Attention is all you need

NIPS' 17

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- Novelty : first transduction model entirely based on attention
- 2 main contributions:
  - 1) parallelization
    - Attention on each position (X need to wait previous hidden state like RNN)
  - 2) reduction of computation

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Model Architecture

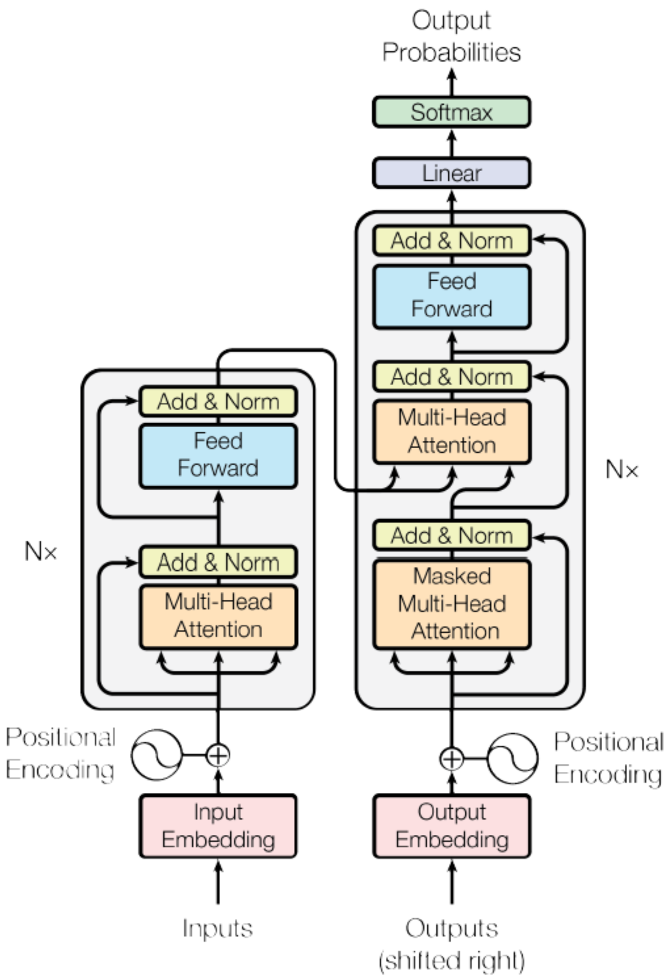

Figure 1: The Transformer - model architecture.

- Encoder-decoder structure
  - Autoregressive (use all previous info)
  - x1,x2,…,xn -> z1,z2,…zn -> y1,y2…,ym
- Encoder
  - Multi-Head Attention + feed forward
  - N layers
- Decoder
  - Multi-Head Attention + feed forward + linear & softmax
  - N layers
- Attention -> Key / Value / Query

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Attention

- Seq2seq model -> long term dependency problem
  - Solve: context vector can't deliver all information
- Assumption
  - Encoder time t vector similar with Decoder time $t-1$ vector
  - Similar -> increased value of each position in a vector

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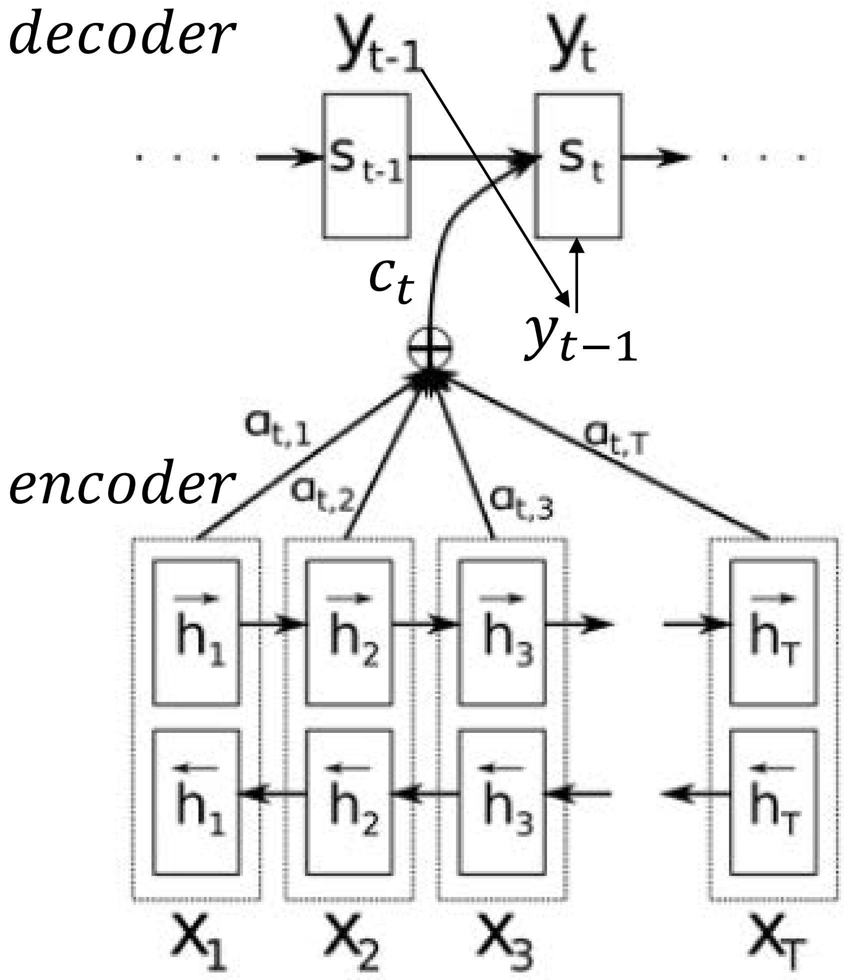
Attention



- x_t: input from encoder in time t
- y_t: output from decoder in time t
- h_n : encoder nth hidden state vector
- s_t: decoder hidden state vector in time t
- $a_{t,n}$: n^{th} weight in time t (=attention vector)
  - Which vector to look into
- c_t: context vector in time t
- T = length of the sequence
- $s_t = f(s_{t-1}, y_{t-1}, c_t)$
- Assumption -> training is finished

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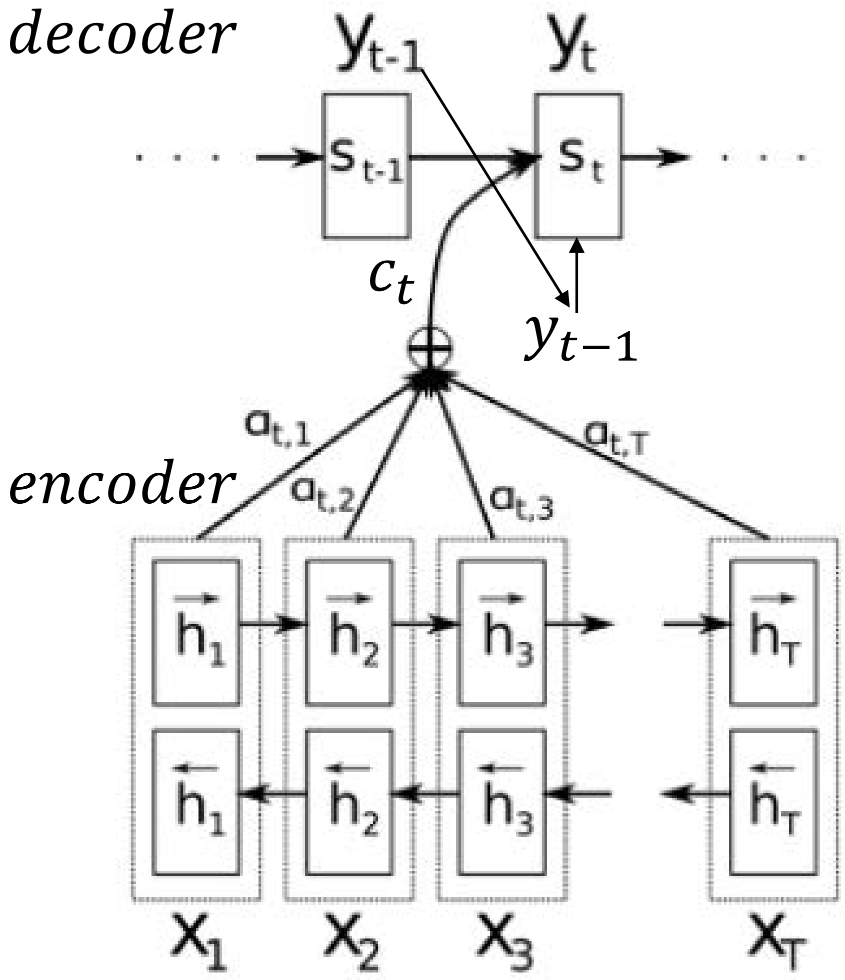
Attention



- $s_t = f(s_{t-1}, y_{t-1}, c_t)$
- $c_t = \sum_{i=1}^{T} a_{t,i}\, h_i$
  - weighted sum of attention vector
- $a_{t,i}$ = softmax(e_{ti})
- e_{ti} = score value
  - a(s_{t-1}, h_i)
  - a : alignment model (extracts similarity)
  - Various methods for alignment model
  - a : $v_a^T \tanh(W_a[s_{t-1}, h_i])$
    - V, W -> parameters
    - Earned during training
  - a : $[s_{t-1}^T h_i] \rightarrow e_{ti} = [s_{t-1}^T h_1, s_{t-1}^T h_2, \ldots, s_{t-1}^T h_N]$

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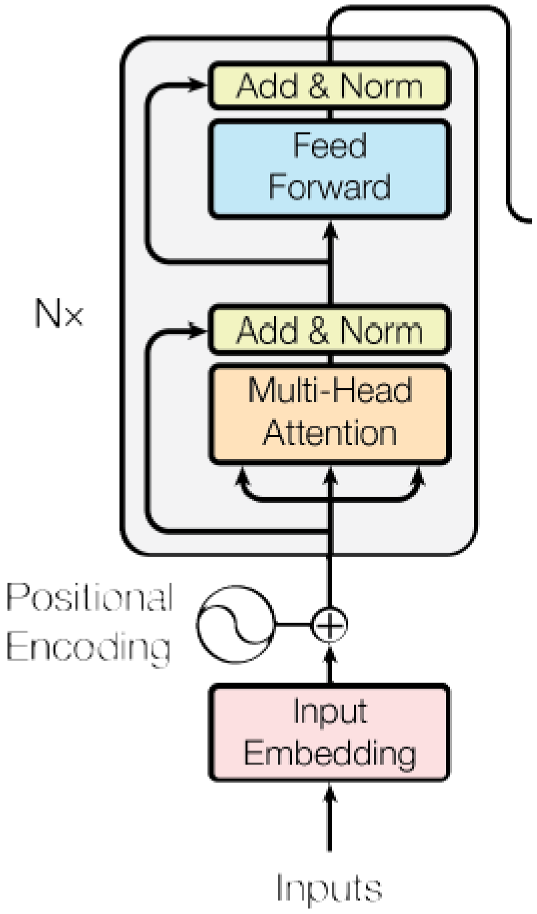
Transformer – Encoder



- Positional Encoding
- Multi-head self attention & position-wise fully connected feed-forward network
- Layer normalization
- Residual connection for two sublayers
  - x+Sublayer(x)
- Stacked N layers

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Positional Encoding

$$PE_{(pos,2i)} = \sin(pos/1000^{2i/d_{model}})$$
$$PE_{(pos,2i+1)} = \cos(pos/1000^{2i/d_{model}})$$

- Word Embedding -> positional information
- Positional encoding vector + embedding vector (same dimension)
- Pos: position / i : dimension
- Function: sinusoidal function with cycle : $1000^{2i/d_{model}} \cdot 2\pi$

- $PE_{pos} = [\cos(pos/1), \sin(pos/1000^{2/d_{model}}), \ldots, \sin(pos/1000^{2i/d_{model}})]$
- Same word have different value in different position
- Linear Function

https://pozalabs.github.io/transformer/

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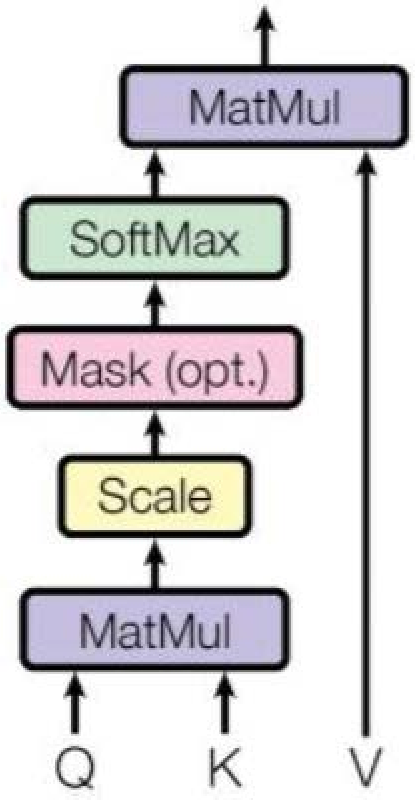
Scaled dot product attention



- $Attention(Q,K,V) = softmax(\mathrm{Q}K^T/\sqrt{d_k})\mathrm{V}$
  - d_k = dimension of K
- Key: hidden state vector of a word
- Value: hidden state vector of a word
- Query: hidden state vector of a word (current-word)
- dot product -> similarity between K & Q
- Scaling -> Softmax: big value have minimal gradient
- Softmax * V -> Attention(Q,K,V) increases as value and query are similar
- Faster than additive attention

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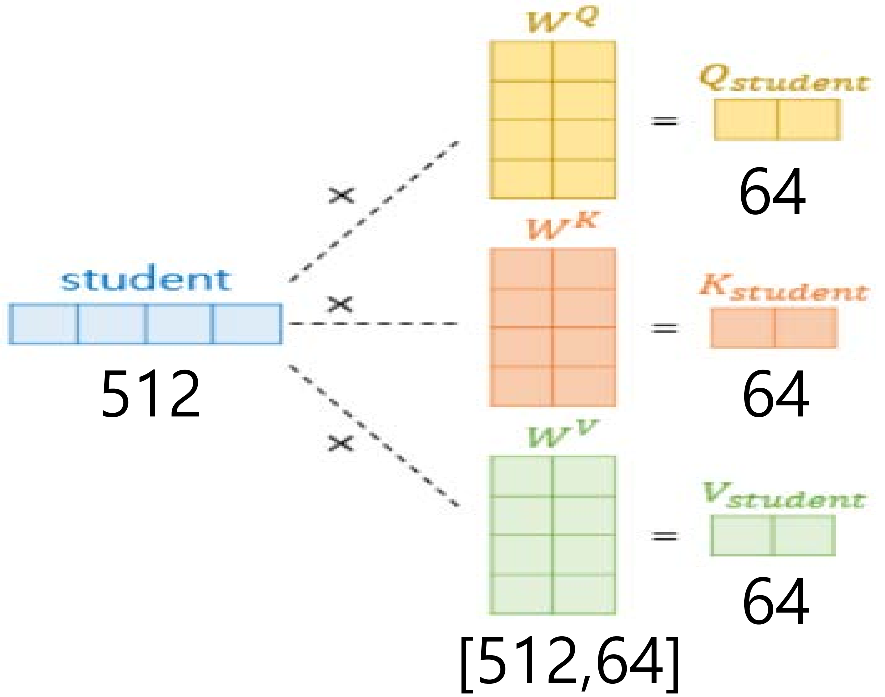
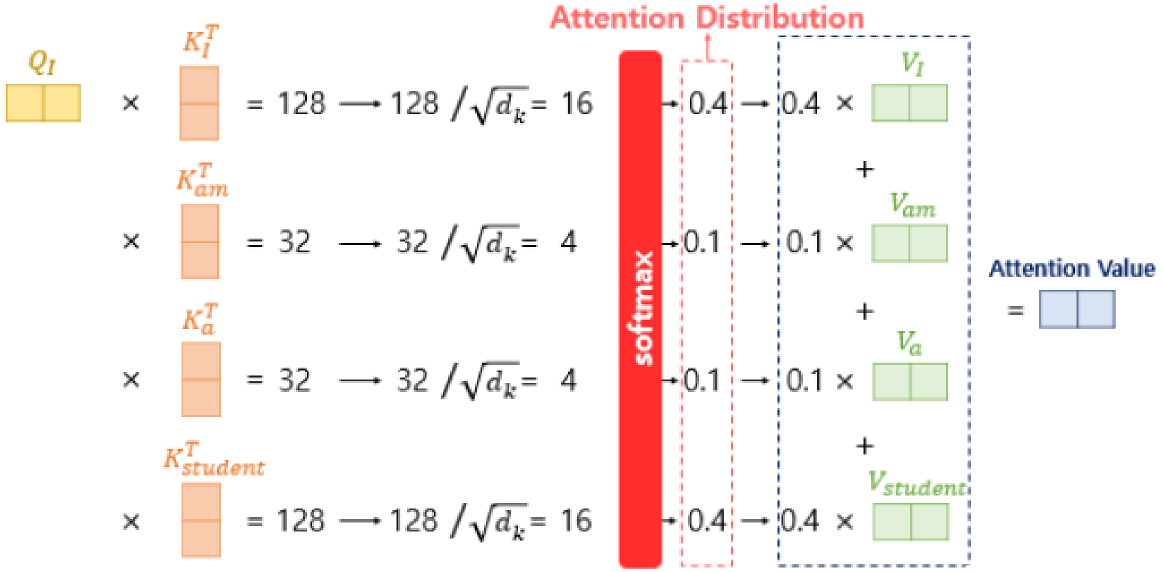
Scaled dot product attention – K, V, Q

$$Attention(Q,K,V) = softmax(QK^T/\sqrt{d_k})V$$





- d_{model} = dimension of word embedding = 512 (normally length of longest sentence)
- $d_k = d_V = d_Q = d_{model}$ / num_heads
  - Num_heads = 8

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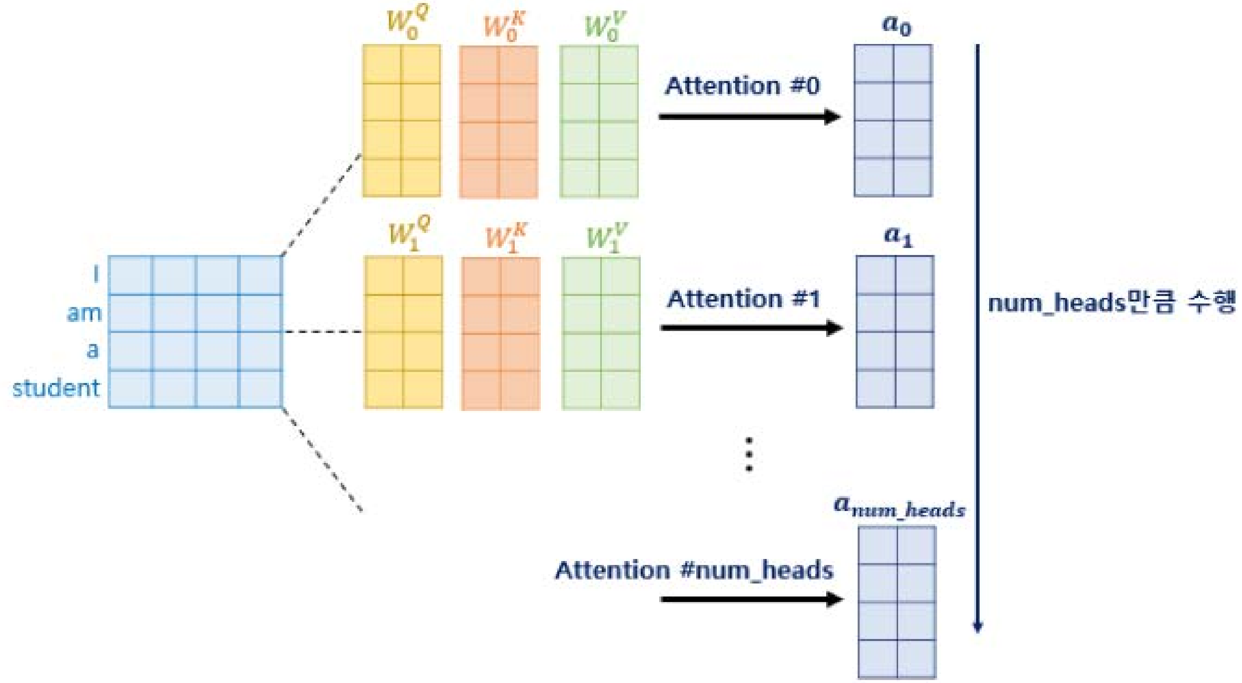
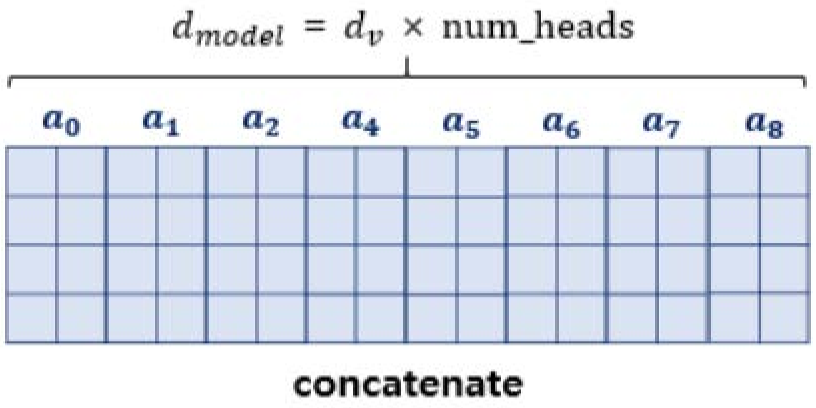
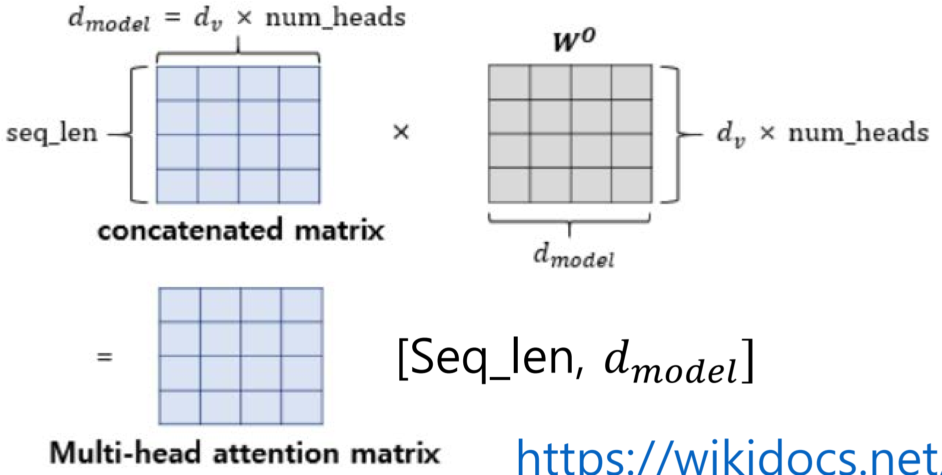
Multi-head Attention –K,V,Q

$$Multi - head\ Attention = Concat(head1, head2, \ldots, headh)\ W^O$$
$$headi\ = \text{Attention}(QWi^Q, KWi^K, VWi^V)$$







[Seq_len, d_{model}]

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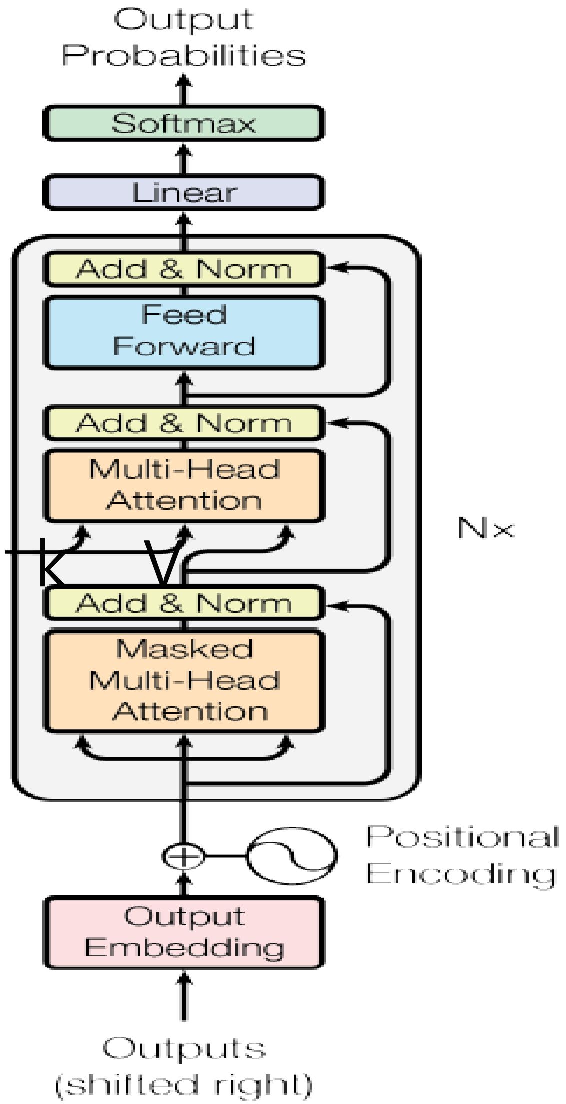
Transformer – Decoder



- Positional Encoding
- Masking
- Multi-head self attention & position-wise fully connected feed-forward network
  - 2^{nd} : from encoder output (key, value)
- Residual connection for three sublayers
  - x+Sublayer(x)
- Layer normalization
- Linear / Softmax

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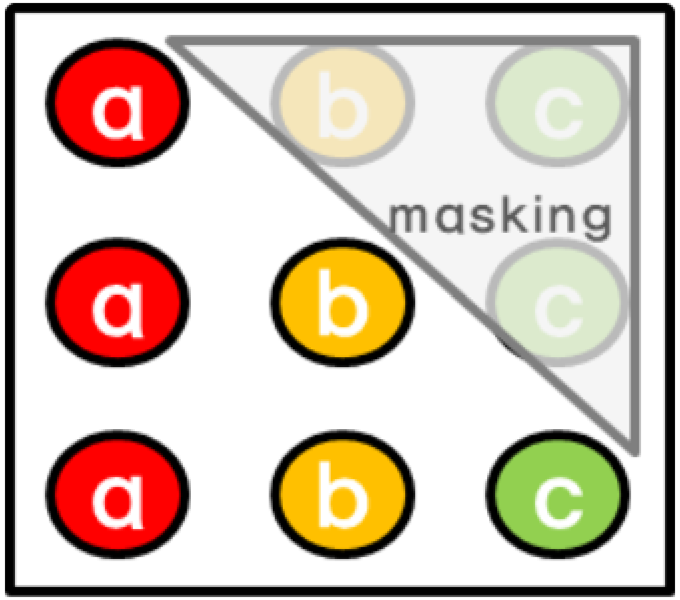
Masking



1 Attention until a -> don't look into b,c

2 Attention until a,b -> don't look into c

3 Attention until a,b,c

Masked input value = $-\infty$

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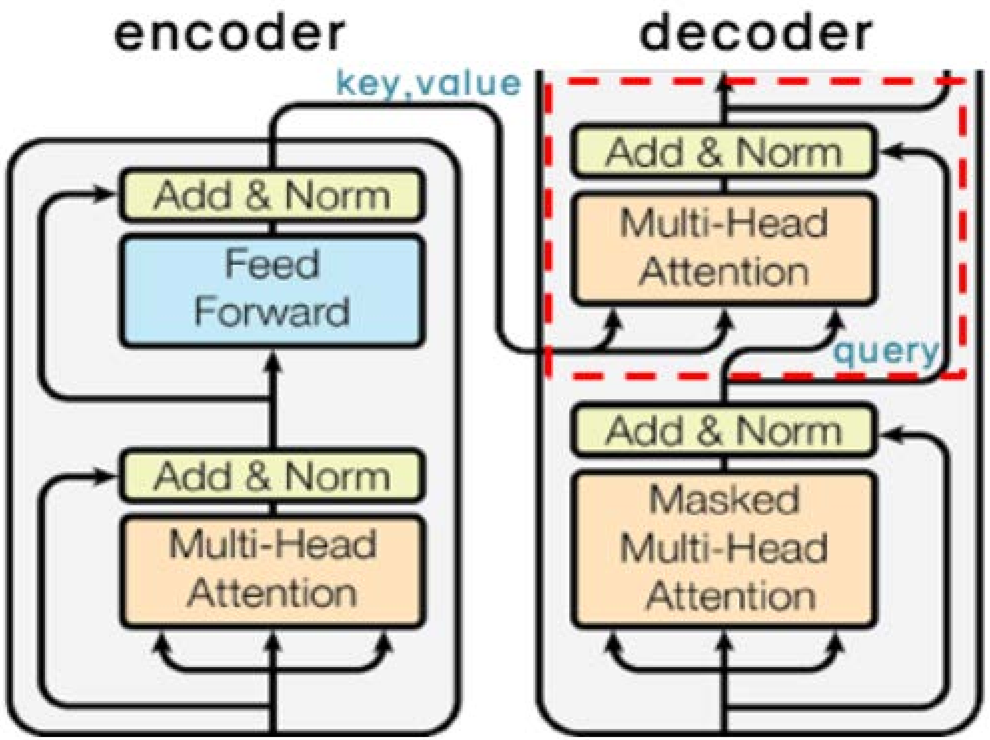
Encoder – Decoder



- Query from decoder attention layer -> attention until i^{th} position due to masking out
- Can give attention to all positions

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Regularization

1. Dropout to output of each sub-layer
2. Dropout to output to positional encoding
3. Label smoothing

Strength of Self Attention

1. Computational complexity
2. Parallelization
3. Shorten path length

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Result

- Task: Machine Translation (WMT 2014 English-to-German translation & WMT 2014 English-to-French translation task)

Table 2: The Transformer achieves better BLEU scores than previous state-of-the-art models on the English-to-German and English-to-French newstest2014 tests at a fraction of the training cost.

Model	BLEU		Training Cost (FLOPs)	
	EN-DE	EN-FR	EN-DE	EN-FR
ByteNet [15]	23.75			
Deep-Att + PosUnk [32]		39.2		$1.0 \cdot 10^{20}$
GNMT + RL [31]	24.6	39.92	$2.3 \cdot 10^{19}$	$1.4 \cdot 10^{20}$
ConvS2S [8]	25.16	40.46	$9.6 \cdot 10^{18}$	$1.5 \cdot 10^{20}$
MoE [26]	26.03	40.56	$2.0 \cdot 10^{19}$	$1.2 \cdot 10^{20}$
Deep-Att + PosUnk Ensemble [32]		40.4		$8.0 \cdot 10^{20}$
GNMT + RL Ensemble [31]	26.30	41.16	$1.8 \cdot 10^{20}$	$1.1 \cdot 10^{21}$
ConvS2S Ensemble [8]	26.36	**41.29**	$7.7 \cdot 10^{19}$	$1.2 \cdot 10^{21}$
Transformer (base model)	27.3	38.1	$\mathbf{3.3 \cdot 10^{18}}$	
Transformer (big)	**28.4**	**41.0**	$2.3 \cdot 10^{19}$	