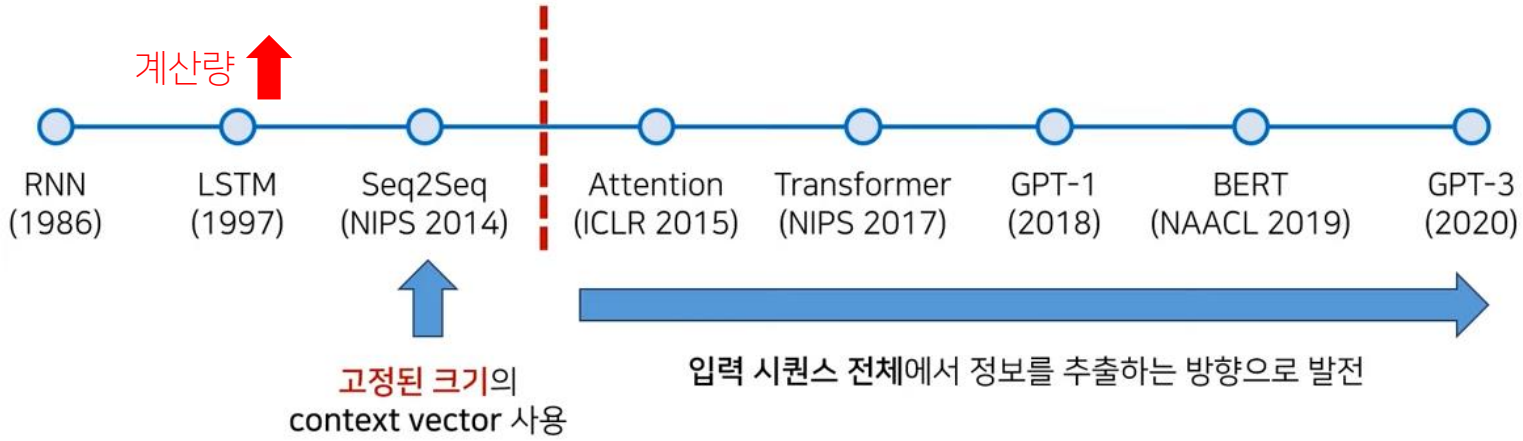
₊·* 2021 SMARCLE Paper Review ʕ·*

# Transformer - Attention Is All You Need
(NIPS 2017)

지능기전공학부 무인이동체공학전공
송혜원

SMARCLE

# Seq2Seq의 문제점



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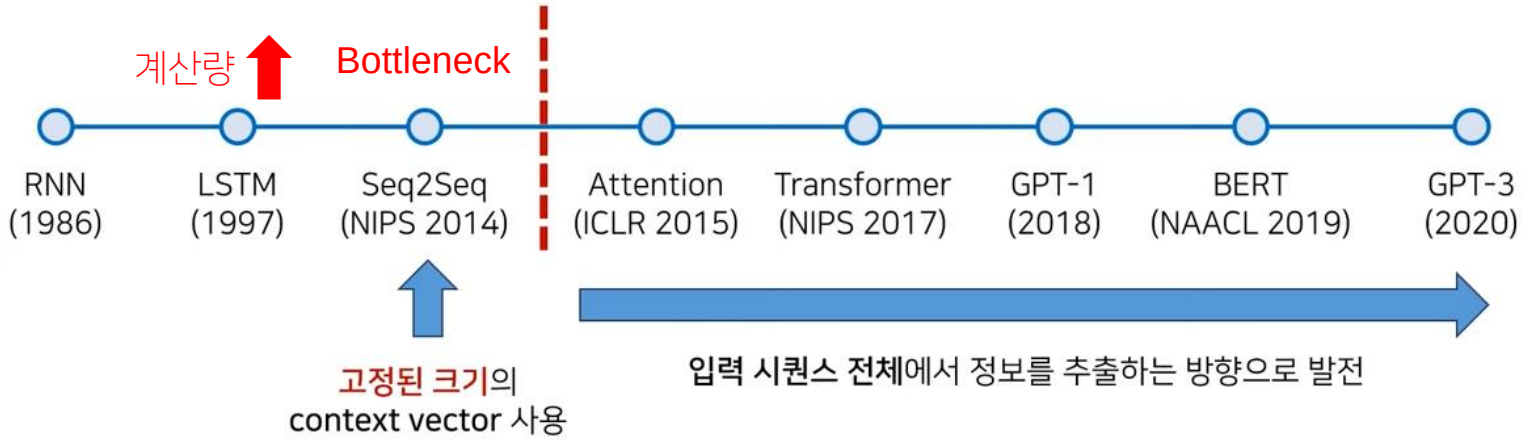
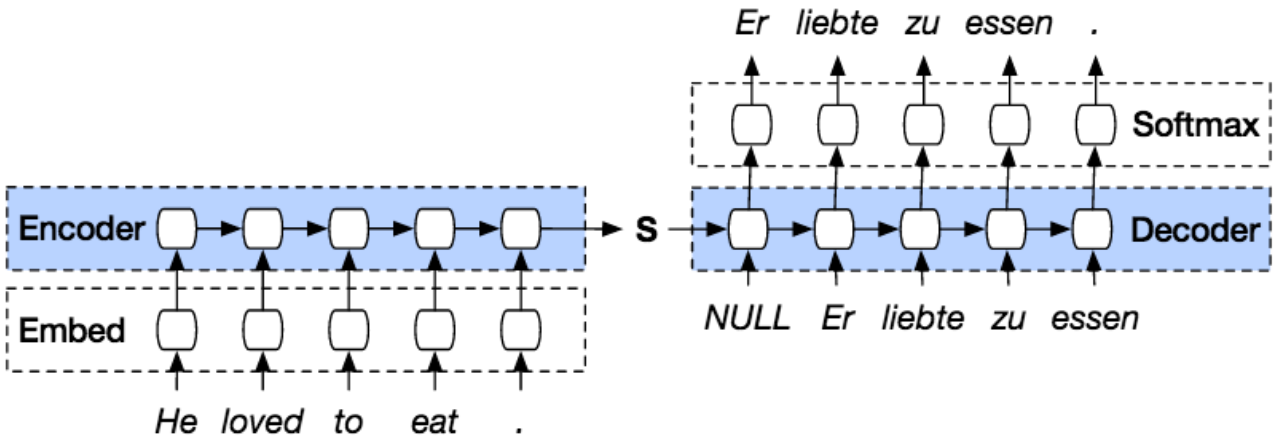


# Attention

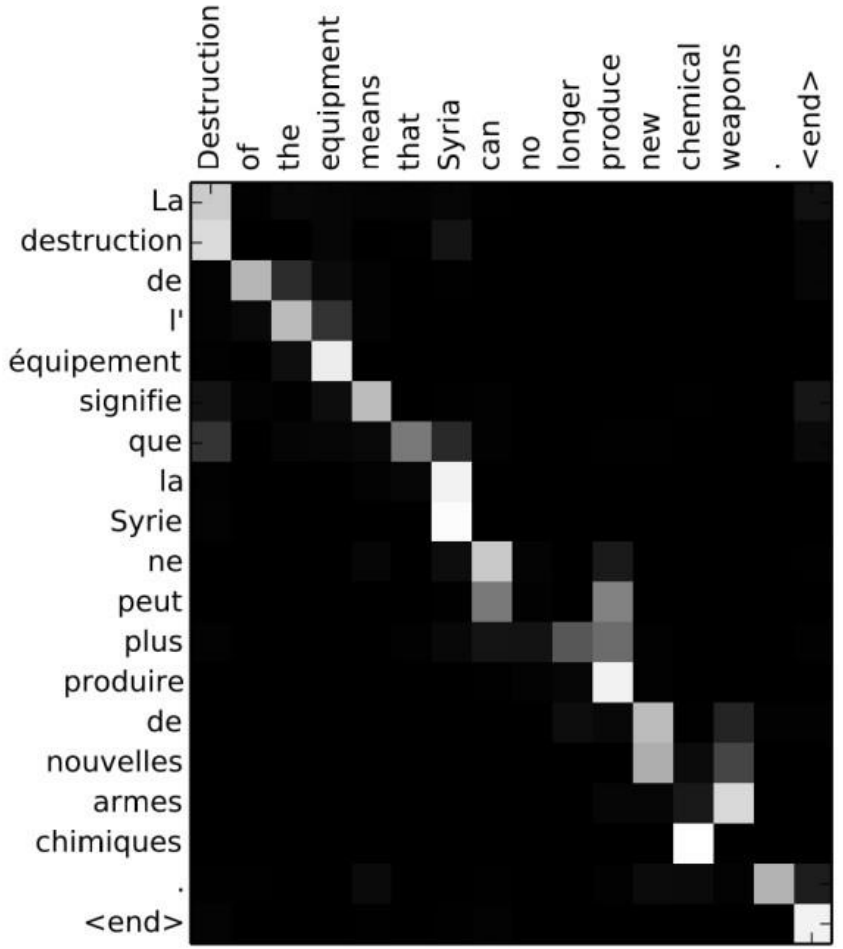
이전엔 입력을
하나의 **context vector**로 압축

↓

**Attention** 기법은
문장 자체를 입력으로!

↓

어떤 단어가 어떤 단어와
가장 연관성이 있는지 알 수 있게 됨



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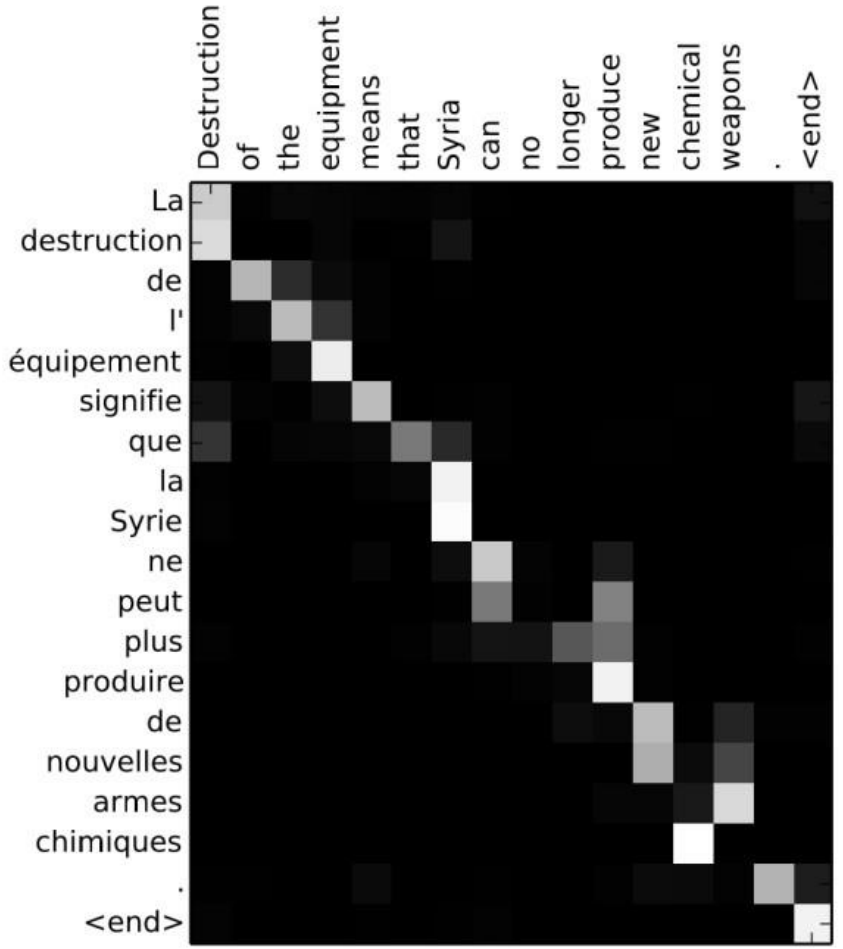
**Attention Is All You Need!!**



Part 1.

# Transformer_Input

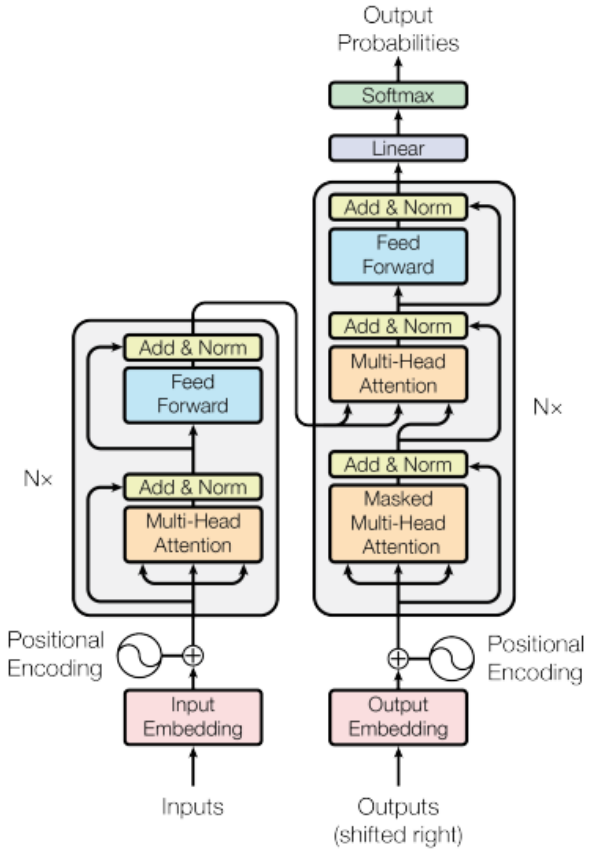



Figure 1: The Transformer - model architecture.

Dog loves potato

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Dog | | | | ... | | | | |
| loves | | | | ... | | | | |
| potato | | | | ... | | | | |

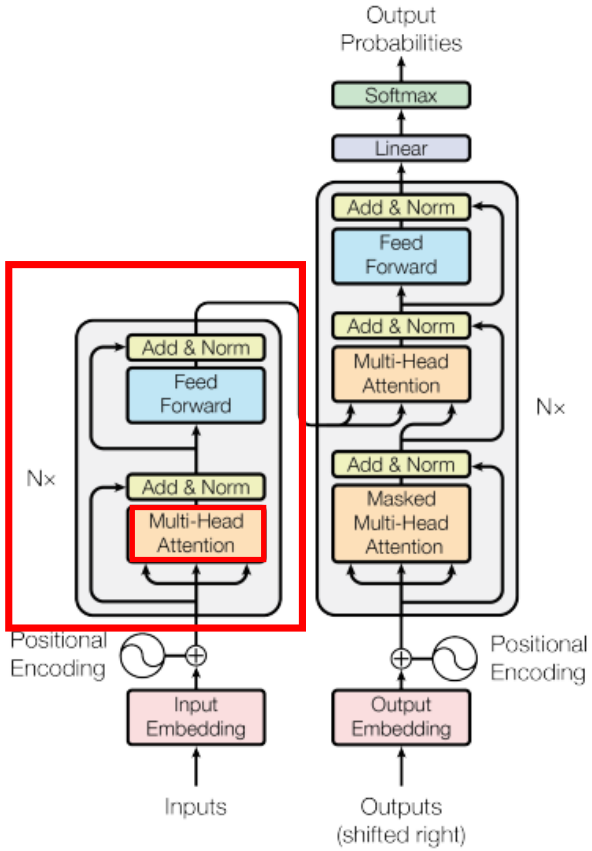
512

문장 전체를 통째로 넣다보니 단어의 위치 정보를 알 수 없음

➡ **Positional Encoding** 통해 위치 정보를 따로 더해줌!

Part 2.

# Transformer_Encoder Self-Attention

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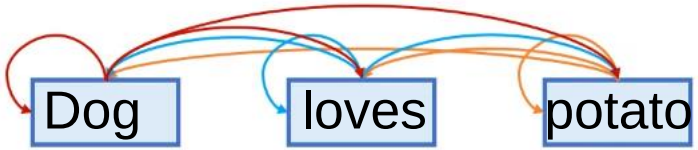
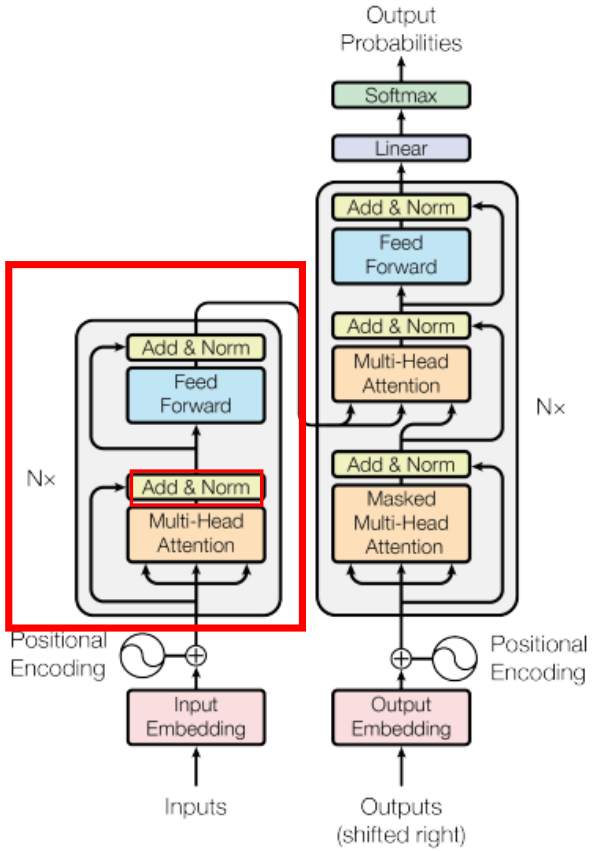
Encoder Self-Attention:



Part 2.

# Transformer_Encoder

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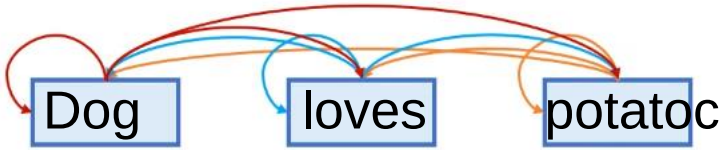
Encoder Self-Attention:




Residual learning

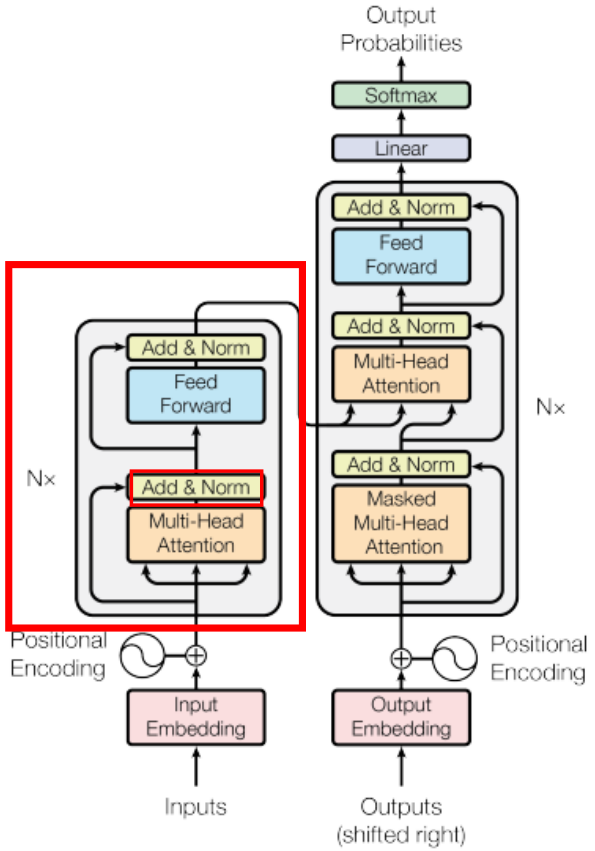
- 특정 layer를 건너뜀

Gradient vanishing 완화

Global optima 잘 찾을 수 있음

Part 2.

# Transformer_Encoder

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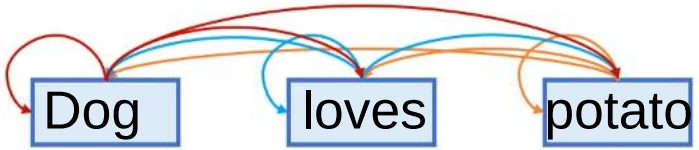


Residual learning

- 특정 layer를 건너뜀

  Gradient vanishing 완화

  Global optima 잘 찾을 수 있음

인풋의 다양한 특징 **attention** 위해 **n**개의 **layer** 병렬로 쌓음

Part 3.

# Transformer_Masked Decoder Self-Attention

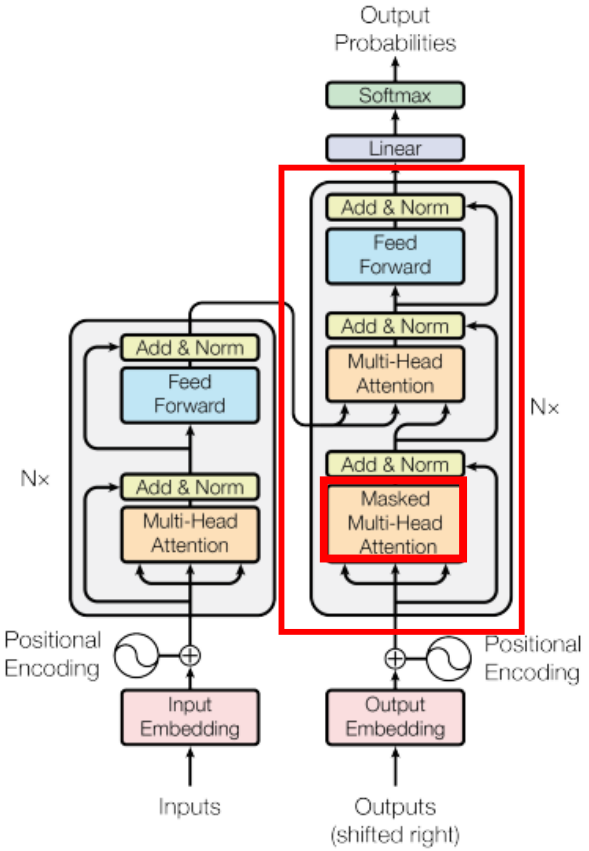


Figure 1: The Transformer - model architecture.

Masked Decoder Self-Attention: 강아지는 감자를 좋아해

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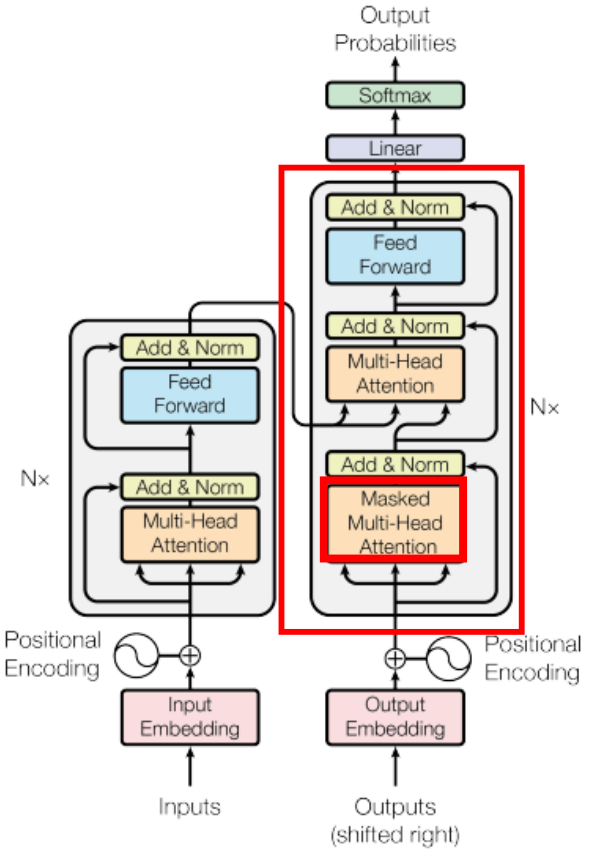


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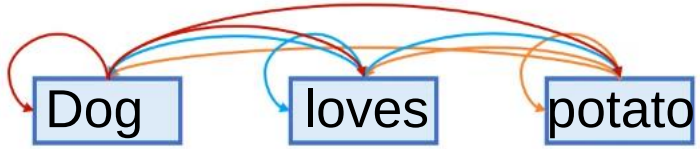
Masked Decoder Self-Attention:


Encoder Self-Attention:



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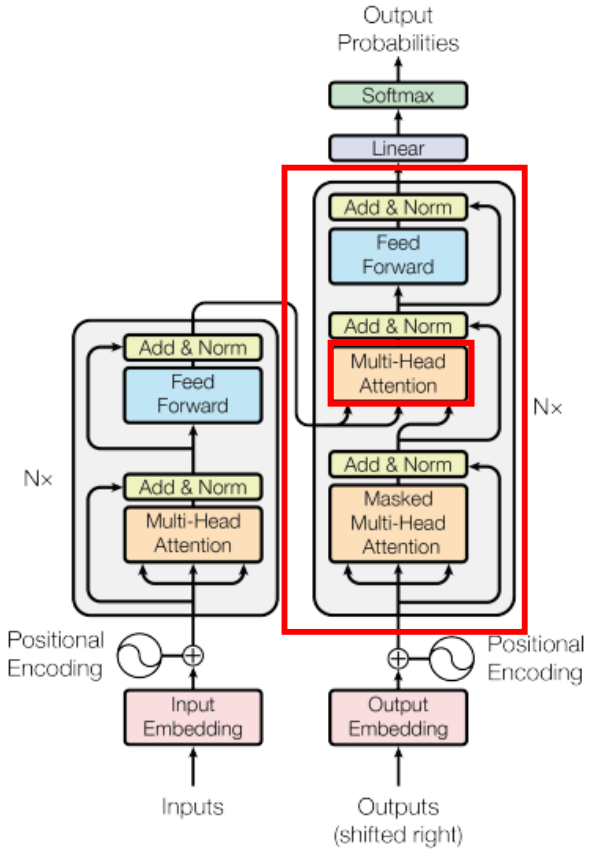


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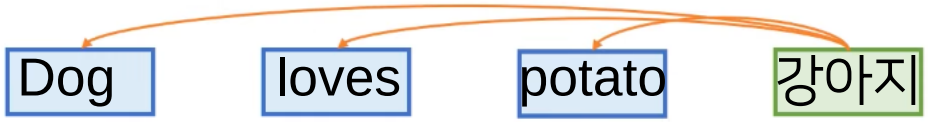
Encoder-Decoder Attention:

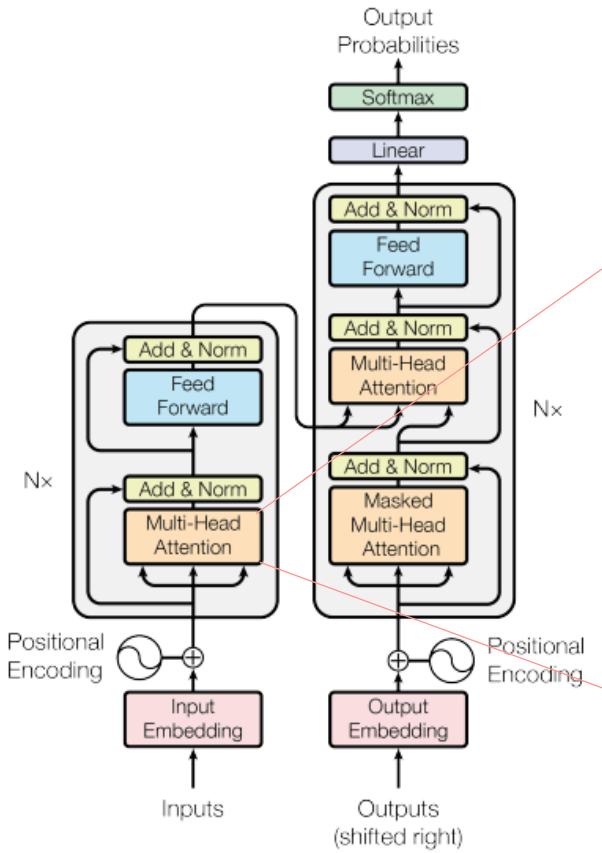



- 인코더 파트에서 나온 출력 결과를 디코더마다 적용하여 전적으로 활용
- 시퀀스가 끝날 때까지 반복

Part 4.

# Transformer_Multi-Head Attention?

Q(Query) : 물어보는 주체  K(Key) : 대상  V(Value) : 가중치



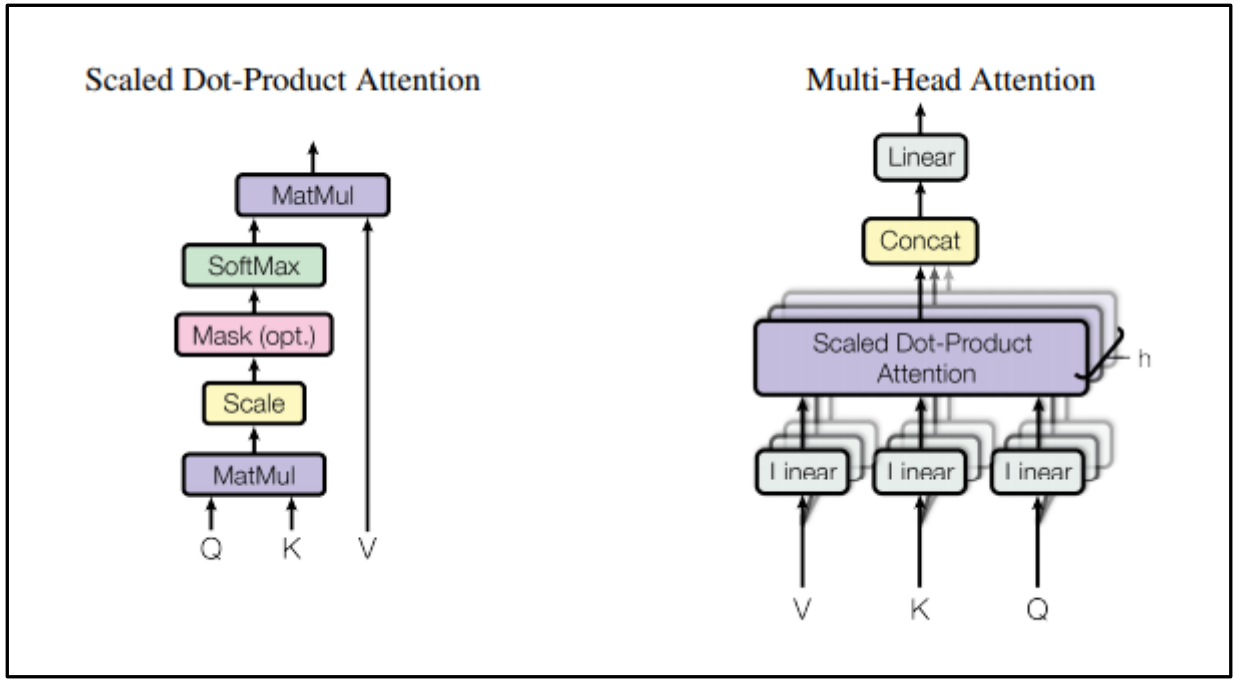
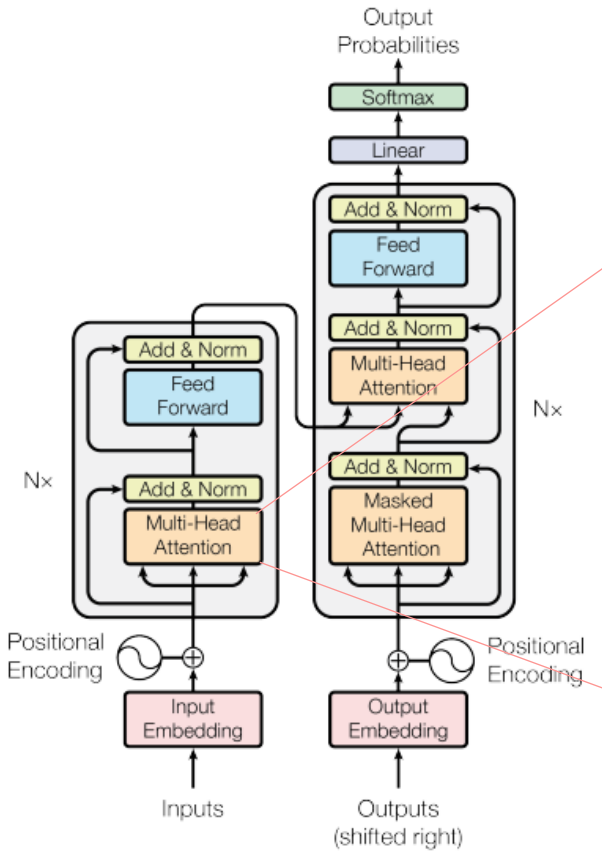




Figure 1: The Transformer - model architecture.

Part 4.

# Transformer_Multi-Head Attention?

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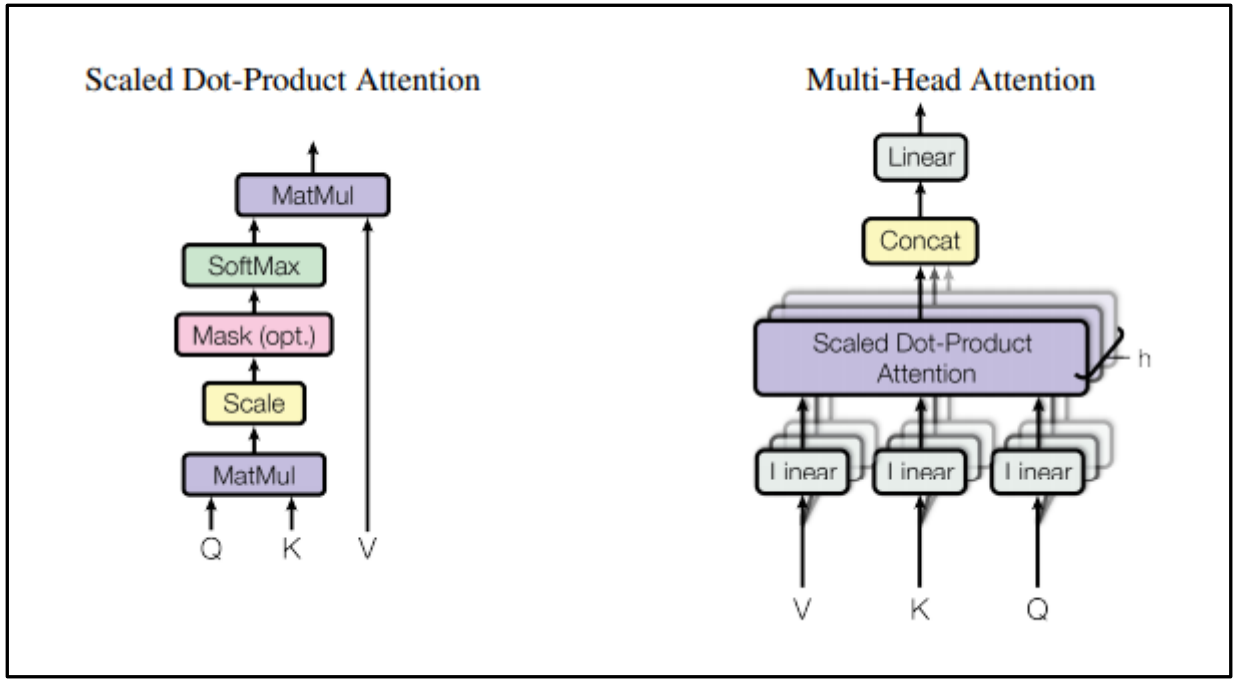
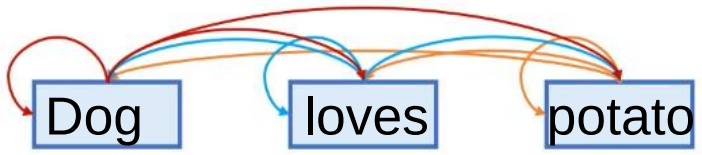



Encoder Self-Attention:



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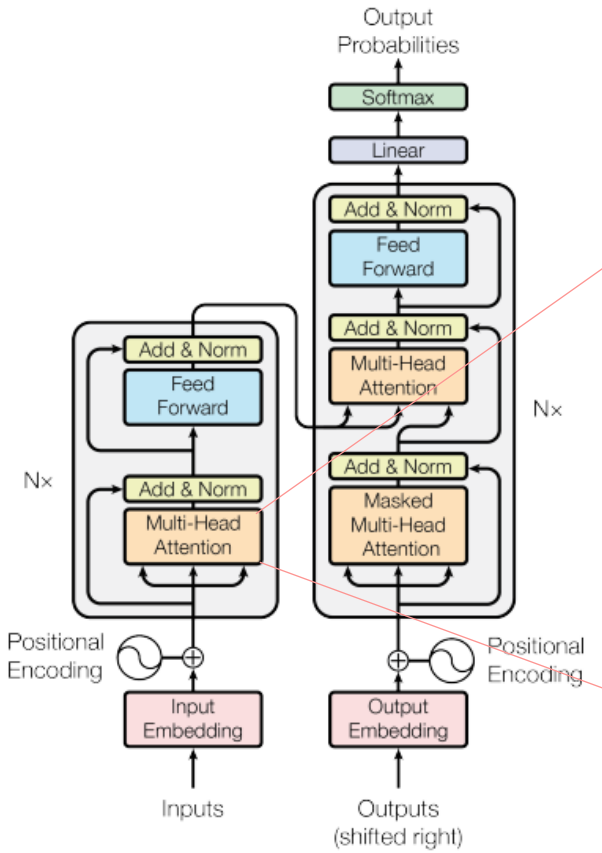


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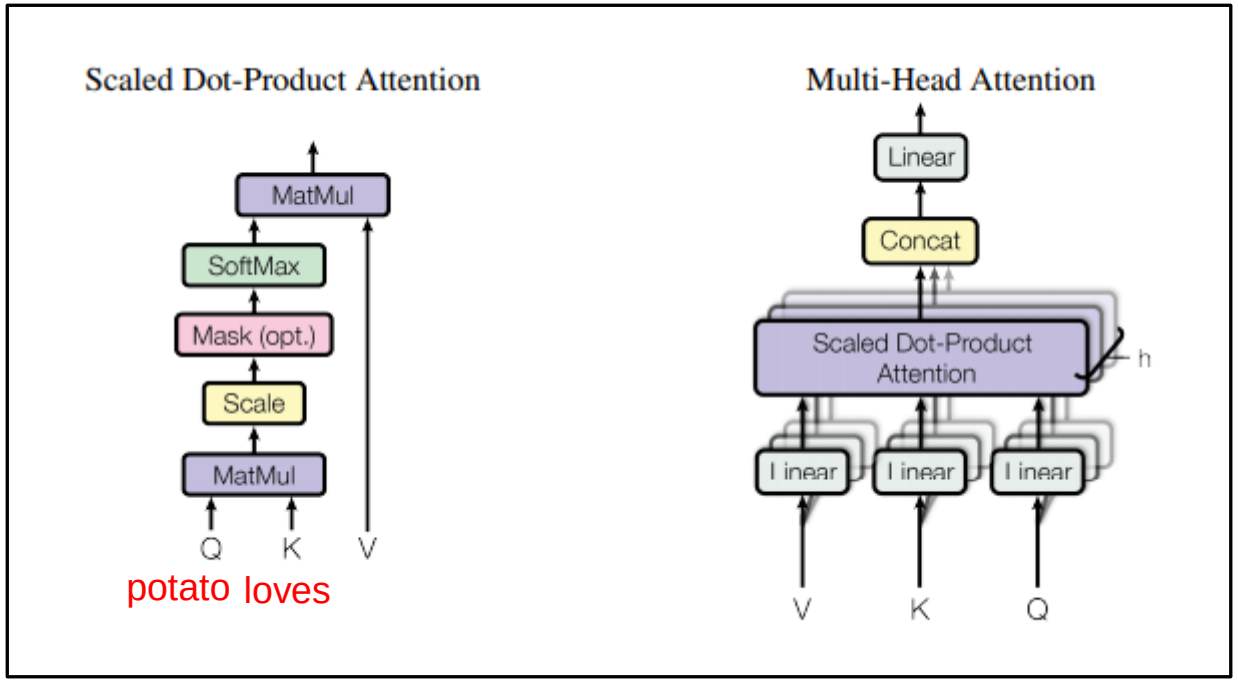
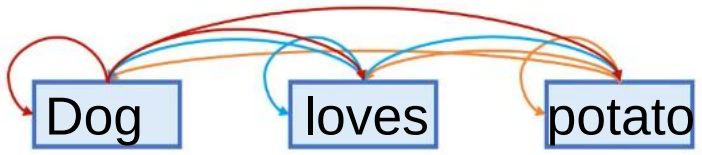



Encoder Self-Attention:



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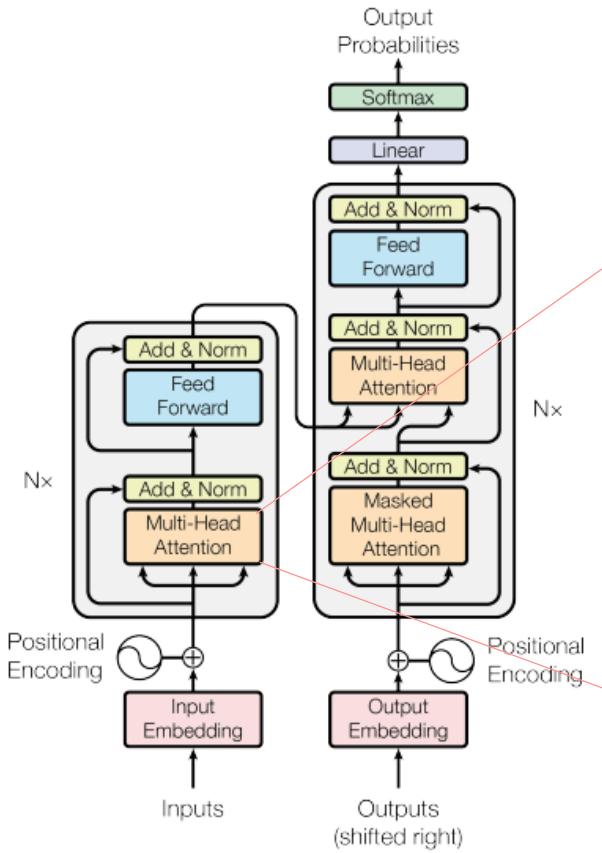


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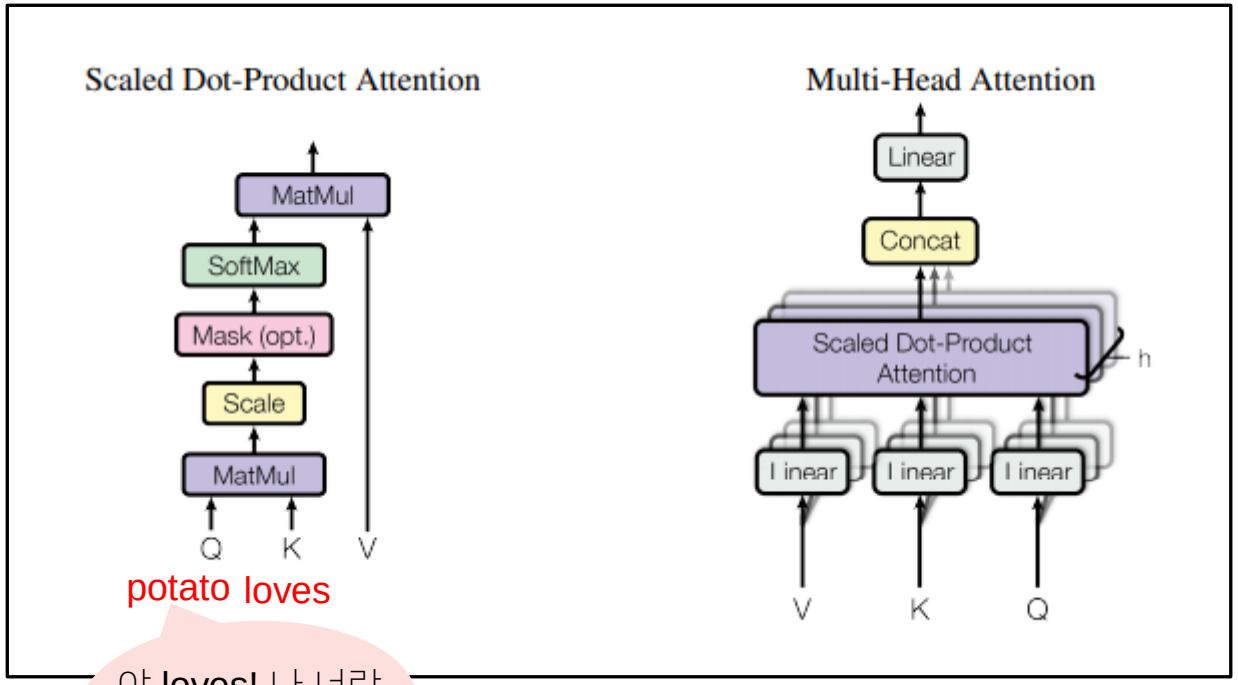
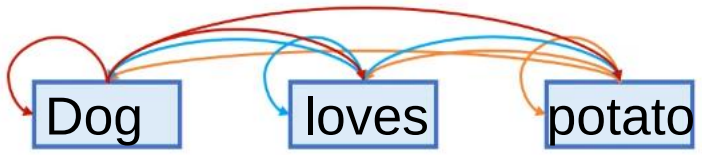


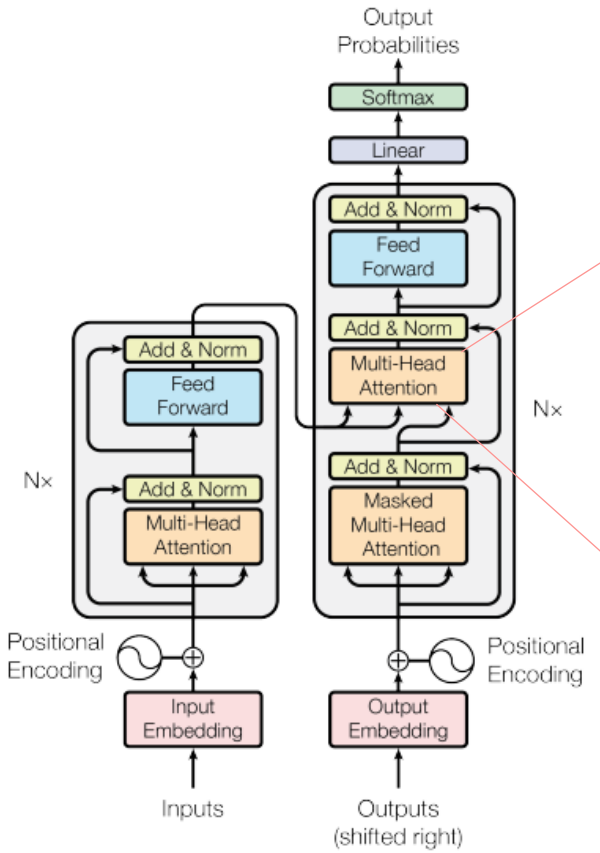

야 loves! 나 너랑 얼마나 관련있어?

Encoder Self-Attention:



Part 4.

# Transformer_Multi-Head Attention?

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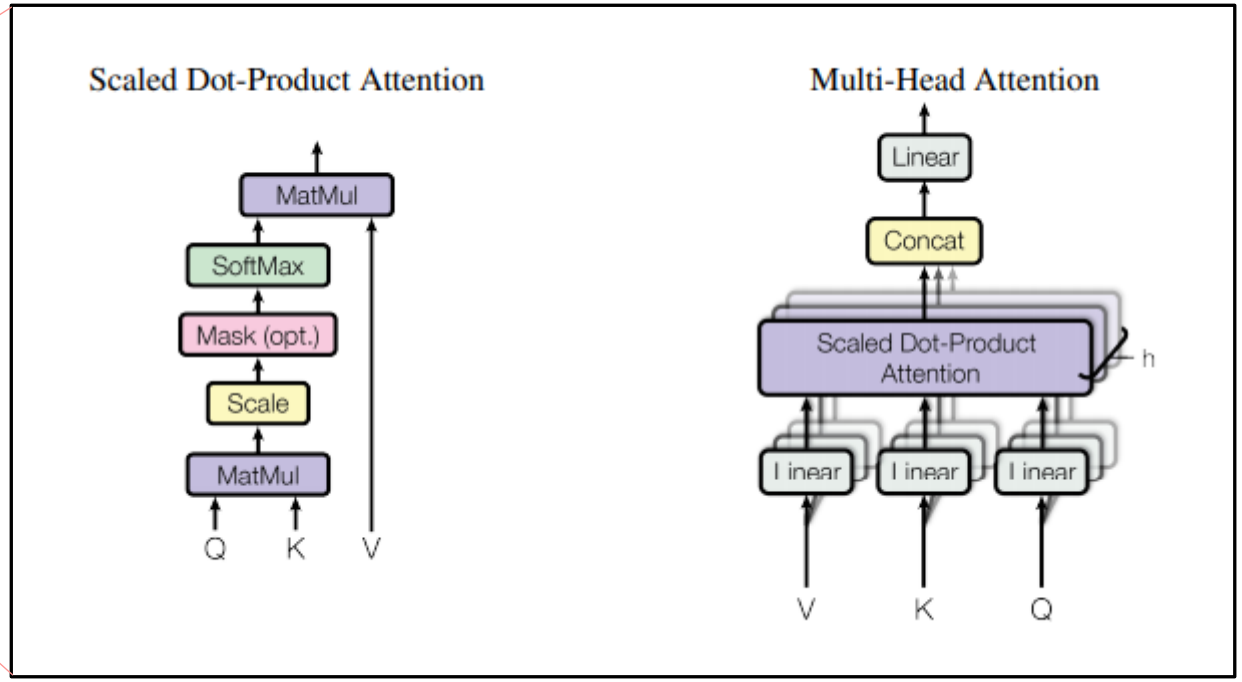
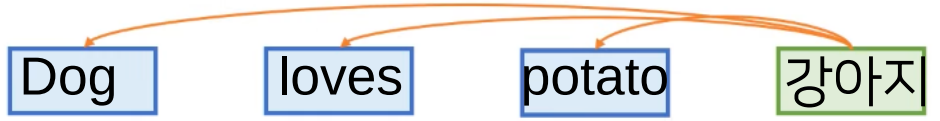



Encoder-Decoder Attention:



Part 4.

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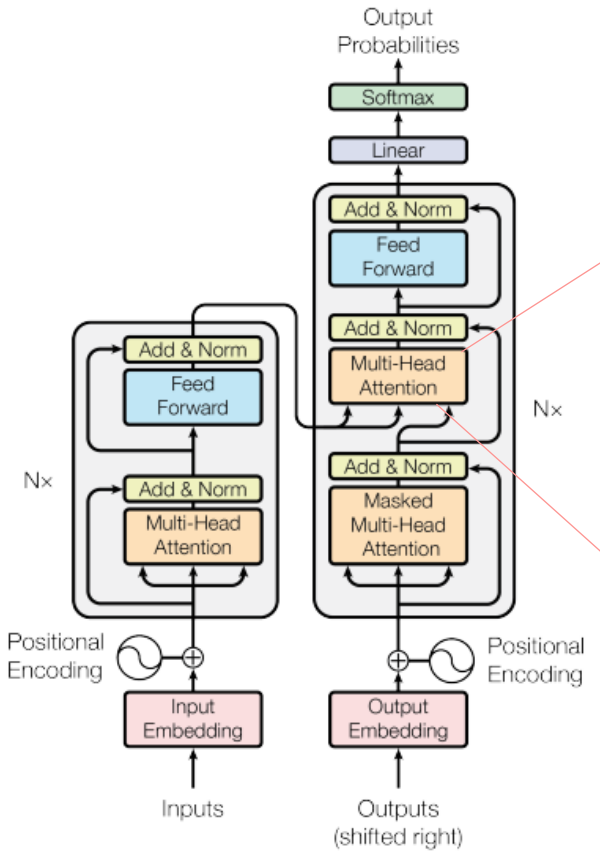


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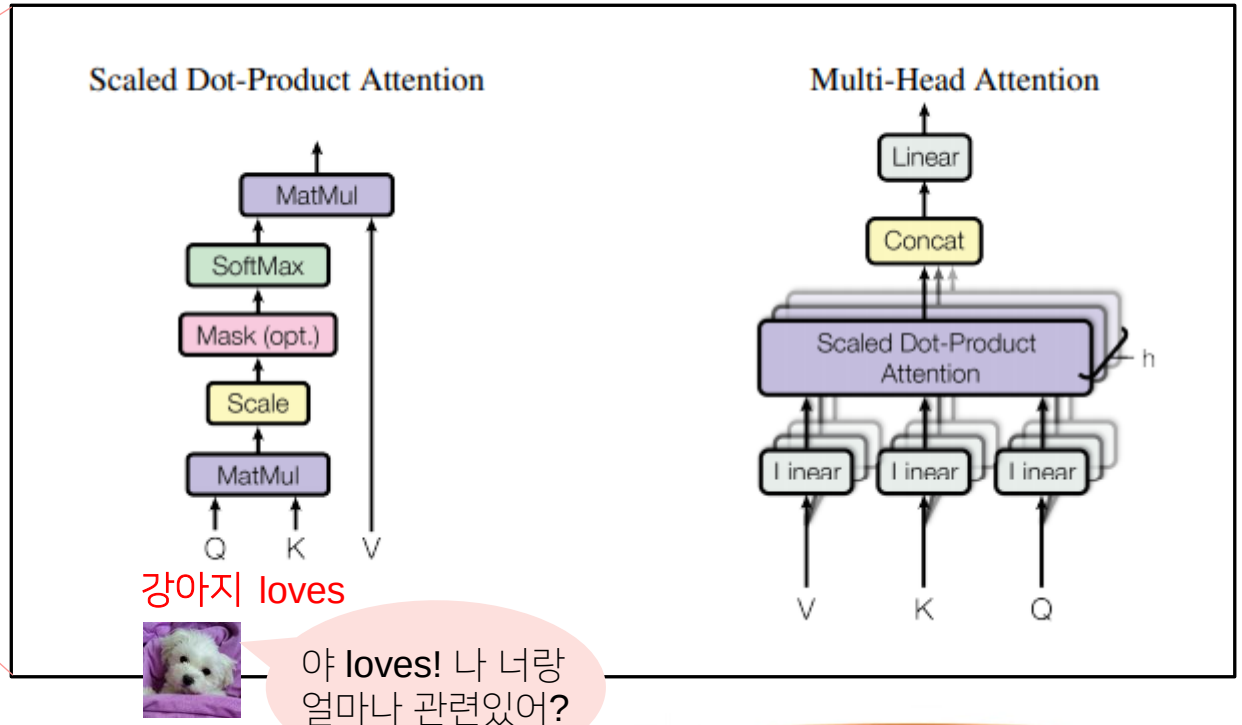
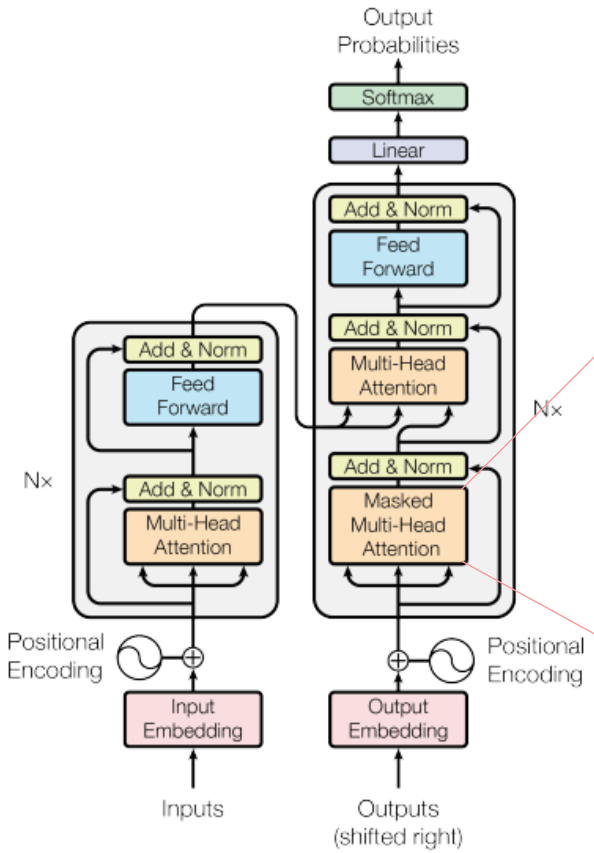



Encoder-Decoder Attention: Dog loves potato 강아지

Part 4.

# Transformer_Multi-Head Attention?

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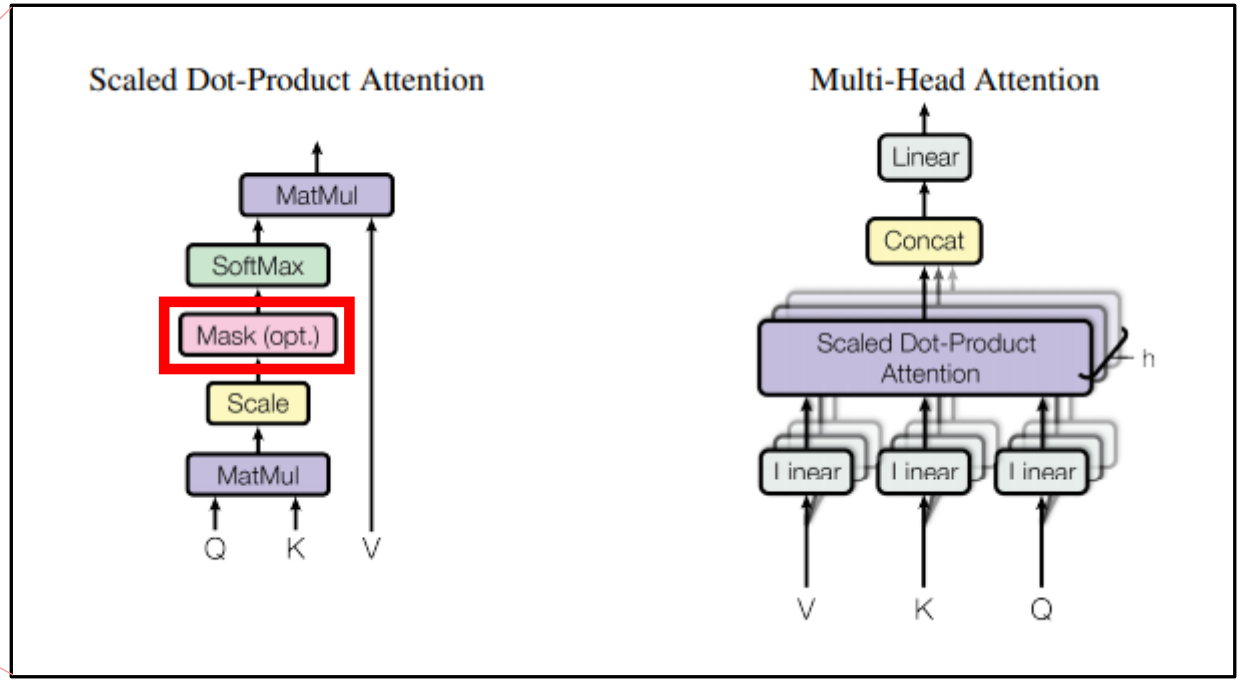
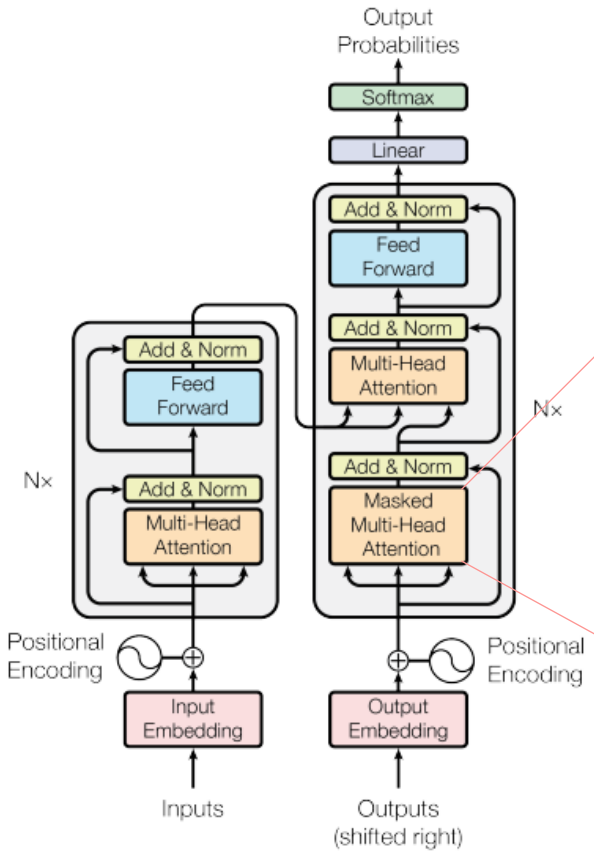



Masked Decoder Self-Attention: 강아지는 감자를 좋아해

Part 4.

# Transformer_Multi-Head Attention?

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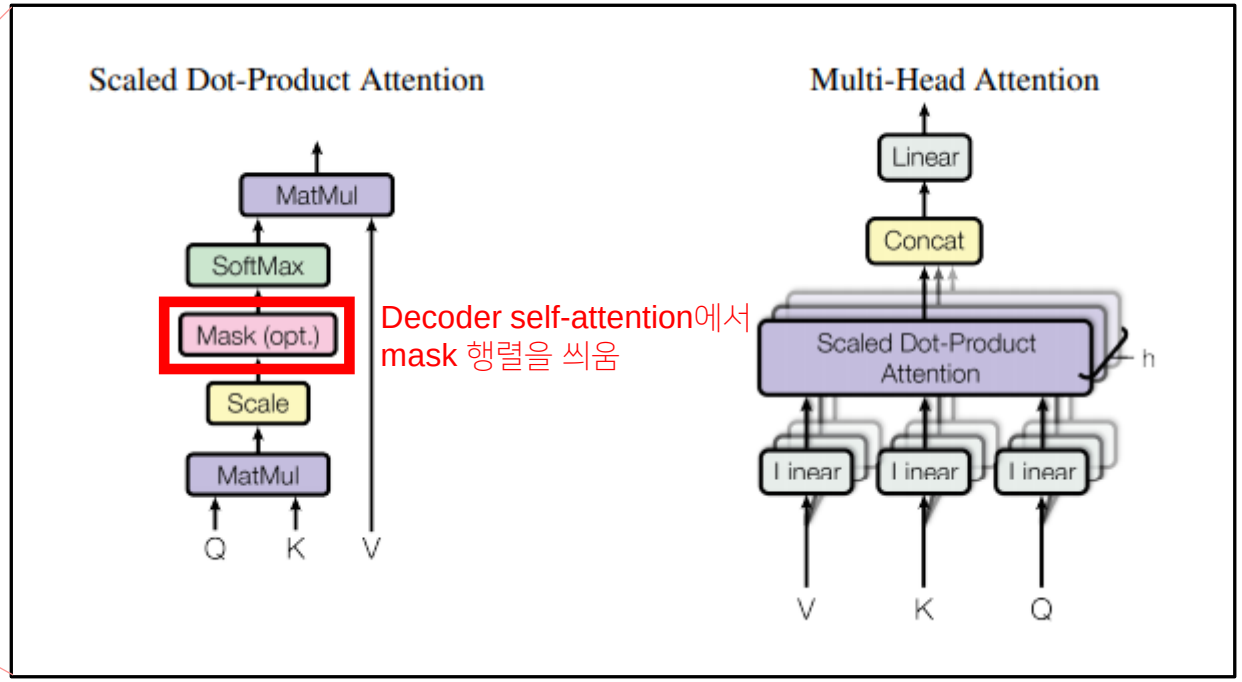



Masked Decoder Self-Attention: 강아지는 감자를 좋아해

Part 5.

# Transformer_Positional Encoding

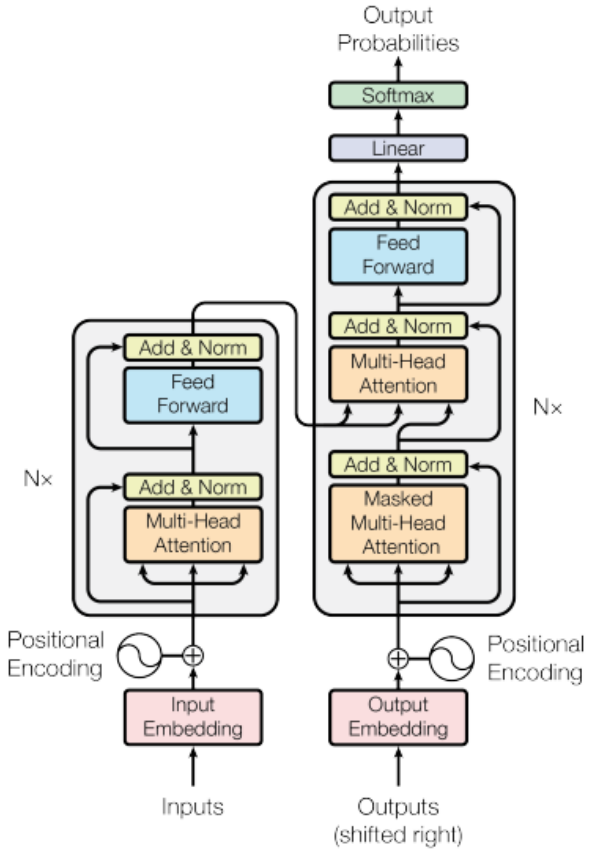



Figure 1: The Transformer - model architecture.

In this work, we use sine and cosine functions of different frequencies:

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

where $pos$ is the position and $i$ is the dimension. That is, each dimension of the positional encoding corresponds to a sinusoid. The wavelengths form a geometric progression from $2\pi$ to $10000 \cdot 2\pi$. We chose this function because we hypothesized it would allow the model to easily learn to attend by relative positions, since for any fixed offset $k$, $PE_{pos+k}$ can be represented as a linear function of $PE_{pos}$.

We also experimented with using learned positional embeddings [9] instead, and found that the two versions produced nearly identical results (see Table 3 row (E)). We chose the sinusoidal version because it may allow the model to extrapolate to sequence lengths longer than the ones encountered during training.

- 본문에서는 주기함수를 이용해서 단어의 위치를 정해줌
- 이후 모델들은 학습이 가능한 임베딩 레이어를 넣어주는 추세

# Transformer_Conclusion

Table 3: Variations on the Transformer architecture. Unlisted values are identical to those of the base model. All metrics are on the English-to-German translation development set, newstest2013. Listed perplexities are per-wordpiece, according to our byte-pair encoding, and should not be compared to per-word perplexities.

| | $N$ | $d_{\text{model}}$ | $d_{\text{ff}}$ | $h$ | $d_k$ | $d_v$ | $P_{drop}$ | $\epsilon_{ls}$ | train steps | PPL (dev) | BLEU (dev) | params $\times 10^6$ |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| base | 6 | 512 | 2048 | 8 | 64 | 64 | 0.1 | 0.1 | 100K | 4.92 | 25.8 | 65 |
| (A) | | | | 1 | 512 | 512 | | | | 5.29 | 24.9 | |
| | | | | 4 | 128 | 128 | | | | 5.00 | 25.5 | |
| | | | | 16 | 32 | 32 | | | | 4.91 | 25.8 | |
| | | | | 32 | 16 | 16 | | | | 5.01 | 25.4 | |
| (B) | | | | | 16 | | | | | 5.16 | 25.1 | 58 |
| | | | | | 32 | | | | | 5.01 | 25.4 | 60 |
| (C) | 2 | | | | | | | | | 6.11 | 23.7 | 36 |
| | 4 | | | | | | | | | 5.19 | 25.3 | 50 |
| | 8 | | | | | | | | | 4.88 | 25.5 | 80 |
| | | 256 | | | 32 | 32 | | | | 5.75 | 24.5 | 28 |
| | | 1024 | | | 128 | 128 | | | | 4.66 | 26.0 | 168 |
| | | | 1024 | | | | | | | 5.12 | 25.4 | 53 |
| | | | 4096 | | | | | | | 4.75 | 26.2 | 90 |
| (D) | | | | | | | 0.0 | | | 5.77 | 24.6 | |
| | | | | | | | 0.2 | | | 4.95 | 25.5 | |
| | | | | | | | | 0.0 | | 4.67 | 25.3 | |
| | | | | | | | | 0.2 | | 5.47 | 25.7 | |
| (E) | positional embedding instead of sinusoids | | | | | | | | | 4.92 | 25.7 | |
| big | 6 | 1024 | 4096 | 16 | | | 0.3 | | 300K | **4.33** | **26.4** | 213 |

기본

key dimension

↓ 수치 bad

model 크기

↑ 수치 good

dropout

good

p.e 유사

base랑 차이 거의 x

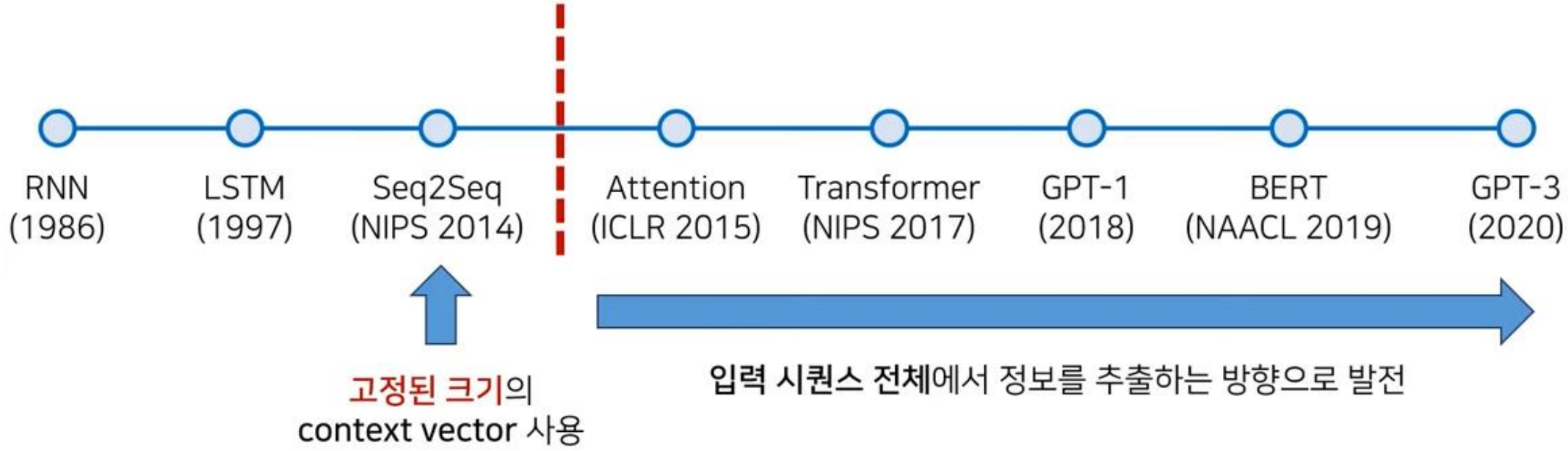
# Transformer_Conclusion

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 [18] | 23.75 | | | |
| Deep-Att + PosUnk [39] | | 39.2 | | $1.0 \cdot 10^{20}$ |
| GNMT + RL [38] | 24.6 | 39.92 | $2.3 \cdot 10^{19}$ | $1.4 \cdot 10^{20}$ |
| ConvS2S [9] | 25.16 | 40.46 | $9.6 \cdot 10^{18}$ | $1.5 \cdot 10^{20}$ |
| MoE [32] | 26.03 | 40.56 | $2.0 \cdot 10^{19}$ | $1.2 \cdot 10^{20}$ |
| Deep-Att + PosUnk Ensemble [39] | | 40.4 | | $8.0 \cdot 10^{20}$ |
| GNMT + RL Ensemble [38] | 26.30 | 41.16 | $1.8 \cdot 10^{20}$ | $1.1 \cdot 10^{21}$ |
| ConvS2S Ensemble [9] | 26.36 | **41.29** | $7.7 \cdot 10^{19}$ | $1.2 \cdot 10^{21}$ |
| Transformer (base model) | 27.3 | 38.1 | **$3.3 \cdot 10^{18}$** | |
| Transformer (big) | **28.4** | **41.8** | $2.3 \cdot 10^{19}$ | |

Part 7.

# Transformer_TBC..



감사합니다 :-3

SMARCLE