

# CS551: Introduction to Deep Learning

## Transformer



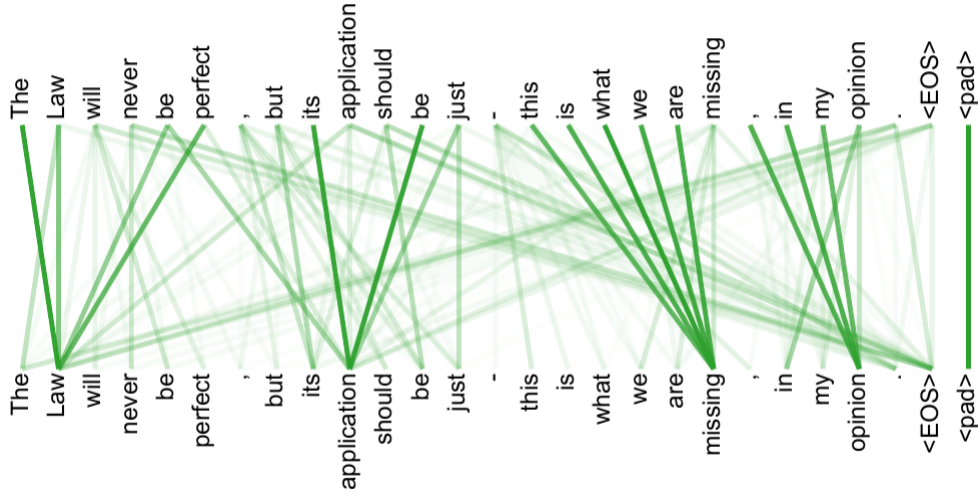
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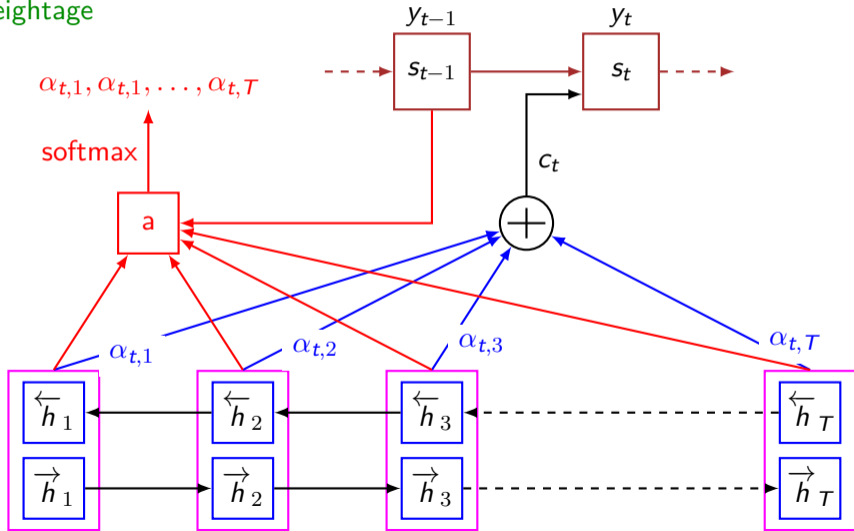
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# Attention

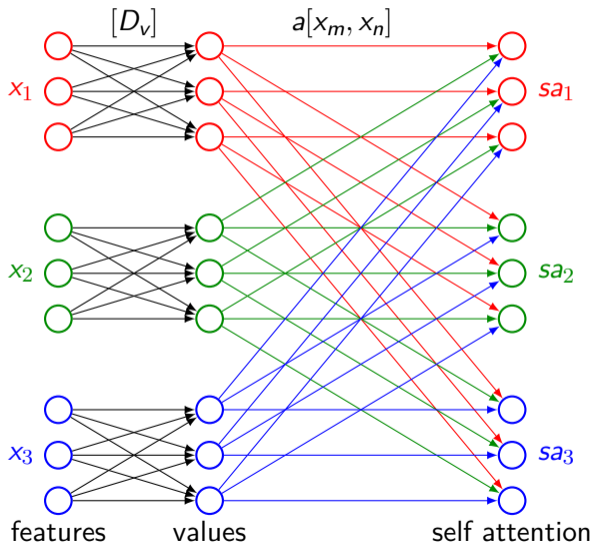


# Attention with RNN

- $\alpha_t = NN(s_{t-1}, h_t)$
- Softmax is used for weightage
- Context =  $\sum_t \alpha_t h_t$



# Self Attention

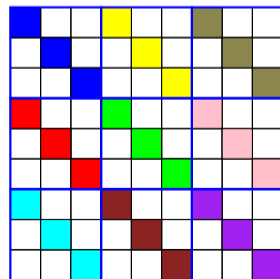
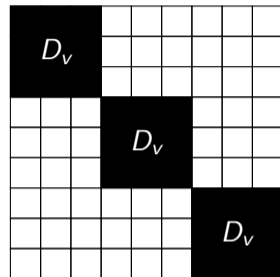
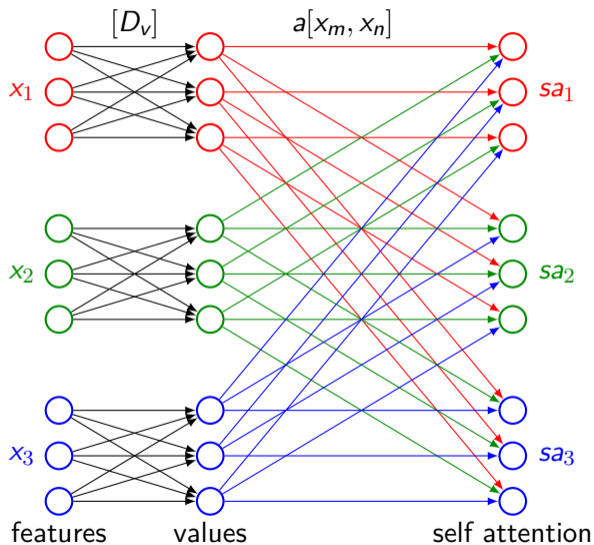


$$v_m = \text{ReLU}(b_v + D_v \times x_m)$$

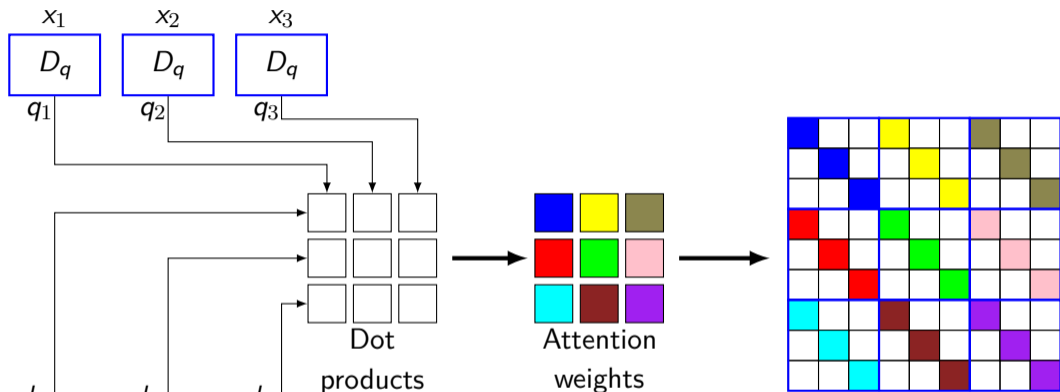
$$sa_n[x_1, \dots, x_N] = \sum_{m=1}^N a[x_m, x_n] \times v_m$$

$$a[\bullet, x_n] \geq 0, \quad \sum_{m=1}^N a[x_m, x_n] = 1$$

# Self attention



# Computing attention weights

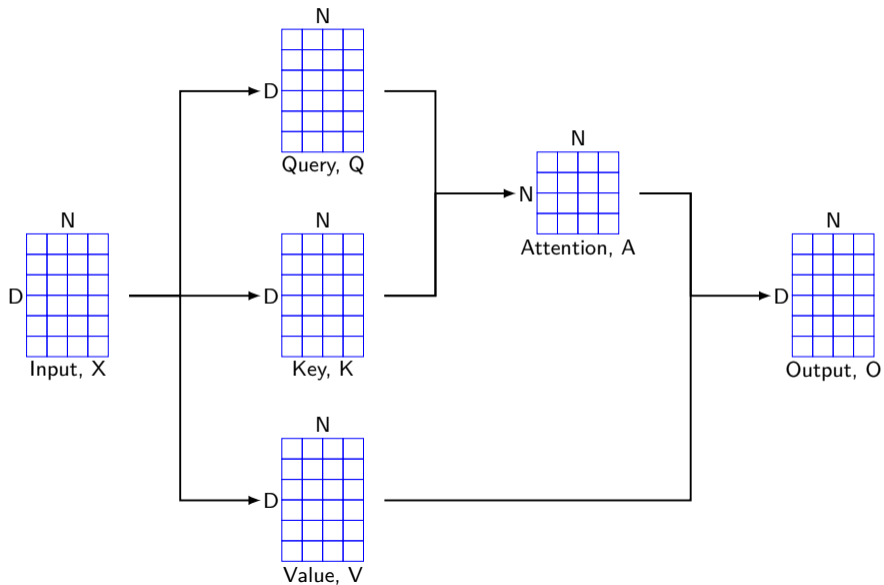


$$q_n = \text{ReLU}(b_q + D_q \times x_n)$$

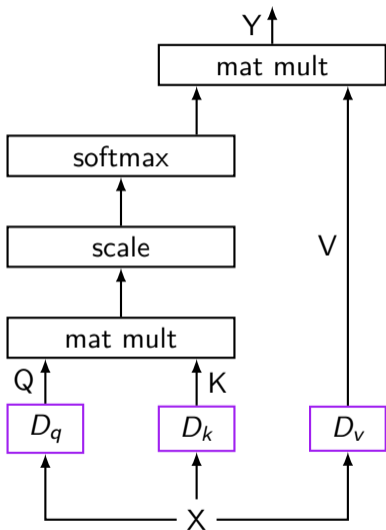
$$k_m = \text{ReLU}(b_k + D_k \times x_m)$$

$$a[x_m, x_n] = \text{softmax}_m[k_{\bullet}^T q_n] = \frac{\exp[k_m^T q_n]}{\sum_{i=1}^N \exp[k_i^T q_n]}$$

# Self-attention: Complete view



# Self attention: Block diagram

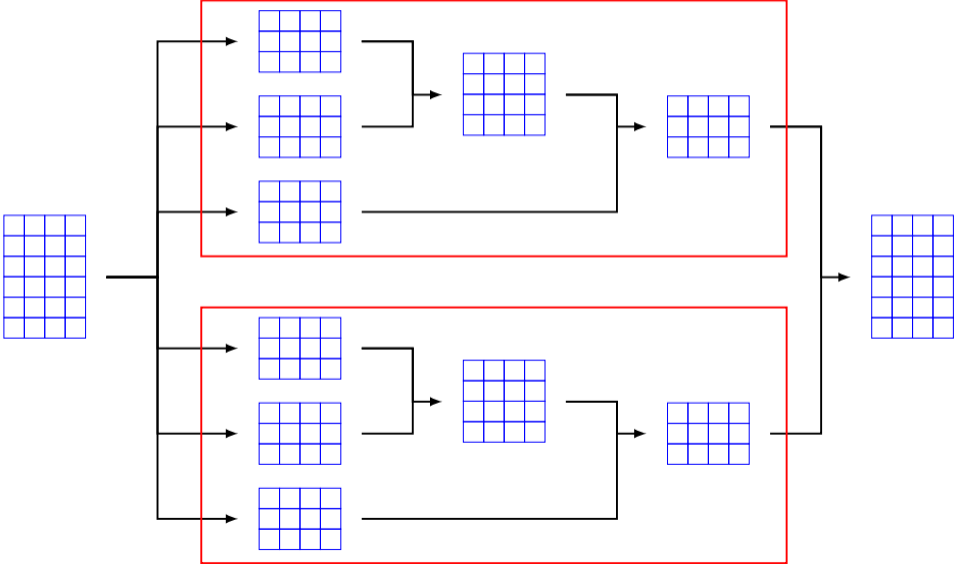


$$\text{scale: } \left[ \frac{K^T Q}{\sqrt{D}} \right]$$

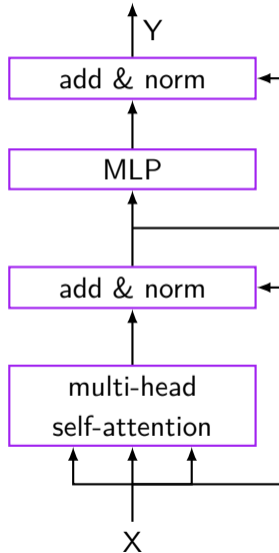
$$Y = \text{Sa}[X] = V \cdot \text{softmax} \left[ \frac{K^T Q}{\sqrt{D}} \right]$$



# Multi-head self attention



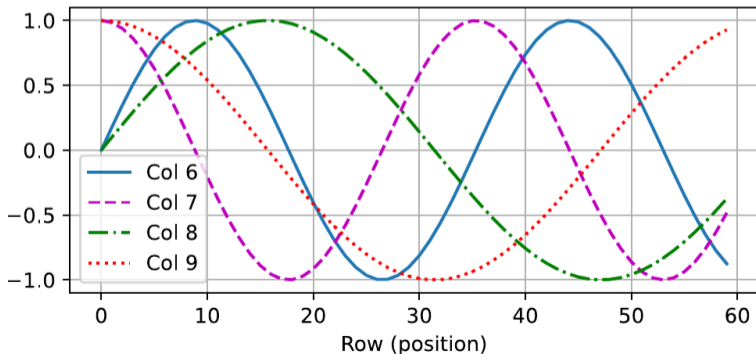
# Transformer layer



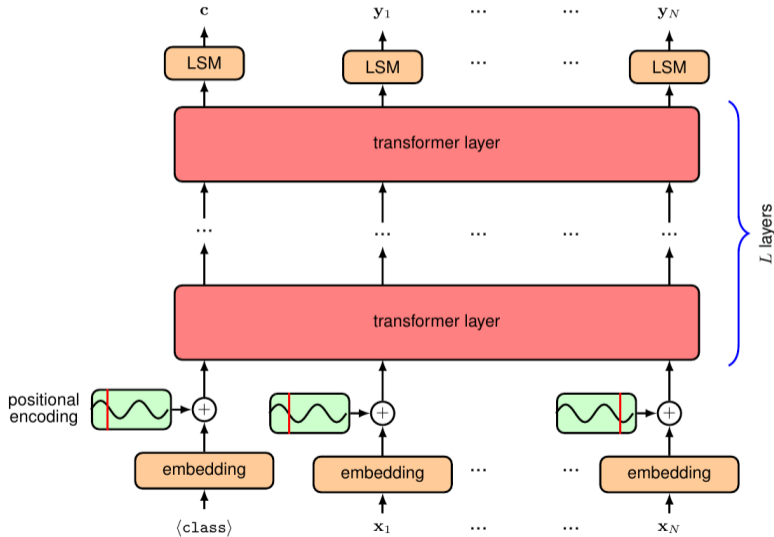
# Positional embedding

- Input  $X \in \mathbb{R}^{N \times D}$  contains the  $D$ -dimensional embeddings for  $N$  tokens of a sequence
- The positional encoding outputs  $X + P$  using a positional embedding matrix  $P \in \mathbb{R}^{N \times D}$  of the same shape, whose element on the  $i$ th row and the  $(2j)$ th or the  $(2j + 1)$ th column is

$$p_{i,2j} = \sin\left(\frac{i}{10000^{2j/D}}\right), \quad p_{i,2j+1} = \cos\left(\frac{i}{10000^{2j/D}}\right)$$

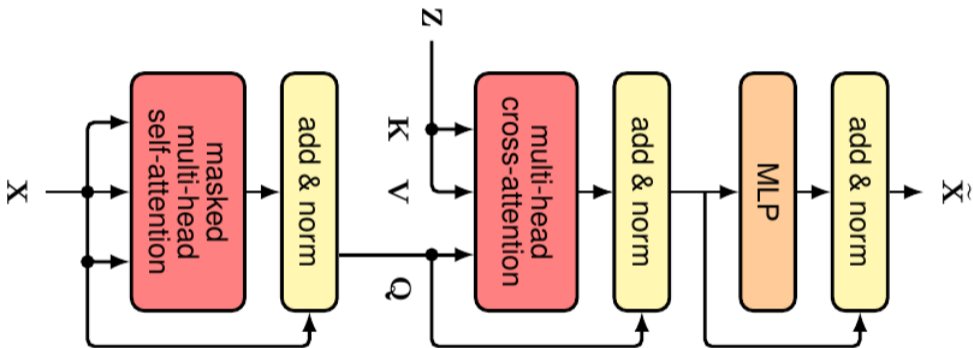


# Transformer: Encoder

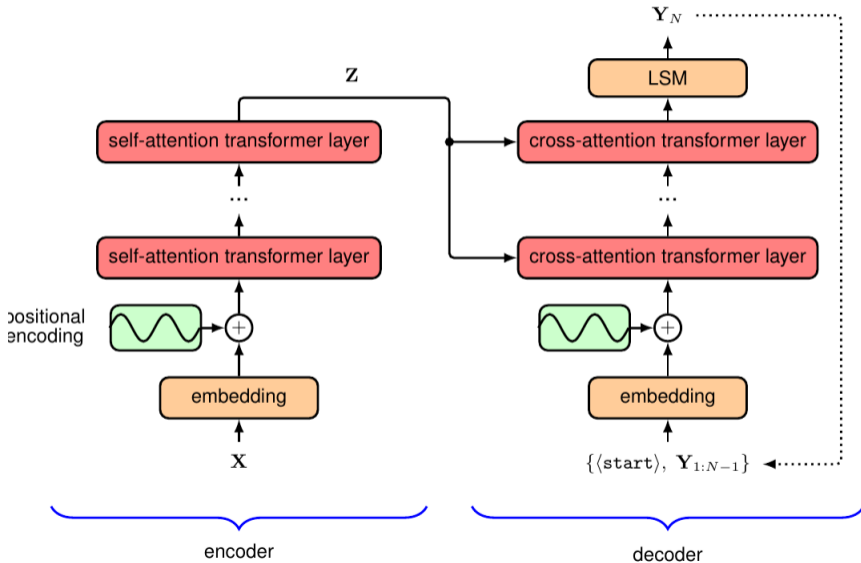




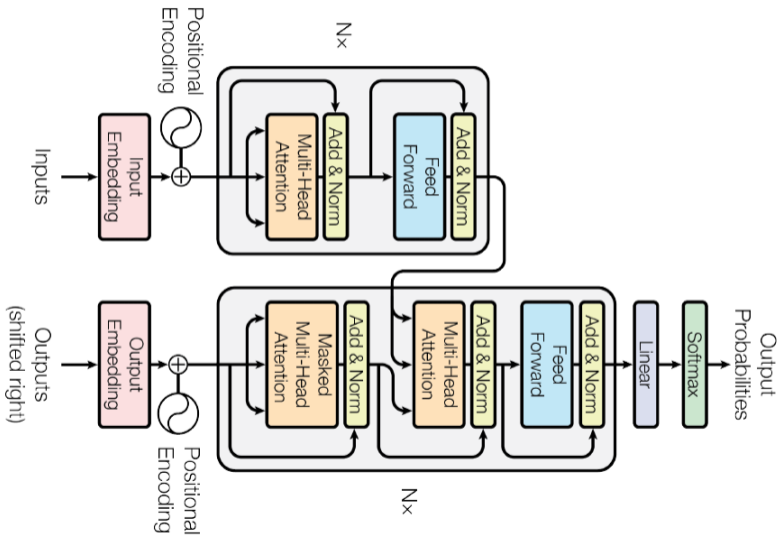
# Transformer: Cross attention



# Transformer: Encoder-Decoder

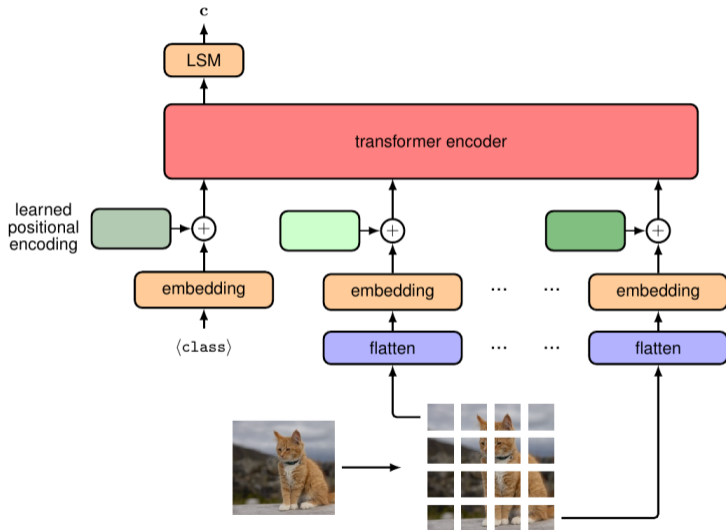


# Transformer: Encoder-Decoder





# Vision Transformer



# Summary

- We have seen self-attention, multi-head attention and transformer layer
- Positional embedding is crucial
- Transformer has low complexity per layer
- Many computations can be parallelized
- It can handle long range dependencies in the text
- Performs very well for text data