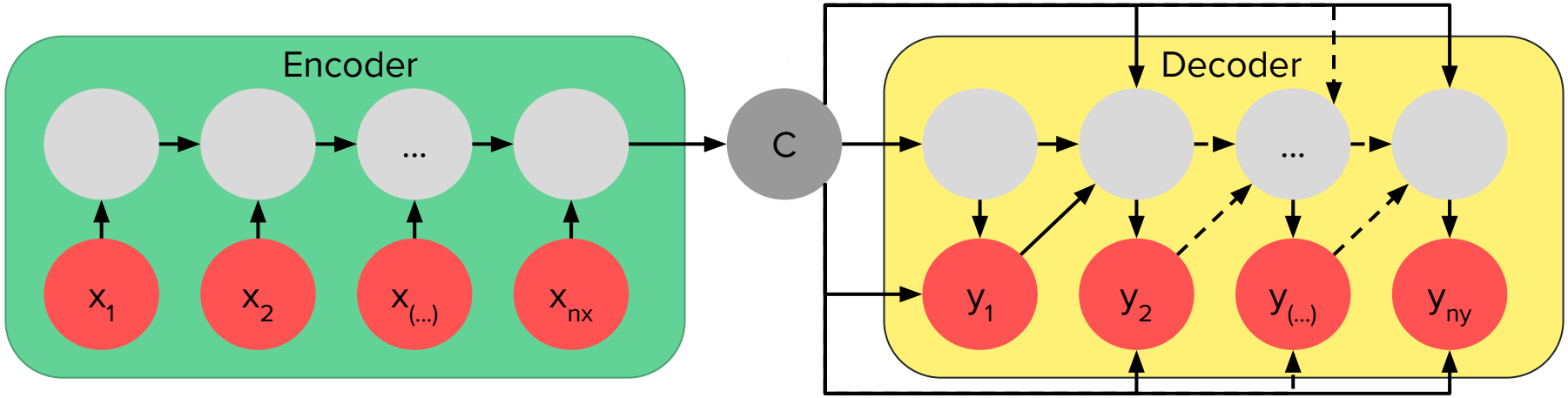
- What is the relation between the input and output of an autoencoder?
- What are the two main blocks in an autoencoder?
- What can you use an autoencoder for?
- How are variational autoencoders different from standard autoencoders?
- What does the Kullback-Leibler divergence measure?
- What are the two main blocks in a generative adversarial network?

Transformers



Sequence Modeling with Deep Neural Networks

- Popular choice: Recurrent neural networks with Encoder-Decoder architecture
- Input and output sequences can have different lengths:
  - Process input with encoder (reader) into context C
  - Decoder (writer) generates output from context C



Problem: Long-Term Memory

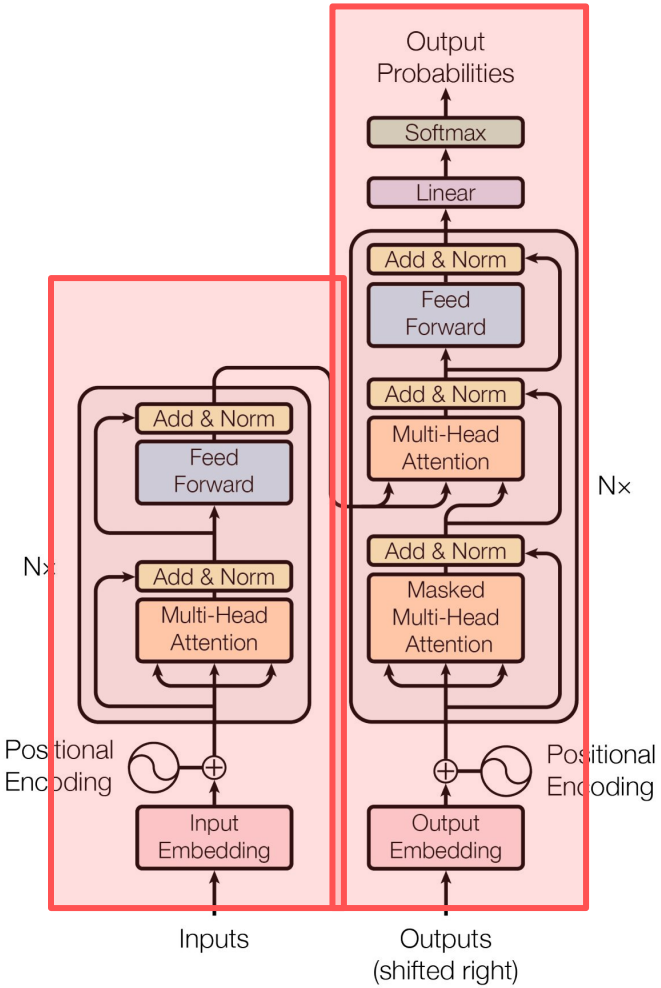
- CNNs: Fixed window
- RNNs: Short reference window
- LSTMs/GRUs: Longer reference window

“When I woke up, I saw the most incredible thing that I’ve ever witnessed. I tried to understand what was happening, but at that moment, I just stared blankly at it.”

Transformers LSTM RNN CNN

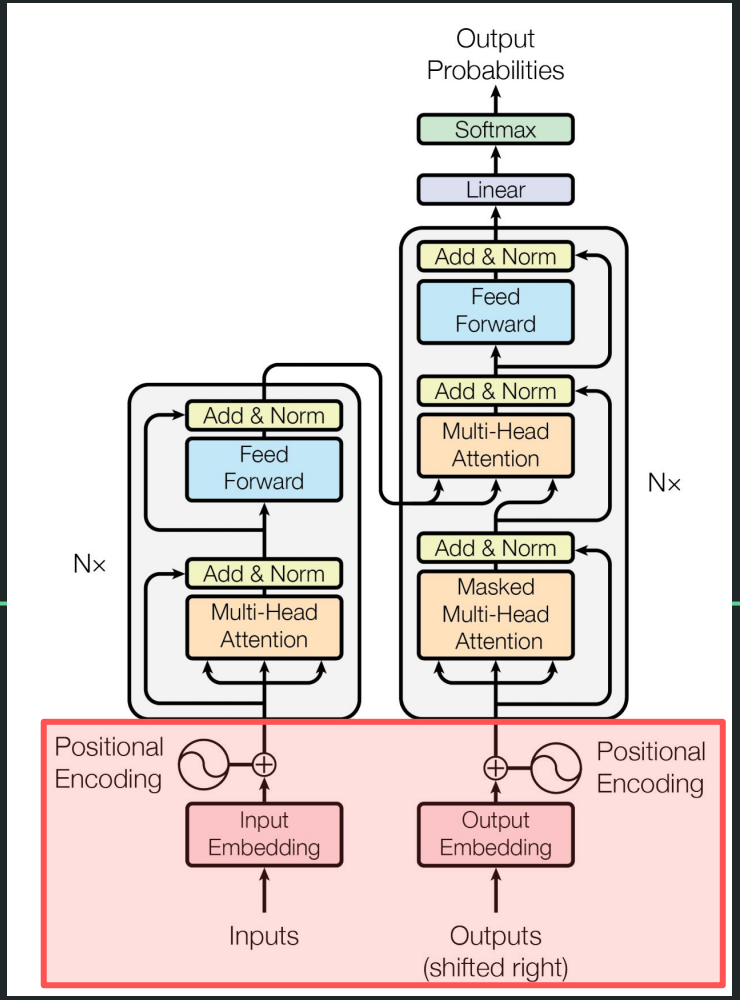
What is a Transformer?

- Architecture based on auto-regressive Encoder-Decoder architecture
- Input sequence can be processed in parallel
- Key-ingredient: Attention mechanism



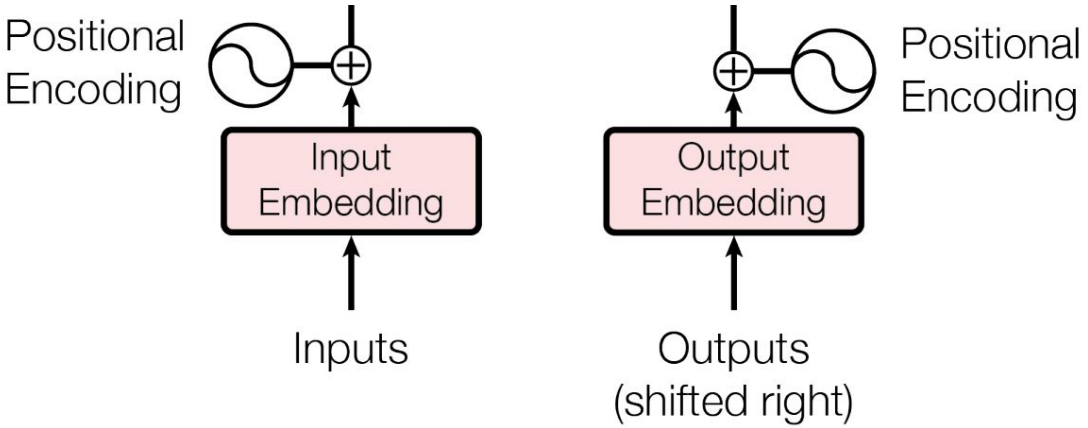
Source: [2]

Input Embedding & Positional Encoding



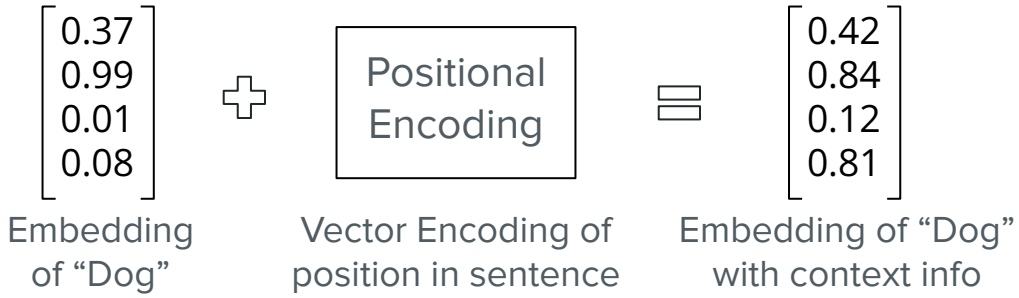
Input embedding and positional encoding

- Input embedding transforms the input into a vector
  - Words in language processing using Word2Vec
  - Image to features using CNN backbone



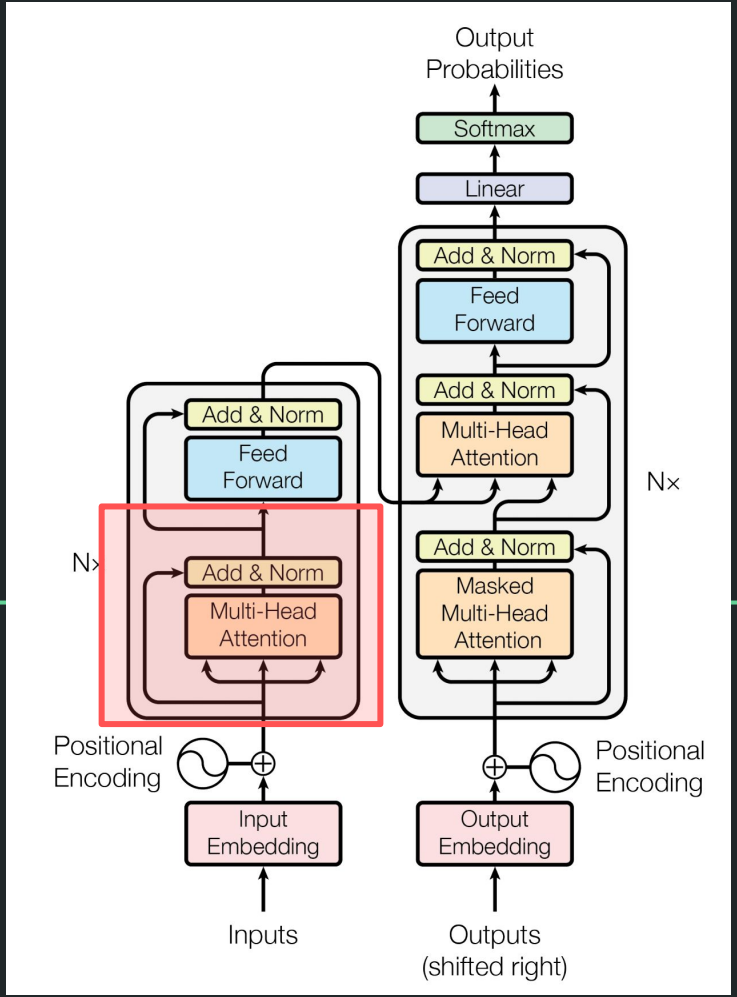
Input embedding and positional encoding

- Input embedding transforms the input into a vector
  - Words in language processing using Word2Vec
  - Image to features using CNN backbone
- Positional Encoding adds contextual information of the position within the input sequence



$$PE_{(pos,2i)} = sin(pos/10000^{2i/d_{\text{model}}})$$
$$PE_{(pos,2i+1)} = cos(pos/10000^{2i/d_{\text{model}}})$$

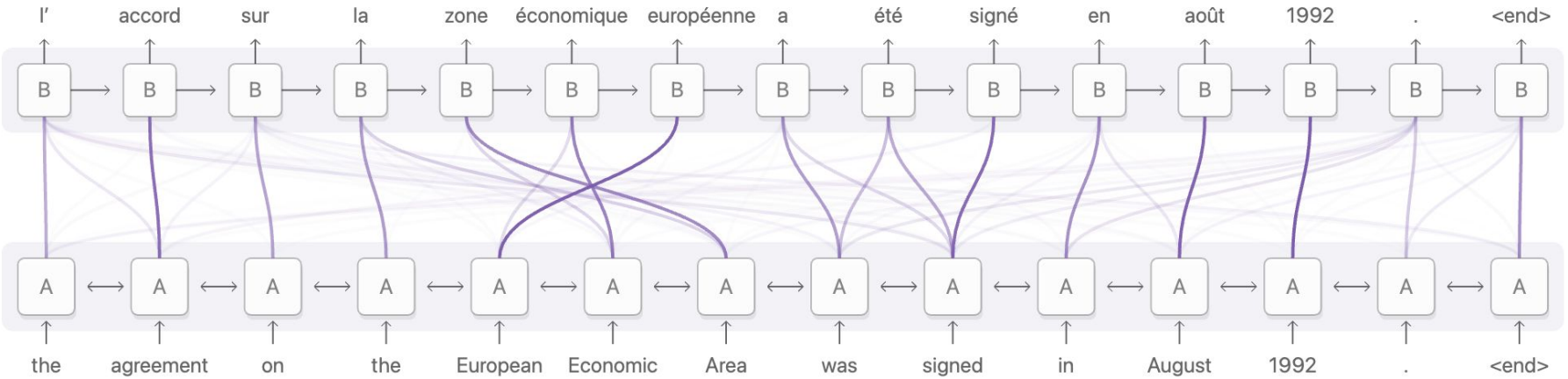
Attention


Output Probabilities
Softmax
Linear
Add & Norm
Feed Forward
Add & Norm
Multi-Head Attention
Add & Norm
Masked Multi-Head Attention
Nx
Add & Norm
Feed Forward
Add & Norm
Multi-Head Attention
Nx
Positional Encoding
Positional Encoding
Input Embedding
Output Embedding
Inputs
Outputs (shifted right)

Attention and Self-Attention

What part of the input should be focused on?

- Captures contextual information between elements in the input sequence

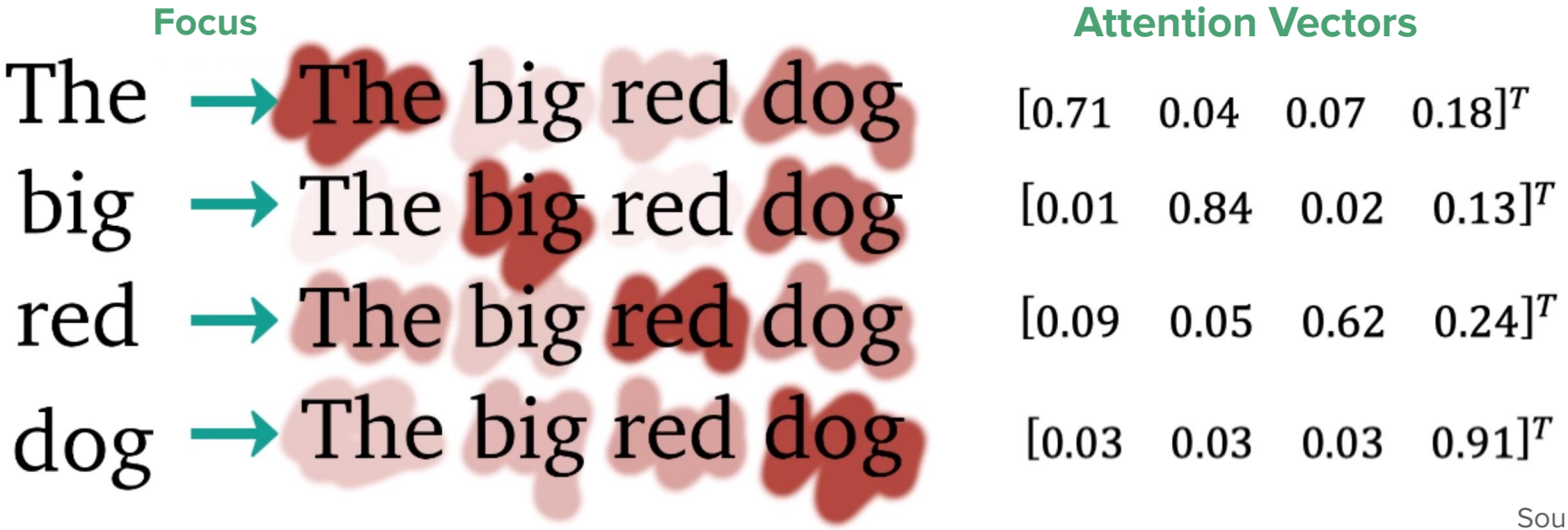


Source: [9]

Attention and Self-Attention

What part of the input should be focused on?

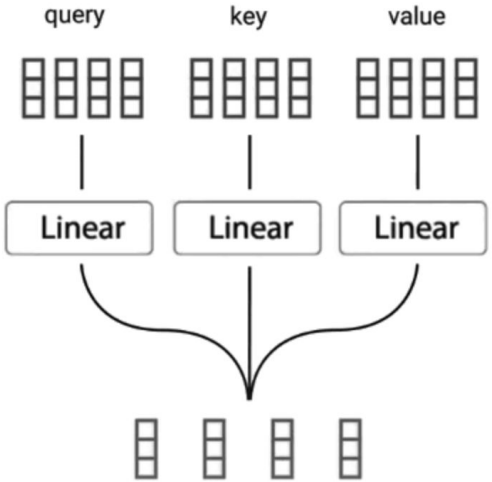
- Captures contextual information between elements in the input sequence
- Self-Attention associate each word of the input sequence to every other word

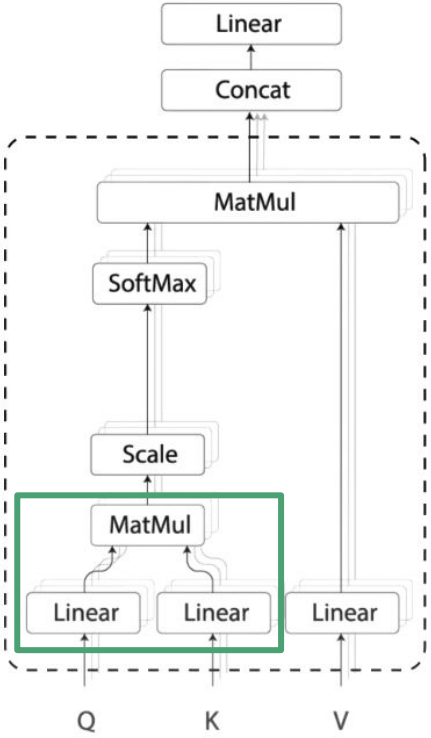


Source: [1]

Implementing Attention

- Conceptualized as a retrieval problem with a Query lookup in a set of Key-Value pairs
- Implemented by a series of matrix multiplications





Source: [8]

Implementing Attention

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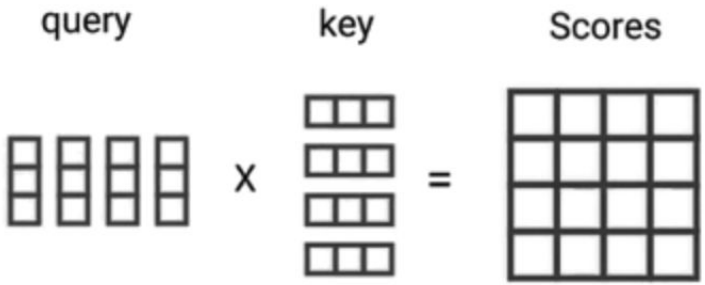
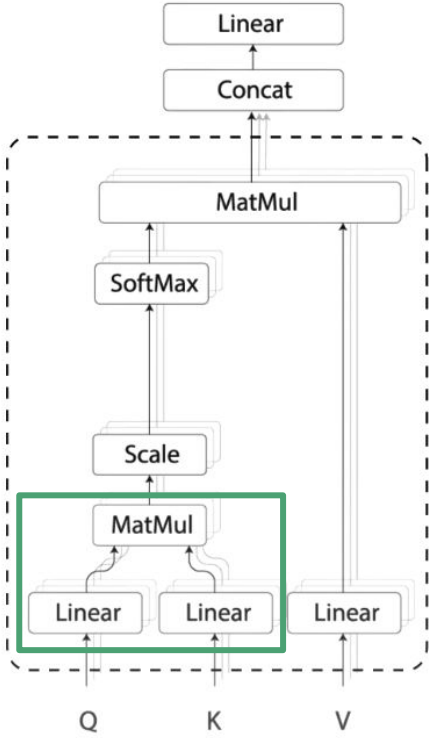


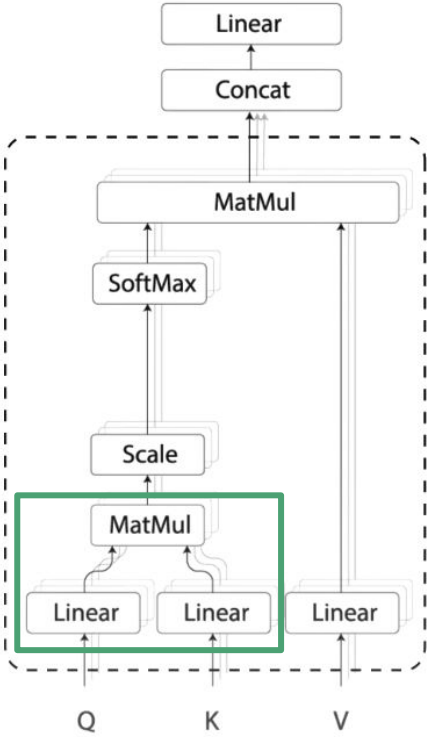


Source: [8]

Implementing Attention

- Conceptualized as a retrieval problem with a Query lookup in a set of Key-Value pairs
- Implemented by a series of matrix multiplications

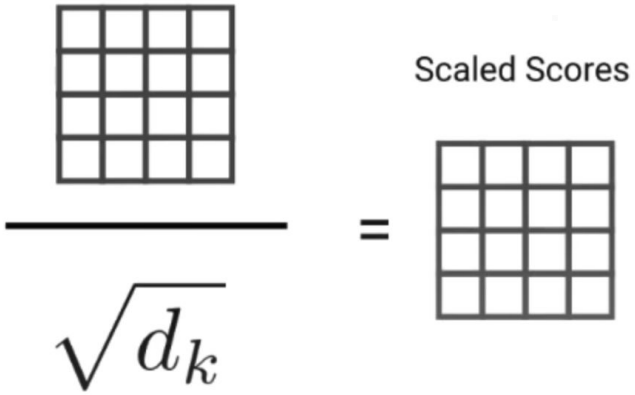
	Hi	how	are	you
Hi	98	27	10	12
how	27	89	31	67
are	10	31	91	54
you	12	67	54	92

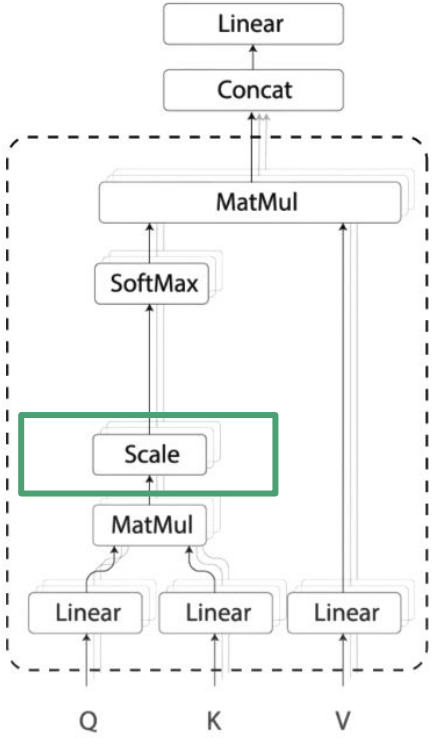


Source: [8]

Implementing Attention

- Conceptualized as a retrieval problem with a Query lookup in a set of Key-Value pairs
- Implemented by a series of matrix multiplications





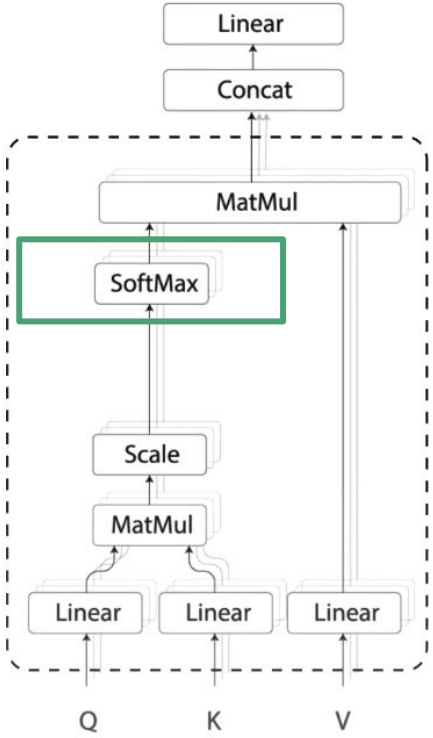
Source: [8]

Implementing Attention

- Conceptualized as a retrieval problem with a Query lookup in a set of Key-Value pairs
- Implemented by a series of matrix multiplications

Softmax(▦) =

	Hi	how	are	you
Hi	0.7	0.1	0.1	0.1
how	0.1	0.6	0.2	0.1
are	0.1	0.3	0.6	0.1
you	0.1	0.3	0.3	0.3



Source: [8]

Implementing Attention

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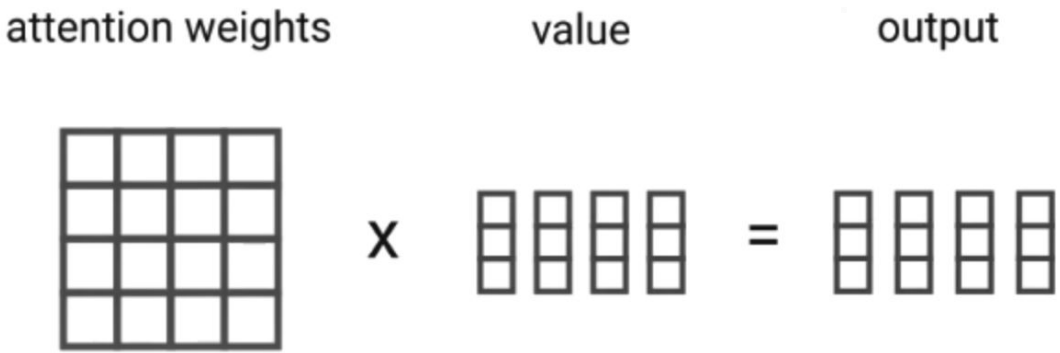
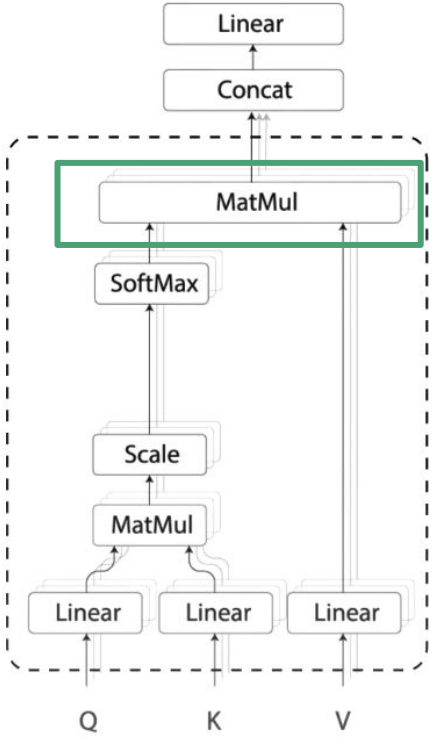
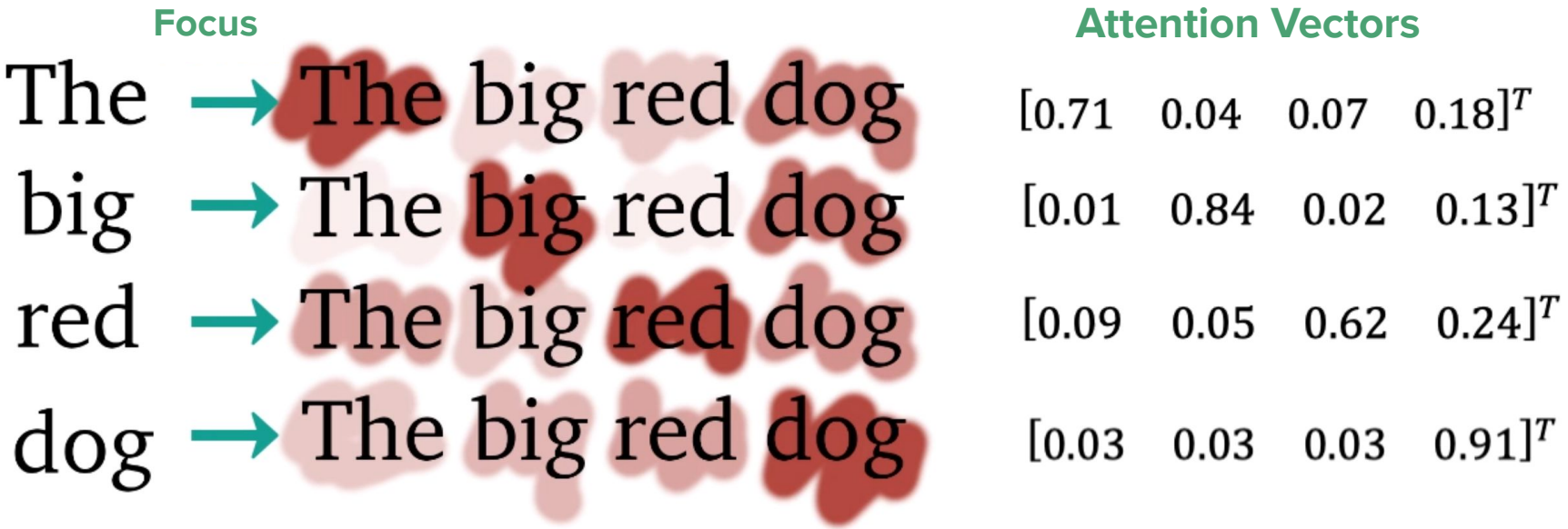




Source: [8]

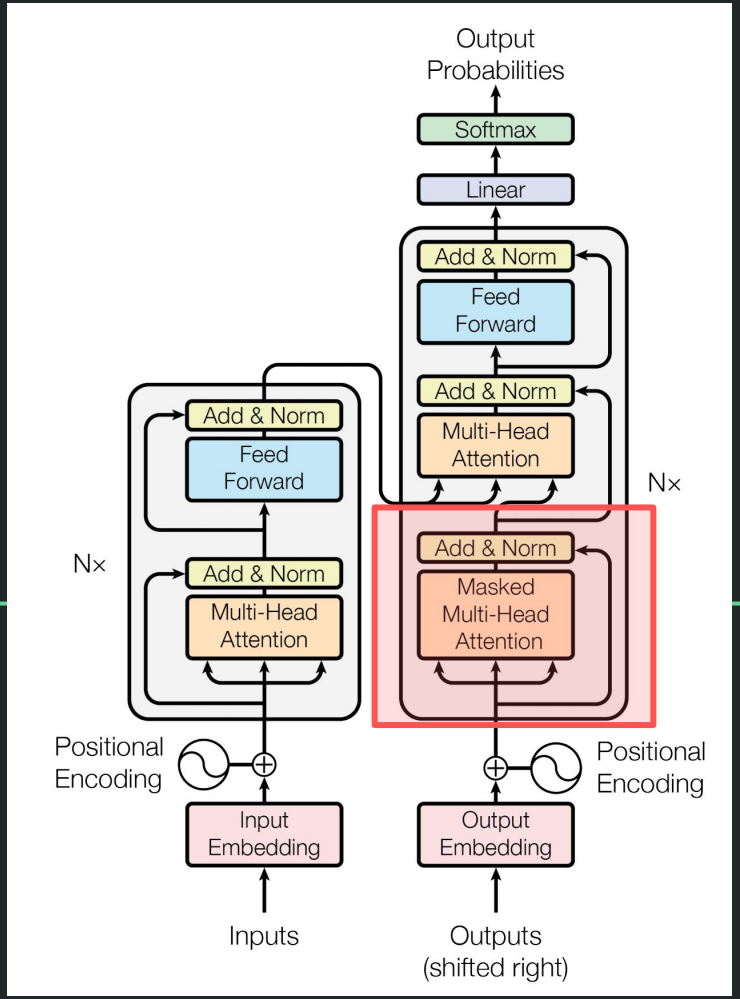
Multi-Headed Attention

- Self-attention tends to put too much weight on itself.
- Replicating the attention layer and averaging the result reduces this problem



Source: [1]

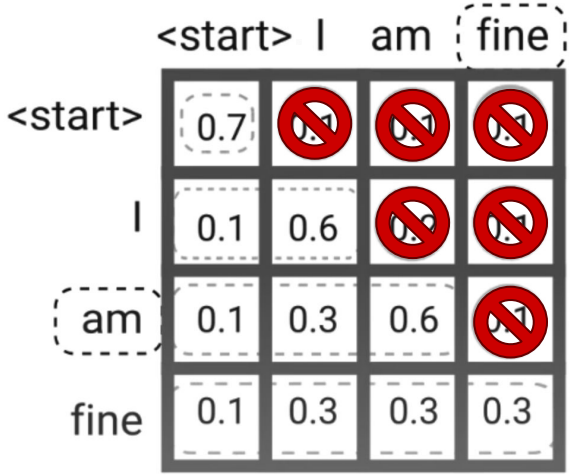
Masked Attention



Masked (Multi-headed) Attention

Attention in decoder very similar to attention in encoder, but:

- When processing the output sequence, we must only look into the past



Masked (Multi-headed) Attention

Attention in decoder very similar to attention in encoder, but:

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Masked (Multi-headed) Attention

Attention in decoder very similar to attention in encoder, but:

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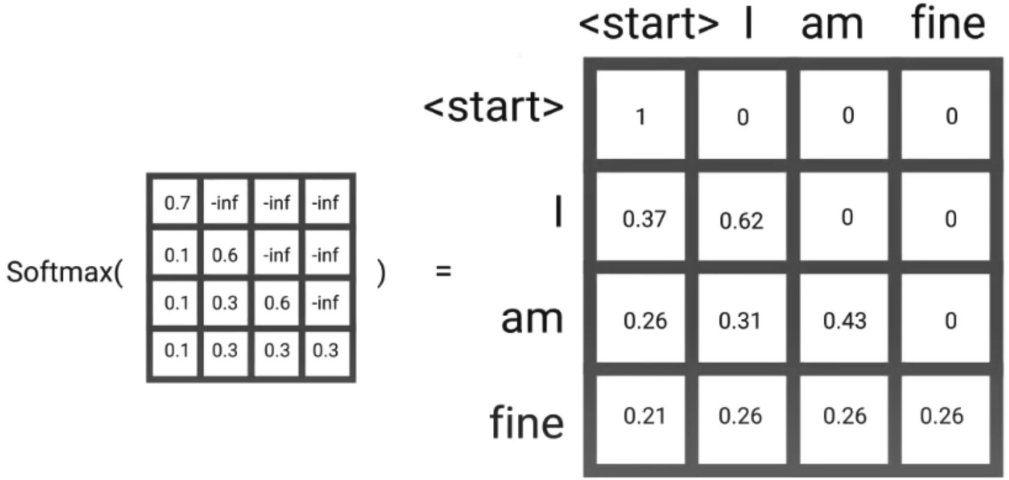
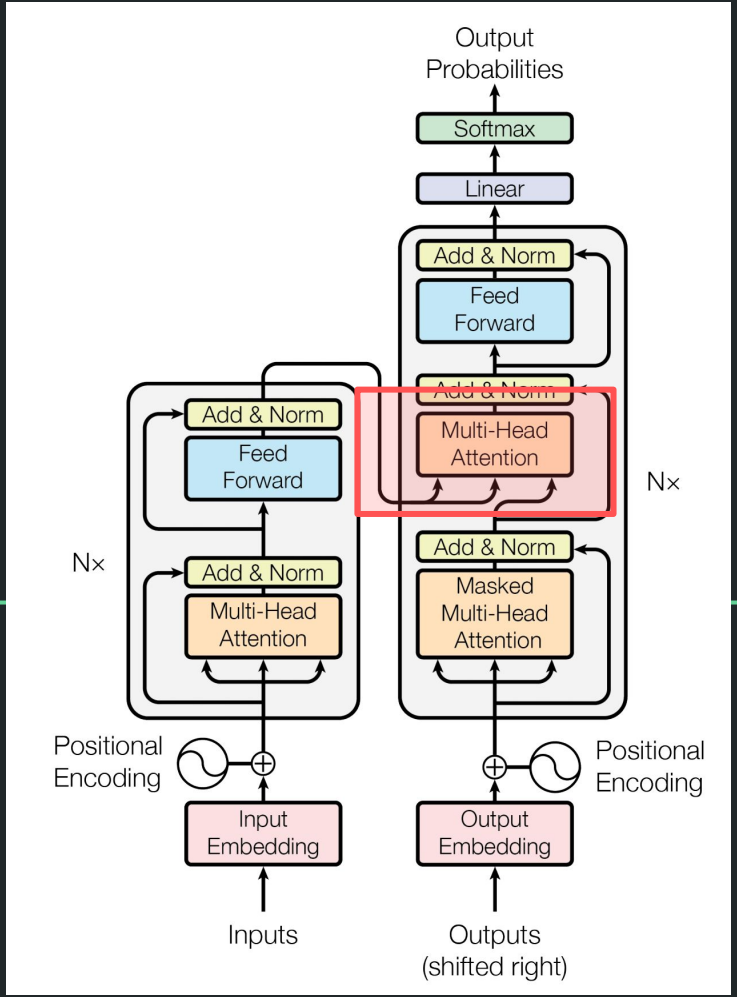
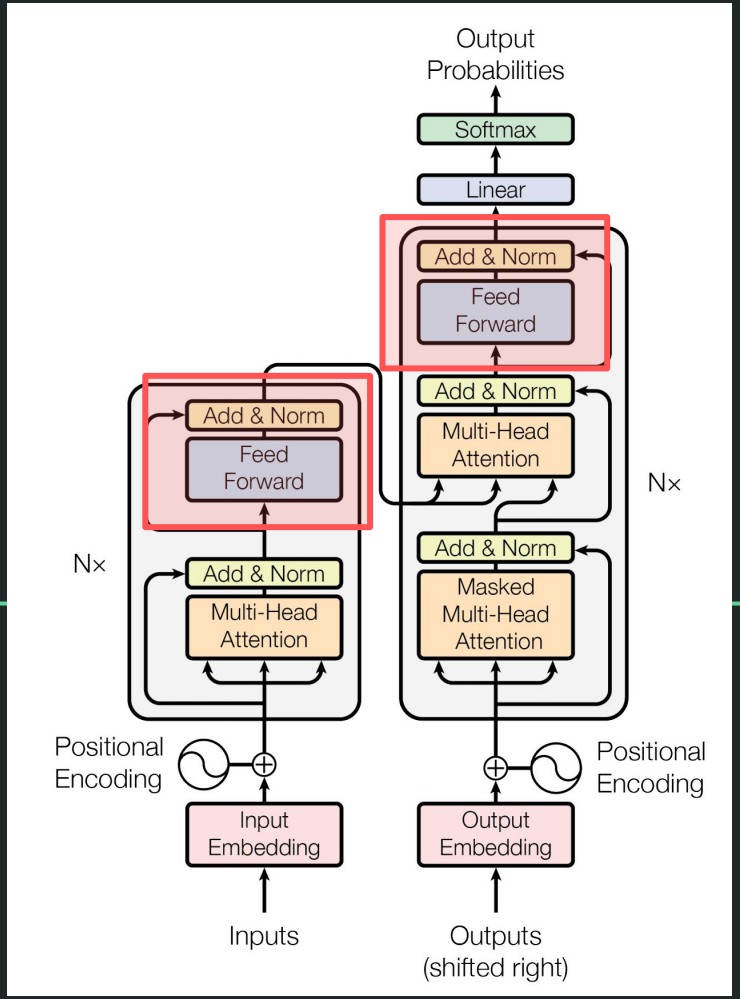


Attention between Input and Output Seq.

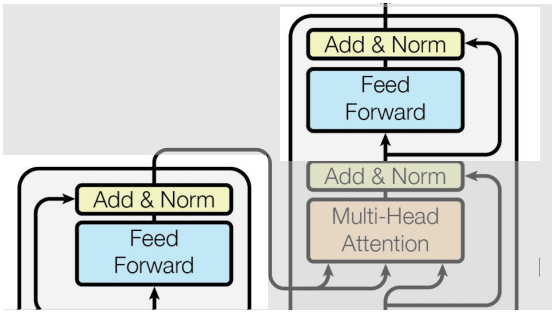


Feed Forward & Norm

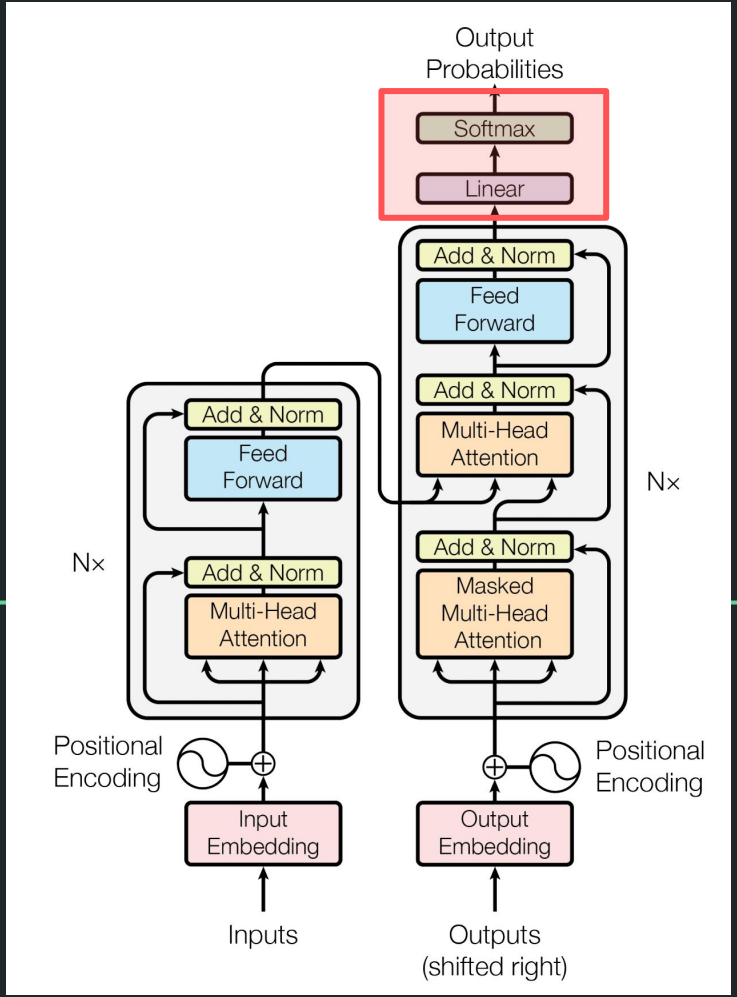


Feed Forward Network

- Feed forward Neural Network: used to transform the attention vectors into a format that is digestible by the next block
  - Allows parallelization: all input words can be passed in at the same time because attention blocks are independent of each other

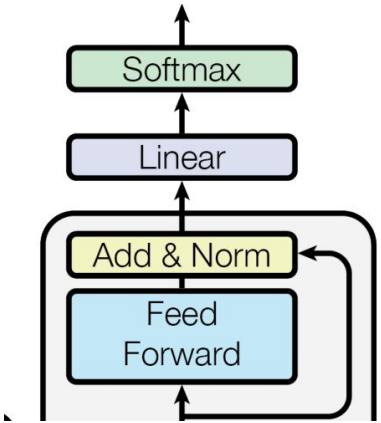


Linear & Softmax

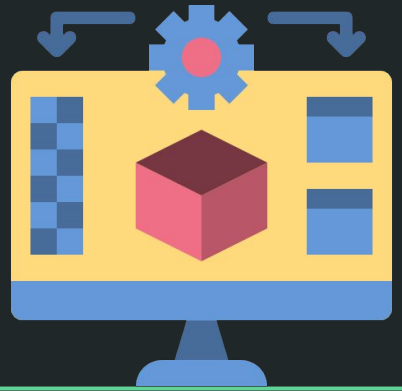


Output

- Linear Layer: Expand dimensions to vocabulary size in the output
- Softmax: Compute human-interpretable probabilities



Architectures



Encoder-decoder / Encoder-only / Decoder-only

Encoder-decoder:

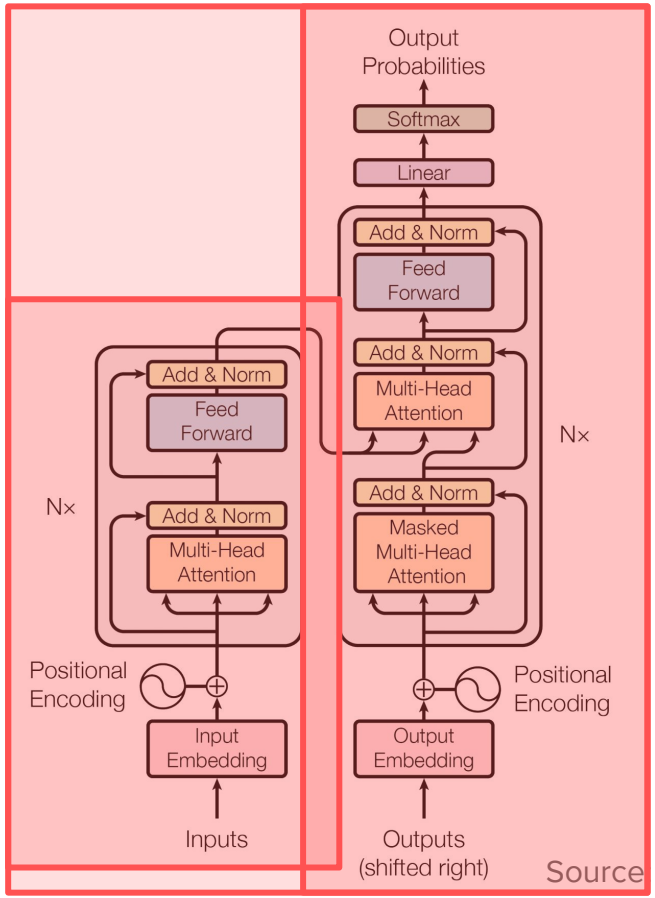
- Bidirectional encoder without masking
- Autoregressive decoder with masked attention

Encoder-only:

- Bidirectional encoder without masking
- Used to generate a dense embedding through unsupervised learning
- Typically is used with a fine-tuned head for downstream tasks, e.g., classification

Decoder-only:

- Just tokenization and positional embedding
- Autoregressive decoder with masked attention
- No cross-attention

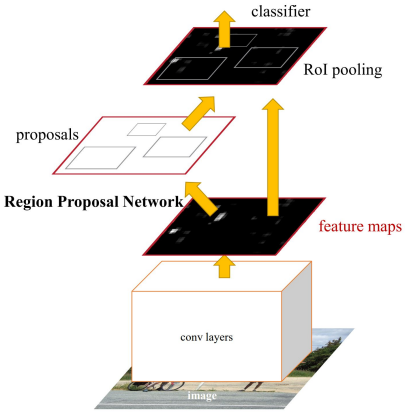


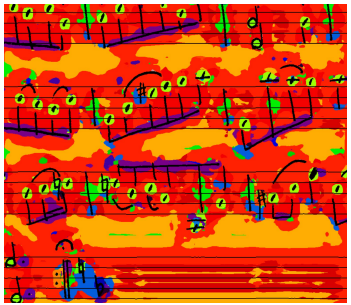
Source [2]

Transformers for Object Detection

State-of-the-art Object Detection

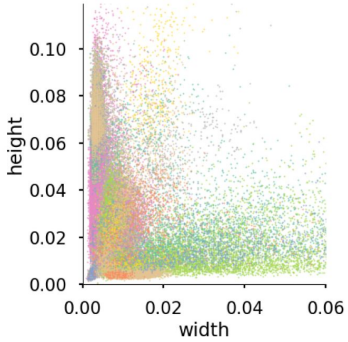
- Uses Deep Convolutional Neural Networks
- Problem can be formulated as surrogate regression and classification task:
  - Finding interesting regions in the image (“proposals”)
  - Classifying and refining these proposals
  - Formulated as
    - one-shot detector with a dense set of proposals (YOLO)
    - two-step process with sparse set of proposals (Faster R-CNN)
- Problem can be formulated as segmentation and clustering task:
  - Extract pixel-wise information
  - Group pixels into connected regions that depict to the same object

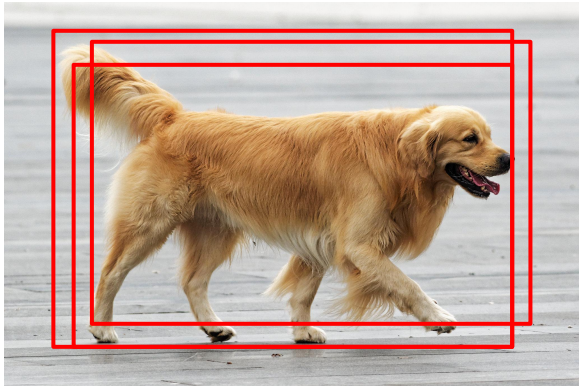




Problematic Issues

- Hand-designed method for anchor generation
  - Requires prior knowledge about the dataset
  - Heuristic to assign target box to anchors
- Non-maximum suppression for near-duplicate predictions
- How to handle fragmented objects in clustering-based approaches?



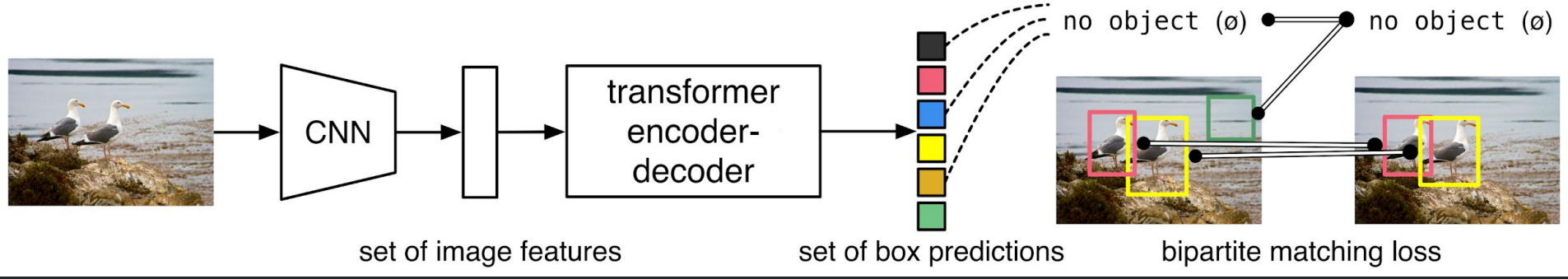


Ideally

Directly predict set of bounding boxes

DEtection TRansformer

End-to-End Object Detection with Transformers



Conventional CNN backbone (e.g., ResNet-50)

Source: [3]

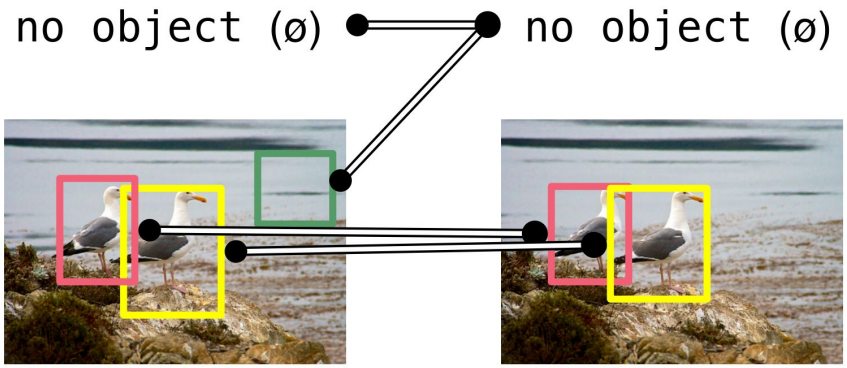
Bipartite Matching Loss

Challenge:

- Determine a unique matching between proposals and ground truth bounding boxes

Solution:

- Search for permutation with the lowest *pair-wise matching cost*
  - Taking into account class prediction and similarity of bounding boxes
- Efficiently computed using Hungarian algorithm

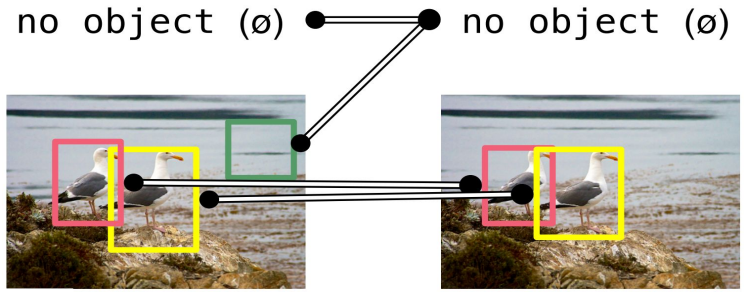


bipartite matching loss

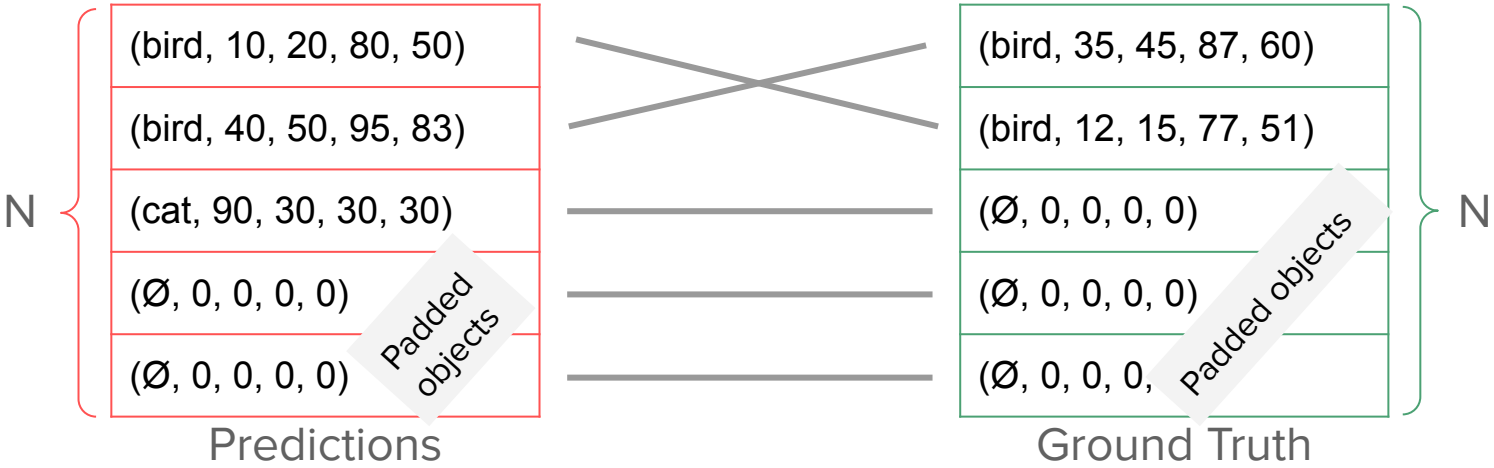
$$\hat{\sigma} = \arg\min_{\sigma \in \mathfrak{S}_N} \sum_{i}^{N} \mathcal{L}_{\text{match}}(y_i, \hat{y}_{\sigma(i)})$$

$$\mathcal{L}_{\text{match}}(y_i, \hat{y}_{\sigma(i)}) = -\mathbb{1}_{\{c_i \neq \varnothing\}} \hat{p}_{\sigma(i)}(c_i) + \mathbb{1}_{\{c_i \neq \varnothing\}} \mathcal{L}_{\text{box}}(b_i, \hat{b}_{\sigma(i)})$$

Bipartite Matching Loss - Example



bipartite matching loss



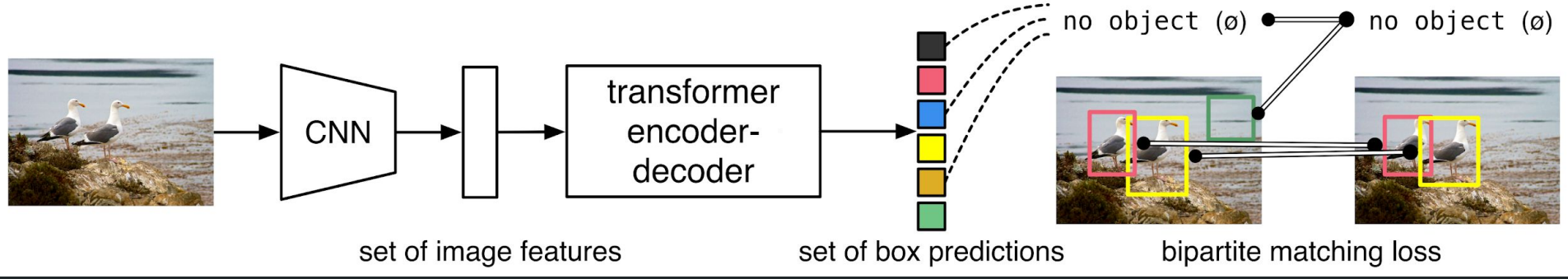
Bipartite Matching Loss

$$\mathcal{L}_{\text{Hungarian}}(y, \hat{y}) = \sum_{i=1}^{N} \Big[\underbrace{-\log \hat{p}_{\hat{\sigma}(i)}(c_i)}_{\text{Standard Cross-Entropy loss}} + \underbrace{\mathbb{1}_{\{c_i \neq \varnothing\}}}_{\text{No loss for 'No Object'-boxes}} \mathcal{L}_{\text{box}}(b_i, \hat{b}_{\hat{\sigma}}(i)) \Big]$$

$$\mathcal{L}_{\text{box}}(b_i, \hat{b}_{\sigma(i)}) = \lambda_{\text{iou}} \underbrace{\mathcal{L}_{\text{iou}}(b_i, \hat{b}_{\sigma(i)})}_{\text{Scale-invariant}} + \lambda_{\text{L1}} \underbrace{||b_i - \hat{b}_{\sigma(i)}||_1}_{\text{Scale-sensitive}}$$

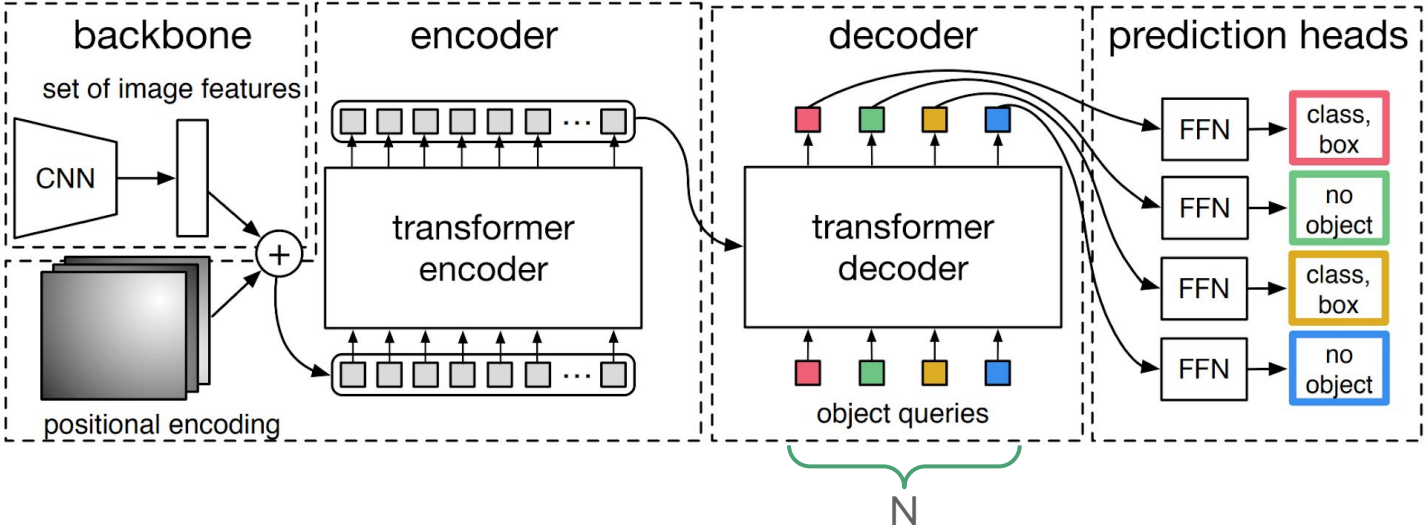
DEtection TRansformer

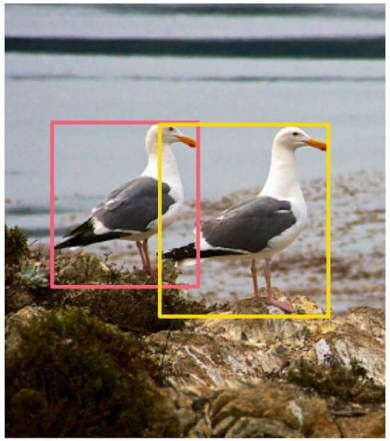
End-to-End Object Detection with Transformers



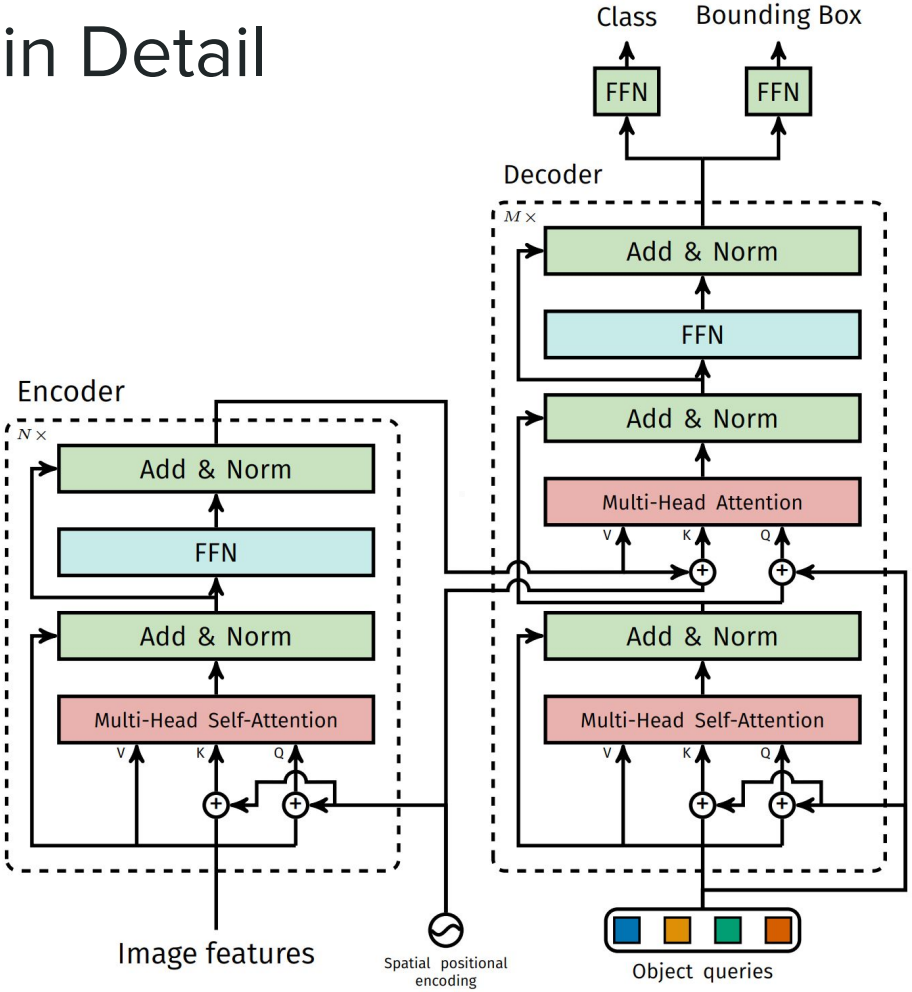
Transformer for Object Detection

- Similar to Transformers for NLP
- Instead of feeding back predictions and predicting one box at a time, all boxes are predicted simultaneously



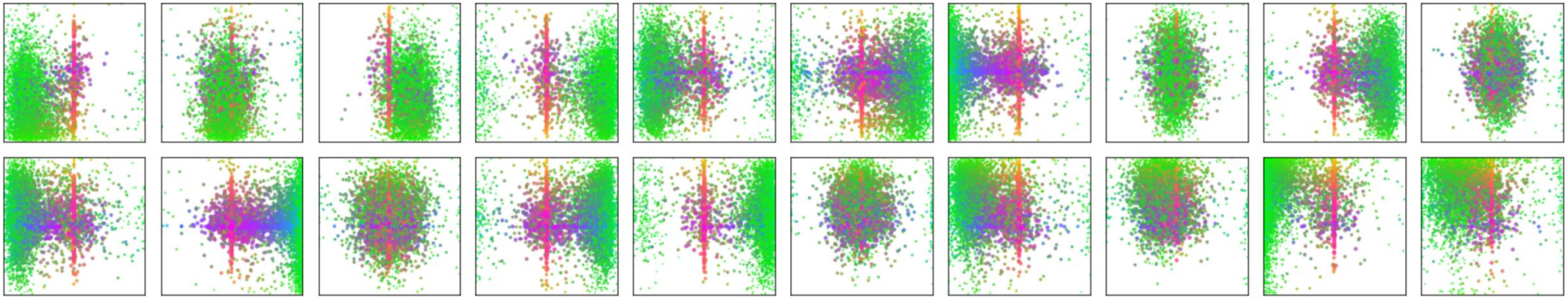


Architecture in Detail



Object Queries

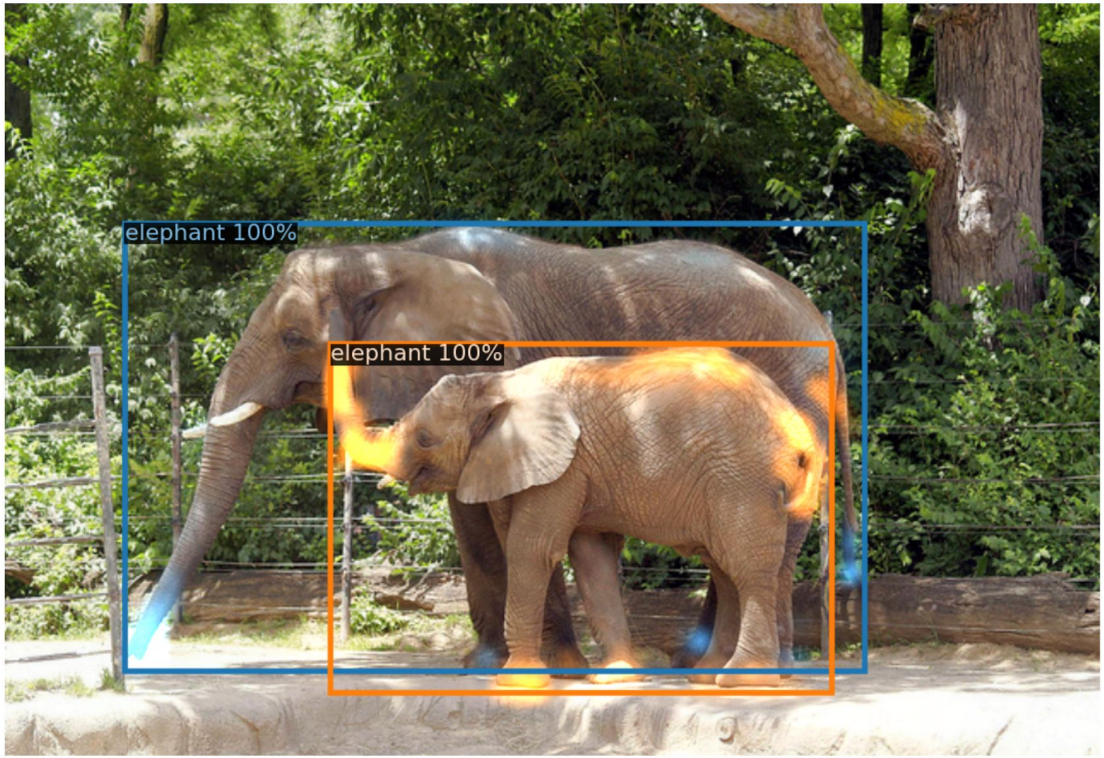
- Learnt object queries, that can “ask” different things
- Similar to guided anchoring

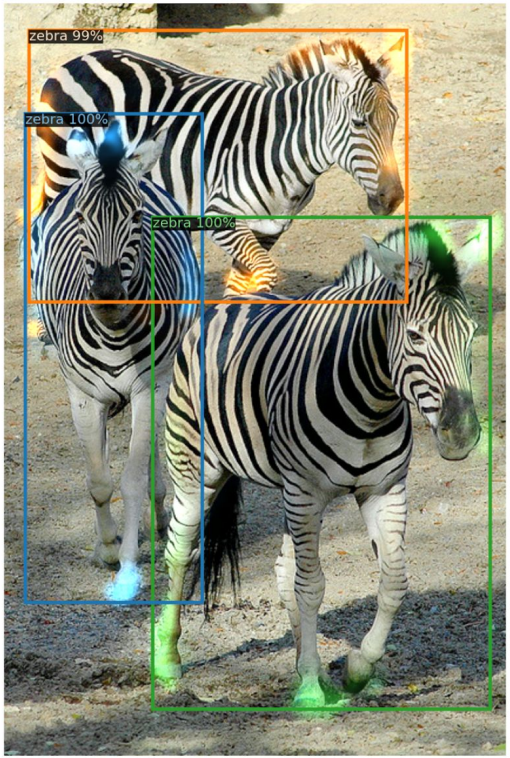


Visualization of all box predictions on all images from COCO 2017 val set for 20/100 prediction slots.

Green = Small boxes, Red = Large horizontal boxes, Blue = Large vertical boxes

Visualization of Decoder Attention



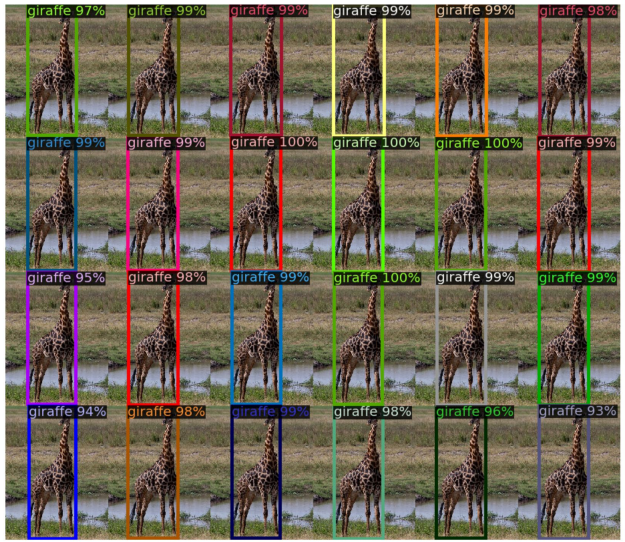


Inference code

```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)
```

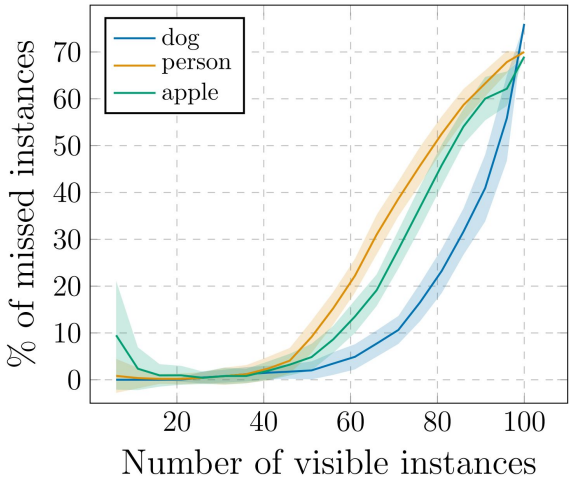
Strengths

- Generalizes well to unseen number of instances
- Can be extended to perform Panoptic Segmentation



Caveats

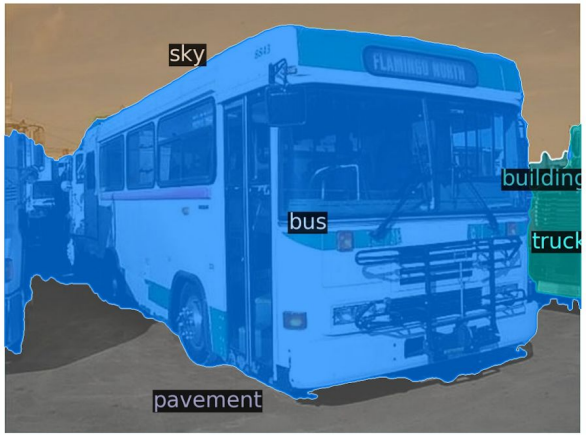
- Very long training schedule
- Does not perform very well on small objects
- Does not perform very well with many objects (coming near max. nr of obj.)
- But in general performs comparable or better than Faster R-CNN

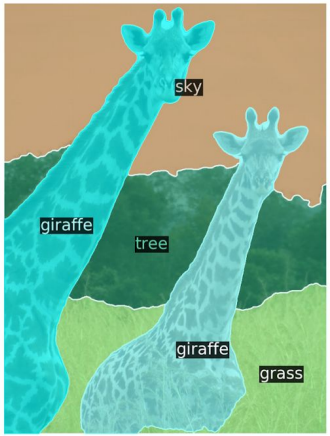


Model	GFLOPS/FPS	#params	AP	AP_{50}	AP_{75}	AP_S	AP_M	AP_L
Faster RCNN-DC5	320/16	166M	39.0	60.5	42.3	21.4	43.5	52.5
Faster RCNN-FPN	180/26	42M	40.2	61.0	43.8	24.2	43.5	52.0
Faster RCNN-R101-FPN	246/20	60M	42.0	62.5	45.9	25.2	45.6	54.6
Faster RCNN-DC5+	320/16	166M	41.1	61.4	44.3	22.9	45.9	55.0
Faster RCNN-FPN+	180/26	42M	42.0	62.1	45.5	26.6	45.4	53.4
Faster RCNN-R101-FPN+	246/20	60M	44.0	63.9	**47.8**	**27.2**	48.1	56.0
DETR	86/28	41M	42.0	62.4	44.2	20.5	45.8	61.1
DETR-DC5	187/12	41M	43.3	63.1	45.9	22.5	47.3	61.1
DETR-R101	152/20	60M	43.5	63.8	46.4	21.9	48.0	61.8
DETR-DC5-R101	253/10	60M	**44.9**	**64.7**	47.7	23.7	**49.5**	**62.3**

Playing with DETR

Source code: https://github.com/facebookresearch/detr





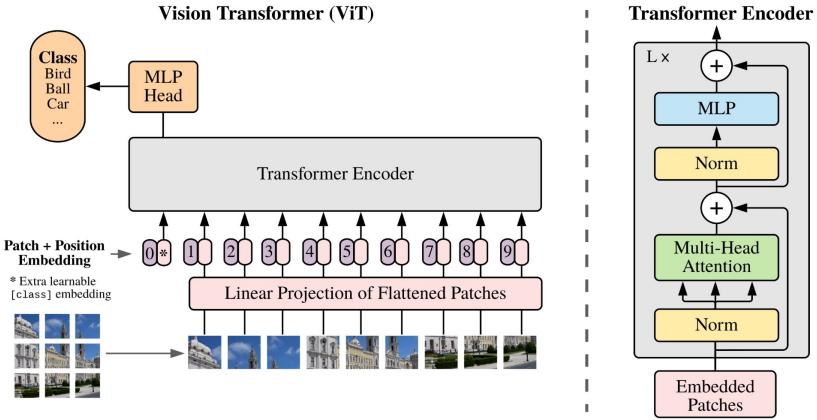
Advances in Transformers

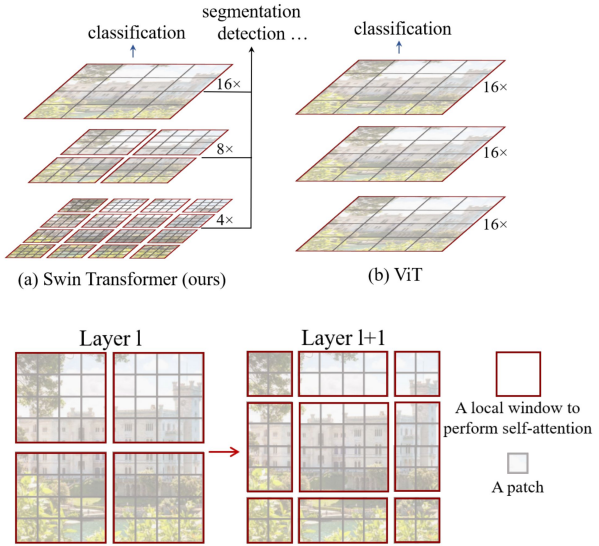
Advances in Transformers

- Embeddings from Language Models (ELMo): Replaces fixed embedding with context-aware embeddings [10]
- ULM-FiT: Process for fine-tuning language models for various tasks [11]
- BERT: Efficient pre-training by masking inputs in bidirectional transformers [12]
- Reformer: Local-sensitive hashing for more efficient attention [13]
- Linformer: Self-attention with linear complexity by approximating stochastic self-attention matrix with low-rank matrix [14]
- Lightweight Convolutions: Replacing self-attention with convolutions [15]

Advances in Vision Transformer

- Replacing Convolutions entirely with Transformers [16]
- Shifting the windows in Vision Transformers (Swin Transformers) [17, 18]
- Improving certain aspects of Detection Transformer [19]
- Using attention visualizations for explainability [20]





Summary

- Transformers are powerful models for sequence-to-sequence problems
- Transformers consist of encoder and decoder block with attention mechanisms
- (Self-)Attention allows the network to learn where to pay attention to
- Many current advances
  - More efficient pre-training
  - More efficient self-attention
- Popular architectural variants are
  - encoder-only architecture for training a dense embedding
  - decoder-only architecture for text generation
- Transformers can also be used for Object Detection by formulating it as a direct box prediction problem, transforming a set of object queries into unique bounding boxes

Literature

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- https://www.vulture.com/2017/06/transformers-mythology-explained.html
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