Tokens-to-Token ViT: Training Vision Transformers from Scratch on ImageNet

李玉光

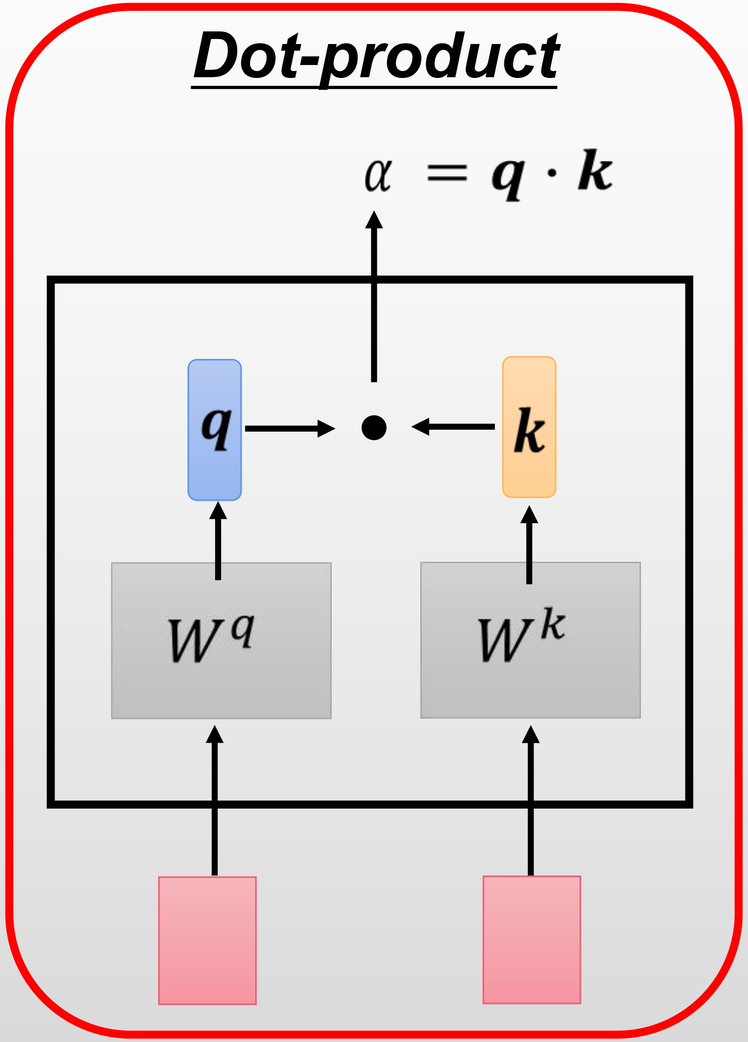
预备知识

1.self-attention

2.transformer

3VIT

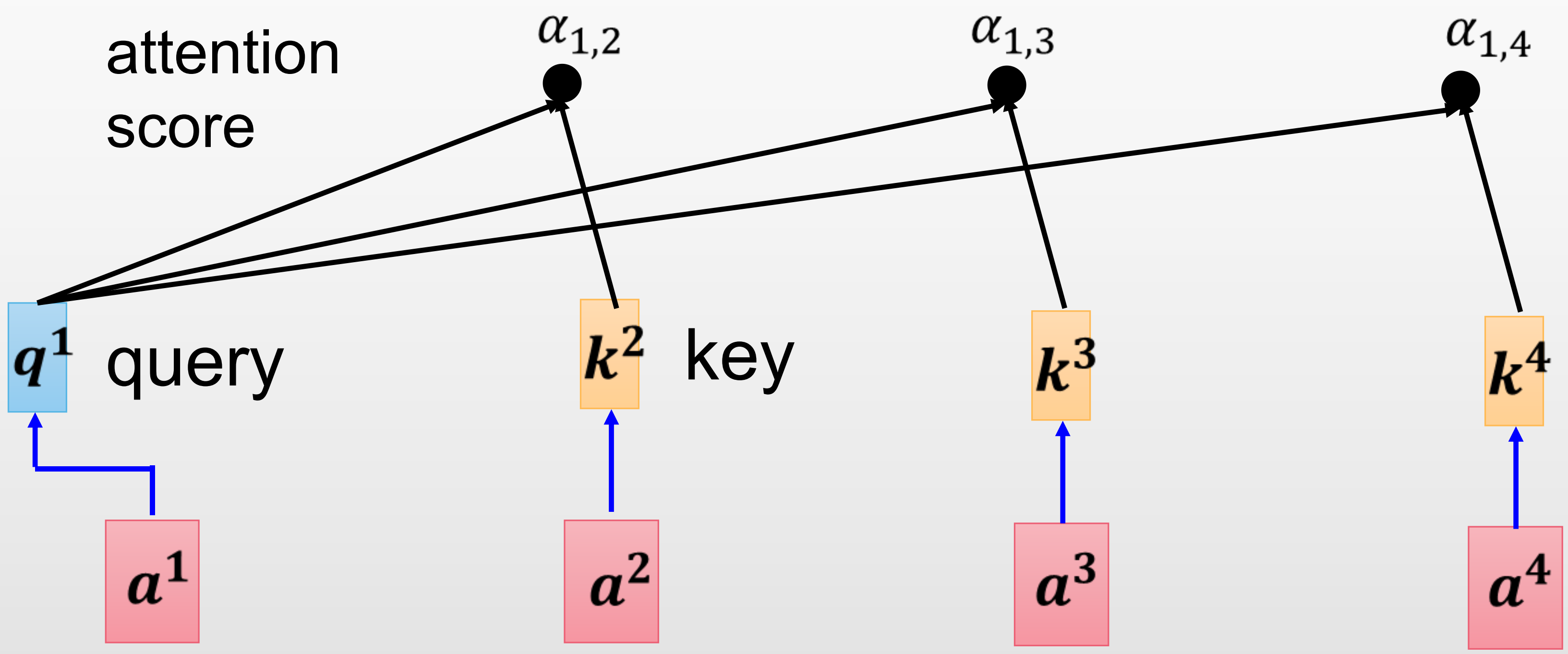
SELF-ATTENTION



- 2005年，Bahdanau等人在论文《Neural Machine Translation by Jointly Learning to Align and Translate》
- Google 机器翻译团队在NIPS 2017上发表的《Attention is All You Need》
- GoogleMind 2014年发表《Recurrent Models of Visual Attention》

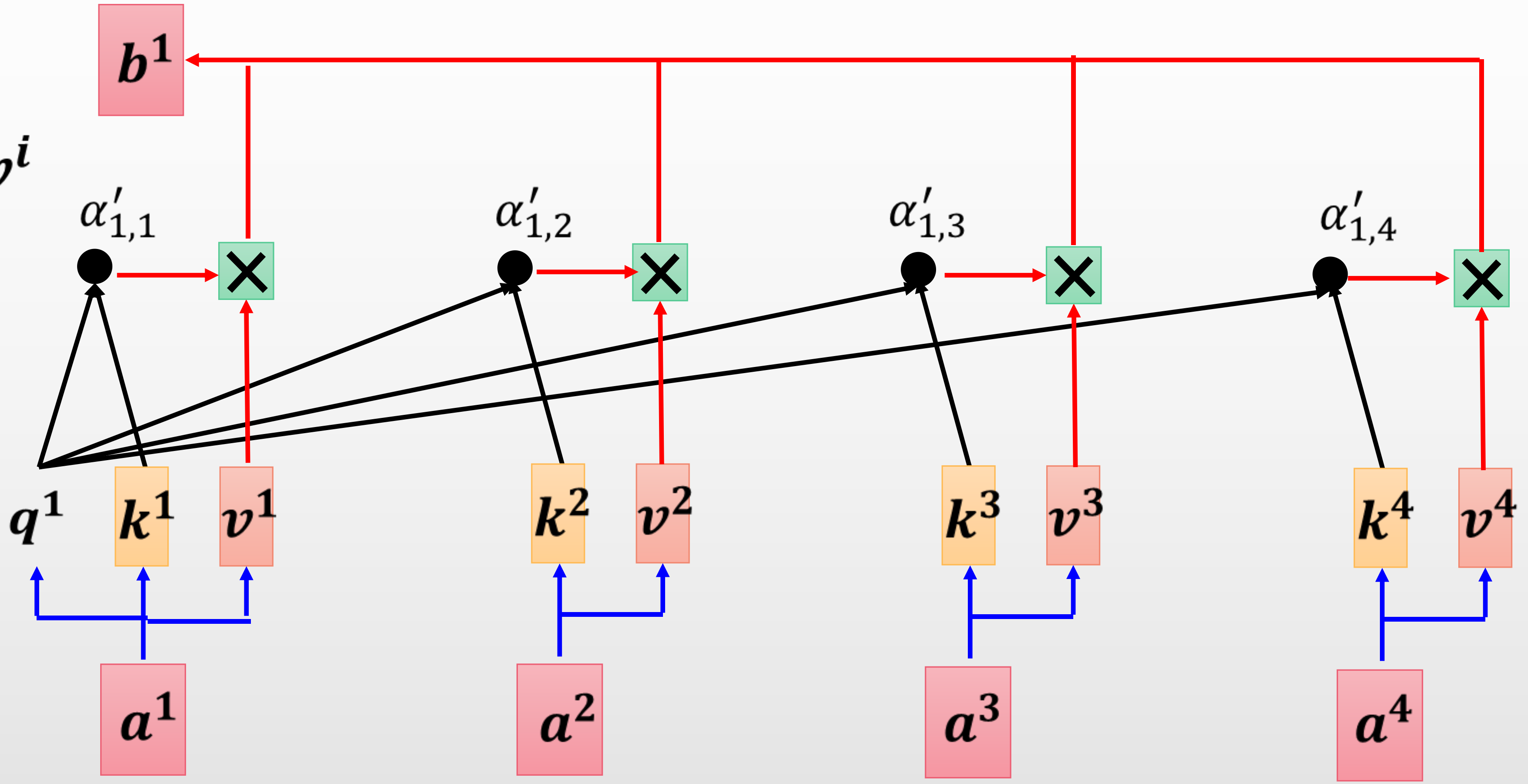
SELF-ATTENTION

$$\alpha_{1,2} = \boldsymbol{q}^1 \cdot \boldsymbol{k}^2 \qquad \alpha_{1,3} = \boldsymbol{q}^1 \cdot \boldsymbol{k}^3 \qquad \alpha_{1,4} = \boldsymbol{q}^1 \cdot \boldsymbol{k}^4$$



$$\boldsymbol{q}^1 = W^q \boldsymbol{a}^1 \qquad \boldsymbol{k}^2 = W^k \boldsymbol{a}^2 \qquad \boldsymbol{k}^3 = W^k \boldsymbol{a}^3 \qquad \boldsymbol{k}^4 = W^k \boldsymbol{a}^4$$

$$b^1 = \sum_i \alpha'_{1,i} v^i$$



$v^2 = W^v a^2$ $\quad$ $v^3 = W^v a^3$ $\quad$ $v^4 = W^v a^4$

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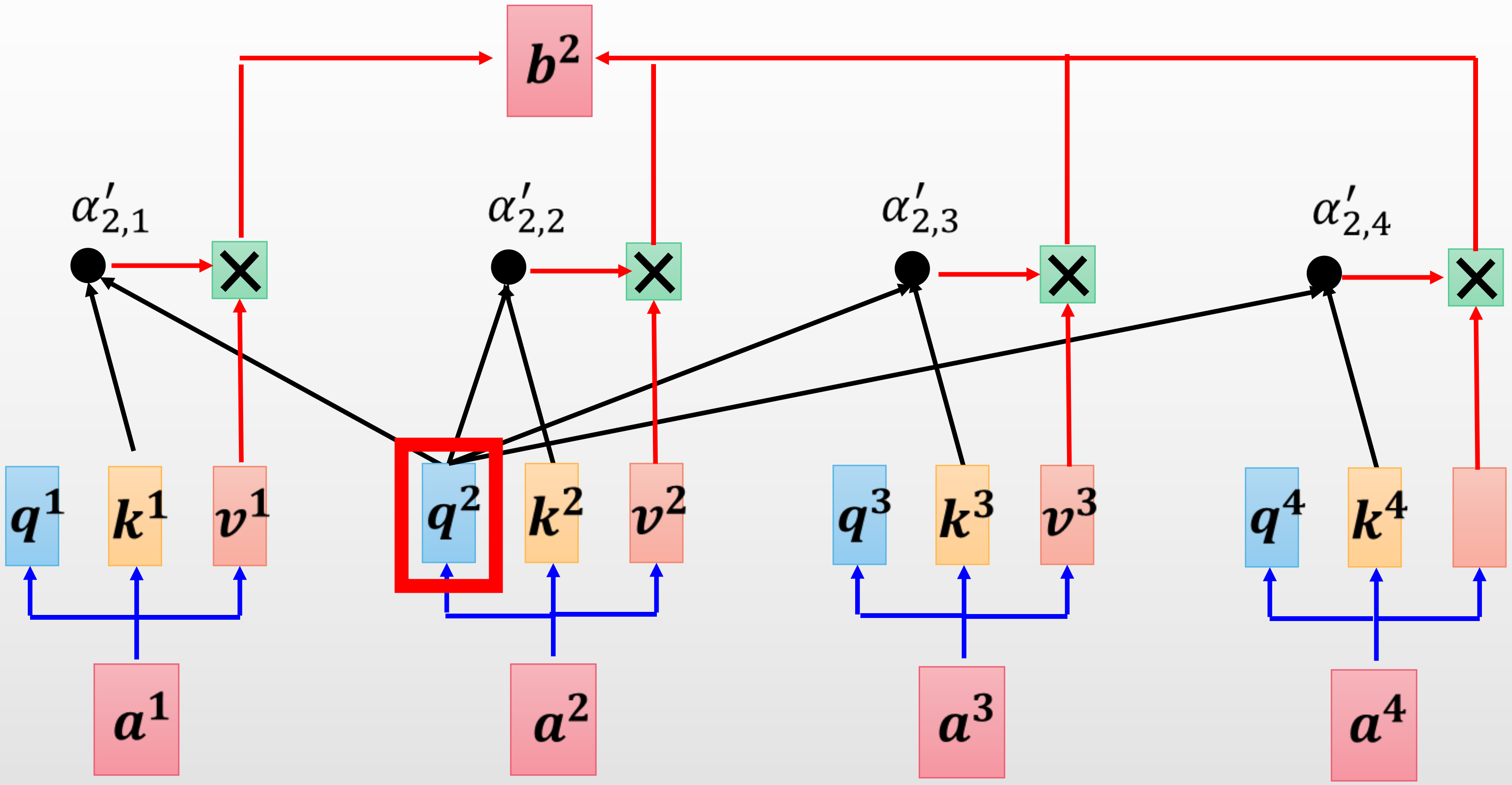

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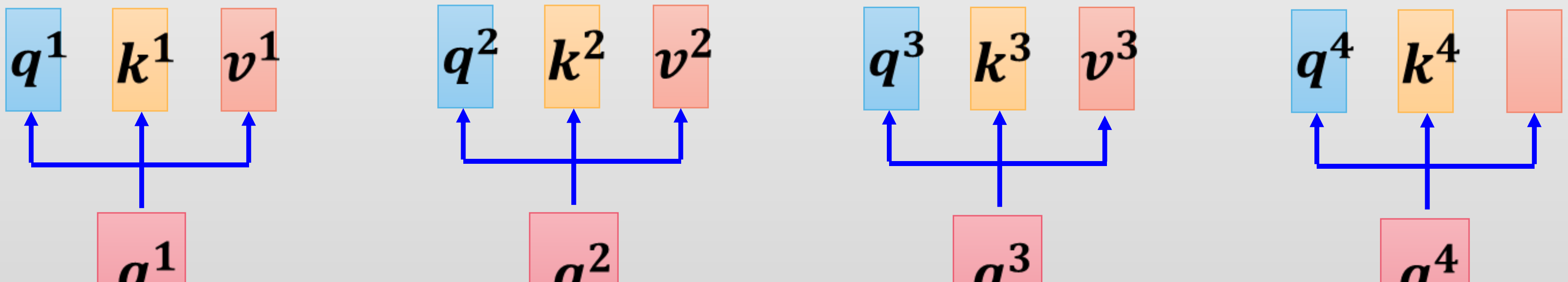
$$q^i = W^q a^i \qquad \underbrace{q^1\, q^2\, q^3\, q^4}_{Q} = W^q\, \underbrace{a^1\, a^2\, a^3\, a^4}_{I}$$

$$k^i = W^k a^i \qquad \underbrace{k^1\, k^2\, k^3\, k^4}_{K} = W^k\, \underbrace{a^1\, a^2\, a^3\, a^4}_{I}$$

$$v^i = W^v a^i \qquad \underbrace{v^1\, v^2\, v^3\, v^4}_{V} = W^v\, \underbrace{a^1\, a^2\, a^3\, a^4}_{I}$$



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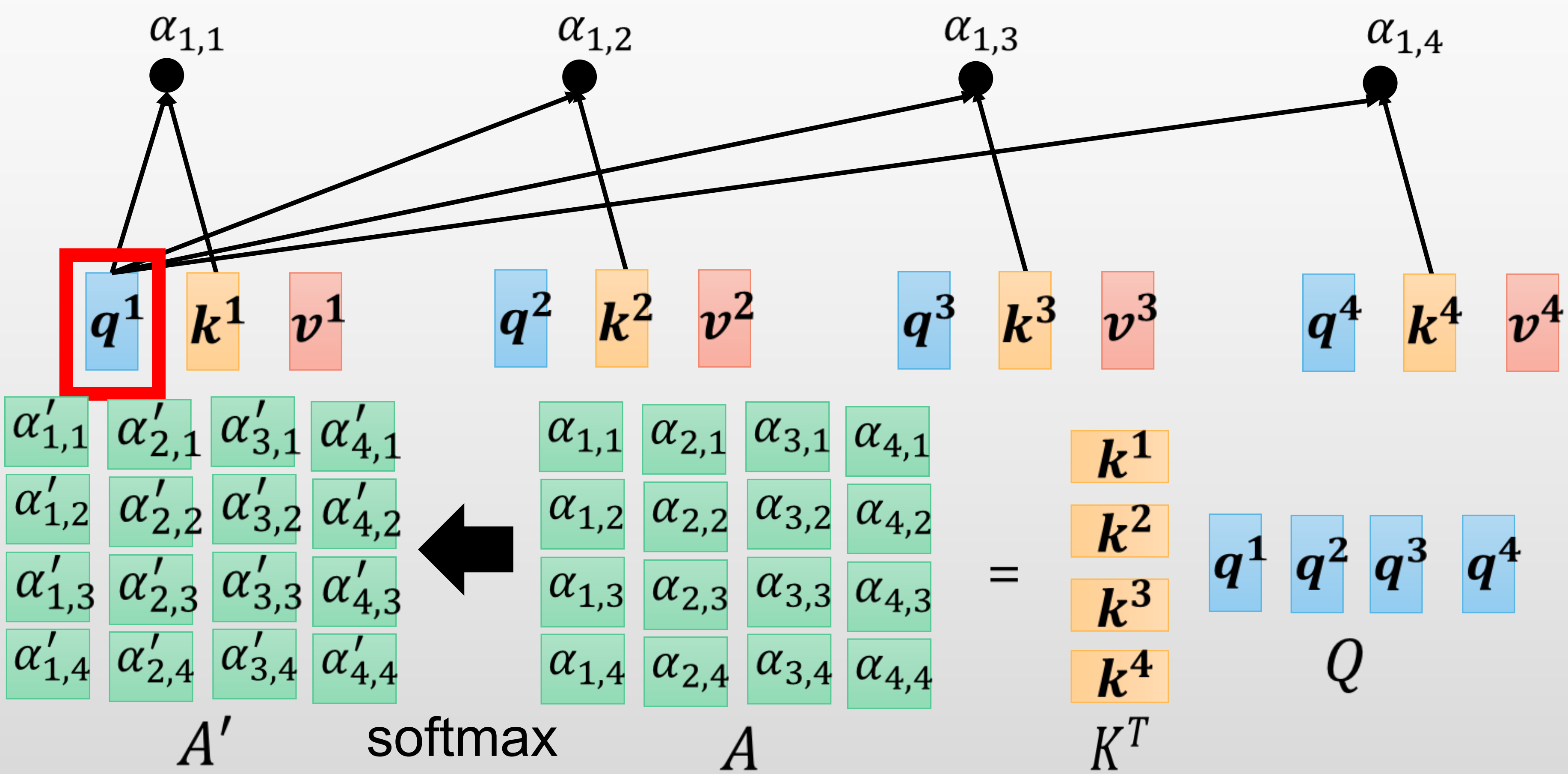
$$\alpha_{1,1} = \boldsymbol{k}^1 \boldsymbol{q}^1 \qquad \alpha_{1,2} = \boldsymbol{k}^2 \boldsymbol{q}^1$$

$$\alpha_{1,3} = \boldsymbol{k}^3 \boldsymbol{q}^1 \qquad \alpha_{1,4} = \boldsymbol{k}^4 \boldsymbol{q}^1$$

$$\begin{bmatrix} \alpha_{1,1} \\ \alpha_{1,2} \\ \alpha_{1,3} \\ \alpha_{1,4} \end{bmatrix} = \begin{bmatrix} \boldsymbol{k}^1 \\ \boldsymbol{k}^2 \\ \boldsymbol{k}^3 \\ \boldsymbol{k}^4 \end{bmatrix} \boldsymbol{q}^1$$



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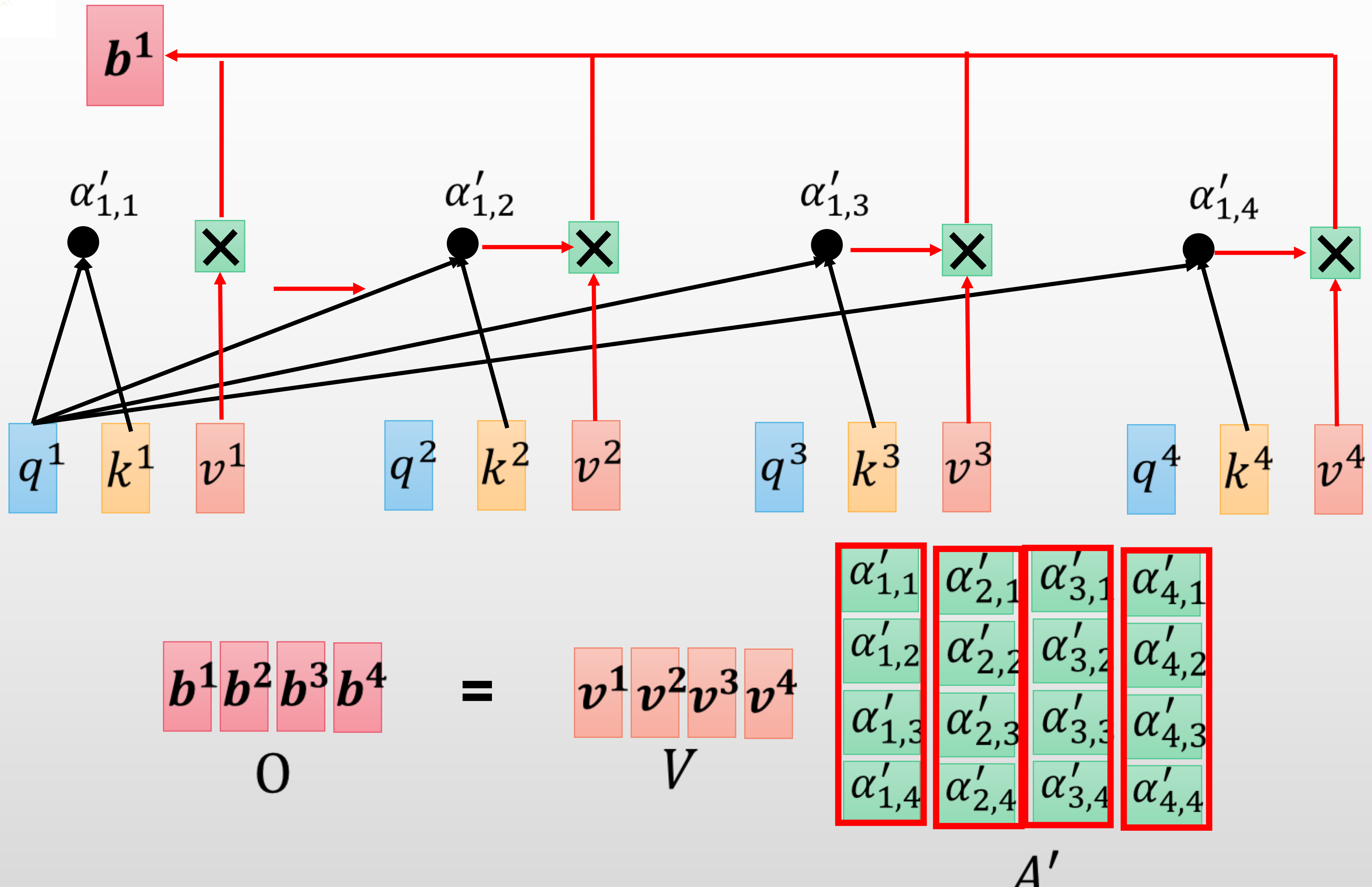

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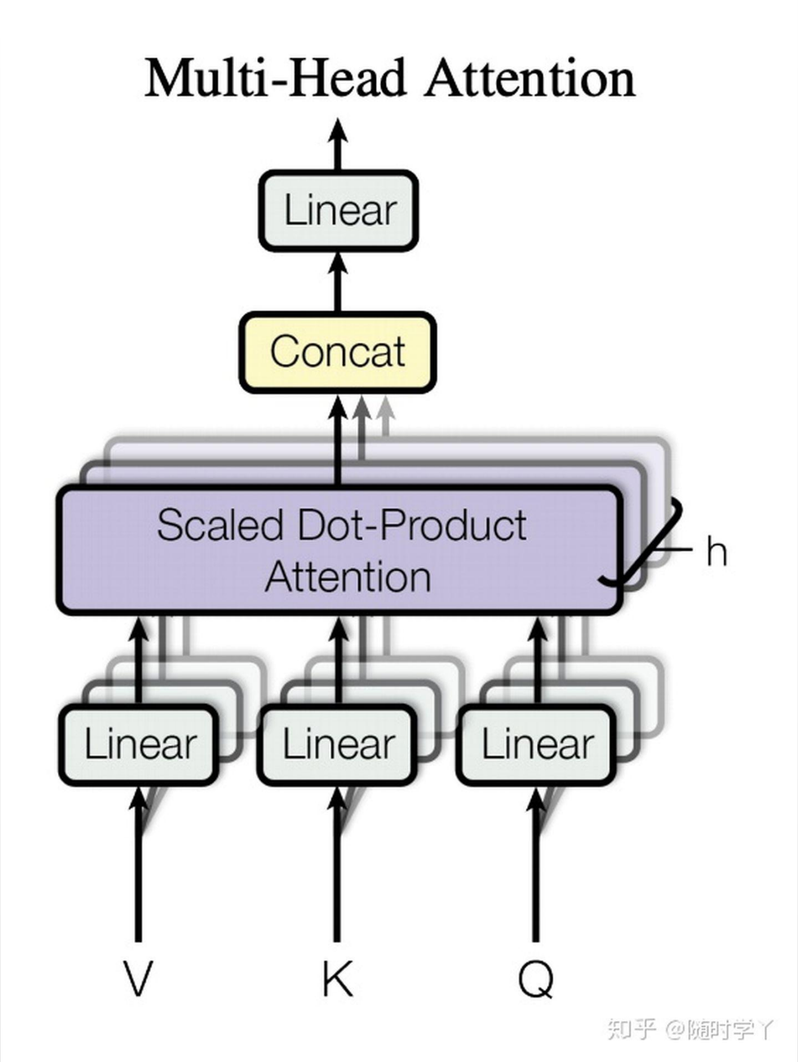

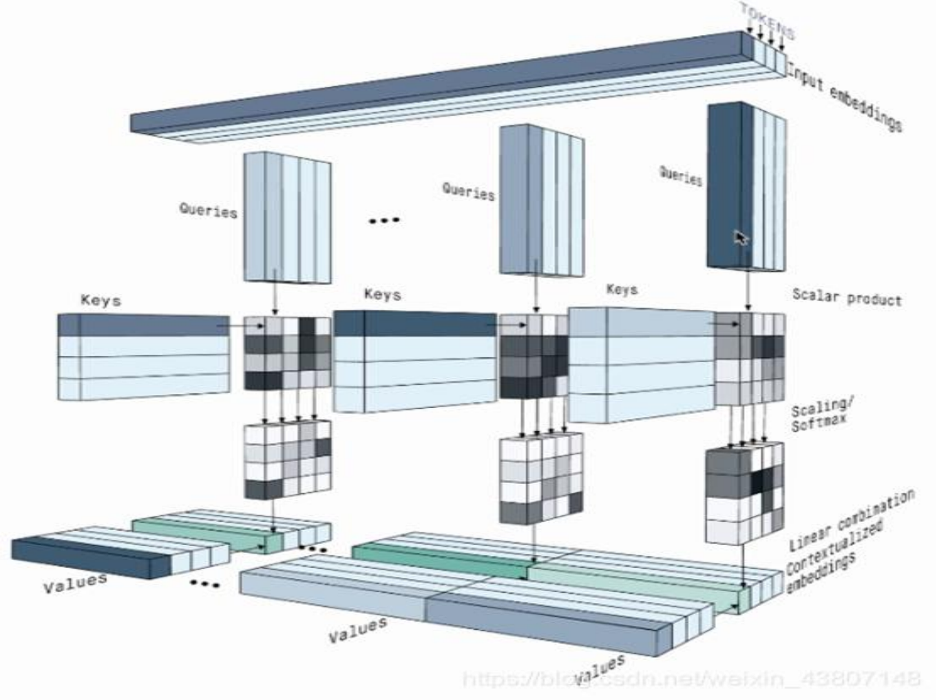

$$Q_i = QW_i^Q, K_i = KW_i^K, V_i = VW_i^V, i = 1, \ldots, 8$$

$$head_i = Attention(Q_i, K_i, V_i), i = 1, \ldots, 8$$

$$MultiHead(Q, K, V) = Concact(head_1, \ldots, head_8)W^O$$

这里，我们假设

$$Q, K, V \in R^{512}, W_i^Q, W_i^K, W_i^V \in R^{512\times 64}, W^O \in R^{512\times 512}, head_i \in R^{64}$$

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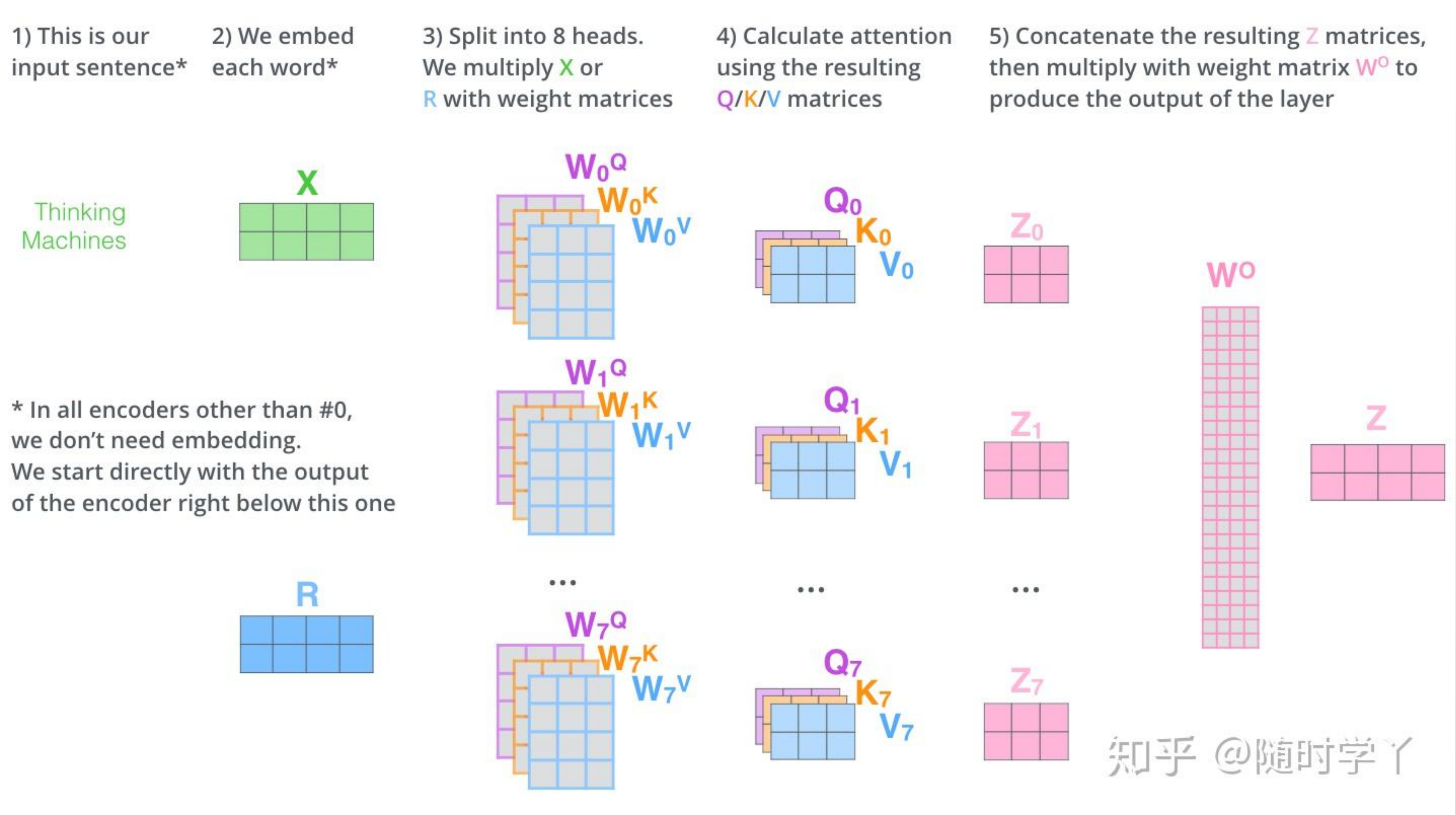
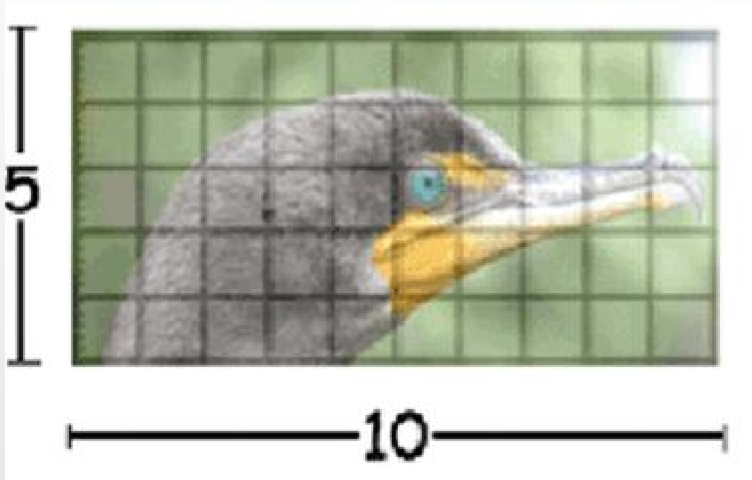
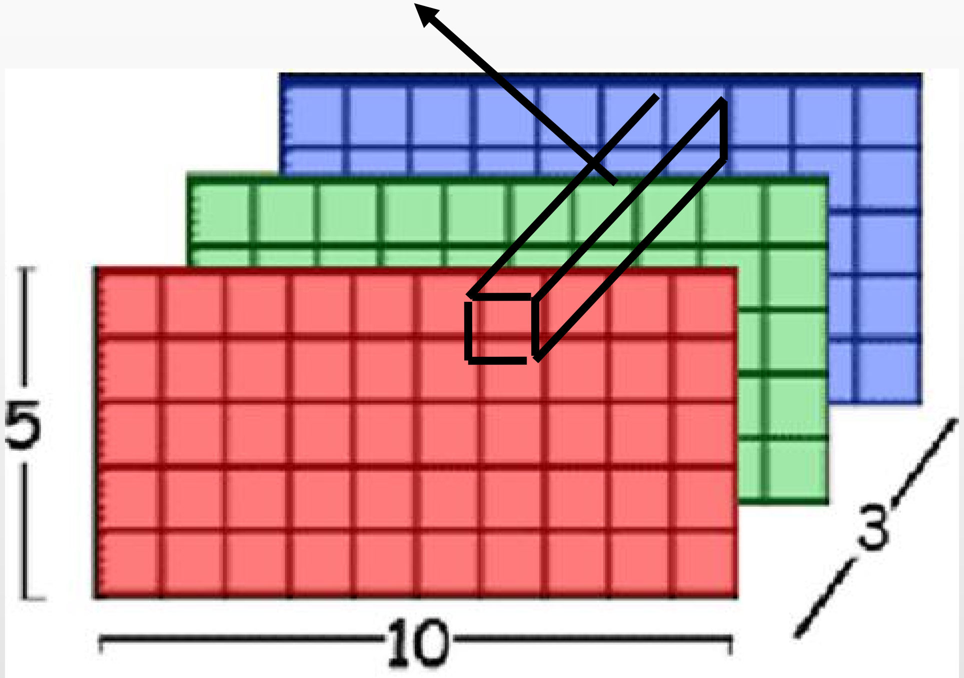


Self-attention for Image

An **image** can also be
considered as a **vector set**.

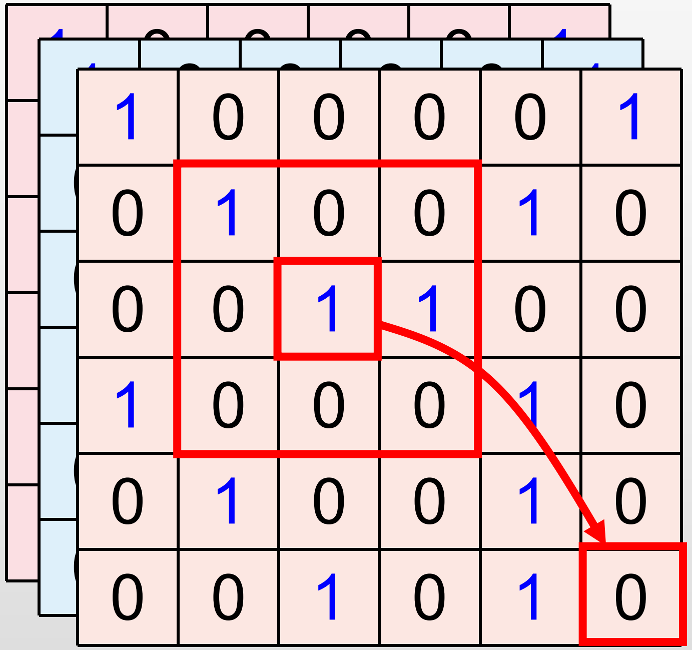


This is a vector.



Source of image: https://www.researchgate.net/figure/Color-image-representation-and-RGB-matrix_fig15_282798184

Self-attention v.s. CNN



CNN: self-attention that can only attends in a receptive field

- CNN is simplified self-attention.

Self-attention: CNN with learnable receptive field

- Self-attention is the complex version of CNN.

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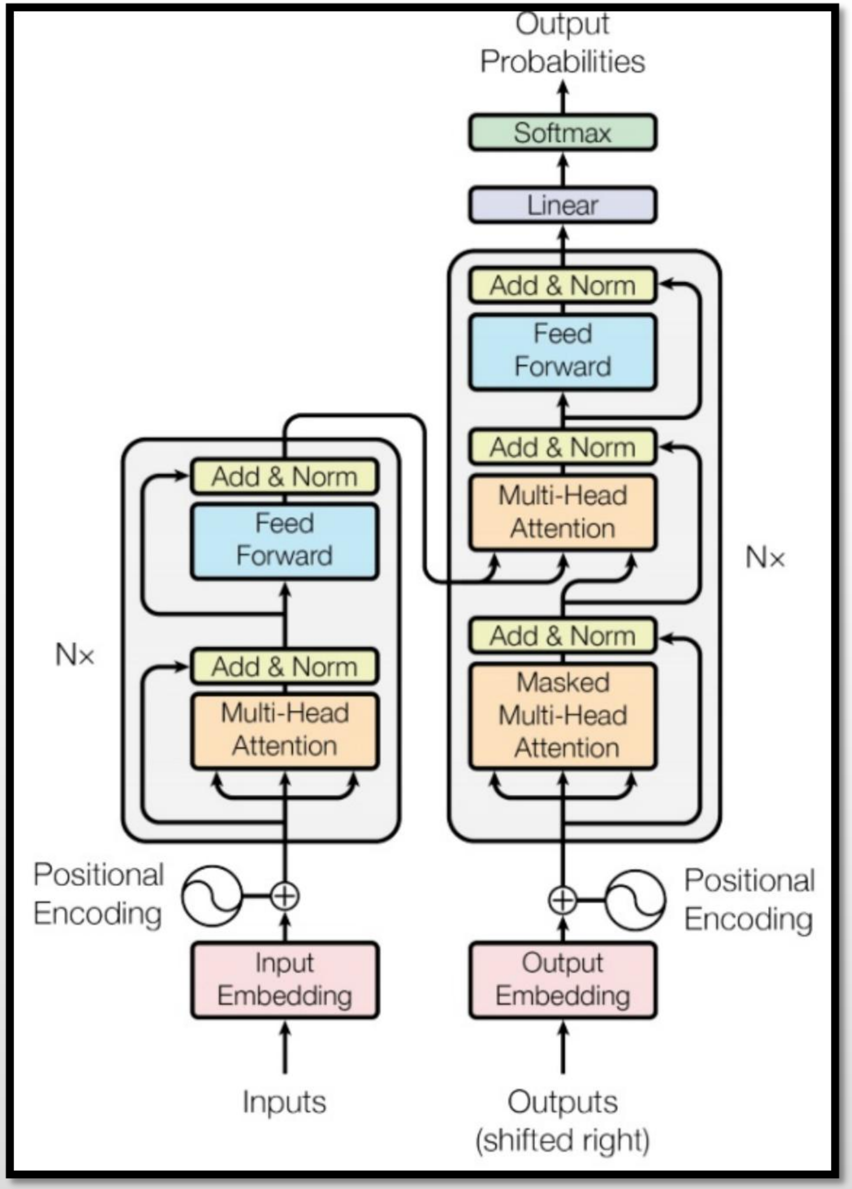
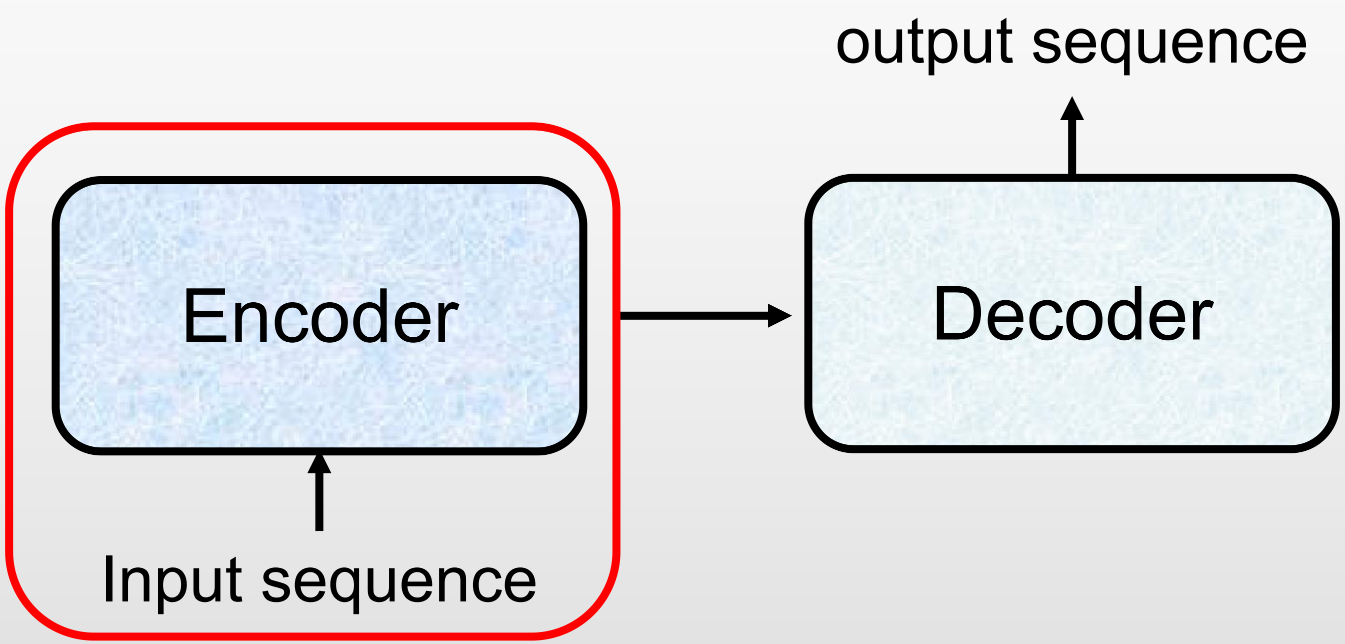
TRANSFORMER

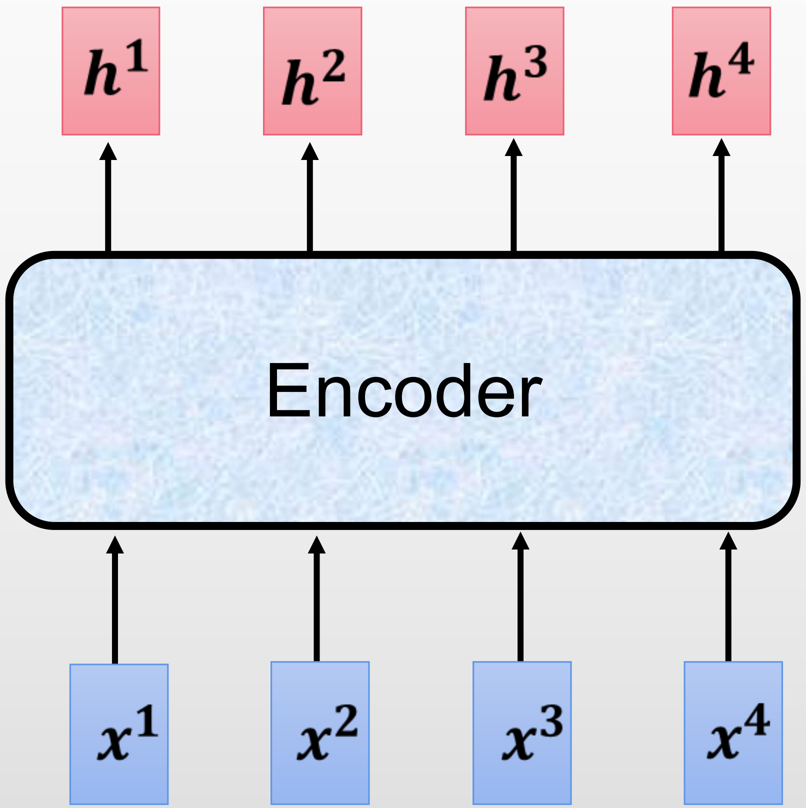
Transformer is the first transduction model relying entirely on self-attention to compute representations of its input and output without using sequence aligned RNNs or convolution。

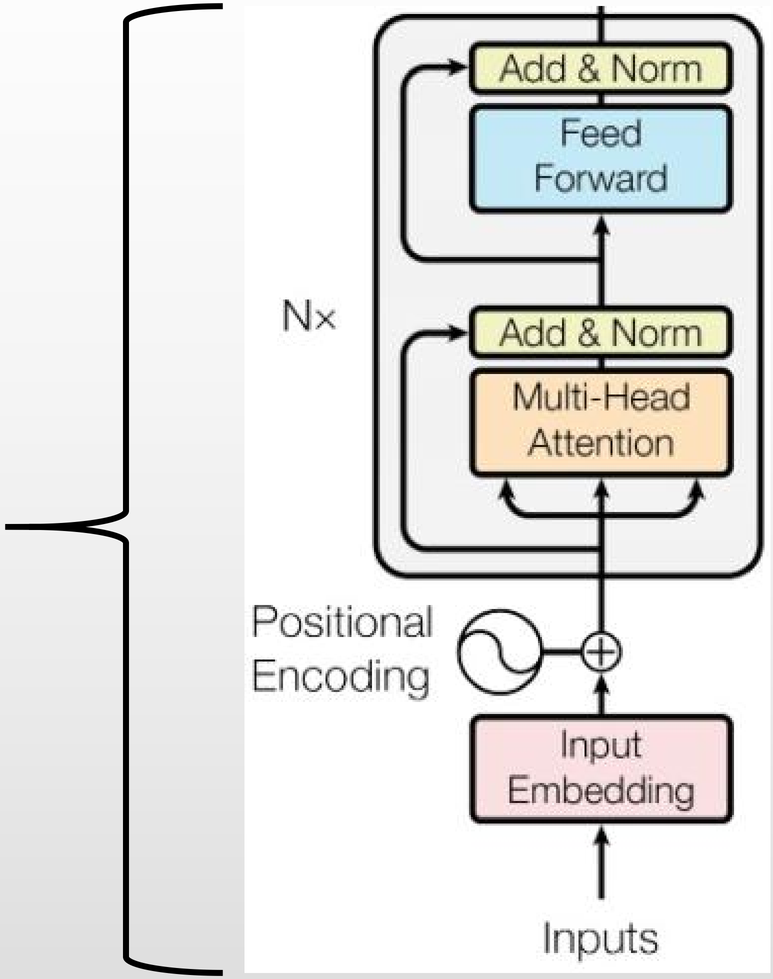


Encoder



You can use **RNN** or **CNN**.





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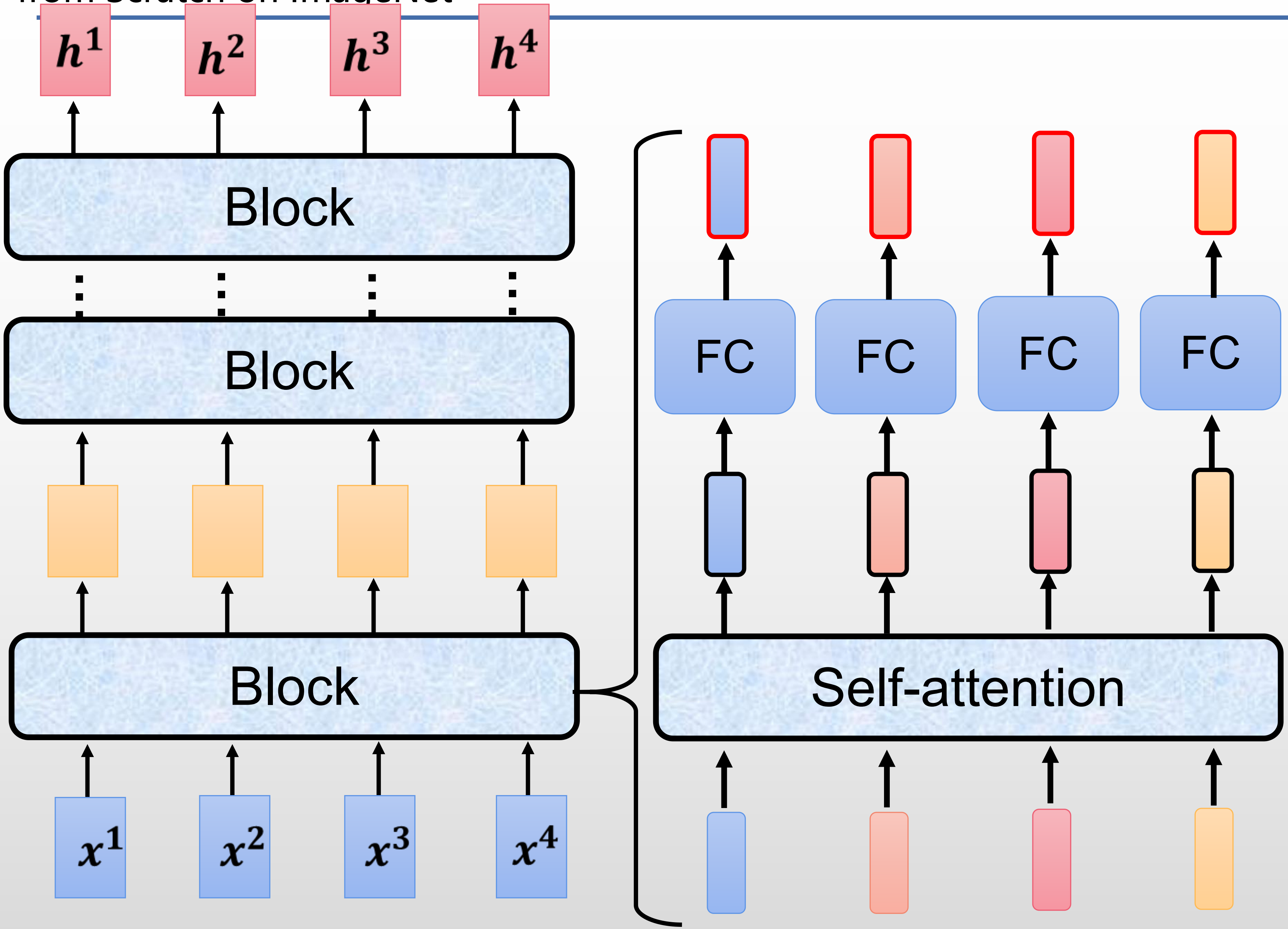
h^1
h^2
h^3
h^4
Block
Block
Block
x^1
x^2
x^3
x^4
FC
FC
FC
FC
Self-attention

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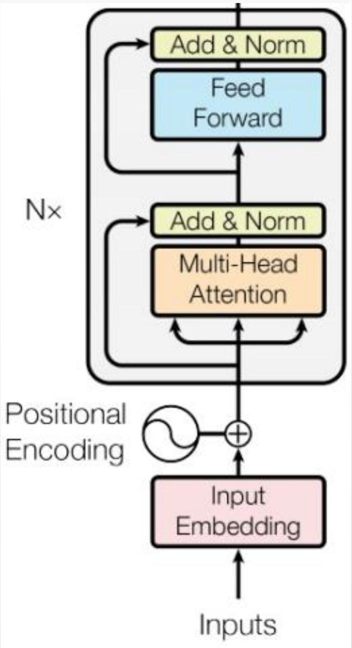
POSITIONAL ENCODING



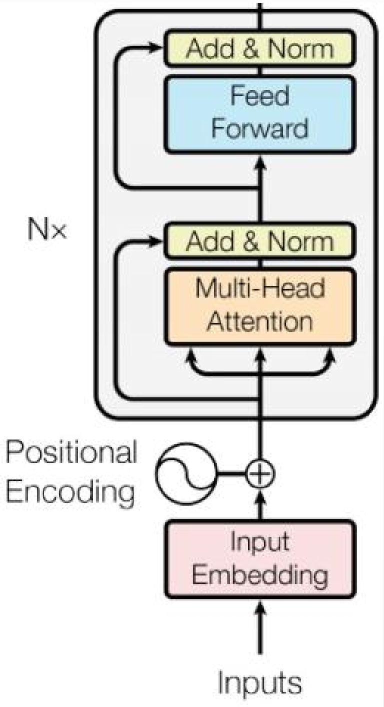
$$PE = pos = 0, 1, 2, \cdots, T-1$$

$$PE = pos/(T-1)$$

$$PE(pos) = \sin\left(\frac{pos}{\alpha}\right)$$

$$PE(pos, 2i) = \sin\left(\frac{pos}{10000^{2i/d_{\text{model}}}}\right)$$

$$PE(pos, 2i+1) = \cos\left(\frac{pos}{10000^{2i/d_{\text{model}}}}\right)$$



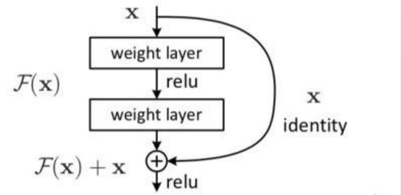
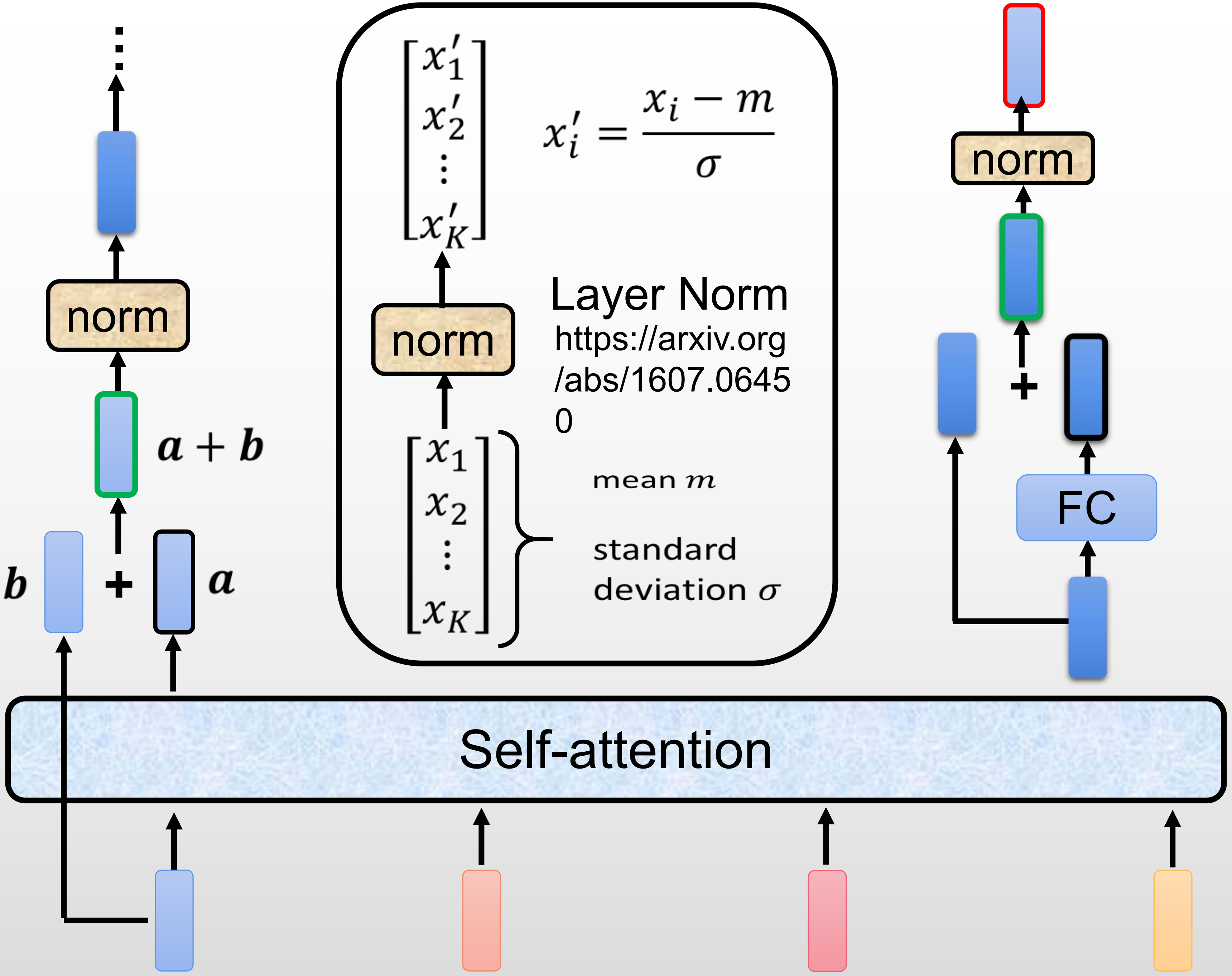


Figure 2. Residual learning: a building block.



$$x_i' = \frac{x_i - m}{\sigma}$$

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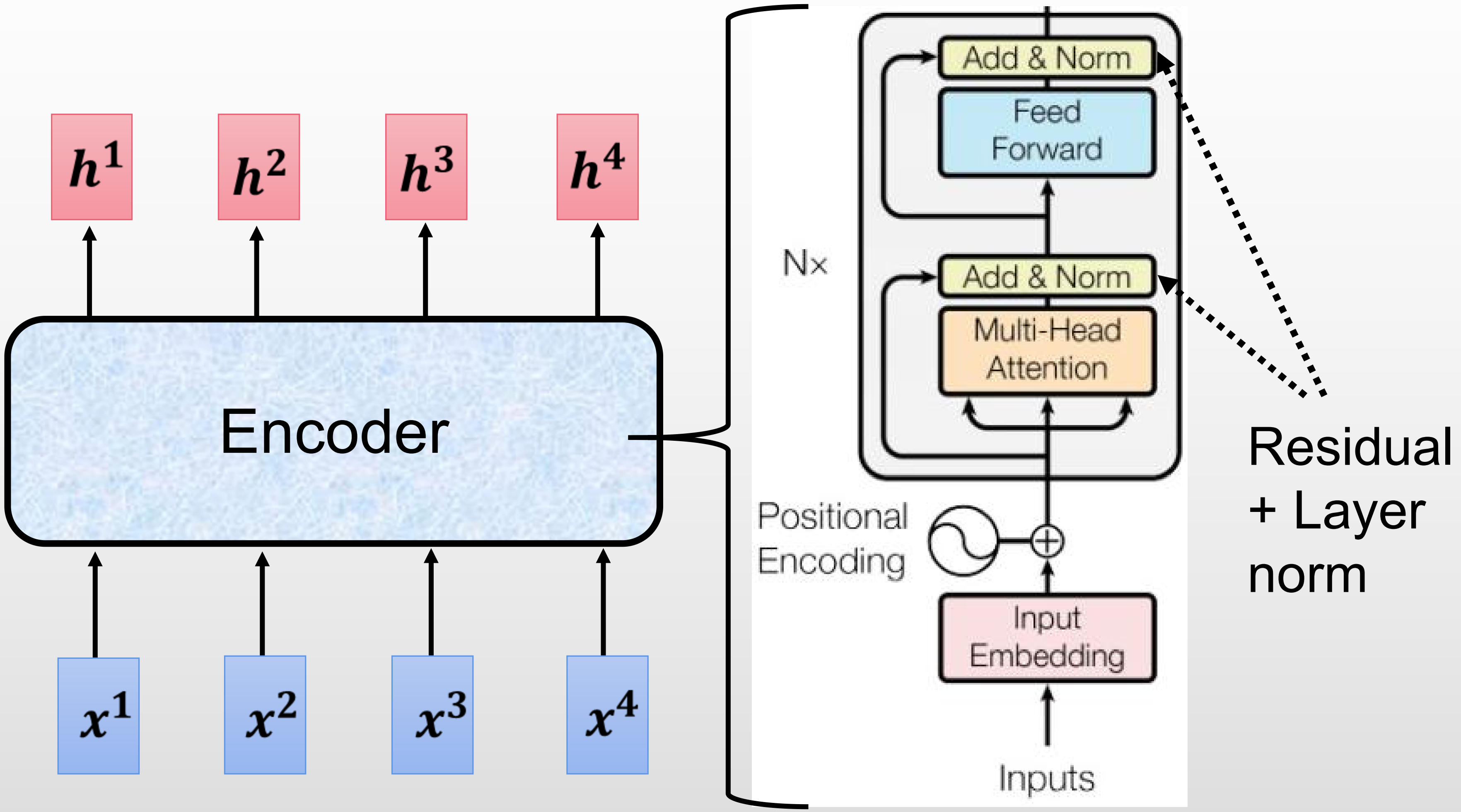
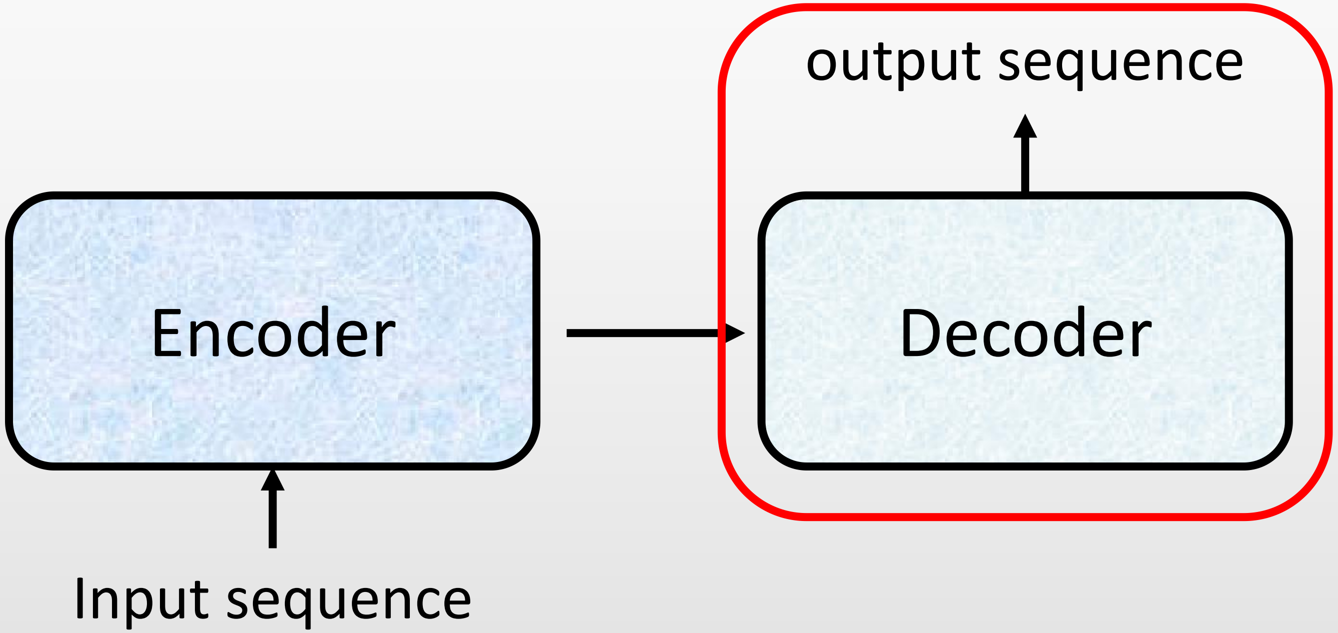


Decoder



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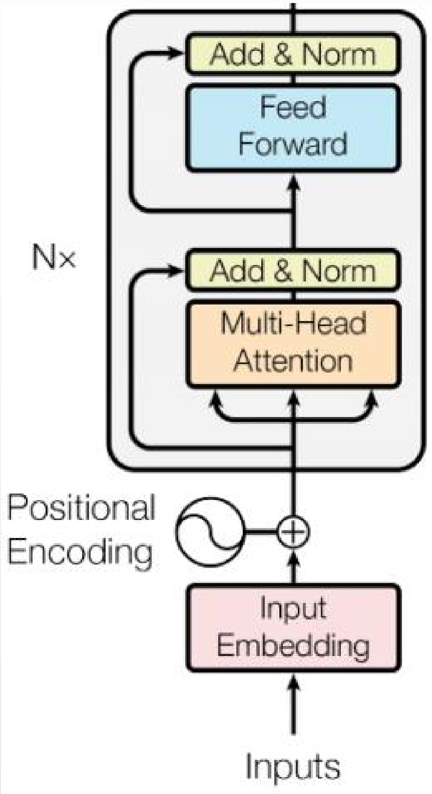

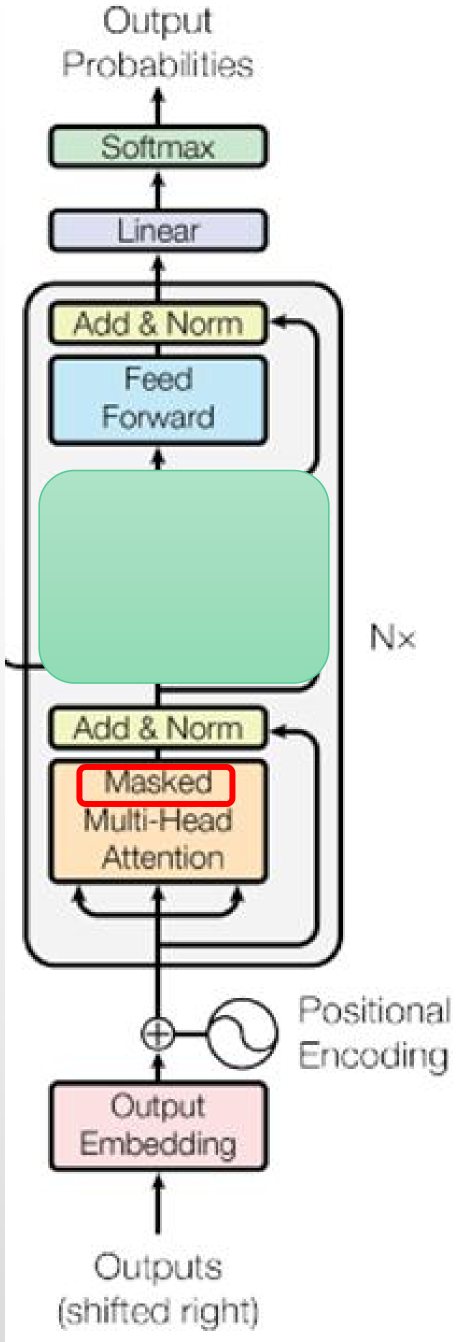

Encoder

Decoder

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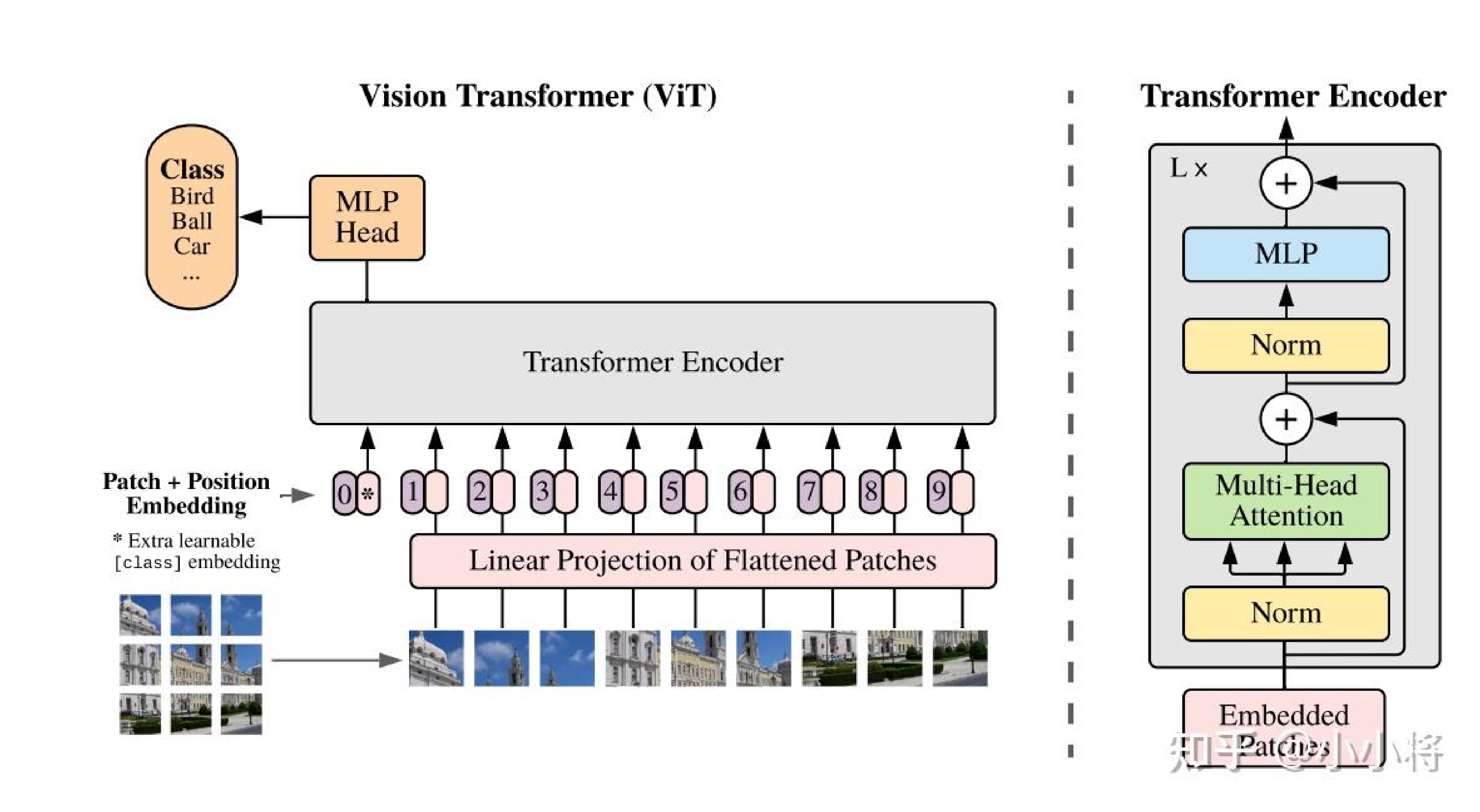
VIT



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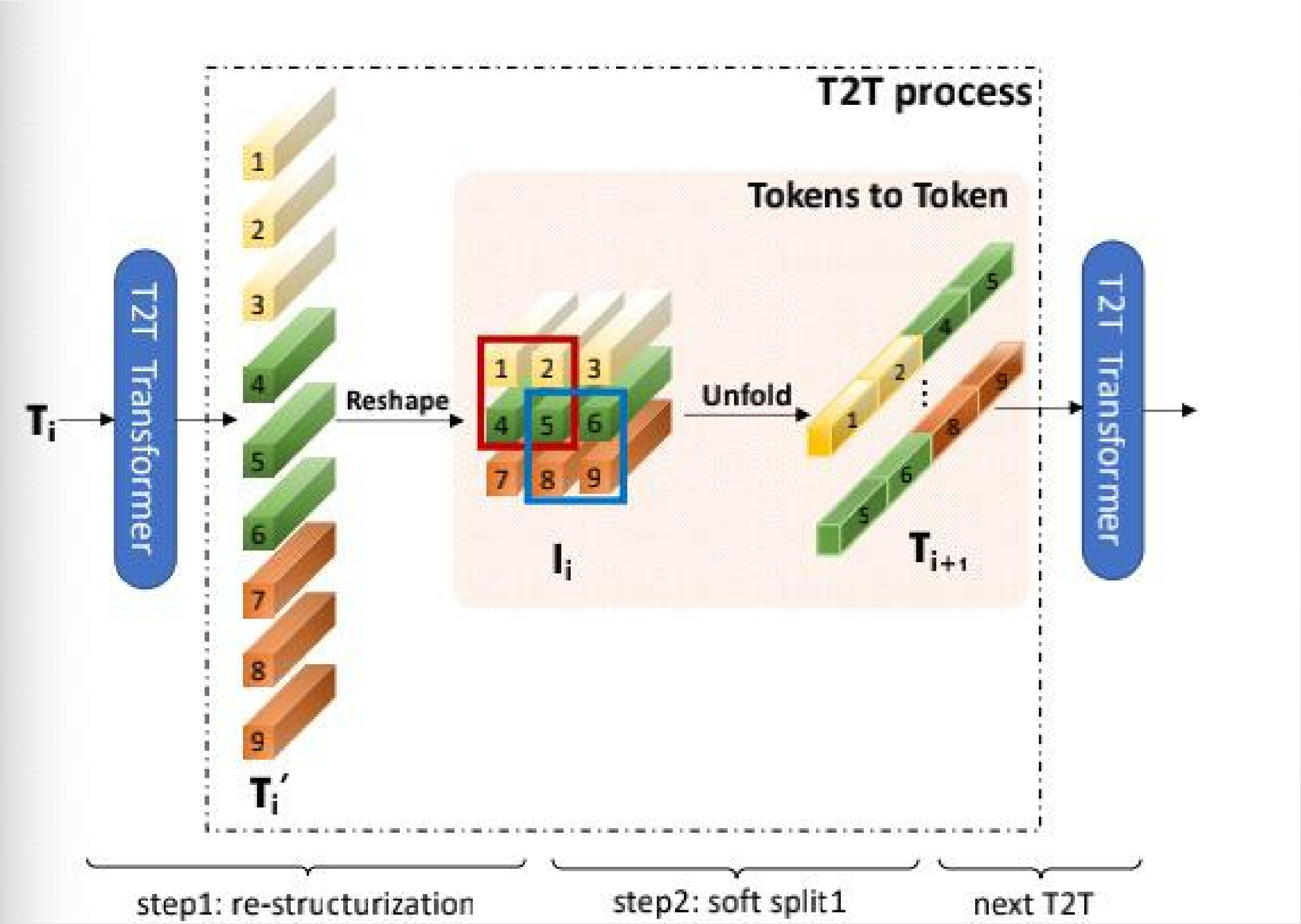
T2T-ViT



1）Restructurization

T' = MLP(MSA(T))

I =reshape（T'）

2）Soft Split

$$T_{i+1} = SS(I_i)\ ,\ i = 1, \cdots, (n-1)$$

Backbone

- Dense Connection，类似于DenseNet；
- Deep-narrow vs shallow-wide结构，类似于Wide-ResNet一文的讨论；
- Channel Attention，类似SENet；
- More Split Head，类似ResNeXt；
- Ghost操作，类似GhostNet。

结论：Deep-Narrow结构可以在通道层面通过减少通道维度减少冗余，可以通过提升深度提升特征丰富性。

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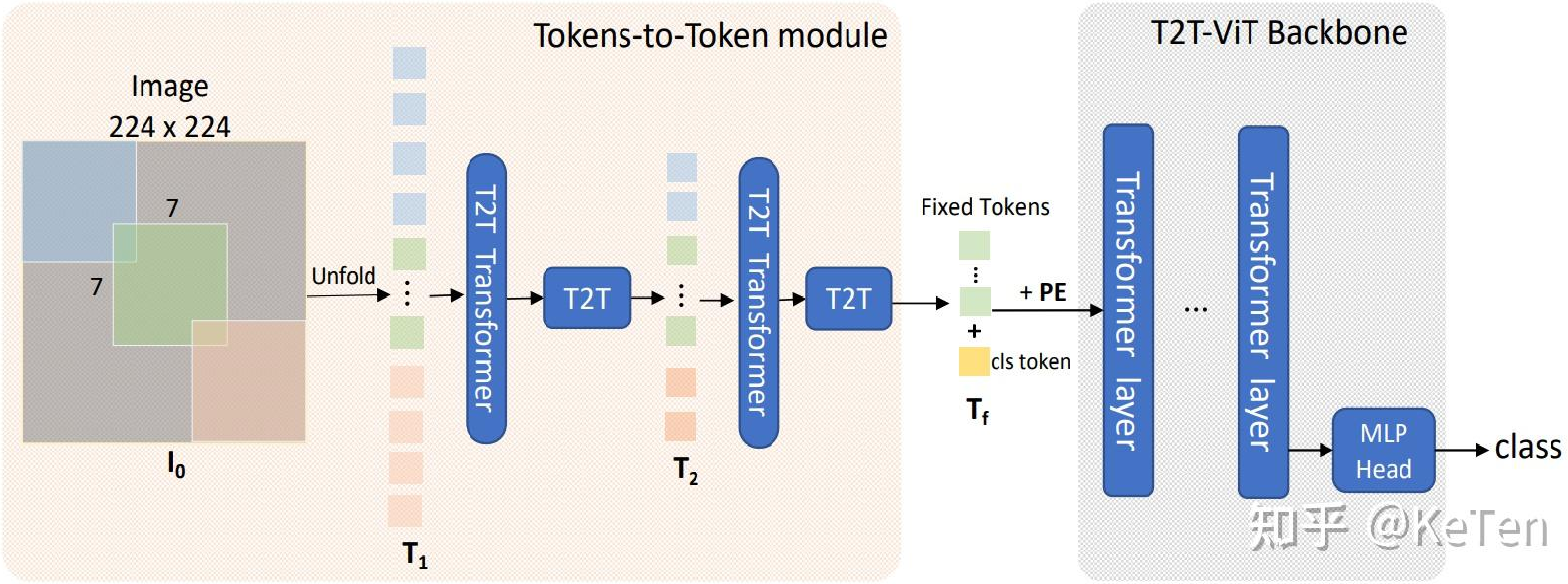

感谢大家！