LangCon 2020

Transformer 구현하기

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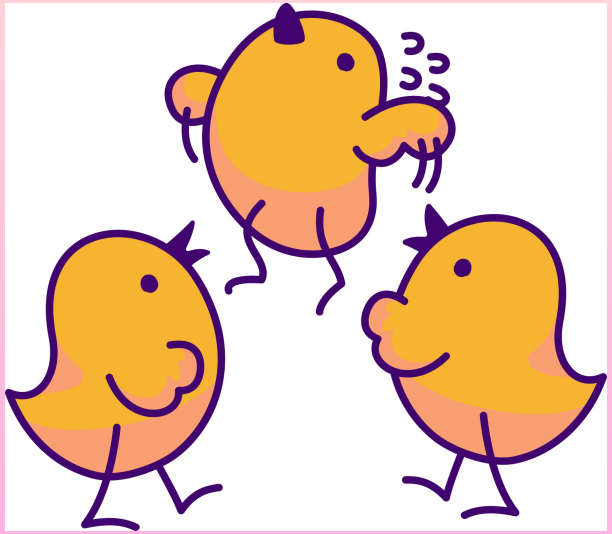
목차



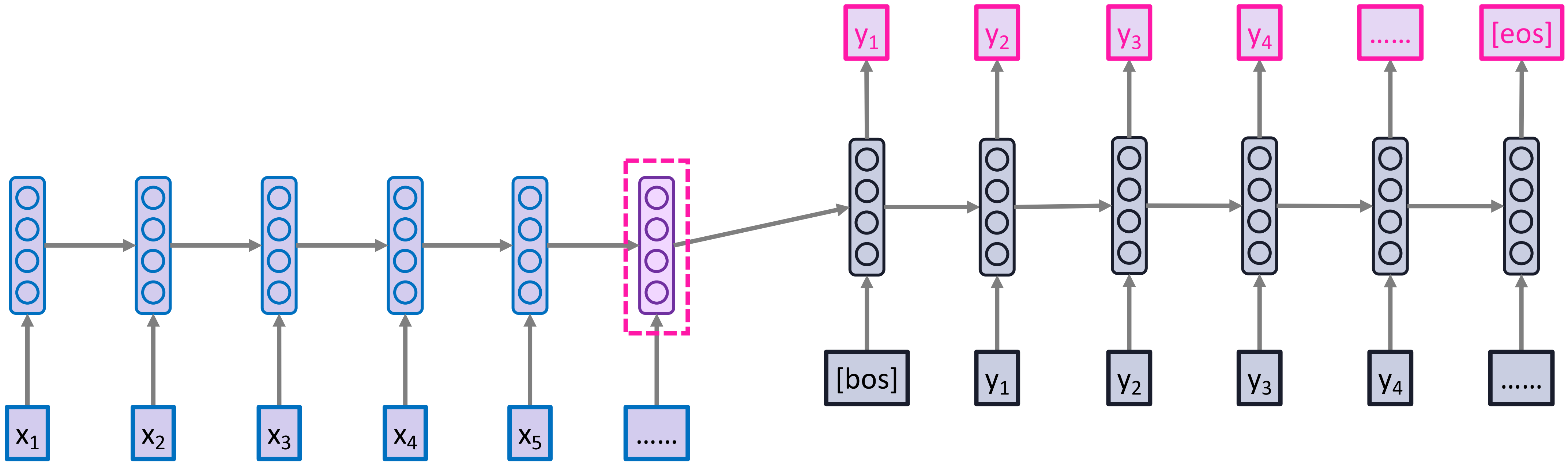
Why Transformer

Why Transformer (Seq2Seq)

Language Conference

Source Sentence Encoding

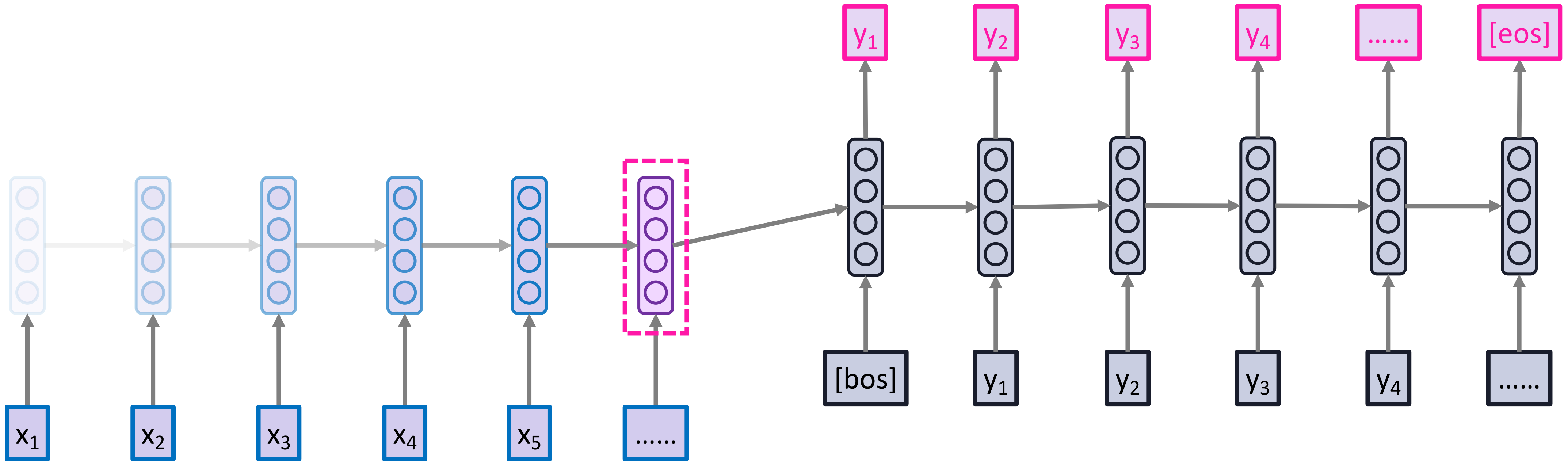
Source Sentence의 모든 정보를 저장 해야 함 (Information bottleneck)



Why Transformer (Seq2Seq)

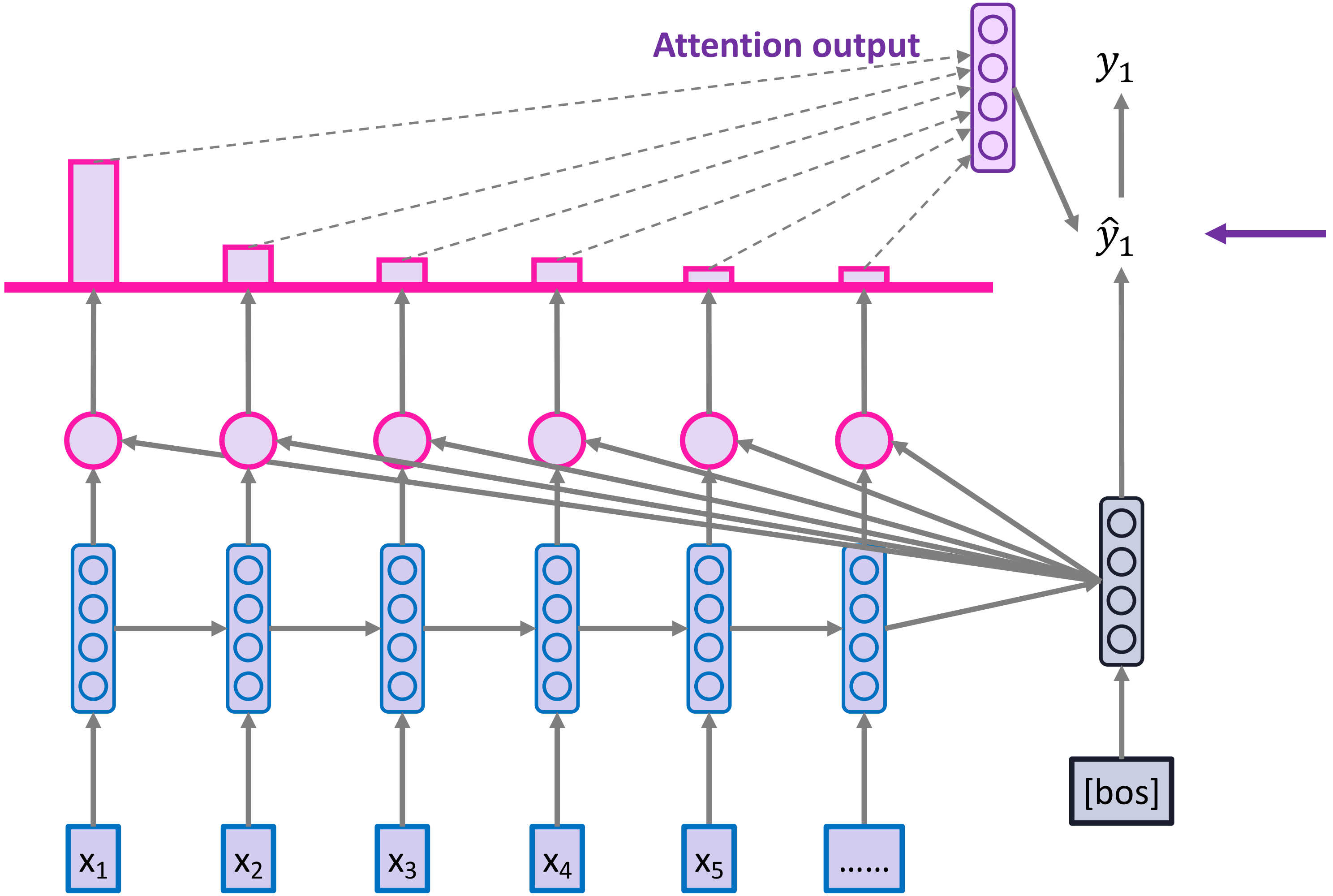
Source Sentence Encoding

과거 step의 정보는 최신 step의 보다 덜 사용 됨(Vanishing Gradient)



Why Transformer (Attention)

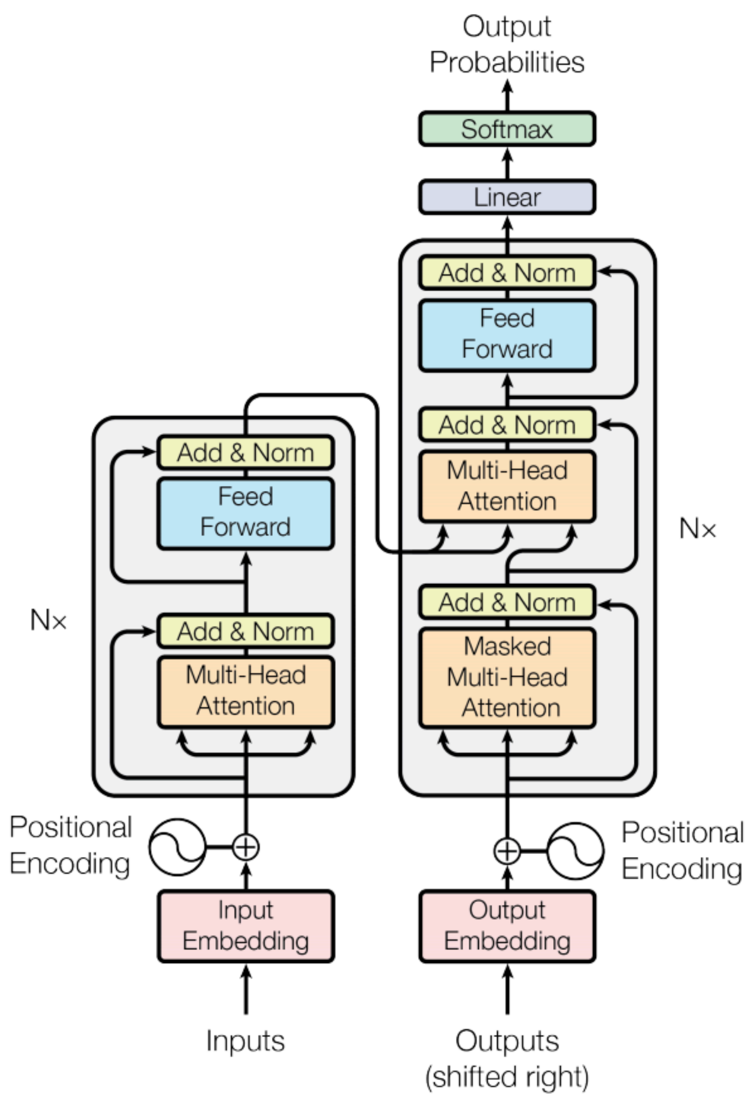
Language Conference

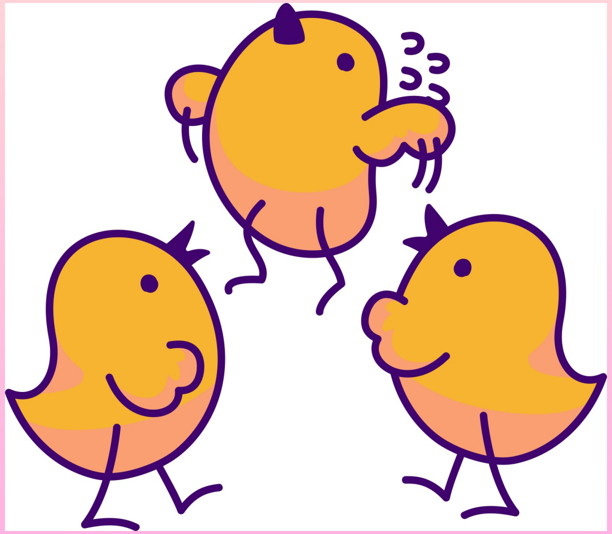


Concatinate attention output with decoder hiddenstate and compute output

Why Transformer (Transformer)

Language Conference





Embedding

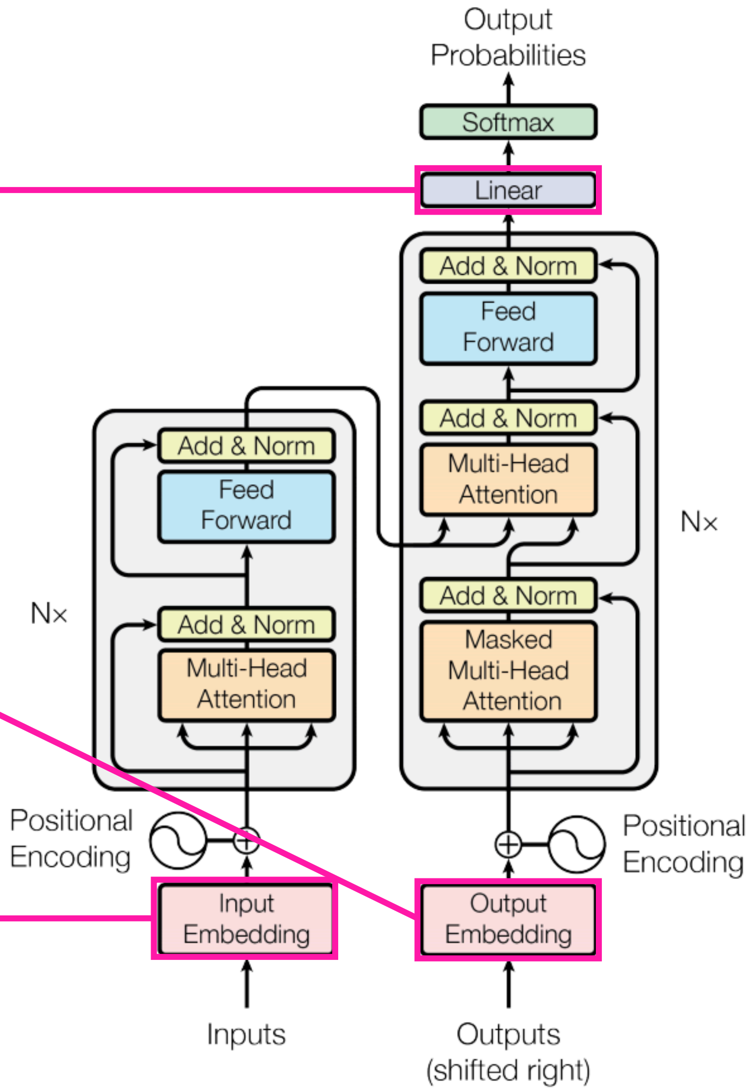
Embedding - Weight Shared

Weight Share

$$\mathbb{R}^{d_{model} \times n_{vocab}}$$

$$\mathbb{R}^{n_{vocab} \times d_{model}}$$

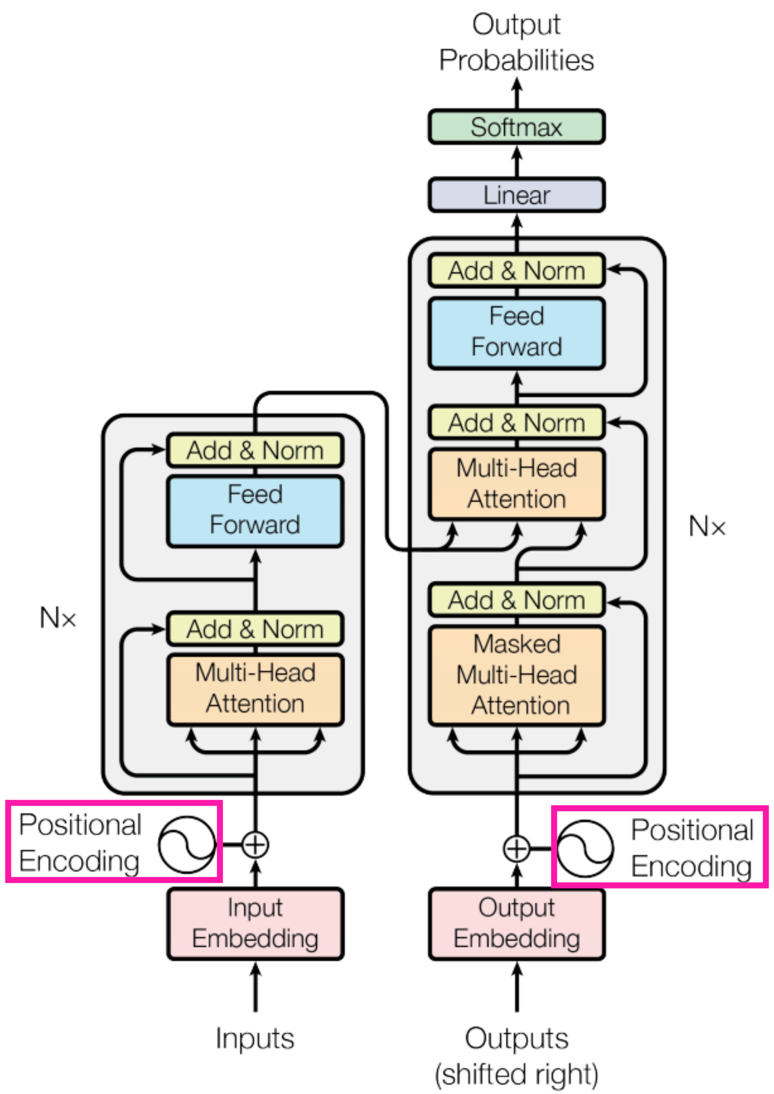
$$\mathbb{R}^{n_{vocab} \times d_{model}}$$



Embedding - Positional Encoding

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

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



Embedding - Positional Encoding

$$PE_{(pos,2i)} = \sin(\boxed{pos/10000^{2i/d_{model}}})$$

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

$pos/10000^{2i/d_{model}}$

$where\ seq = 16, d_{model} = 8$

0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
1	1.0	1.0	0.1	0.1	0.01	0.01	0.001	0.001
2	2.0	2.0	0.2	0.2	0.02	0.02	0.002	0.002
3	3.0	3.0	0.3	0.3	0.03	0.03	0.003	0.003
4	4.0	4.0	0.4	0.4	0.04	0.04	0.004	0.004
5	5.0	5.0	0.5	0.5	0.05	0.05	0.005	0.005

Embedding - Positional Encoding

$$PE_{(pos,2i)} = \boxed{\sin}(pos/10000^{2i/d_{model}})$$

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

$\sin(pos/10000^{2i/d_{model}})$

$where\ seq = 16, d_{model} = 8$

0	0.0000	1.0000	0.0000	1.0000	0.0000	1.0000	0.0000	1.0000
1	0.8415	0.5403	0.0998	0.9950	0.0100	1.0000	0.0010	1.0000
2	0.9093	-0.4161	0.1987	0.9801	0.0200	0.9998	0.0020	1.0000
3	0.1411	-0.9900	0.2955	0.9553	0.0300	0.9996	0.0030	1.0000
4	-0.756	-0.6536	0.3894	0.9211	0.0400	0.9992	0.0040	1.0000
5	-0.959	0.2837	0.4794	0.8776	0.0500	0.9988	0.0050	1.0000

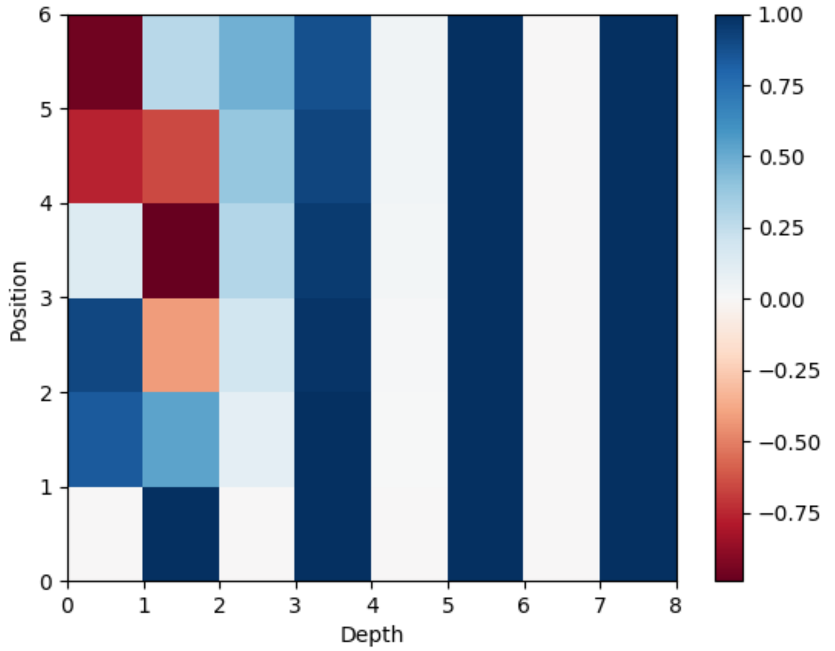
$\cos(pos/10000^{2i/d_{model}})$

Embedding - Positional Encoding

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

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

$where\ seq = 16, d_{model} = 8$

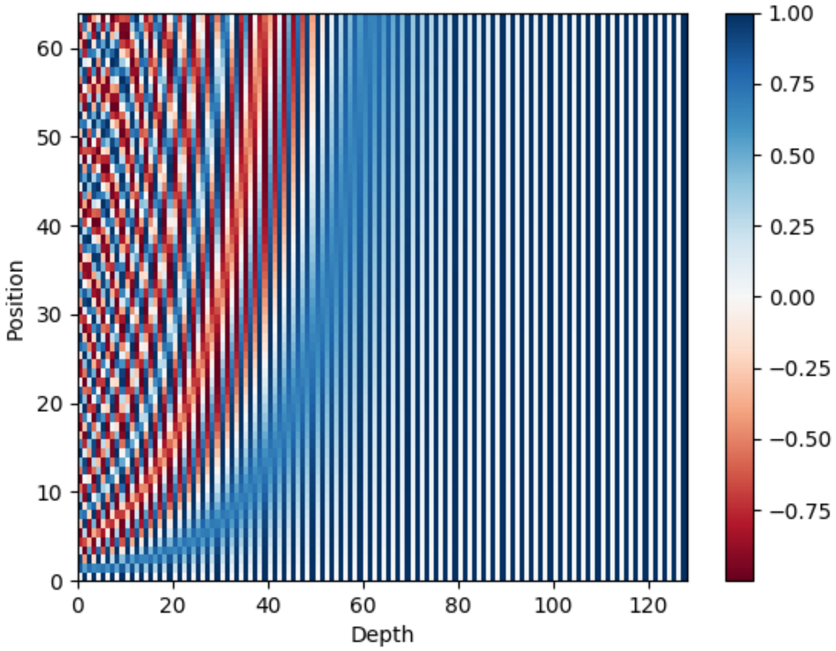


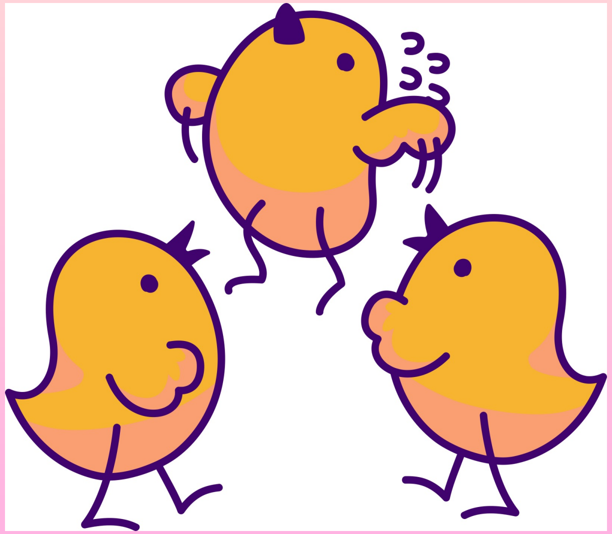
Embedding - Positional Encoding

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

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

$where\ seq = 64, d_{model} = 128$





Scaled Dot-Product Attention

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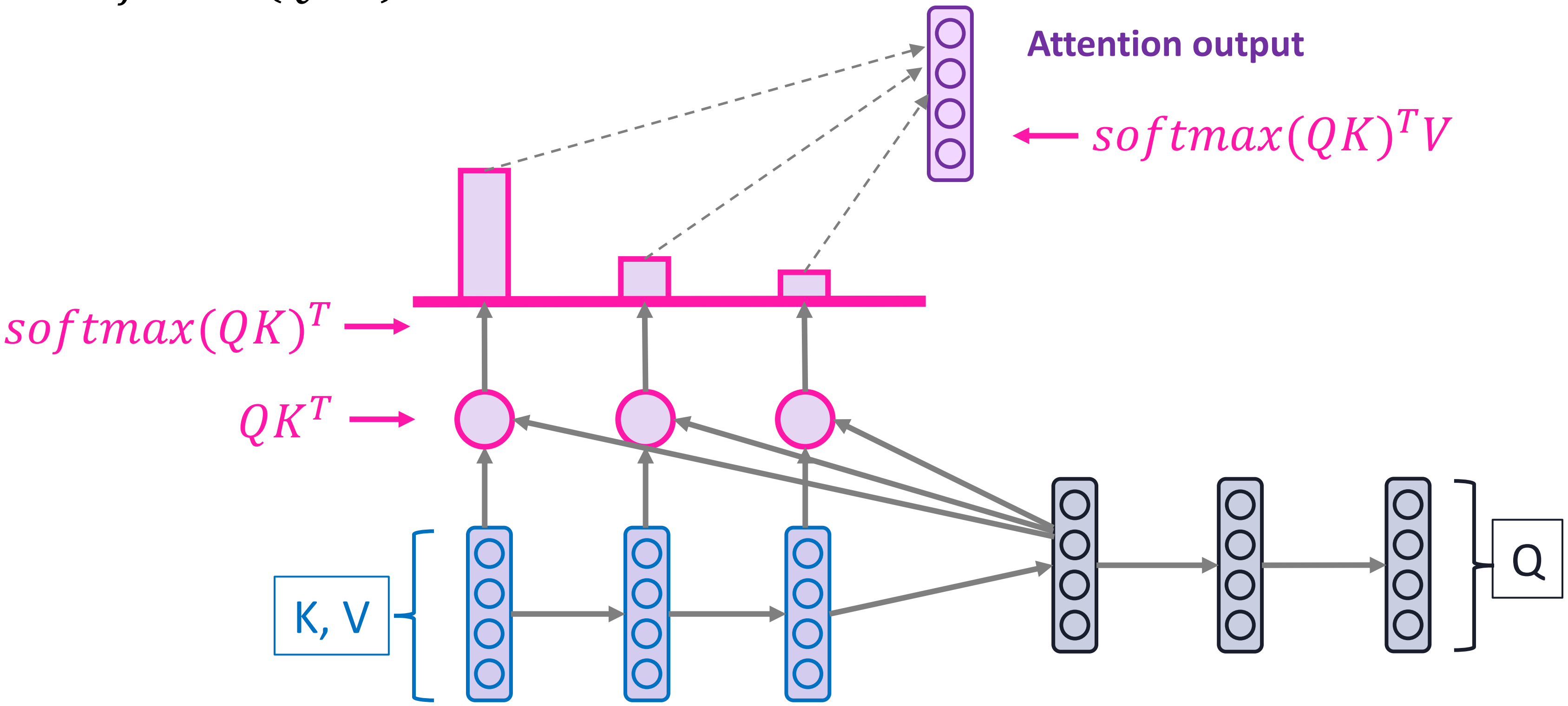
Scaled Dot-Product Attention

Dot-product Attention

$$Attention(Q, K, V) = softmax(QK^T)V$$



Scaled Dot-Product Attention

Dot-product Attention

$$Attention(Q,K,V) = softmax(QK^T)V$$

- $Q \in \mathbb{R}^{|Q| \times d_k}$
- $K \in \mathbb{R}^{|K| \times d_k}$
- $V \in \mathbb{R}^{|K| \times d_v}$
- $QK^T = [|Q| \times d_k] \times [d_k \times |K|]$

Problem of Dot-product Attention

- d_k가 커지면 QK^T의 결과값의 편차가 커짐
- $softmax(QK^T)$의 결과 값이 편차가 커짐
- Gradient가 작아짐
- 학습이 잘 안됨

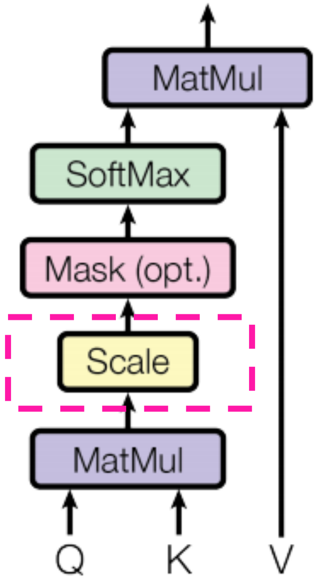
Scaled Dot-product Attention

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

- QK^T의 결과를 $\sqrt{d_k}$로 나눔
- 값의 편차가 줄어듬

Scaled Dot-Product Attention

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



Scaled Dot-Product Attention

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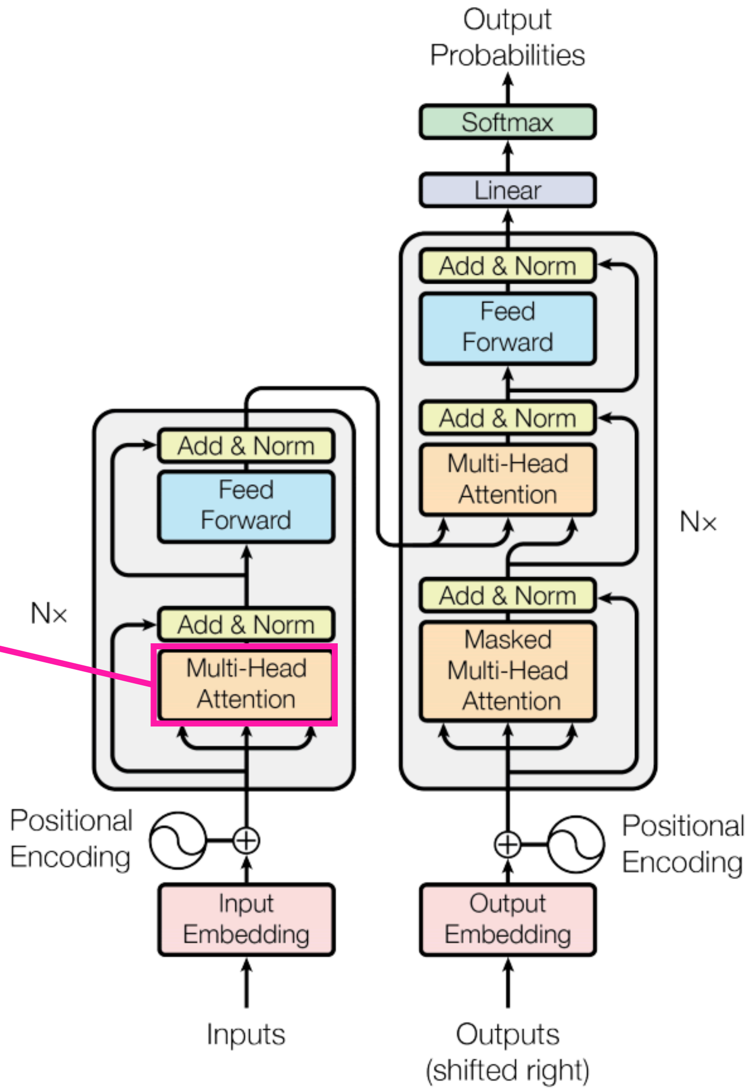
- Q: encoder hidden
- K: encoder hidden
- V: encoder hidden

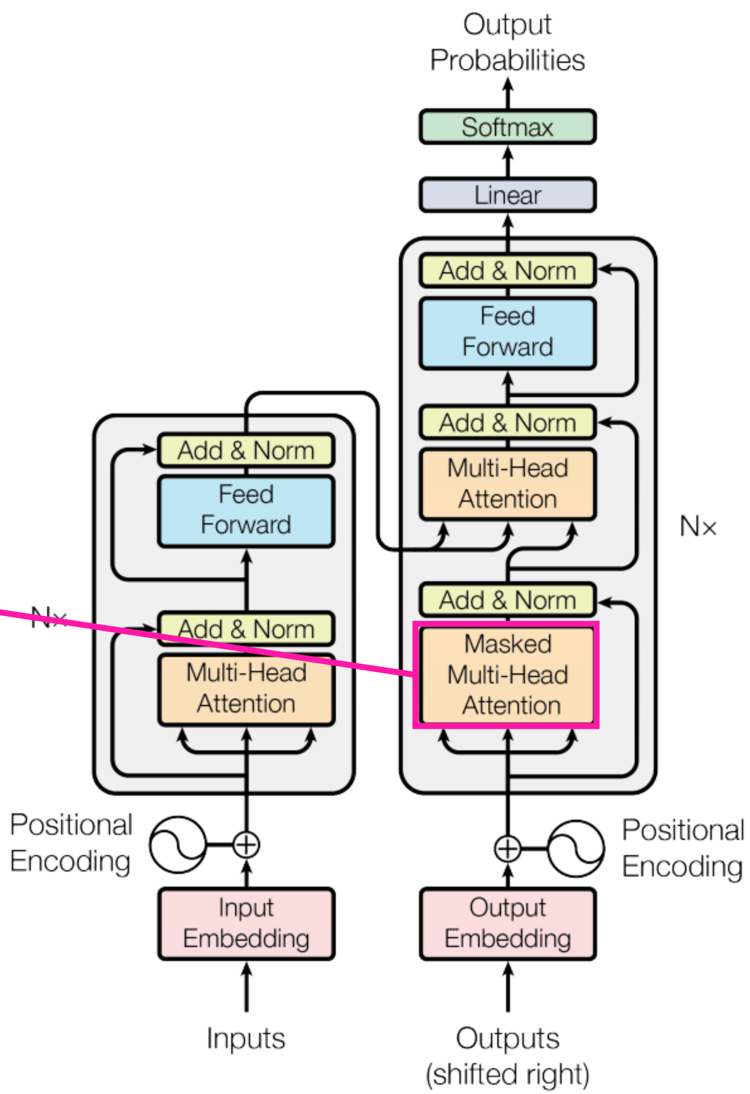
Encoder Self Attention



Scaled Dot-Product Attention

- Q: decoder hidden
- K: decoder hidden
- V: decoder hidden

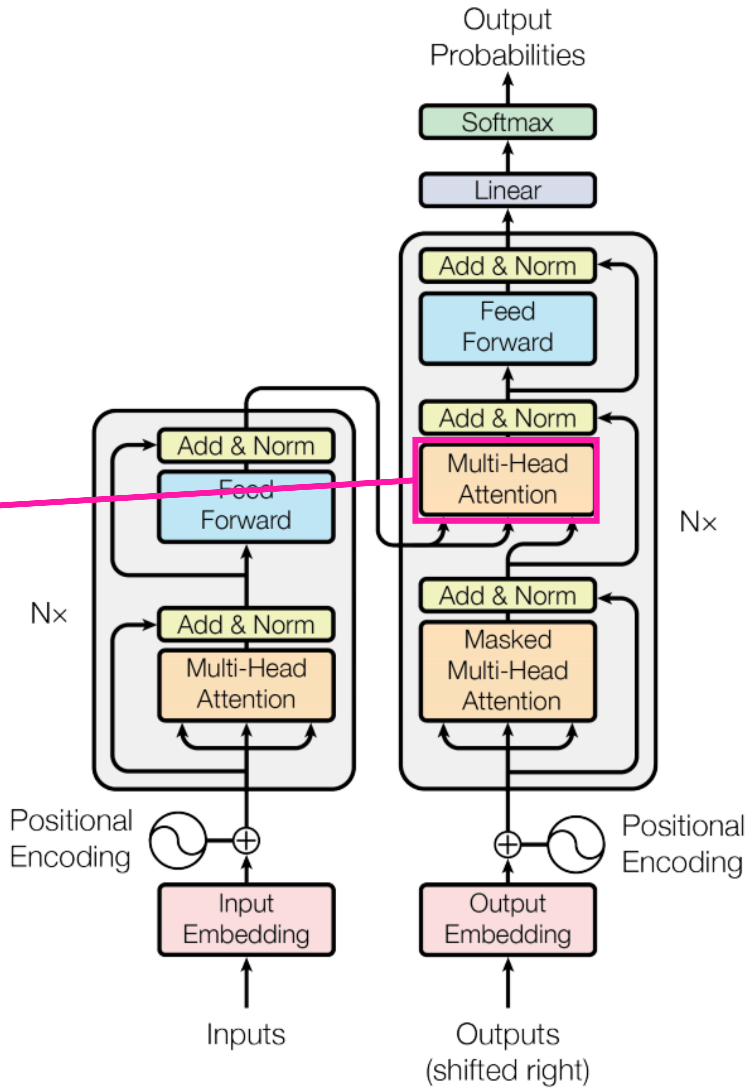
Decoder Self Attention (masked)



Scaled Dot-Product Attention

- **Q: decoder hidden**
- **K: encoder hidden**
- **V: encoder hidden**

Encoder-Decoder Attention



Scaled Dot-Product Attention

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

K

V

→

Education	0.1	0.2	0.3	0.4
is	0.2	0.3	0.4	0.5
most	0.3	0.4	0.5	0.6
powerful	0.4	0.3	0.2	0.1
weapon	0.5	0.4	0.3	0.2
[pad]	0.1	0.1	0.1	0.1

$[\boldsymbol{seq_K} \times \boldsymbol{d_{model}}]$

- $\boldsymbol{seq_K}$: 6
- $\boldsymbol{d_{model}}$: 4

Q

→

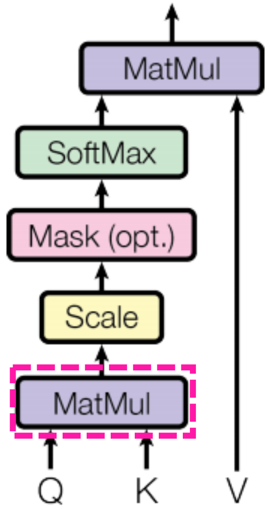
교육은	0.1	0.2	0.3	0.4
가장	0.2	0.3	0.4	0.5
중요한	0.3	0.4	0.5	0.6
무기이다	0.4	0.3	0.2	0.1
[pad]	0.1	0.1	0.1	0.1

$[\boldsymbol{seq_Q} \times \boldsymbol{d_{model}}]$

- $\boldsymbol{seq_Q}$: 5
- $\boldsymbol{d_{model}}$: 4

Scaled Dot-Product Attention

$$Attention(Q,K,V) = softmax\left(\frac{\boxed{QK^T}}{\sqrt{d_k}}\right)V$$



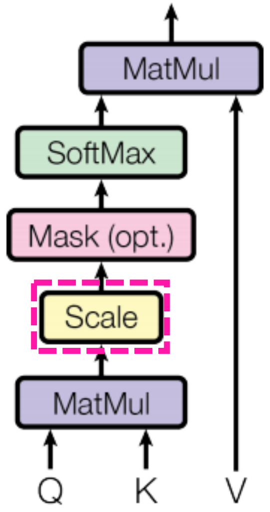
$\boxed{QK^T}$ →

	Education	is	most	powerful	weapon	[pad]
교육은	0.3	0.4	0.5	0.2	0.3	0.1
가장	0.4	0.54	0.68	0.3	0.44	0.14
중요한	0.5	0.68	0.86	0.4	0.58	0.18
무기이다	0.2	0.3	0.4	0.3	0.4	0.1
[pad]	0.1	0.14	0.18	0.1	0.14	0.04

$$[seq_Q \times d_{model}] \times [d_{model} \times seq_K] = [seq_Q \times seq_K]$$

Scaled Dot-Product Attention

$$Attention(Q,K,V) = softmax\left(\frac{QK^T}{\boxed{\sqrt{d_k}}}\right)V$$

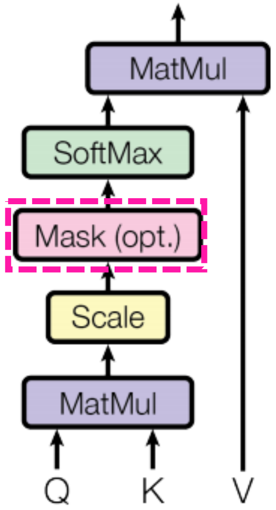


$$\frac{QK^T}{\sqrt{d_k}} \rightarrow$$

	Education	is	most	powerful	weapon	[pad]
교육은	0.15	0.2	0.25	0.1	0.15	0.05
가장	0.2	0.27	0.34	0.15	0.22	0.07
중요한	0.25	0.34	0.43	0.2	0.29	0.09
무기이다	0.1	0.15	0.2	0.15	0.2	0.05
[pad]	0.05	0.07	0.09	0.05	0.07	0.02

Scaled Dot-Product Attention

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

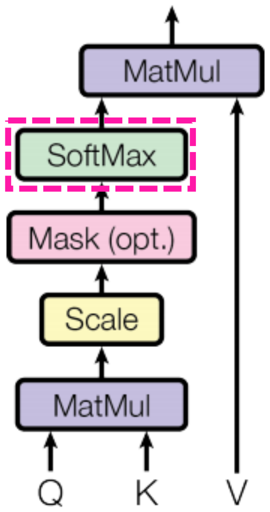


$$mask\left(\frac{QK^T}{\sqrt{d_k}}\right)$$

	Education	is	most	powerful	weapon	[pad]
교육은	0.15	0.2	0.25	0.1	0.15	-inf
가장	0.2	0.27	0.34	0.15	0.22	-inf
중요한	0.25	0.34	0.43	0.2	0.29	-inf
무기이다	0.1	0.15	0.2	0.15	0.2	-inf
[pad]	0.05	0.07	0.09	0.05	0.07	-inf

Scaled Dot-Product Attention

$$Attention(Q,K,V) = \boxed{softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right)V$$

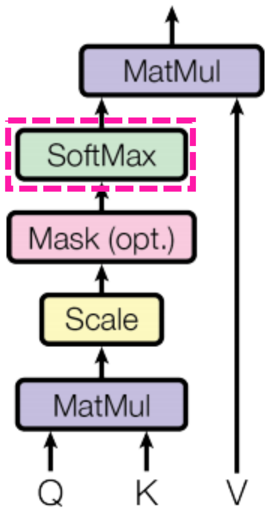


$$softmax\left(\frac{QK^T}{\sqrt{d_k}}\right) \rightarrow$$

	Education	is	most	powerful	weapon	[pad]
교육은	0.19	0.20	0.21	0.18	0.10	0
가장	0.19	0.20	0.22	0.18	0.19	0
중요한	0.18	0.20	0.22	0.18	0.19	0
무기이다	0.18	0.19	0.20	0.19	0.20	0
[pad]	0.19	0.20	0.20	0.19	0.20	0

Scaled Dot-Product Attention

$$Attention(Q,K,V) = softmax\left(\frac{QK^T}{\sqrt{d_k}}\right)\boxed{V}$$

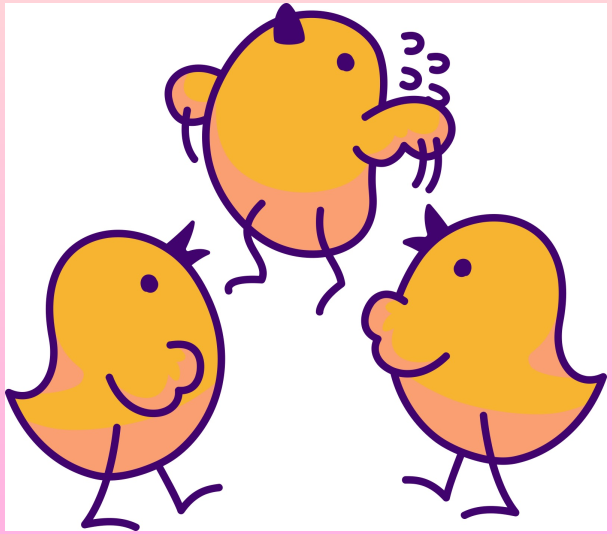


$$\boldsymbol{softmax\left(\frac{QK^T}{\sqrt{d_k}}\right)V}$$

교육은	0.29	0.32	0.34	0.36
가장	0.29	0.32	0.34	0.37
중요한	0.29	0.32	0.34	0.37
무기이다	0.30	0.32	0.34	0.36
[pad]	0.30	0.32	0.34	0.36

Weighted sum of V

$$[\boldsymbol{seq_Q \times seq_K}] \times [\boldsymbol{seq_K \times d_{model}}] = [\boldsymbol{seq_Q \times d_{model}}]$$



Scaled Dot-Product Attention (masked)

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Scaled Dot-Product Attention (masked)

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

K

V

Education	0.1	0.2	0.3	0.4
is	0.2	0.3	0.4	0.5
most	0.3	0.4	0.5	0.6
powerful	0.4	0.3	0.2	0.1
weapon	0.5	0.4	0.3	0.2
[pad]	0.1	0.1	0.1	0.1

$[\boldsymbol{seq_K} \times \boldsymbol{d_{model}}]$

- $\boldsymbol{seq_K}$: 6
- $\boldsymbol{d_{model}}$: 4

Q

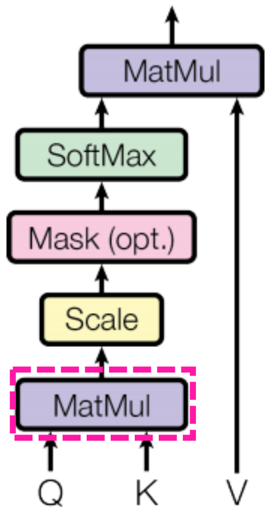
교육은	0.1	0.2	0.3	0.4
가장	0.2	0.3	0.4	0.5
중요한	0.3	0.4	0.5	0.6
무기이다	0.4	0.3	0.2	0.1
[pad]	0.1	0.1	0.1	0.1

$[\boldsymbol{seq_Q} \times \boldsymbol{d_{model}}]$

- $\boldsymbol{seq_Q}$: 5
- $\boldsymbol{d_{model}}$: 4

Scaled Dot-Product Attention (masked)

$$Attention(Q,K,V) = softmax\left(\frac{\boxed{QK^T}}{\sqrt{d_k}}\right)V$$



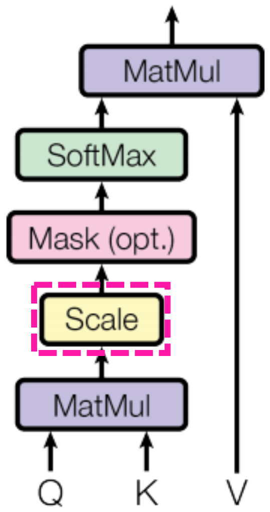
QK^T →

	Education	is	most	powerful	weapon	[pad]
교육은	0.3	0.4	0.5	0.2	0.3	0.1
가장	0.4	0.54	0.68	0.3	0.44	0.14
중요한	0.5	0.68	0.86	0.4	0.58	0.18
무기이다	0.2	0.3	0.4	0.3	0.4	0.1
[pad]	0.1	0.14	0.18	0.1	0.14	0.04

$$[seq_Q \times d_{model}] \times [d_{model} \times seq_K] = [seq_Q \times seq_K]$$

Scaled Dot-Product Attention (masked)

$$Attention(Q,K,V) = softmax\left(\frac{QK^T}{\boxed{\sqrt{d_k}}}\right)V$$

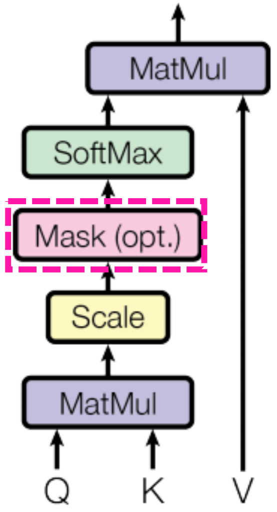


$$\frac{QK^T}{\sqrt{d_k}} \rightarrow$$

	Education	is	most	powerful	weapon	[pad]
교육은	0.15	0.2	0.25	0.1	0.15	0.05
가장	0.2	0.27	0.34	0.15	0.22	0.07
중요한	0.25	0.34	0.43	0.2	0.29	0.09
무기이다	0.1	0.15	0.2	0.15	0.2	0.05
[pad]	0.05	0.07	0.09	0.05	0.07	0.02

Scaled Dot-Product Attention (masked)

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



$$mask\left(\frac{QK^T}{\sqrt{d_k}}\right)$$

	Education	is	most	powerful	weapon	[pad]
교육은	0.15	-inf	-inf	-inf	-inf	-inf
가장	0.2	0.27	-inf	-inf	-inf	-inf
중요한	0.25	0.34	0.43	-inf	-inf	-inf
무기이다	0.1	0.15	0.2	0.15	-inf	-inf
[pad]	0.05	0.07	0.09	0.05	0.07	-inf

Can't see next value

Scaled Dot-Product Attention (masked)

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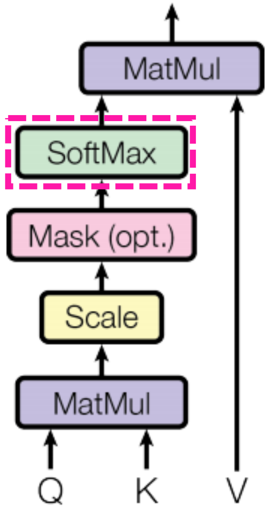
$$Attention(Q,K,V) = \boxed{softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right)V$$

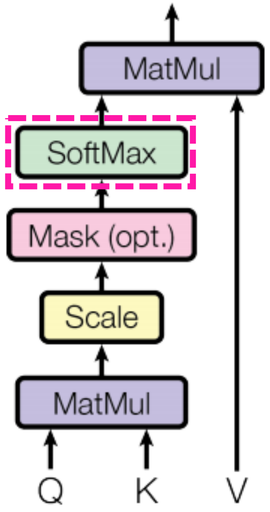


$$softmax(\frac{QK^T}{\sqrt{d_k}})$$

	Education	is	most	powerful	weapon	[pad]
교육은	1.00	0	0	0	0	0
가장	0.48	0.51	0	0	0	0
중요한	0.30	0.33	0.36	0	0	0
무기이다	0.23	0.24	0.26	0.24	0	0
[pad]	0.19	0.20	0.20	0.19	0.20	0

Scaled Dot-Product Attention (masked)

$$Attention(Q,K,V) = softmax\left(\frac{QK^T}{\sqrt{d_k}}\right)\boxed{V}$$

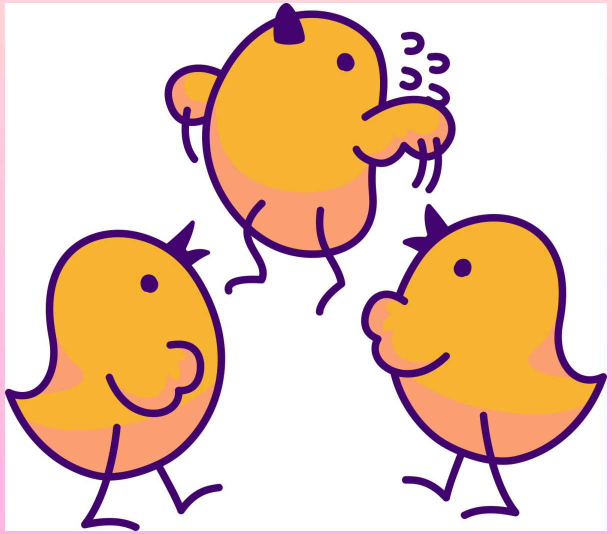


$$softmax\left(\frac{QK^T}{\sqrt{d_k}}\right)V$$

교육은	0.1	0.2	0.3	0.4
가장	0.15	0.25	0.35	0.45
중요한	0.20	0.30	0.40	0.50
무기이다	0.25	0.30	0.35	0.40
[pad]	0.30	0.32	0.34	0.36

Weighted sum of V

$$[seq_Q \times seq_K] \times [seq_K \times d_{model}] = [seq_Q \times d_{model}]$$

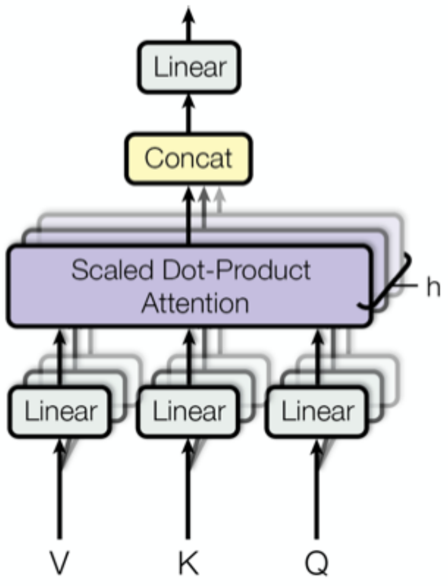


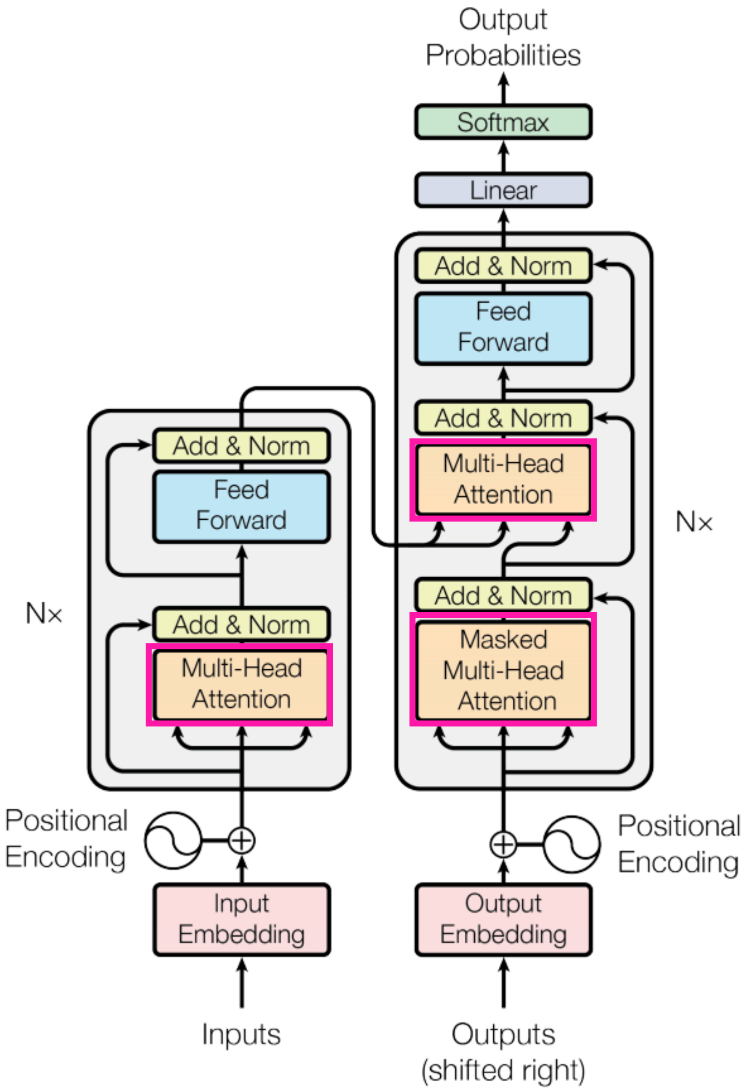
Multi-Head Attention

Multi-Head Attention

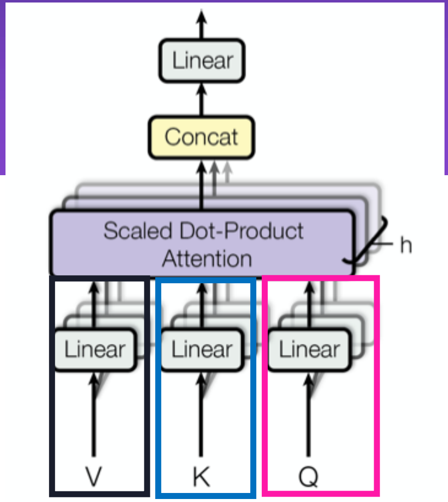
$$MultiHead(Q,K,V) = concatenate(head_1, \ldots, head_h)W^O$$

$$where\ head_i = Attention(QW_i^Q, KW_i^K, VW_i^V)$$



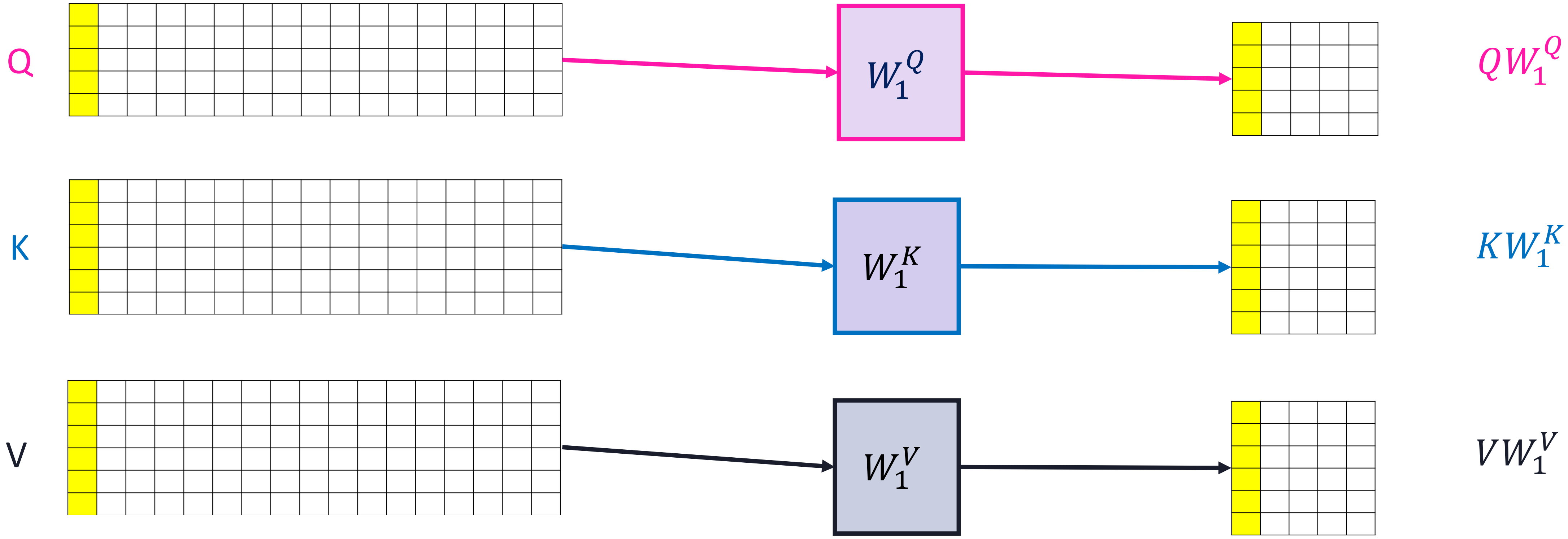


Multi-Head Attention



$$MultiHead(Q, K, V) = concatenate(head_1, \dots, head_h)W^O$$

$$where\ head_i = Attention(\boxed{QW_i^Q}, \boxed{KW_i^K}, \boxed{VW_i^V})$$



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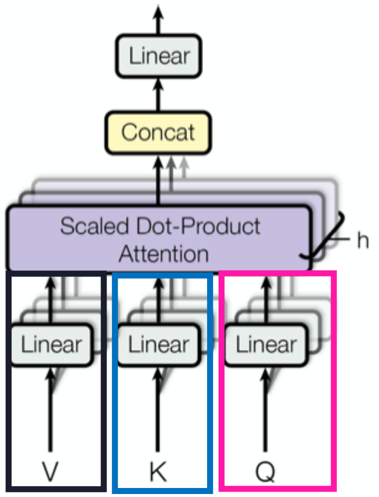

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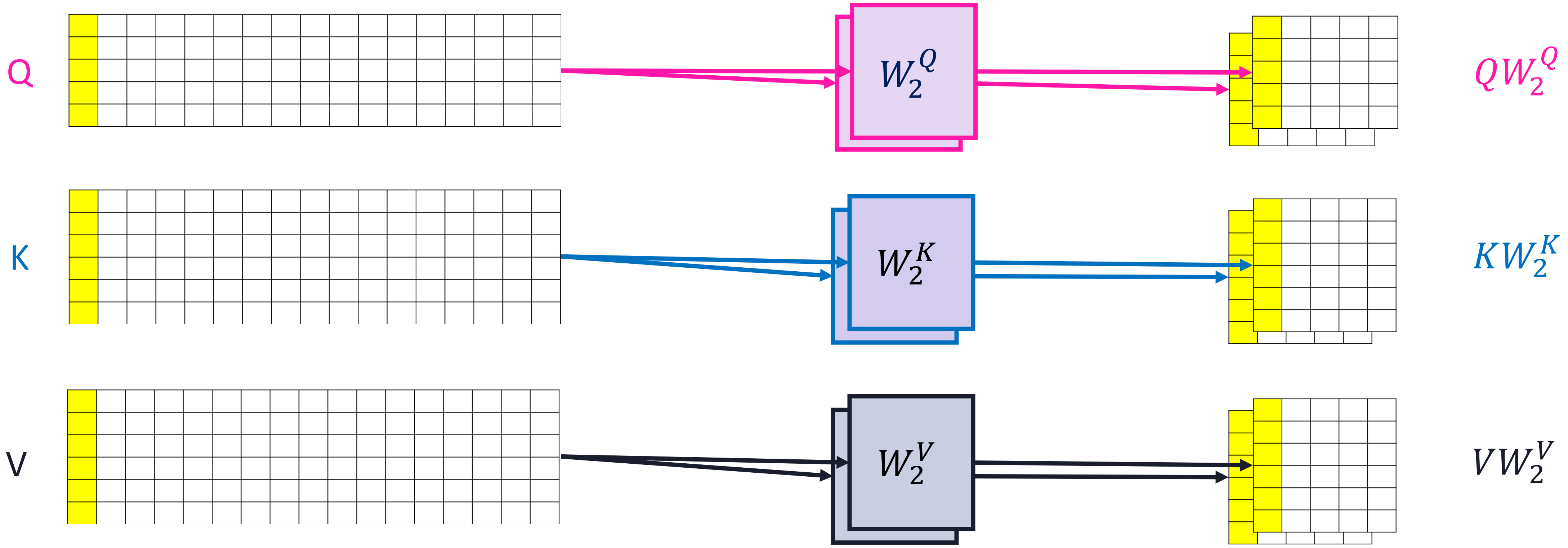

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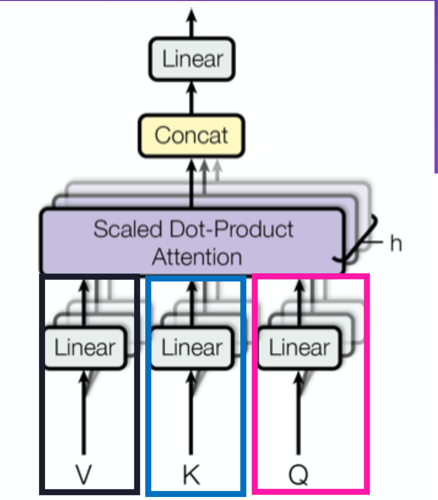

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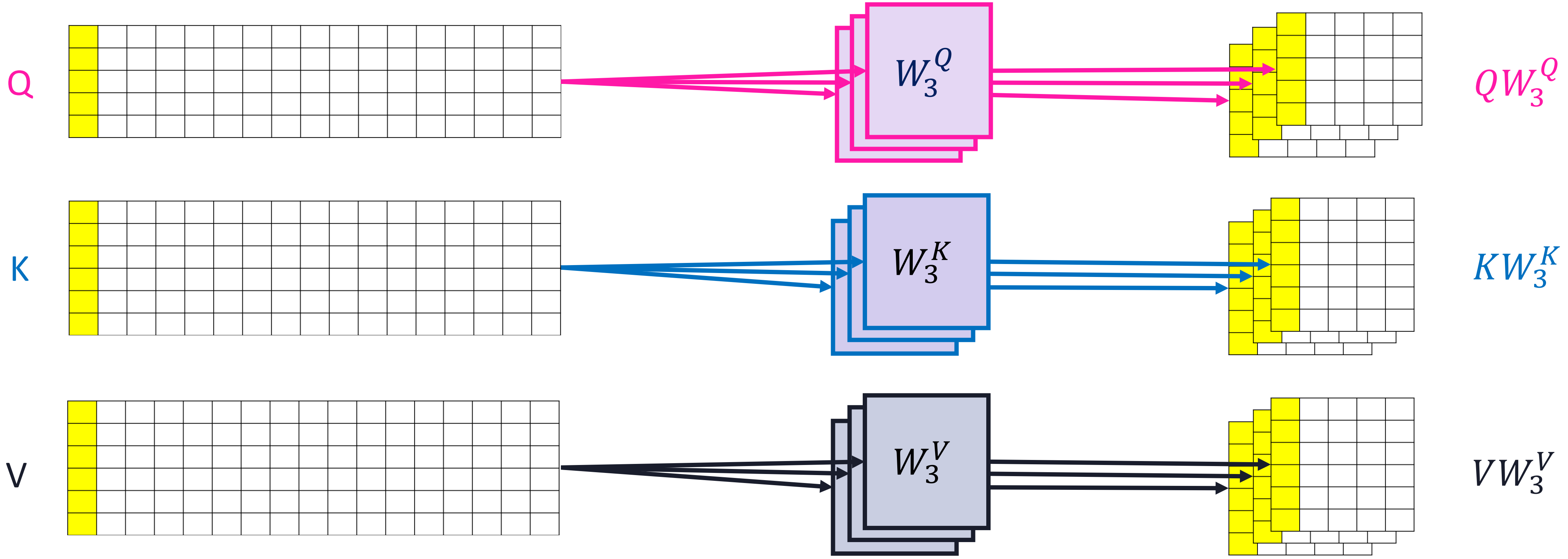

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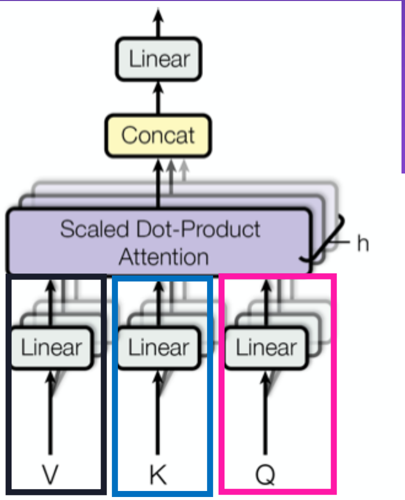

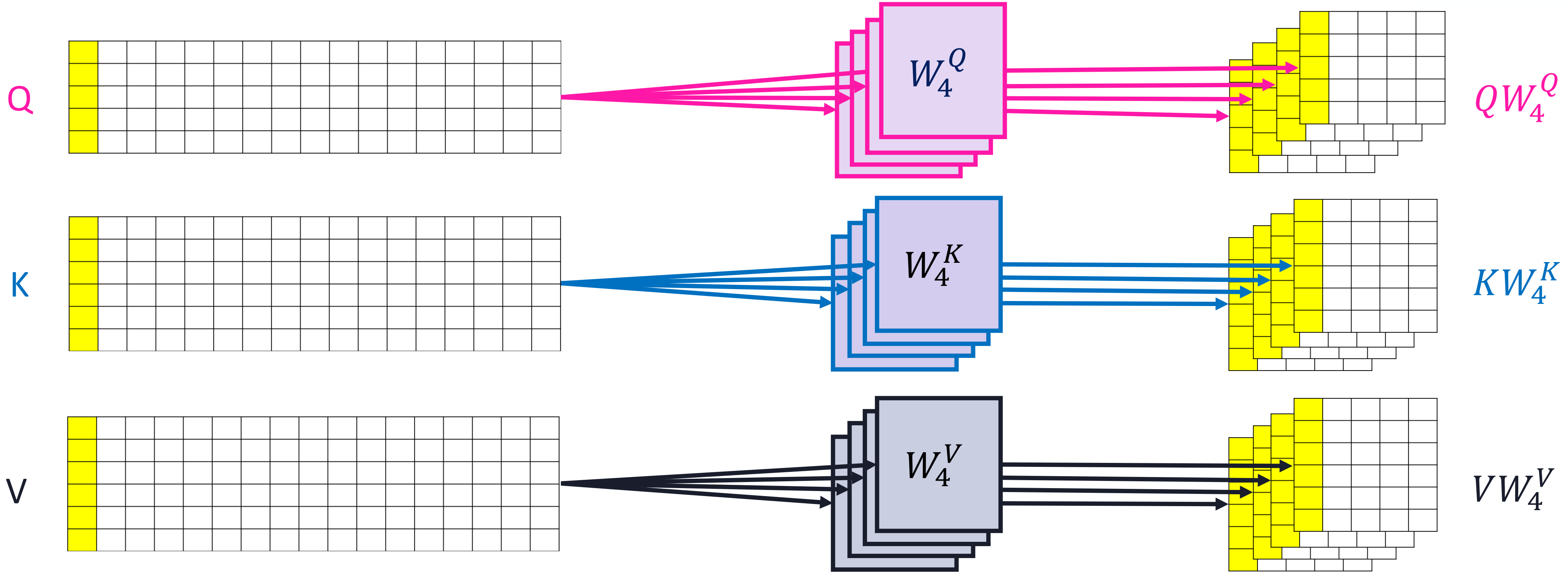

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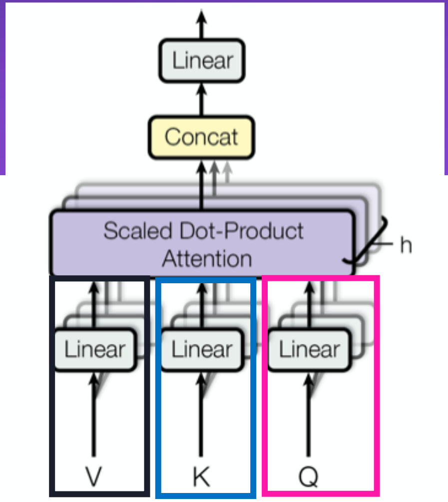
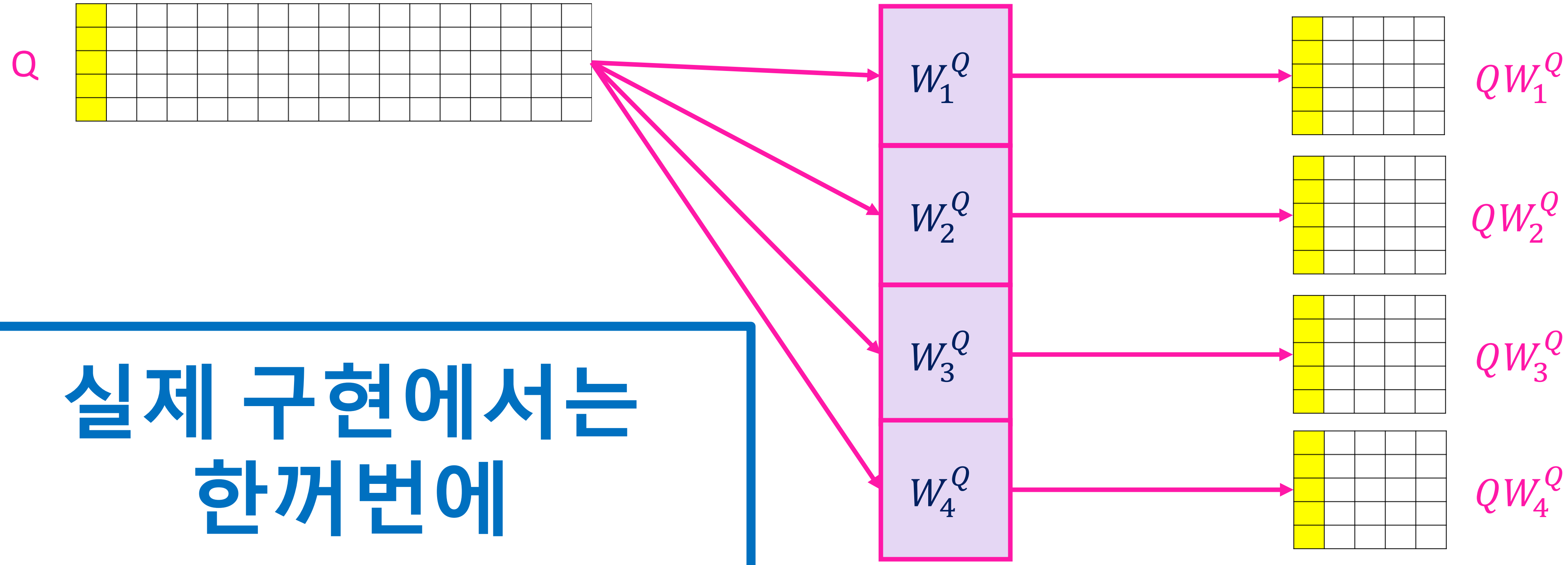
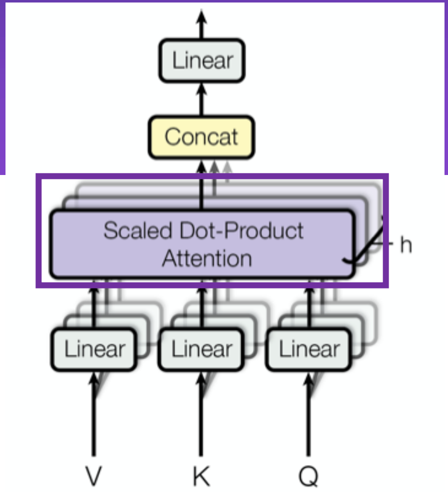




실제 구현에서는 한꺼번에

Multi-Head Attention



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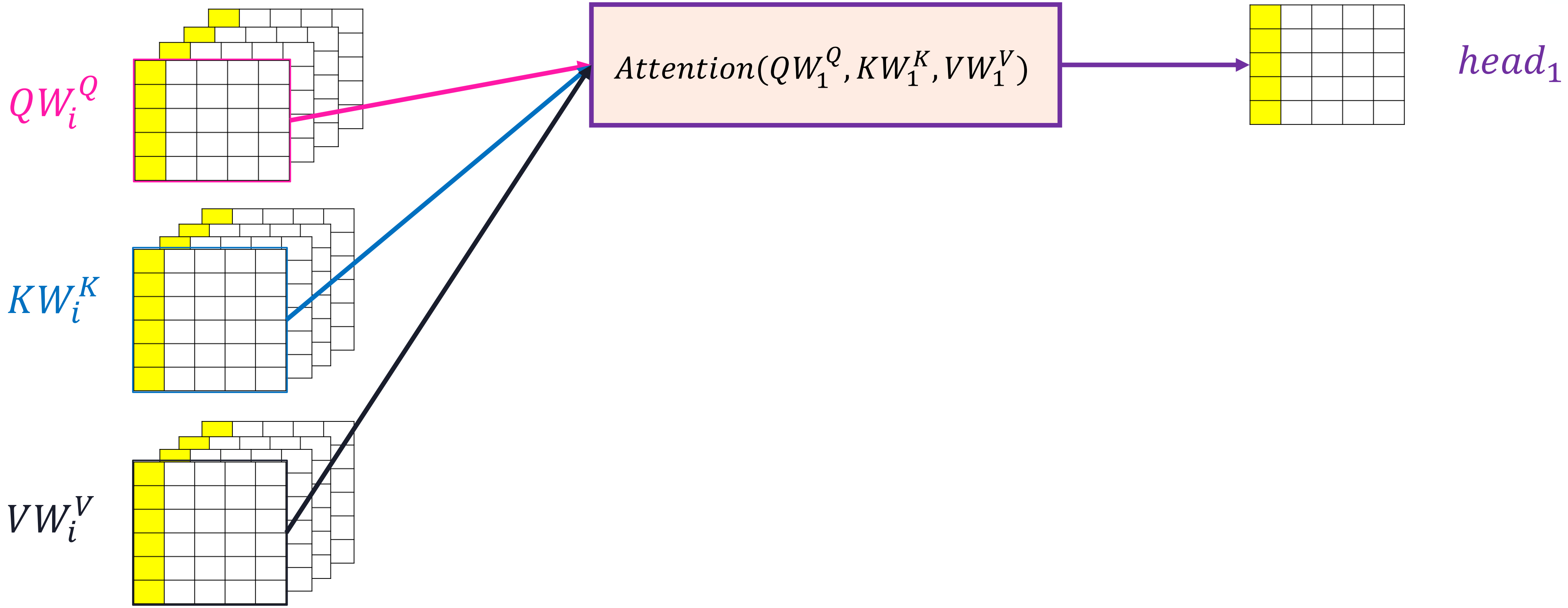

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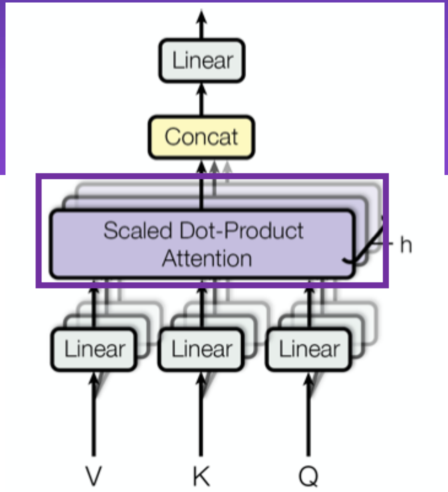

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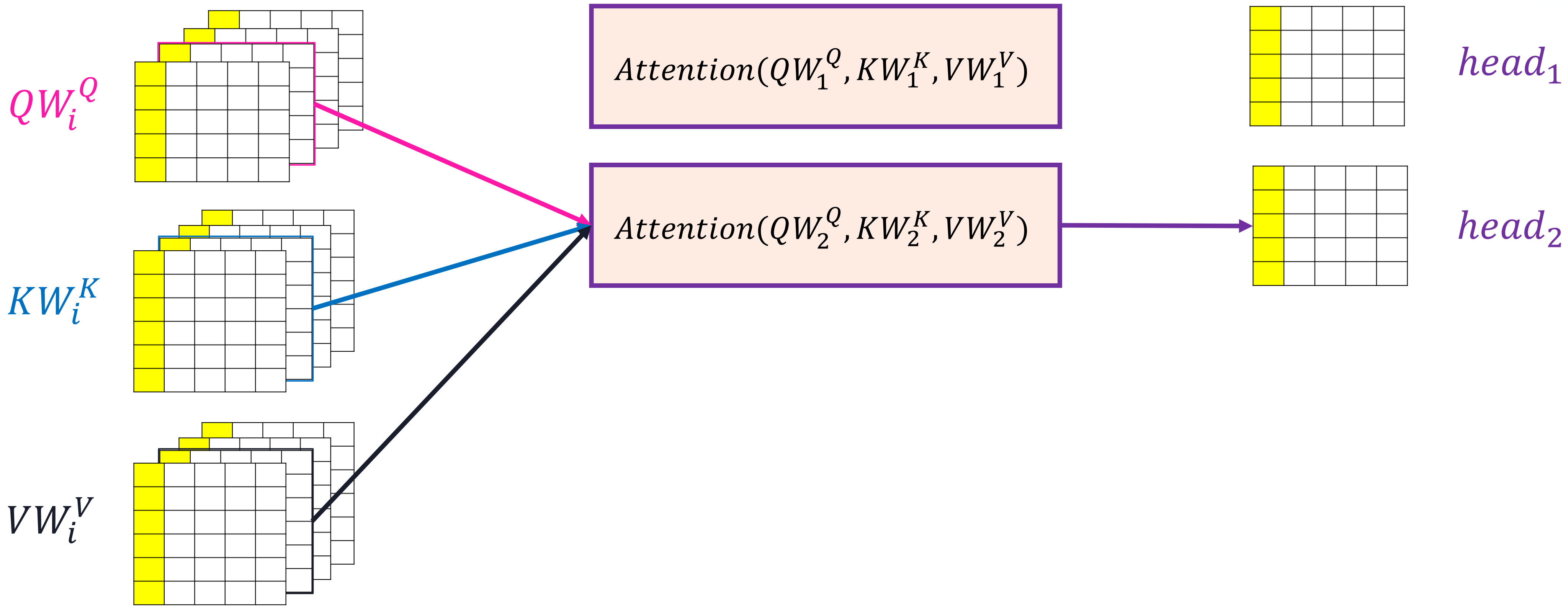

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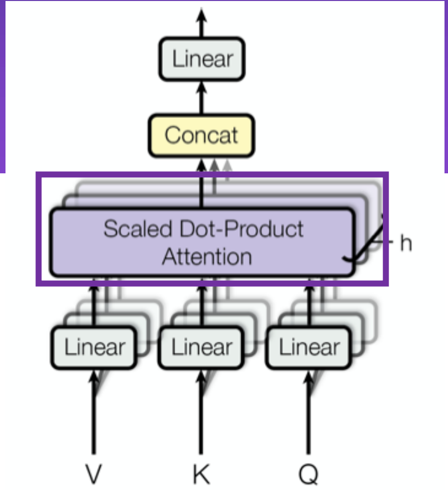

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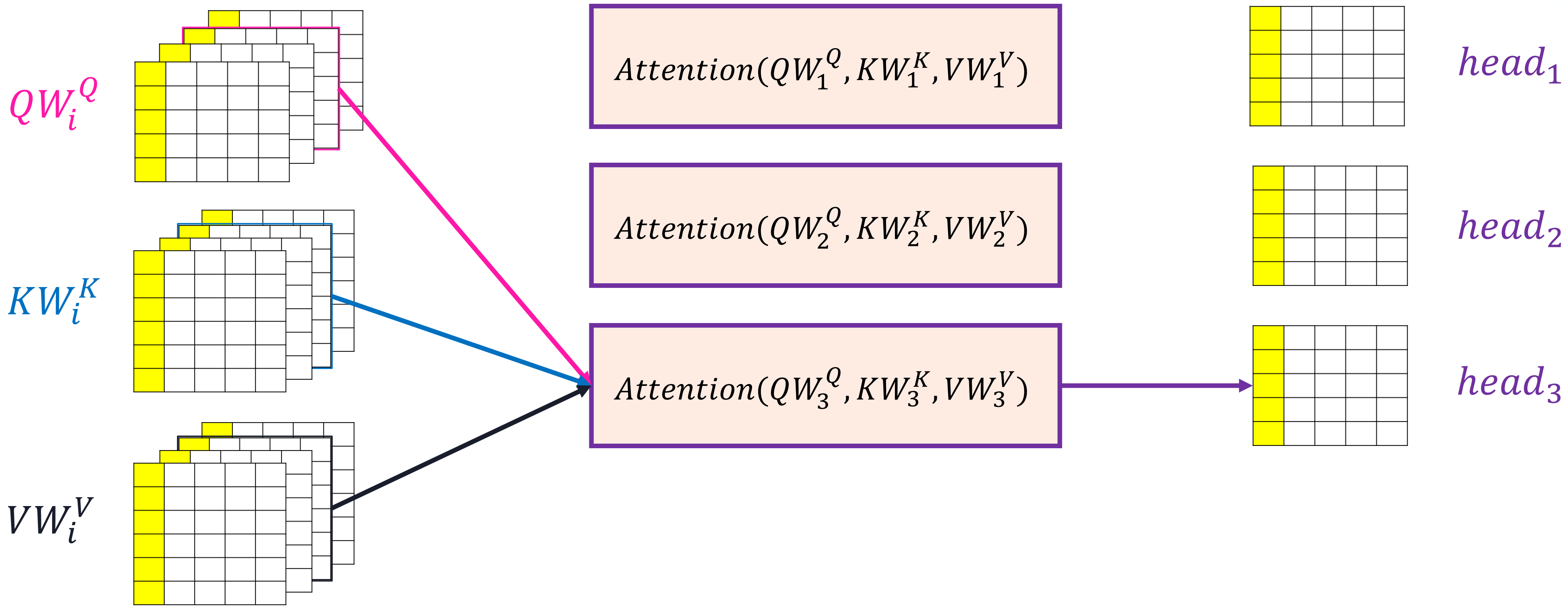

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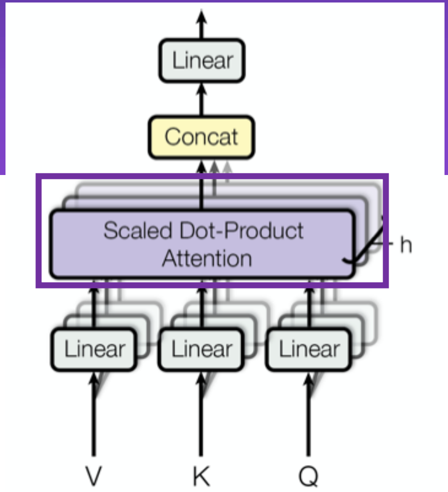

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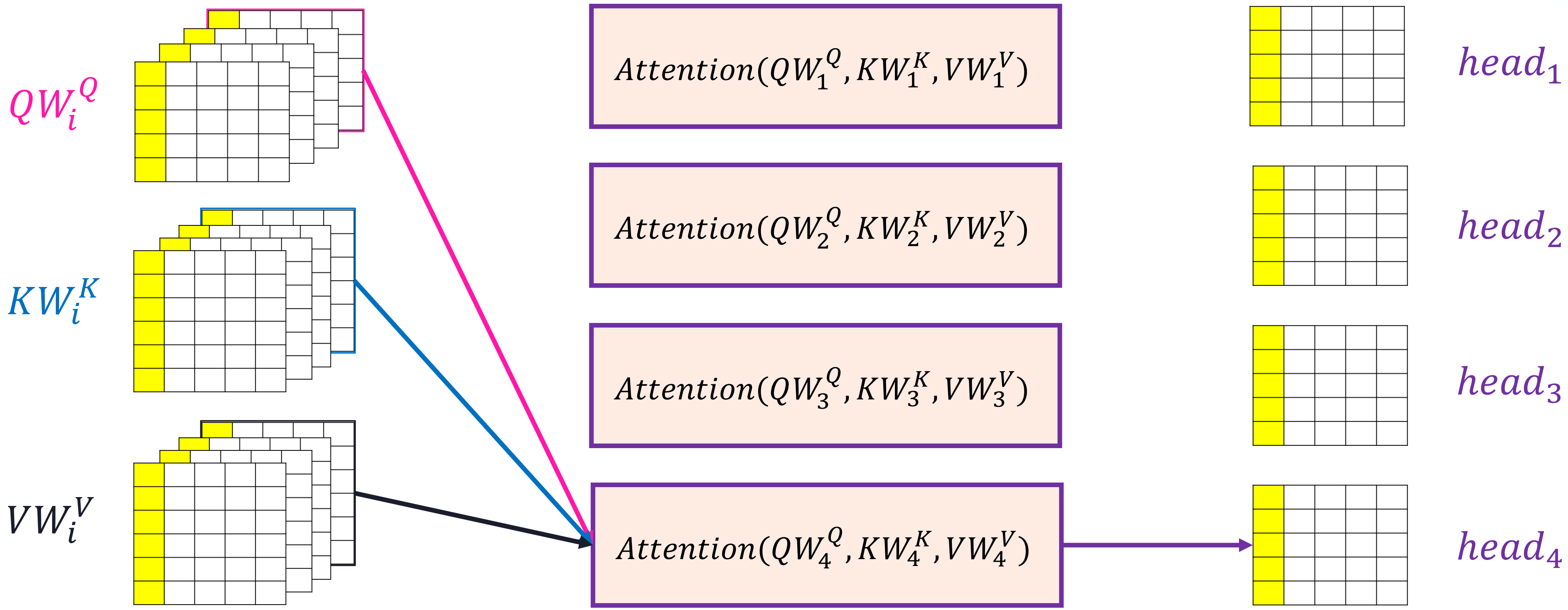

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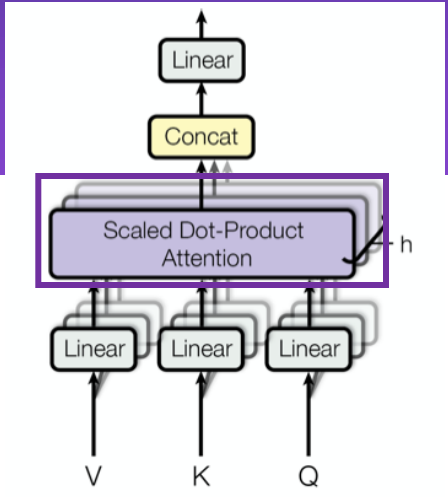
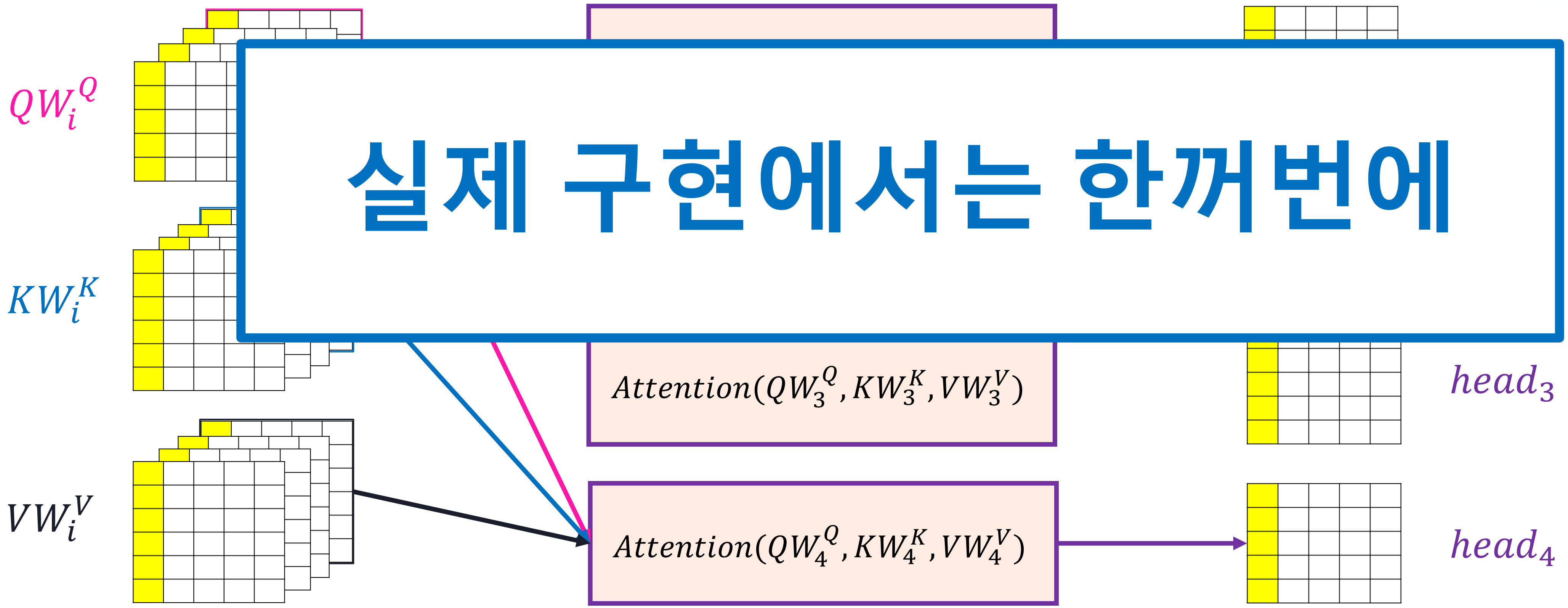
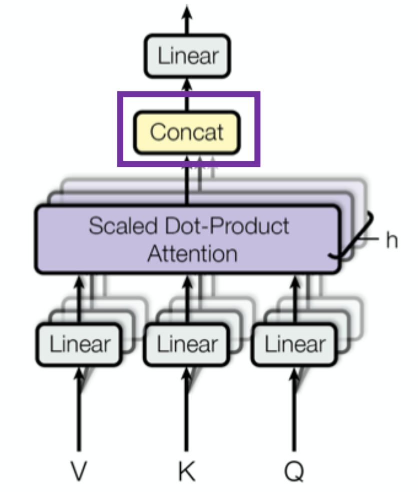




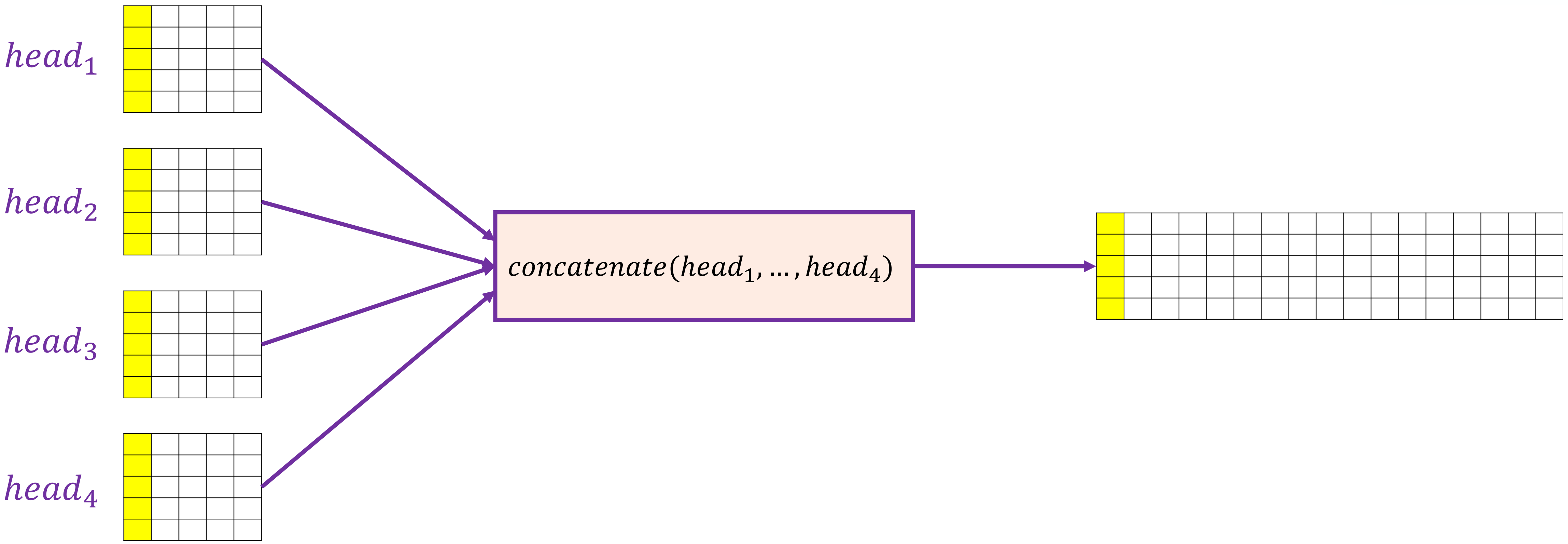
실제 구현에서는 한꺼번에

Multi-Head Attention



$$MultiHead(Q,K,V) = \boxed{concatenate}(head_1, \ldots, head_h)W^O$$

$$where\ head_i = Attention(QW_i^Q, KW_i^K, VW_i^V)$$



Multi-Head Attention

$$MultiHead(Q, K, V) = concatenate(head_1, \ldots, head_h)\boxed{W^O}$$

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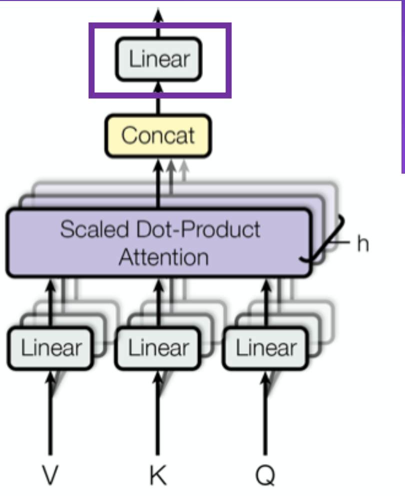
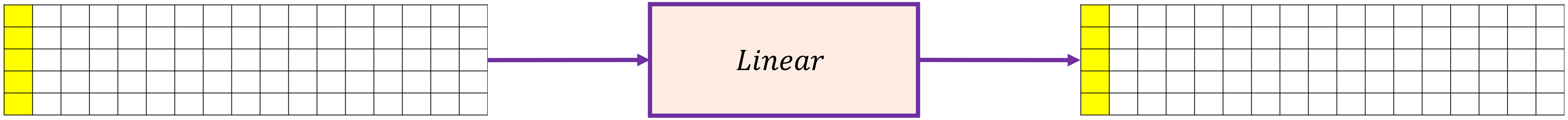
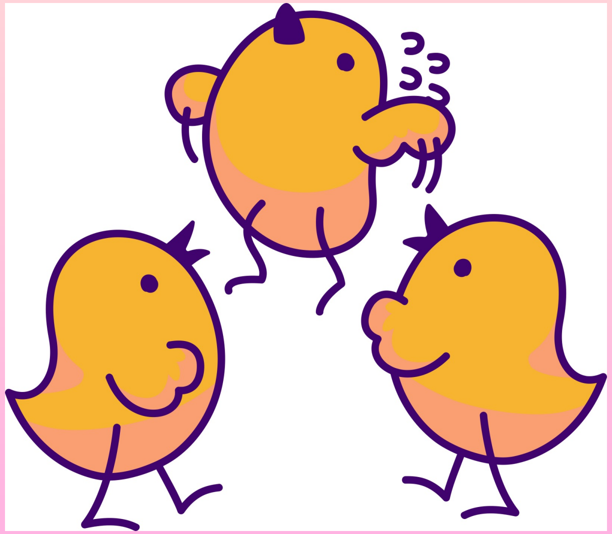


$concatenate(head_1, \ldots, head_4)$





Position-wise Feed-Forward Network

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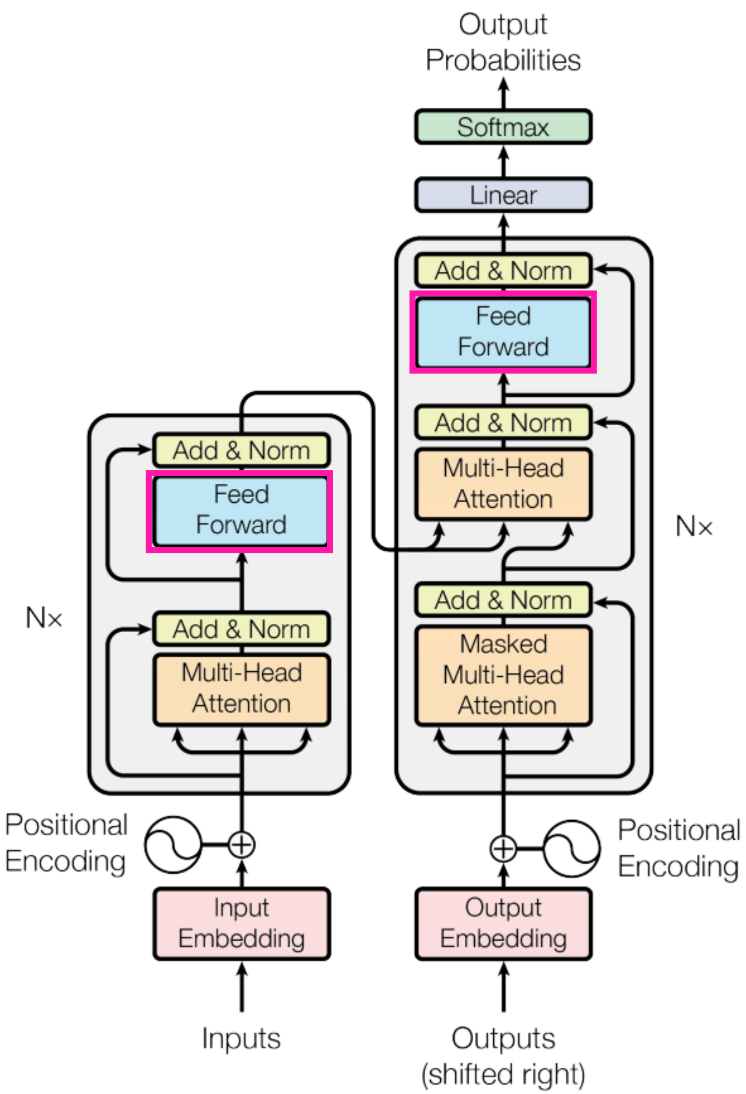
Position-wise Feed-Forward Network

$$FFN(x) = \max(0, xW_1 + b_1)\,W_2 + b_2$$



Position-wise Feed-Forward Network

$$FFN(x) = \max(0, \boxed{xW_1 + b_1})\, W_2 + b_2$$

$x \in \mathbb{R}^{seq \times d_{model}}$

$\downarrow$

$xW_1 + b_1 \longrightarrow$ Linear1

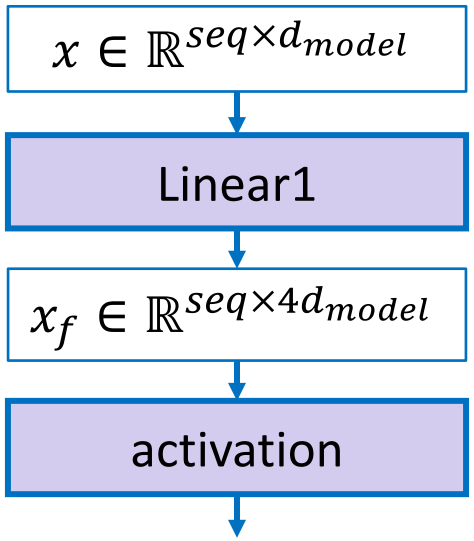
$\downarrow$

$x_f \in \mathbb{R}^{seq \times 4d_{model}}$

Position-wise Feed-Forward Network

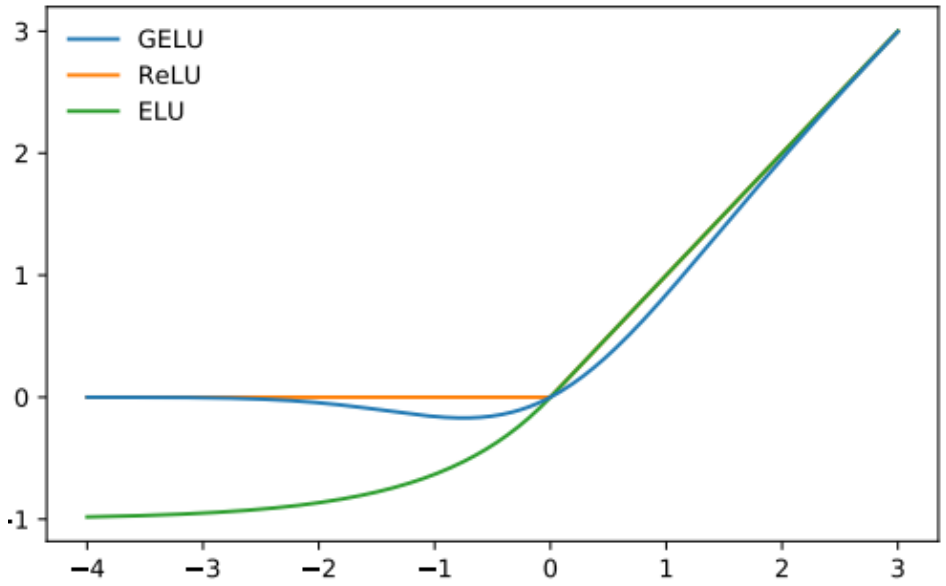
$$FFN(x) = \boxed{\max}(0, xW_1 + b_1)\,W_2 + b_2$$

$\max(0, xW_1 + b_1)$ $\longrightarrow$



Position-wise Feed-Forward Network

$$FFN(x) = \boxed{\max}(0, xW_1 + b_1)W_2 + b_2$$



$x \in \mathbb{R}^{seq \times d_{model}}$

↓

Linear1

↓

$x_f \in \mathbb{R}^{seq \times 4d_{model}}$

↓

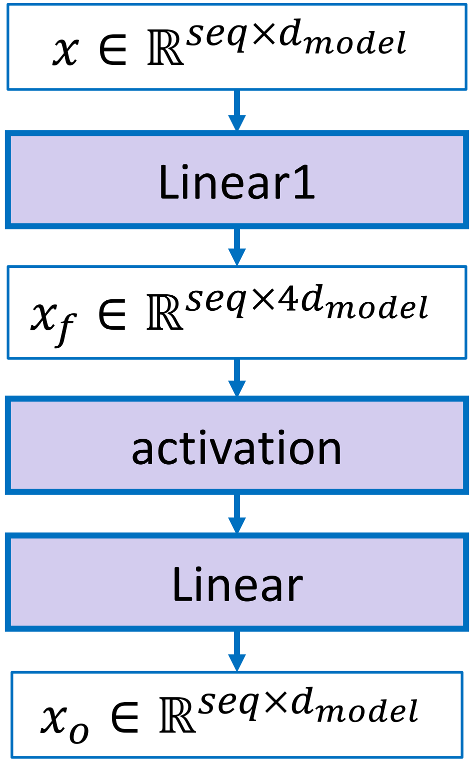
activation

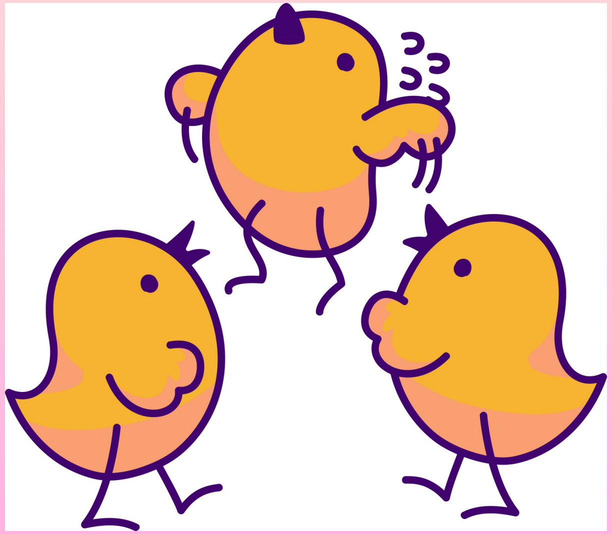
↓

Position-wise Feed-Forward Network

$$FFN(x) = \max(0, xW_1 + b_1)\boxed{W_2 + b_2}$$

$\max(0, xW_1 + b_1)\, W_2 + b_2 \longrightarrow$





Reference

Reference

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