Context-Aware Self-Attention Network

서상우

Context-Aware Self-Attention Networks

- AAAI 2019
- Self-attention의 변형 모델
- Neural Machine Translation Task
- WMT (Conference on Machine Translation)
  - WMT14 English⇒German
  - WMT17 Chinese⇒English

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Context-Aware Self-Attention Networks

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Machine Learning   Natural Language Processing   Machine Translation

标题	引用次数	年份
Multi-Head Attention with Disagreement Regularization J Li, Z Tu, B Yang, MR Lyu, T Zhang EMNLP 2018	7	2018
Modeling Localness for Self-Attention Networks B Yang, Z Tu, DF Wong, F Meng, LS Chao, T Zhang EMNLP 2018	6	2018
Towards Bidirectional Hierarchical Representations for Attention-based Neural Machine Translation B Yang, DF Wong, T Xiao, LS Chao, J Zhu EMNLP 2017	6	2017
Convolutional Self-Attention Networks B Yang, L Wang, DF Wong, LS Chao, Z Tu NAACL 2019	2	2019
Context-Aware Self-Attention Networks B Yang, J Li, D Wong, LS Chao, X Wang, Z Tu AAAI 2019	2	2019
Information Aggregation for Multi-Head Attention with Routing-by-Agreement J Li, B Yang, ZY Dou, X Wang, MR Lyu, Z Tu NAACL 2019		2019
Modeling Recurrence for Transformer J Hao, X Wang, B Yang, L Wang, J Zhang, Z Tu NAACL 2019		2019

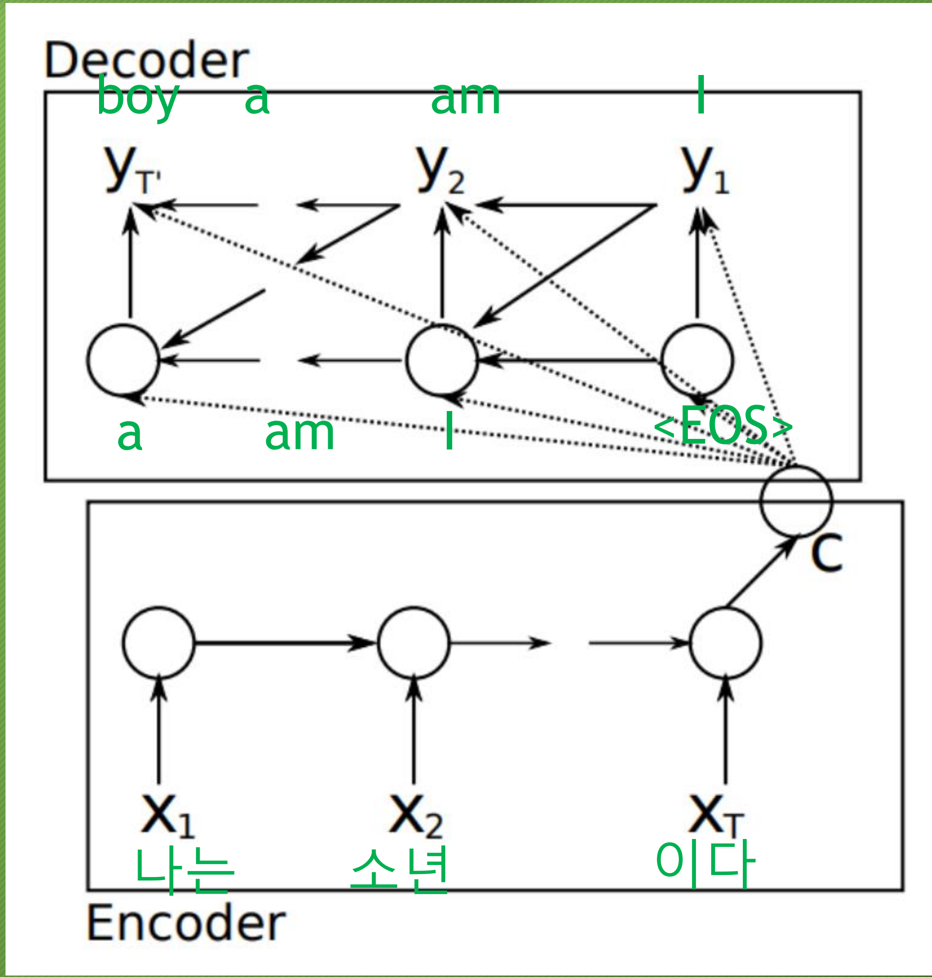
Seq2Seq

- 가장 기본적인 NMT task 모델
- Encoder Input으로 Source Sentence,
- Decoder Output으로 Target Sentence, Input은 shifted right 한 거

$$\mathbf{h}_{\langle t \rangle} = f\left(\mathbf{h}_{\langle t-1 \rangle}, x_t\right),$$

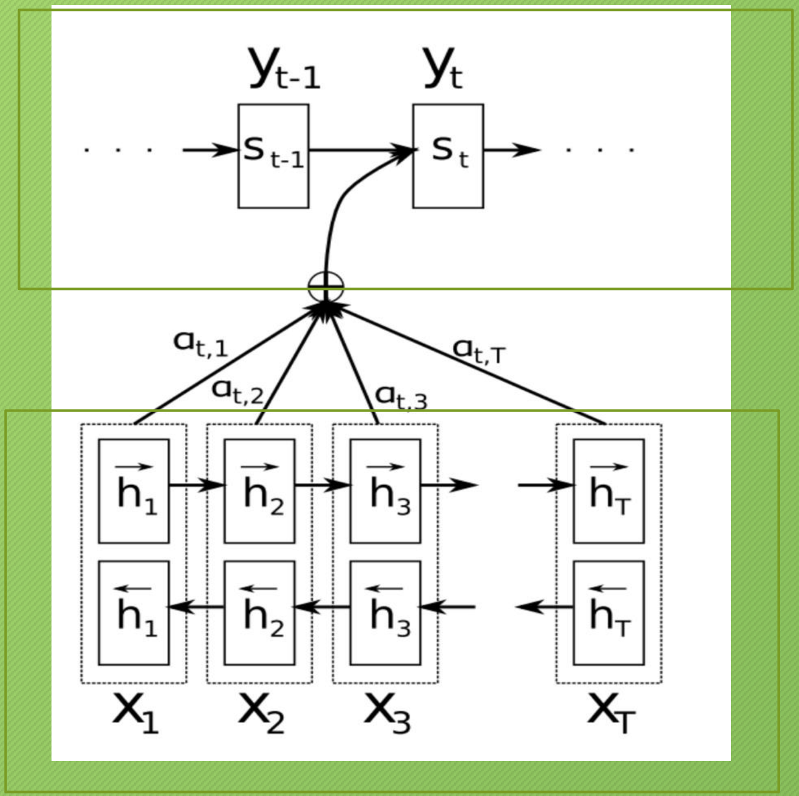
$$\mathbf{h}_{\langle t \rangle} = f\left(\mathbf{h}_{\langle t-1 \rangle}, y_{t-1}, \mathbf{c}\right),$$

$$P(y_t | y_{t-1}, y_{t-2}, \ldots, y_1, \mathbf{c}) = g\left(\mathbf{h}_{\langle t \rangle}, y_{t-1}, \mathbf{c}\right).$$



Attention mechanism

decoder



encoder

$$s_i = f(s_{i-1}, y_{i-1}, c_i).$$

$$p(y_i | y_1, \ldots, y_{i-1}, \mathbf{x}) = g(y_{i-1}, s_i, c_i),$$

$$c_i = \sum_{j=1}^{T_x} \alpha_{ij} h_j.$$

최종 Encoder output c 대신
Input 전체를 의미하는 x

$$\alpha_{ij} = \frac{\exp(e_{ij})}{\sum_{k=1}^{T_x} \exp(e_{ik})},$$

$$e_{ij} = a(s_{i-1}, h_j)$$

$$e_{ij} = s_{i-1} h_j^T$$

(dot product attention)

What is self attention?

- Attention is All You Need (NIPS 2017)에서 제안

- Transformer 블록
  - Self attention
  - Layer normalization
  - Residual network

- CNN, RNN 없이 NMT task의 SOTA

- Seq2Seq 모델의 단점 해결
  - 병렬처리가 불가능 속도 느림
  - Long Term Dependency를 잡을 수 없음 (CNN도 마찬가지)

Transformer block

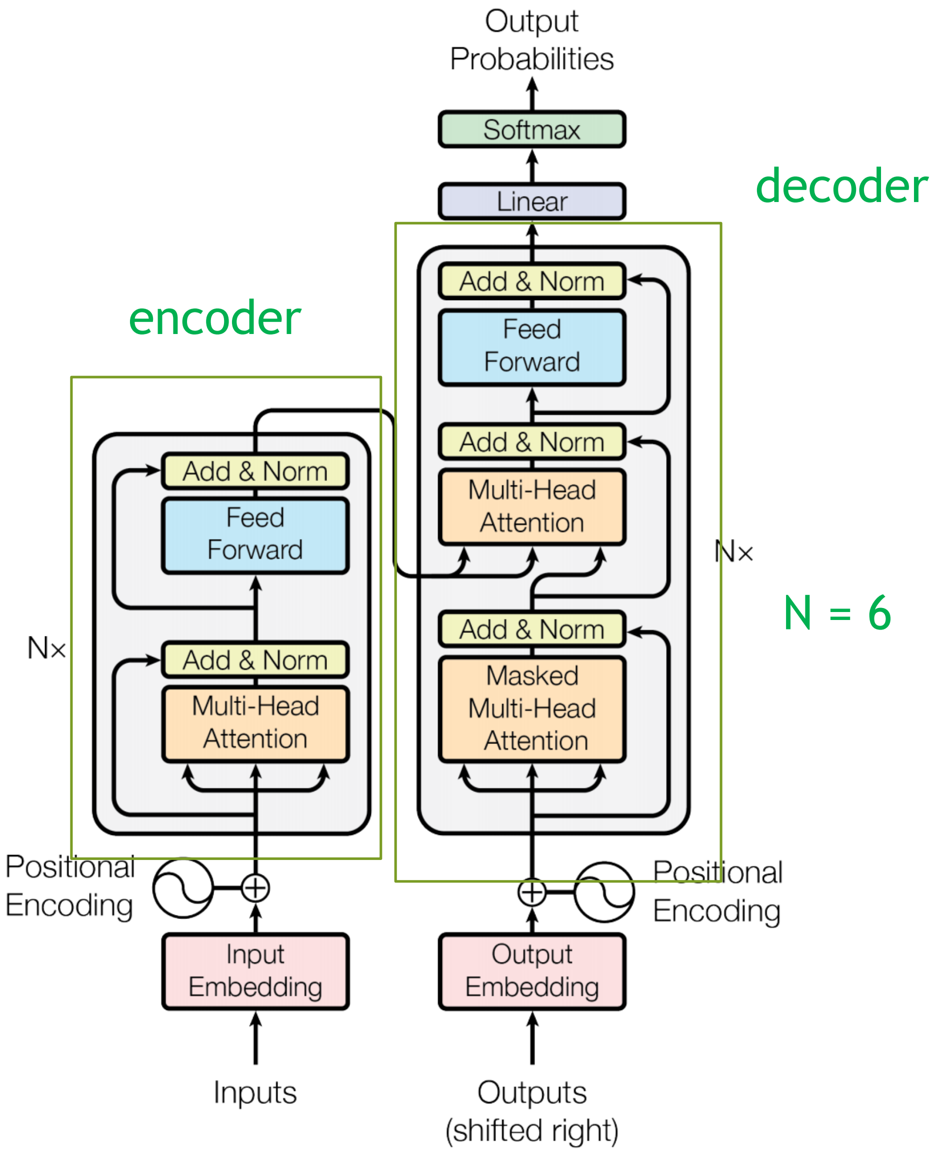
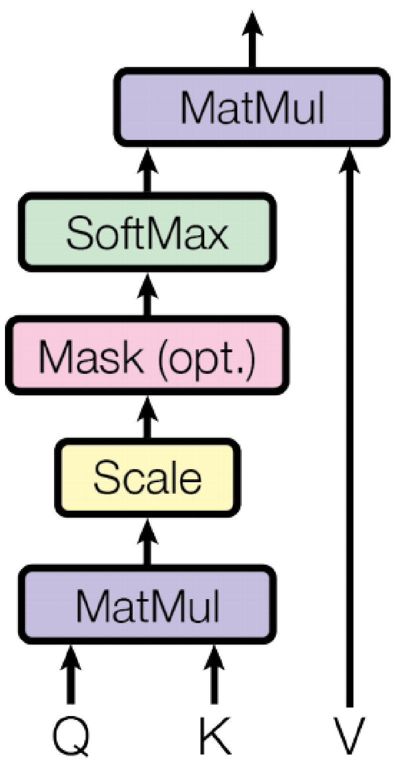


Figure 1: The Transformer - model architecture.

What is self attention?

Scaled Dot-Product Attention



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

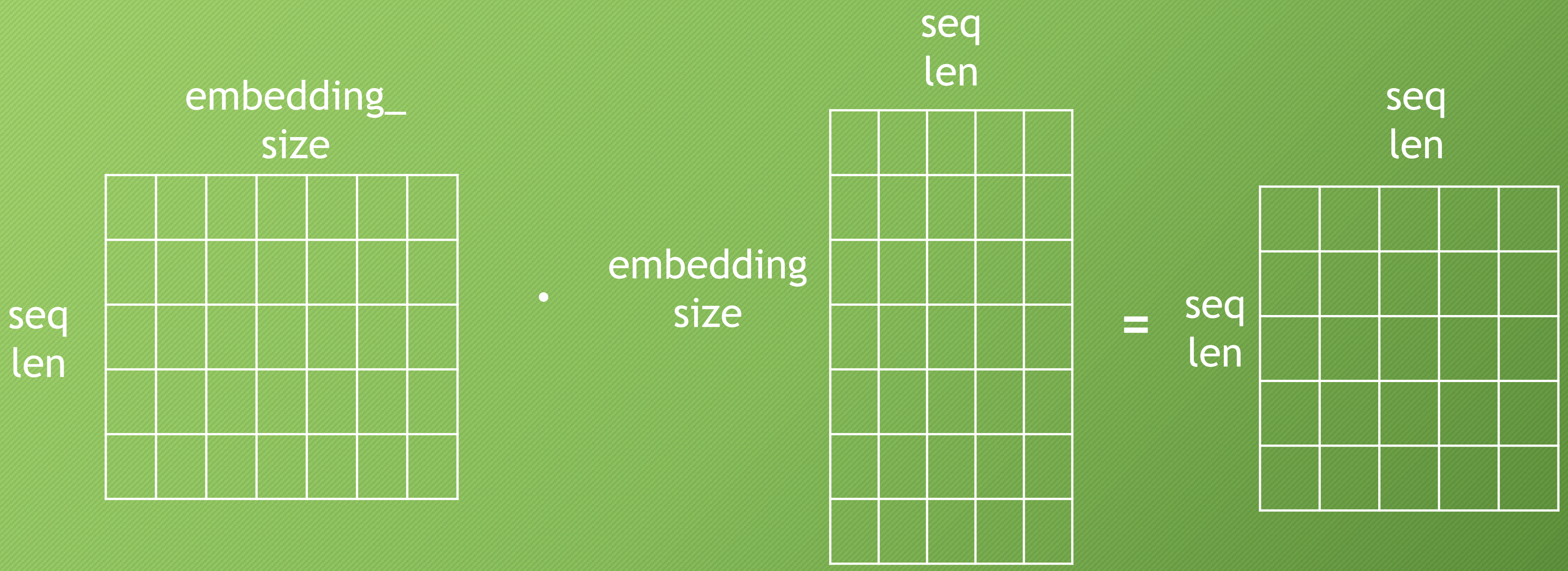
- encoder-decoder attention의 경우,
  Q : 디코더의 이전 레이어 hidden state
  K : 인코더의 output state
  V : 인코더의 output state

- self-attention의 경우,
  Q=K=V : 인코더의 output state (입력 Sentence)

What is self attention?

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

단어 간의 유사도
matrix가 나온다



What is self attention?

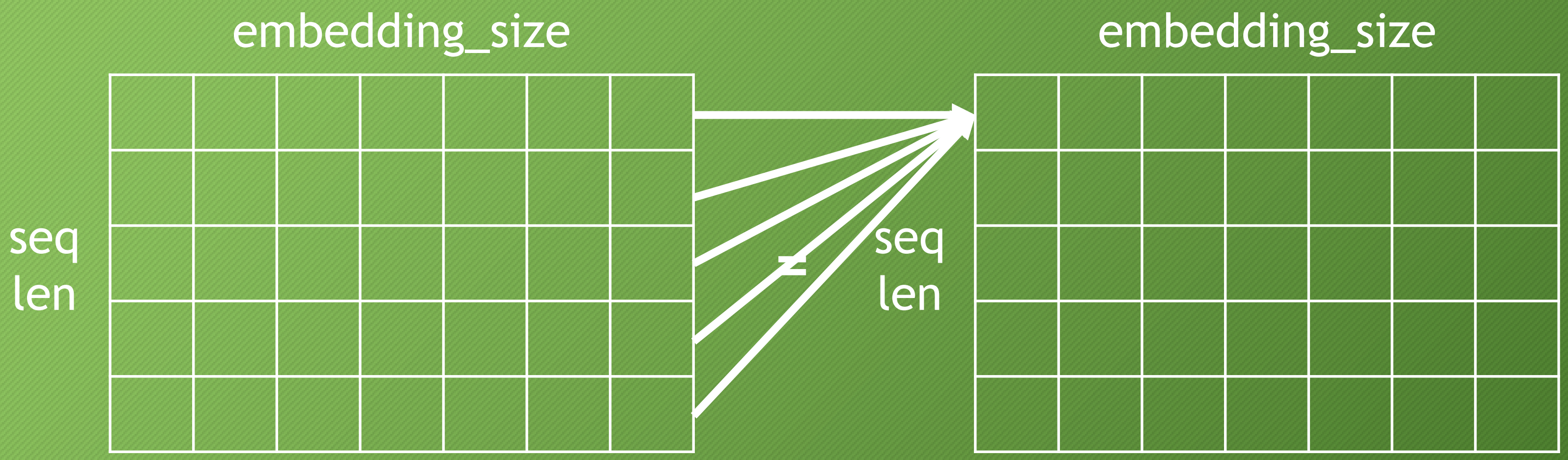
$$\text{Attention}(Q,K,V) = \boxed{\text{softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right)V}$$

Dot product하면 값이 상당히 커진다.

Dot product한 값과 V 값의 스케일을 맞추어 주기 위해 $\sqrt{d_k}$를 나누어 준다.

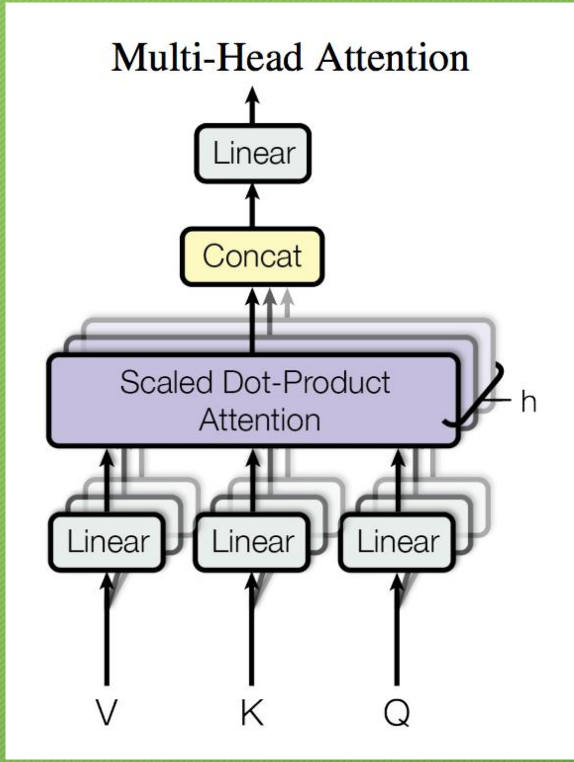
	i	am	sangwoo	…	thanks
i	0.5	0.1	0.3	…	0.1
am	0.1	0.5	0.2	…	0.1
sangwoo	0.3	0.2	0.4	…	
…					
thanks					

·



What is self attention?

- Multi-Head Attention은 self-attention을 여러 개 사용
- 문장 내의 여러 의미를 파악하기 위해 self-attention을 여러 개를 준다.
- 헤드에는 서로 다른 Linear가 곱해져서 들어가기 때문에 여러 의미를 파악 가능



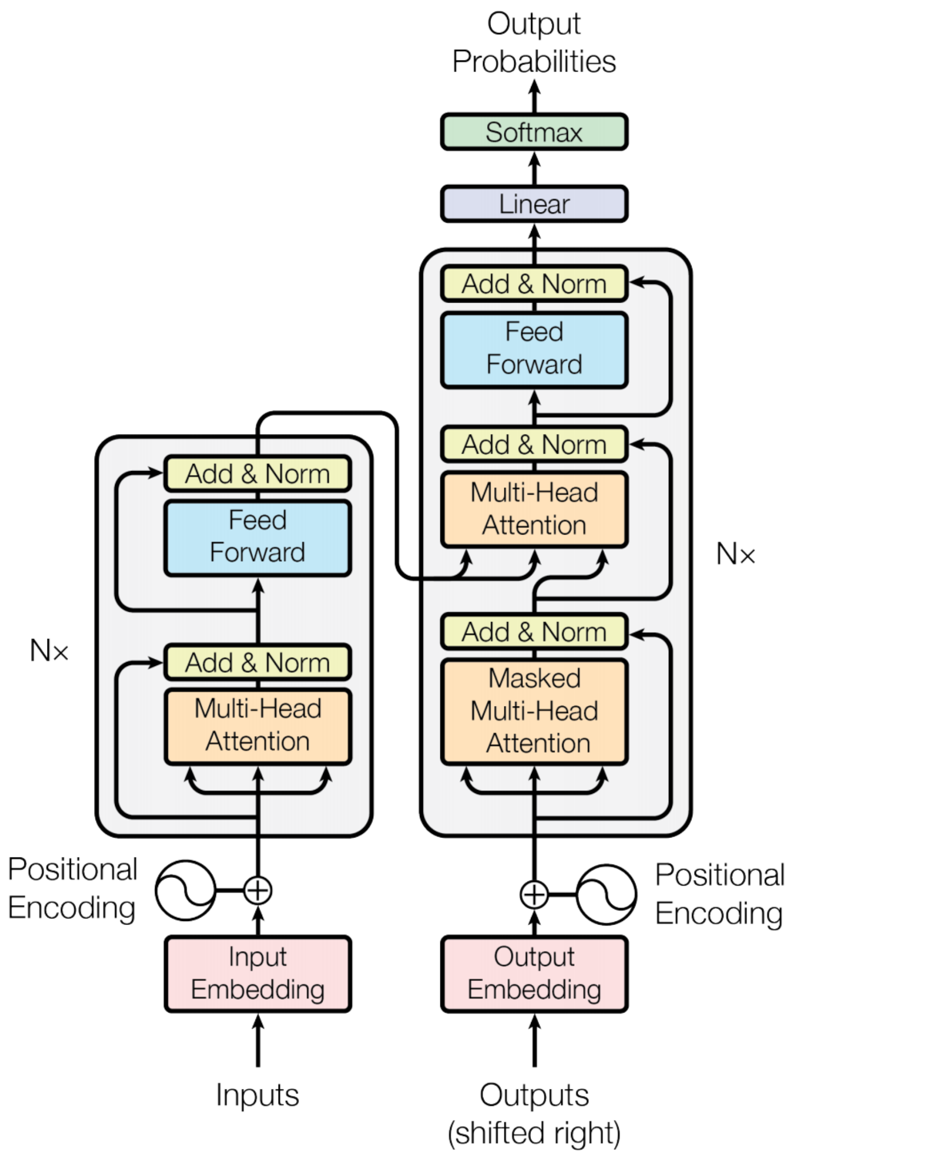


Figure 1: The Transformer - model architecture.

Context-Aware Self-Attention Networks

Self attention review

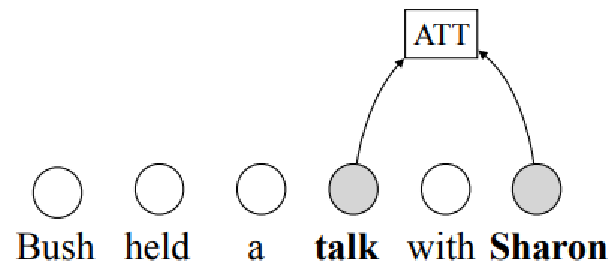
$$\begin{bmatrix} \mathbf{Q} \\ \mathbf{K} \\ \mathbf{V} \end{bmatrix} = \mathbf{H} \begin{bmatrix} \mathbf{W}_Q \\ \mathbf{W}_K \\ \mathbf{W}_V \end{bmatrix},$$

$$\mathbf{O} = \textsc{Att}(\mathbf{Q}, \mathbf{K})\, \mathbf{V},$$

$$\textsc{Att}(\mathbf{Q}, \mathbf{K}) = softmax(\frac{\mathbf{Q}\mathbf{K}^T}{\sqrt{d}}),$$

$$\mathbf{Q}\mathbf{K}^T = (\mathbf{H}\mathbf{W}_Q)(\mathbf{H}\mathbf{W}_K)^T = \mathbf{H}(\mathbf{W}_Q\mathbf{W}_K^T)\mathbf{H}^T,$$

해당 식에는 두 단어 간의 유사도만 구할 뿐 Context를 반영하지 않는다 => Self attention의 문제점



(a) Conventional SANs

Context-Aware Self-Attention Networks

기존의 Q,K 에 C라는 context vectore 더한다!

C와 Q,K 간의 크기를 맞추기 위해 weight matrix U_Q, U_K를 곱한다!

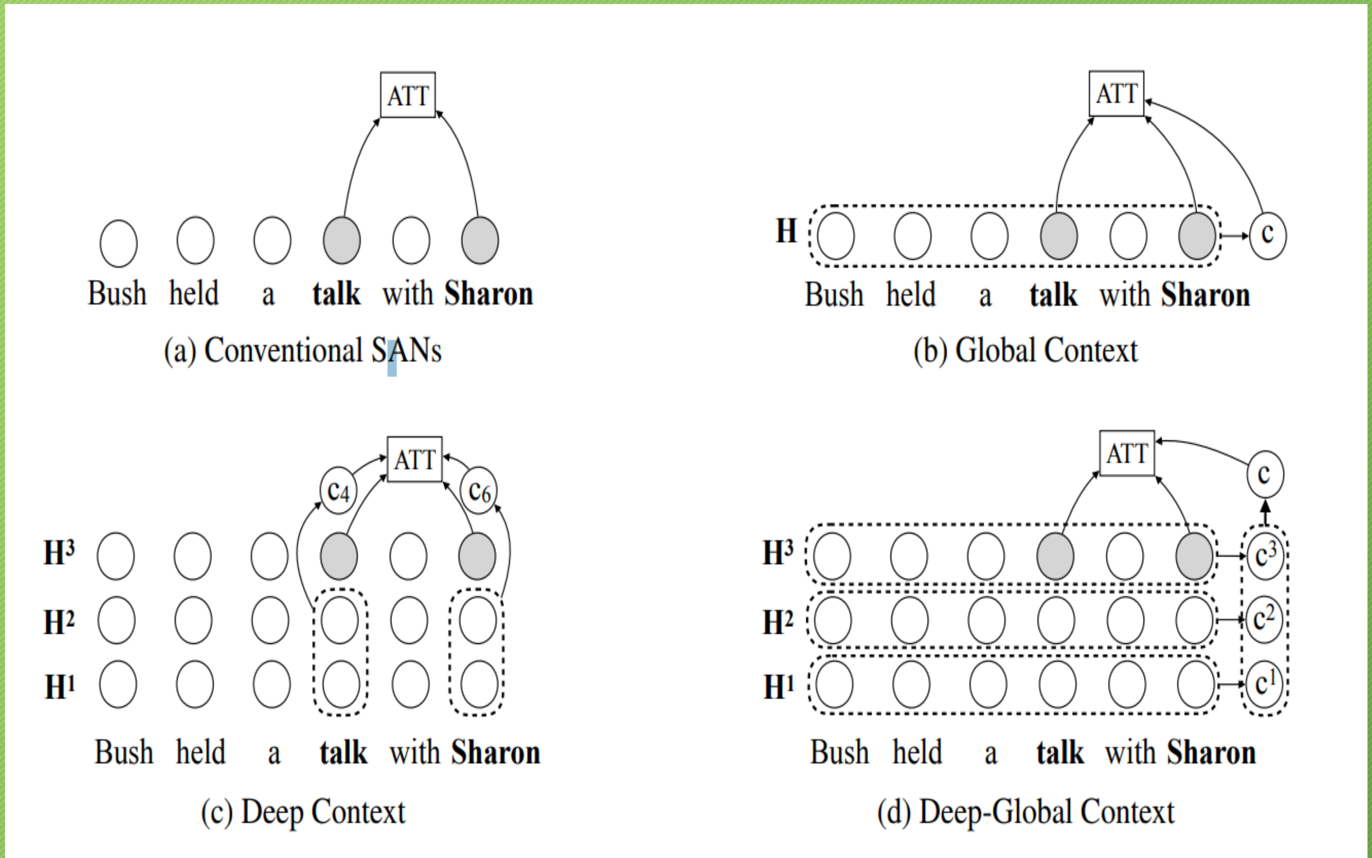
λ_Q, λ_K는 Q,K와 C 중 어떠한 것을 더 사용할 지를 결정하는 gating parameter

λ_Q, λ_K 또한 trainable하게 주어지는 파라미터로 뉴럴 네트워크가 contex와 원래의 값 중에서 어디를 더 치중할 지를 결정

$$\begin{bmatrix} \widehat{\mathbf{Q}} \\ \widehat{\mathbf{K}} \end{bmatrix} = (1 - \begin{bmatrix} \lambda_Q \\ \lambda_K \end{bmatrix}) \begin{bmatrix} \mathbf{Q} \\ \mathbf{K} \end{bmatrix} + \begin{bmatrix} \lambda_Q \\ \lambda_K \end{bmatrix} (\mathbf{C} \begin{bmatrix} \mathbf{U}_Q \\ \mathbf{U}_K \end{bmatrix})$$

$$\begin{bmatrix} \lambda_Q \\ \lambda_K \end{bmatrix} = \sigma(\begin{bmatrix} \mathbf{Q} \\ \mathbf{K} \end{bmatrix} \begin{bmatrix} \mathbf{V}_Q^H \\ \mathbf{V}_K^H \end{bmatrix} + \mathbf{C} \begin{bmatrix} \mathbf{U}_Q \\ \mathbf{U}_K \end{bmatrix} \begin{bmatrix} \mathbf{V}_Q^C \\ \mathbf{V}_K^C \end{bmatrix}),$$

What is context?



- Global context
  - Hidden의 평균 (벡터)

$$\mathbf{c} = \overline{\mathbf{H}}$$

- Deep context
  - 모든 이전의 hidden

$$\mathbf{C} = [\mathbf{H}^1, \ldots, \mathbf{H}^{l-1}]$$

- Deep-Global context
  - 모든 이전의 context (벡터)

$$\mathbf{c} = [\mathbf{c}^1, \ldots, \mathbf{c}^l]$$

BLUE score

$$BLEU = min(1, \frac{output\ length(\text{예측 문장})}{reference\ length(\text{실제 문장})})(\prod_{i=1}^{4} precision_i)^{\frac{1}{4}}$$

- 예측된 sentence : 빛이 쐬는 노인은 완벽한 어두운곳에서 잠든 사람과 비교할 때 강박증이 심해질 기회가 훨씬 높았다
- true sentence : 빛이 쐬는 사람은 완벽한 어둠에서 잠든 사람과 비교할 때 우울증이 심해질 가능성이 훨씬 높았다

- 1-gram precision: $\frac{\text{일치하는}1-gram\text{의 수(예측된 }sentence\text{중에서)}}{\text{모든}1-gram\text{쌍 (예측된 }sentence\text{중에서)}} = \frac{10}{14}$
- 2-gram precision: $\frac{\text{일치하는}2-gram\text{의 수(예측된 }sentence\text{중에서)}}{\text{모든}2-gram\text{쌍 (예측된 }sentence\text{중에서)}} = \frac{5}{13}$
- 3-gram precision: $\frac{\text{일치하는}3-gram\text{의 수(예측된 }sentence\text{중에서)}}{\text{모든}3-gram\text{쌍 (예측된 }sentence\text{중에서)}} = \frac{2}{12}$
- 4-gram precision: $\frac{\text{일치하는}4-gram\text{의 수(예측된 }sentence\text{중에서)}}{\text{모든}4-gram\text{쌍 (예측된 }sentence\text{중에서)}} = \frac{1}{11}$

$$(\prod_{i=1}^{4} precision_i)^{\frac{1}{4}} = (\frac{10}{14} \times \frac{5}{13} \times \frac{2}{12} \times \frac{1}{11})^{\frac{1}{4}}$$

+ 같은 단어가 연속적으로 나올때 과적합 되는 것을 보정(Clipping)

+ 문장길이에 대한 과적합 보정 (Brevity Penalty)

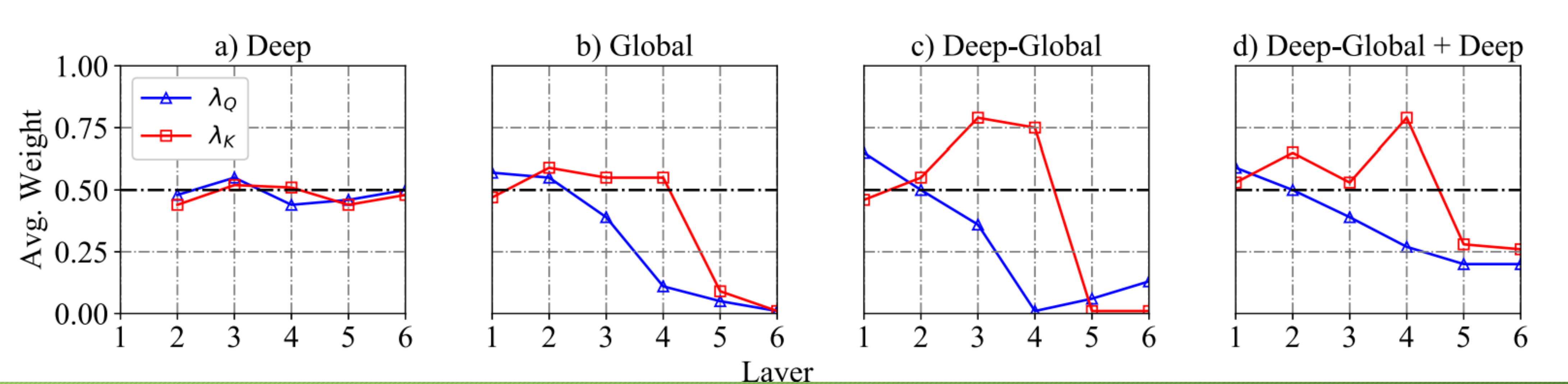
Experiments WMT14 (En⇒De)

#	Model	Applied to	Context Vectors	# Para.	Train	Decode	BLEU
1	BASE	n/a	n/a	88.0M	1.28	1.52	27.31
2	OURS	encoder	*global context*	91.0M	1.26	1.50	27.96
3			*deep-global context*	99.0M	1.25	1.48	28.15
4			*deep context*	95.9M	1.18	1.38	28.01
5			*deep-global context* + *deep context*	106.9M	1.16	1.36	**28.26**
6		decoder	*deep-global context*	99.0M	1.23	1.44	27.94
7			*deep-global context* + *deep context*	106.9M	1.15	1.35	28.02
8		both	5 + 7	125.8M	1.04	1.20	28.16

Experiments WMT17 (Zh⇒En)

System	Architecture	Zh⇒En # Para.	Zh⇒En Train	Zh⇒En BLEU	En⇒De # Para.	En⇒De Train	En⇒De BLEU
Existing NMT systems							
(Vaswani et al. 2017)	TRANSFORMER-BASE	n/a	n/a	n/a	65M	n/a	27.30
	TRANSFORMER-BIG	n/a	n/a	n/a	213M	n/a	28.40
(Hassan et al. 2018)	TRANSFORMER-BIG	n/a	n/a	24.20	n/a	n/a	n/a
Our NMT systems							
this work	TRANSFORMER-BASE	107.9M	1.21	24.13	88.0M	1.28	27.31
	+ Context-Aware SANs	126.8M	1.10	24.67⇑	106.9M	1.16	28.26⇑
	TRANSFORMER-BIG	303.9M	0.58	24.56	264.1M	0.61	28.58
	+ Context-Aware SANs	379.4M	0.41	25.15⇑	339.6M	0.44	28.89

Deep Context vs. Global Context



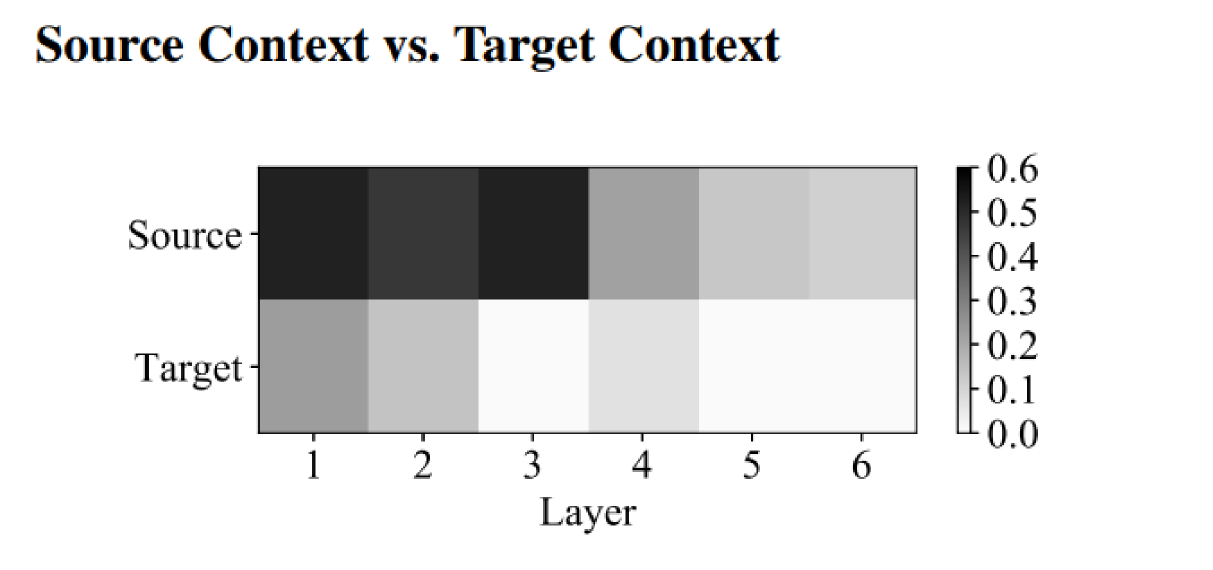
Stable Necessity of Deep Context

The Lower Layer, The More Global Context Required

Other experiment

Model	Query	Key	Dev
TRANSFORMER-BASE	-	-	25.84
+ Context-Aware	✓	✓	**26.42**
	×	✓	26.36
	✓	×	26.20

Keys Required More Global Information



Other experiment