Attention Is All You Need

2021-01-07

전세희

E-DEEP

Introduction

Sequence modeling, Transduction problems(ex. language modeling, machine translation) 에서 RNN(Recurrent Neural Networks), LSTM(Long Short-Term Memory), Gated Recurrent Neural Networks는 SOTA로 굳건히 자리 잡고 있음.

👉 But, 기존 Recurrent models은 이전 시간 state를 input으로 하기 때문에 sequential nature가지고 있음

👉 병렬화 불가

👉 문장의 길이가 길 때 큰 치명적.

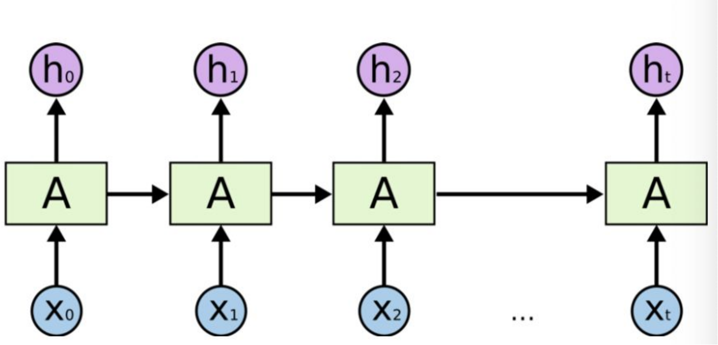
(비록 현재 factorization을 통해 효율성을 확보한 모델도 있지만 여전히 sequential computation의 제약 조건이 남아있다.)

Introduction

- ex)

“The Transformers” are a Japanese [[hardcore punk]] band. The band was formed in 1968, during the height of Japanese music history”

RNN



https://towardsdatascience.com/transformers-141e32e69591

Introduction

ex)

"The Transformers" are a Japanese [[hardcore punk]] band. The band was formed in 1968, during the height of Japanese music history"

LSTM

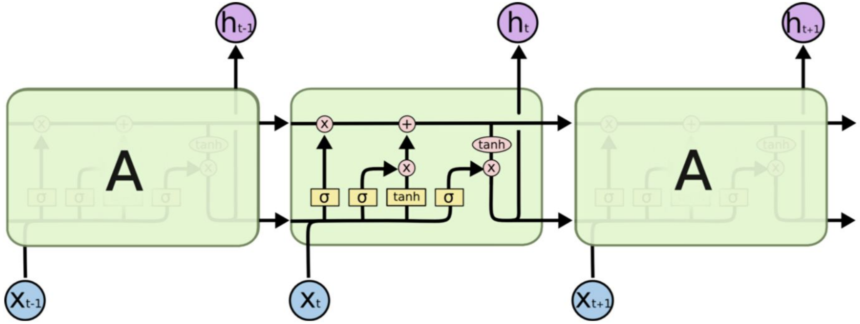


Image from 6

https://towardsdatascience.com/transformers-141e32e69591

Introduction

<Attnetion>

다양한 task에서 필수 파트가 되었다. input이나 output sequence에서 dependencies의 거리에 상관없이 모델링함. 👉 Transformer 라는 모델 제안!

✔️ Recurrence 🙅🏻‍♀️

✔️ Attention만 이용

👉 더 병렬화 가능, Translation에서도 적은 training 시간으로 SOTA 수준의 품질

Model Architecture

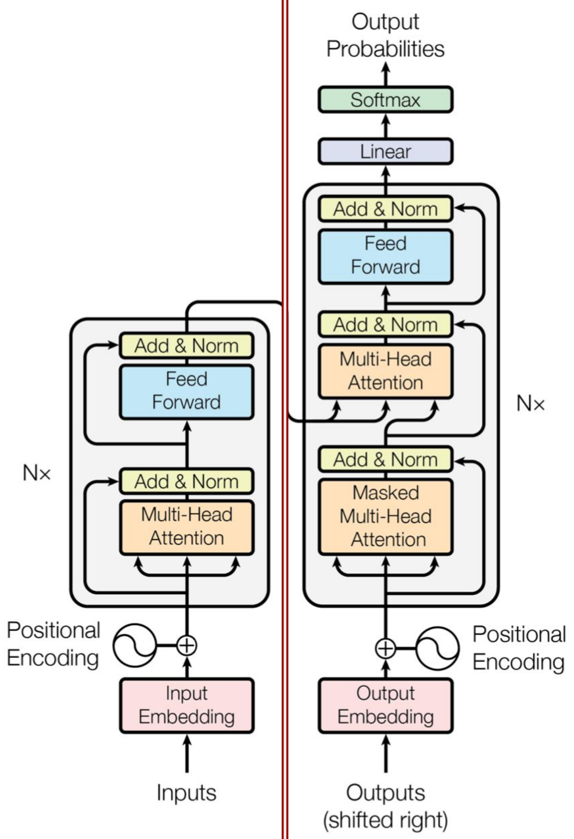


Figure 1: The Transformer - model architecture.

Model Architecture

- **Encoder**

  1. Each layer has 2 sub-layers
  (multi-head self-attention & position-wise fully connected feed-forward network)

  2. Residual connection & layer normalization

$$\mathrm{LayerNorm}(\boxed{x +} \mathrm{Sublayer}(x))$$

residual connection

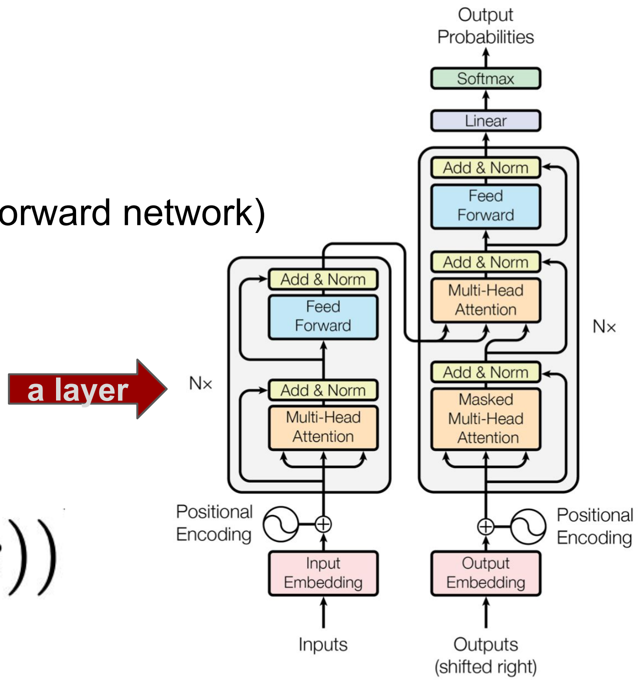


Figure 1: The Transformer - model architecture.

Model Architecture

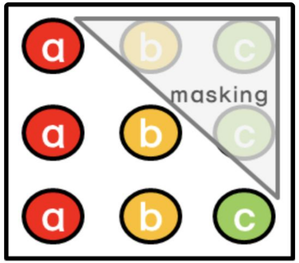
- **Decoder**

1. multi-head self-attention & position-wise fully connected feed-forward network)

2. a third sub-layer, which performs multi-head attention over the **output** of the encoder stack.

3. Residual connection & layer normalization

4. Masking (for preventing positions from attending to subsequent positions)



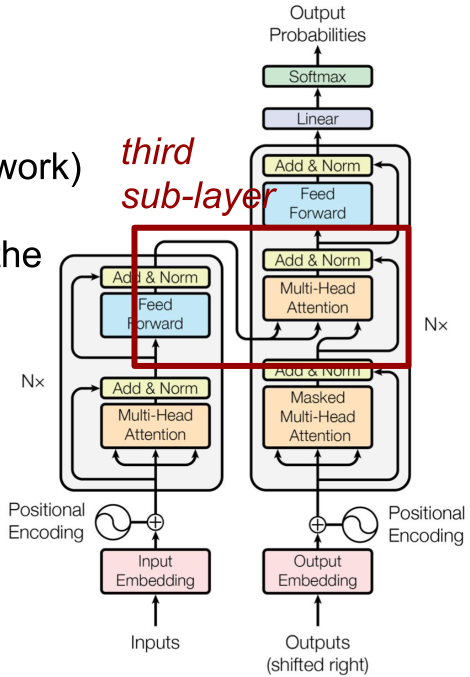
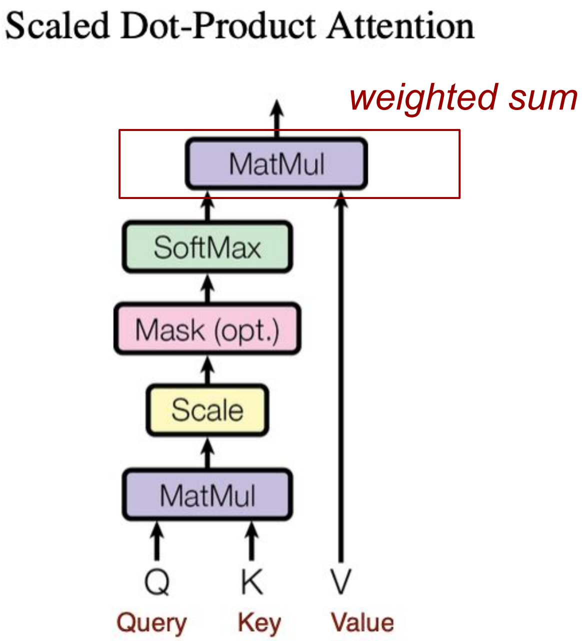
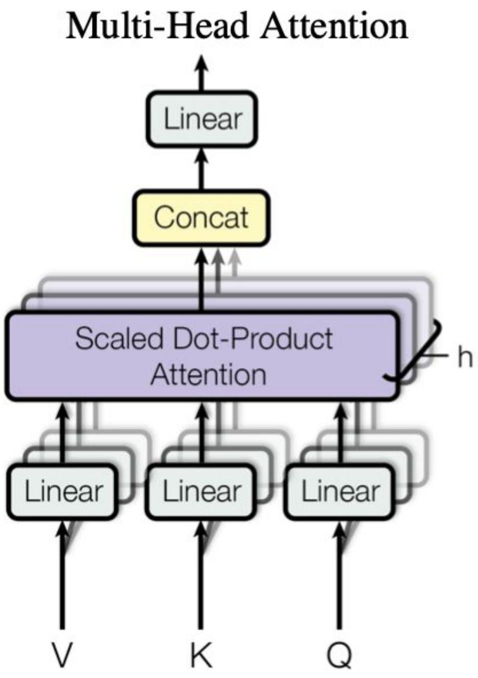


Figure 1: The Transformer - model architecture.

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

Attention


Scaled Dot-Product Attention
weighted sum
MatMul
SoftMax
Mask (opt.)
Scale
MatMul
Q
K
V
Query
Key
Value

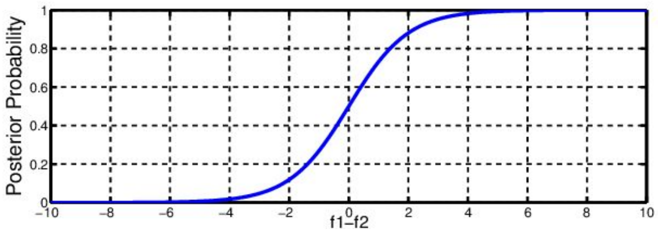

Multi-Head Attention
Linear
Concat
Scaled Dot-Product Attention
h
Linear
Linear
Linear
V
K
Q

Attention

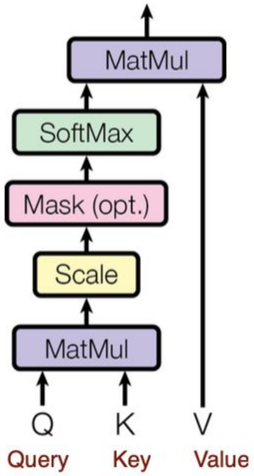
1. Scaled Dot-Product Attention

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

Q. scale하는 이유?



Scaled Dot-Product Attention



2. Multi-Head Attention

$$\mathrm{MultiHead}(Q, K, V) = \mathrm{Concat}(\mathrm{head_1}, ..., \mathrm{head_h})W^O$$
$$\text{where } \mathrm{head_i} = \mathrm{Attention}(QW_i^Q, KW_i^K, VW_i^V)$$

Where the projections are parameter matrices $W_i^Q \in \mathbb{R}^{d_{\text{model}} \times d_k}$, $W_i^K \in \mathbb{R}^{d_{\text{model}} \times d_k}$, $W_i^V \in \mathbb{R}^{d_{\text{model}} \times d_v}$ and $W^O \in \mathbb{R}^{hd_v \times d_{\text{model}}}$.

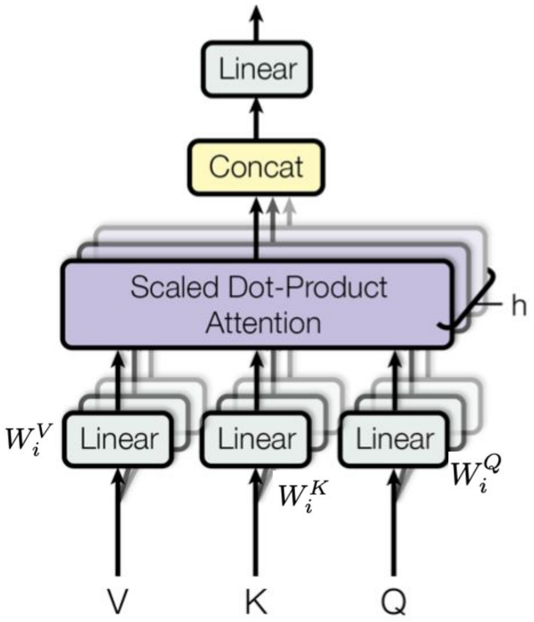
$$QW_i^Q = [d_Q \mathrm{x} d_{model}] \mathrm{x} [d_{model} \mathrm{x} d_k] = [d_Q \mathrm{x} d_k]$$
$$KW_i^K = [d_K \mathrm{x} d_{model}] \mathrm{x} [d_{model} \mathrm{x} d_k] = [d_K \mathrm{x} d_k]$$
$$VW_i^V = [d_V \mathrm{x} d_{model}] \mathrm{x} [d_{model} \mathrm{x} d_v] = [d_V \mathrm{x} d_v]$$

$$\downarrow$$

$$Attention(QW_i^Q, KW_i^K, VW_i^V) = [d_V \mathrm{x} d_v]$$

$$\downarrow$$

$$Concat(QW_i^Q, KW_i^K, VW_i^V)W^O = [d_V \mathrm{x} hd_v] \mathrm{x} [hd_v \mathrm{x} d_{model}] = [d_V \mathrm{x} d_{model}]$$



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

(토큰마다 적용되기 때문에 Position-wise)

Position-wise Feed-Forward Networks

Each of the layers in our encoder and decoder contains ***a fully connected feed-forward network***, which is applied to each position separately and identically.

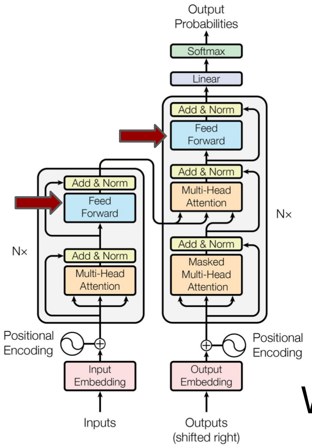
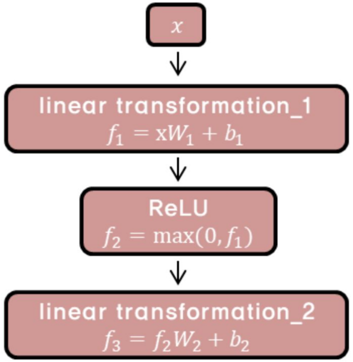


Figure 1: The Transformer - model architecture.

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



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

While the linear transformations are the same across different positions,

they use *different parameters from layer to layer.*

Positional Encoding

🙅🏻‍♀️ No Recurrence

🙅🏻‍♀️ No Convolution

👉🏻 **sequence의 순서정보는 어떻게 이용?**

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

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

왜 삼각함수를 사용? 👀

$$PE_{pos} = [cos(pos/1), sin(pos/10000^{2/d_{model}}), cos(pos/10000)^{2/d_{model}}, \ldots, sin(pos/10000)]$$

- 이때 PE_{pos+k}는 PE_{pos}의 linear function으로 나타낼 수 있습니다. 표기를 간단히 하기 위해 $c = 10000^{\frac{2i}{d_{model}}}$라고 해봅시다.
  $sin(a+b) = sin(a)cos(b) + cos(a)sin(b)$이고
  $cos(a+b) = cos(a)cos(b) - sin(a)sin(b)$ 이므로 다음이 성립합니다.

$$PE_{(pos,2i)} = sin(\frac{pos}{c})$$

$$PE_{(pos,2i+1)} = cos(\frac{pos}{c})$$

$$PE_{(pos+k,2i)} = sin(\frac{pos+k}{c}) = sin(\frac{pos}{c})cos(\frac{k}{c}) + cos(\frac{pos}{c})sin(\frac{k}{c}) = PE_{(pos,2i)}cos(\frac{k}{c}) + cos(\frac{pos}{c})sin(\frac{k}{c})$$

$$PE_{(pos+k,2i+1)} = cos(\frac{pos+k}{c}) = cos(\frac{pos}{c})cos(\frac{k}{c}) - sin(\frac{pos}{c})sin(\frac{k}{c}) = PE_{(pos,2i+1)}cos(\frac{k}{c}) - sin(\frac{pos}{c})sin(\frac{k}{c})$$

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

❓Why Self-Attention

1. computational complexity

2. 병렬화 가능한 계산의 양 👍

3. long-range dependencies사이의 path length

❓Why Self-Attention

3. long-range dependencies사이의 path length

많은 sequence transduction task에서 long-range dependency problem 존재

👉 path가 짧을수록 long-range dependency를 러닝하기 쉬워짐
(즉 거리가 먼 토큰들 사이에도 관계를 찾기 쉬워짐)

Table 1: Maximum path lengths, per-layer complexity and minimum number of sequential operations for different layer types. n is the sequence length, d is the representation dimension, k is the kernel size of convolutions and r the size of the neighborhood in restricted self-attention.

Layer Type	Complexity per Layer	Sequential Operations	Maximum Path Length
Self-Attention	$O(n^2 \cdot d)$	$O(1)$	$O(1)$
Recurrent	$O(n \cdot d^2)$	$O(n)$	$O(n)$
Convolutional	$O(k \cdot n \cdot d^2)$	$O(1)$	$O(log_k(n))$
Self-Attention (restricted)	$O(r \cdot n \cdot d)$	$O(1)$	$O(n/r)$

1. computational complexity

👉 대부분의 경우에 n < d 이기 때문에 self-attention의 complexity가 가장 작음

👉 만약 n이 매우 큰 seq라면, 즉 길이가 매우 긴 seq의 경우에는 neighbor size를 r로 제한시켜 사용함.

(💢 그만큼 max path length가 O(n/r)로 커지는 문제가 있음)

2. 병렬화 가능한 계산의 양 👍 : Sequential하지 않기에 가능

3. long-range dependencies사이의 path length

Training

1. Optimizer : Adam Optimizer

$$lrate = d_{\text{model}}^{-0.5} \cdot \min(step\_num^{-0.5}, step\_num \cdot warmup\_steps^{-1.5})$$

with $\beta_1 = 0.9$, $\beta_2 = 0.98$ and $\epsilon = 10^{-9}$

$$warmup\_steps = 4000$$

👉 warmup_steps까지는 learning rate가 linear하게 증가하다가 warmup_steps를 뛰어넘으면
step_num의 sqrt의 역수로 증가.

Training

2. Regularization

- **Residual Dropout**

👉 각 sub-layer의 output & the sums of the embeddings & positional encodings 에 적용

($P_{drop} = 0.1.$ for the base model)

- **Label Smoothing (모델이 덜 confident하게 만들어 overfitting방지)**

$\epsilon_{ls} = 0.1$

$$q'(k|x) = (1-\epsilon)\delta_{k,y} + \epsilon u(k)$$

Results

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	$\mathbf{3.3 \cdot 10^{18}}$	
Transformer (big)	**28.4**	**41.8**	$2.3 \cdot 10^{19}$	

Conclusion

"Transformer" : Based entirely on attiention, replacing the recurrent layers most commonly used in encoder-decoder architectures with multi-headed self-attention.

😂 Side benefit

self-attention could yield **more interpretable models**

As side benefit, self-attention could yield more interpretable models. We inspect attention distributions from our models and present and discuss examples in the appendix. Not only do individual attention heads clearly learn to perform different tasks, many appear to exhibit behavior related to the syntactic and semantic structure of the sentences.