165B
Machine Learning
Transformer

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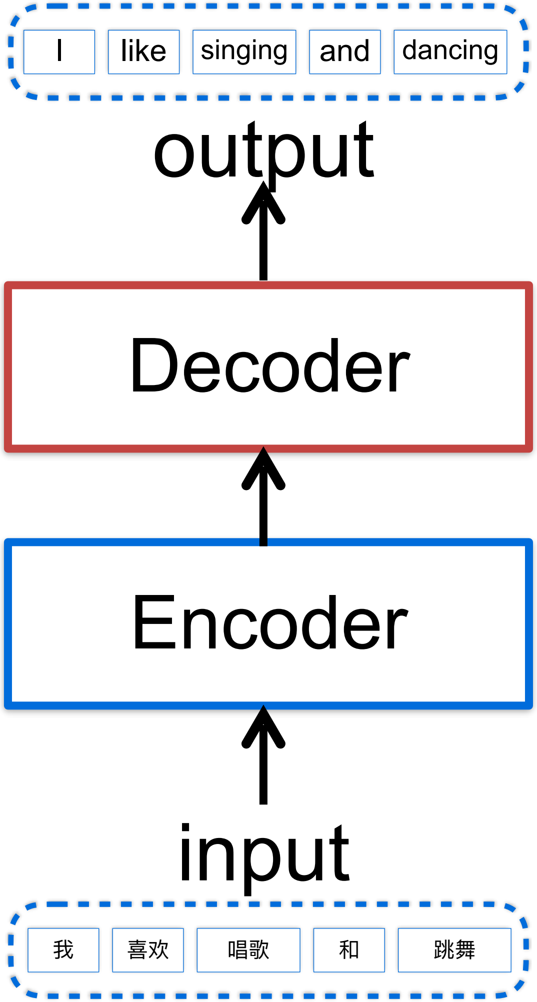
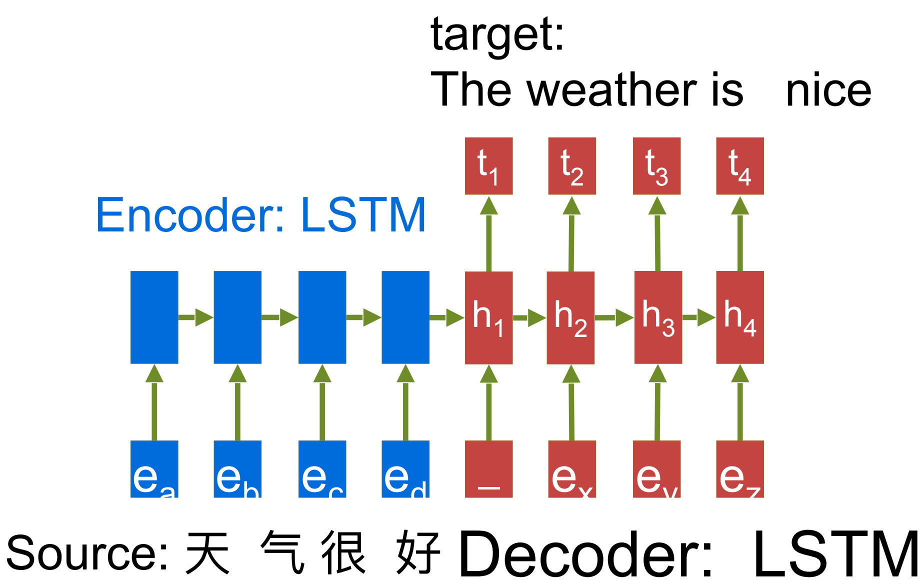
Encoder-Decoder Paradigm



Seq2Seq

- Machine translation as directly learning a function mapping from source sequence to target sequence



$$P(Y|X) = \prod P(y_t | y_{<t}, x)$$

Training loss: Cross-Entropy

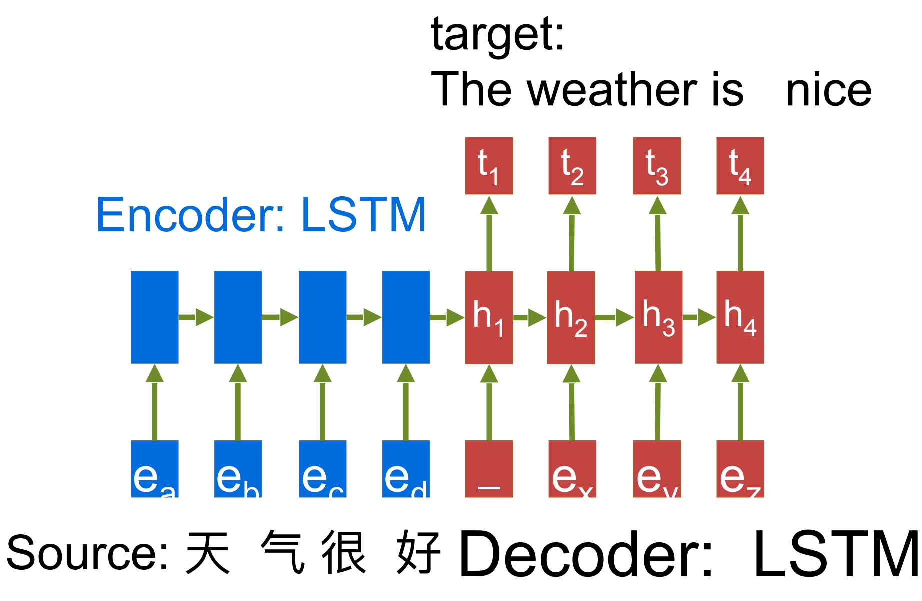
$$l = -\sum_n \sum_t \log f_\theta(x_n, y_{n,1}, \ldots, y_{n,t-1})$$

Teacher-forcing during training.

(pretend to know groundtruth for prefix)

Sutskever et al. Sequence to Sequence Learning with Neural Networks. 2014

Limitation of RNN/LSTM

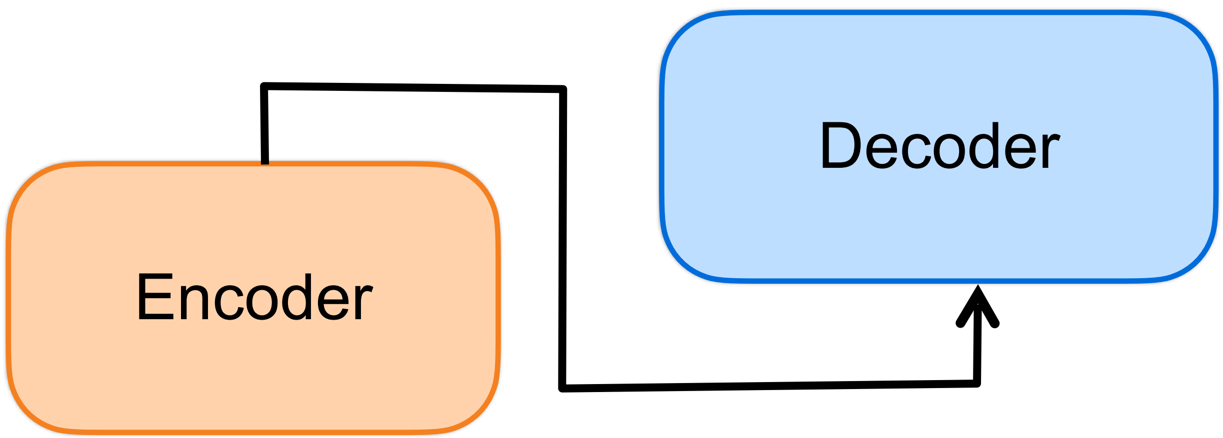


- No full context (only one-side)
  - Bidirectional LSTM encoder could alleviate
  - But still no long context
- Sequential computation in nature (encoder)
  - not possible to parallelize the computation
- Vanishing gradient

Transformer

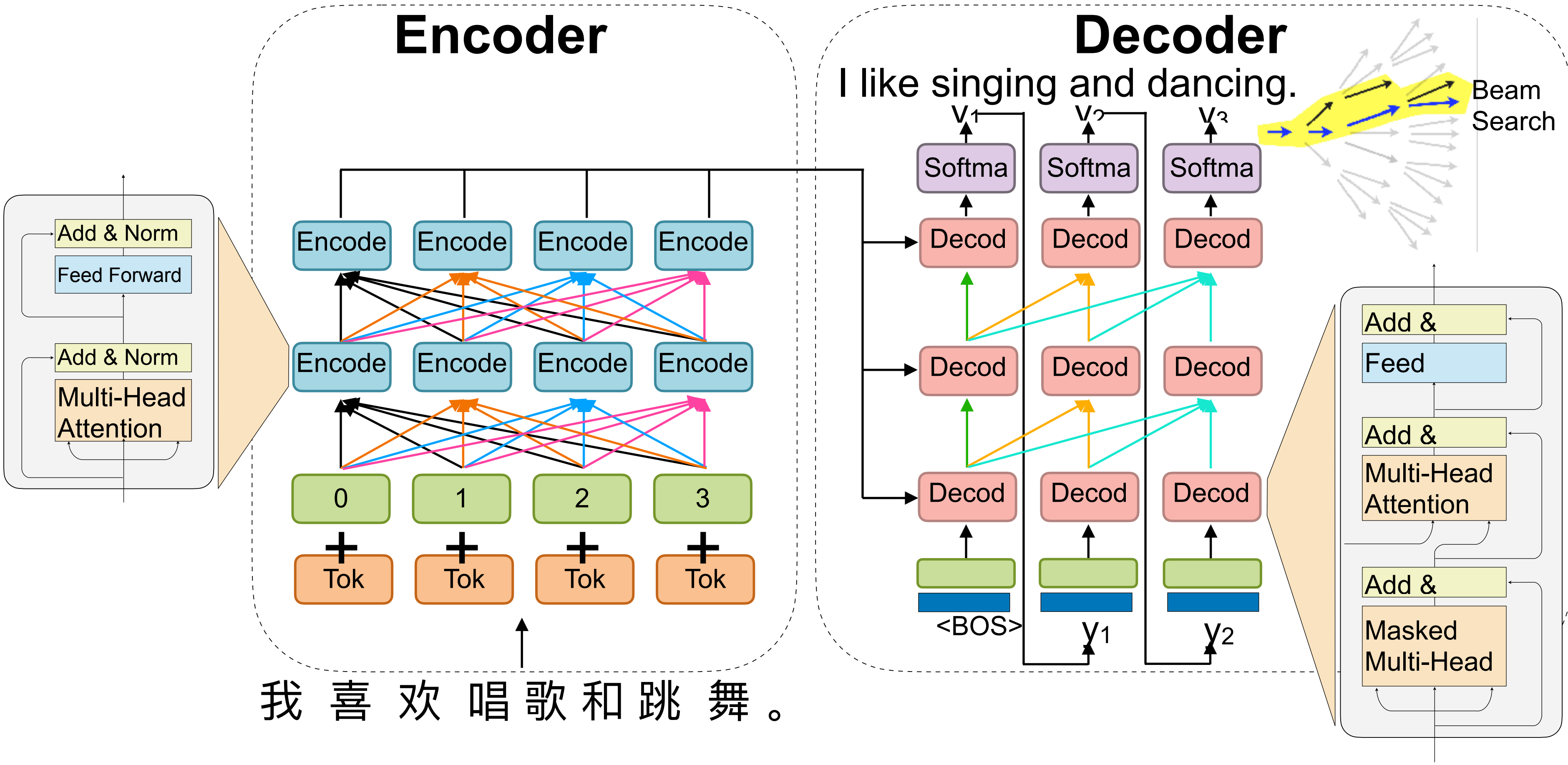
- Only use Attention in both encoder and decoder
- no recurrent

target:
I like singing and dancing.



Source: 我喜欢唱歌和跳舞。

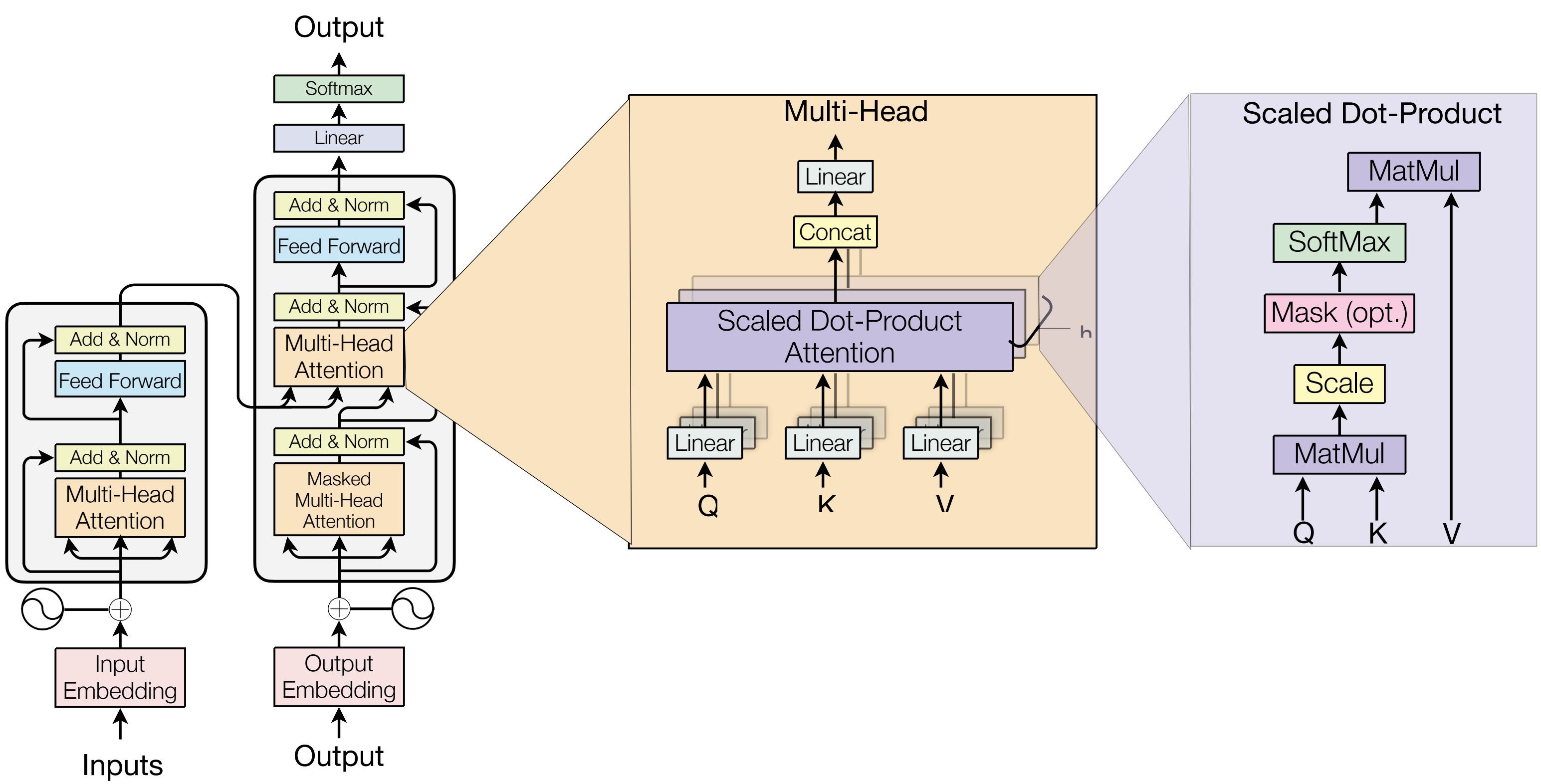
Transformer



Vaswani et al. Attention is All You Need. 2017

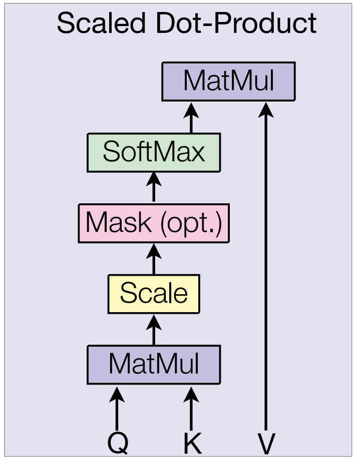
Transformer Multi-head Attention

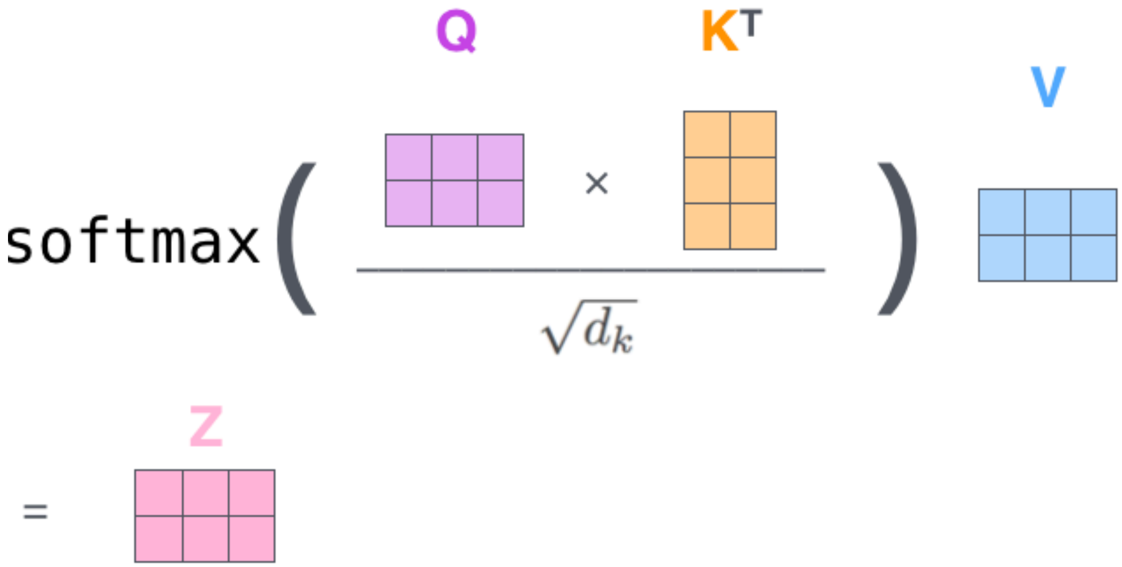
- C layers of encoder (=6)
- D layers of decoder (=6)



Scaled Dot-Product Attention

- $$\text{Attention}(Q, K, V) = \text{Softmax}(\frac{QK^T}{\sqrt{d}})V$$



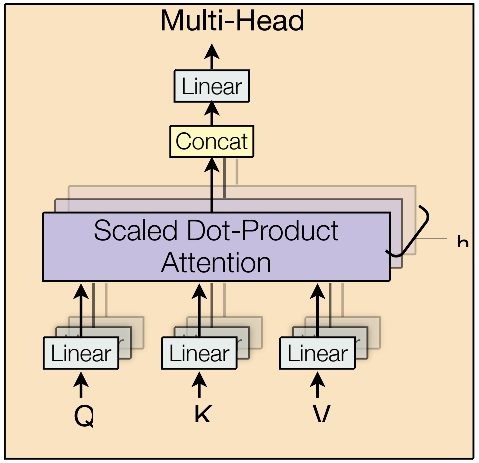


Multi-head Attention

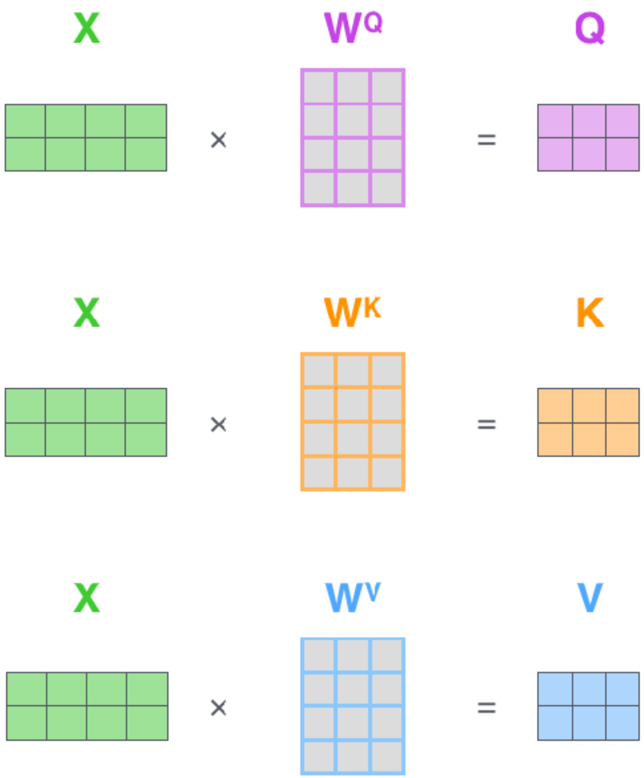
- Instead of one vector for each token
- break into multiple heads
- each head perform attention

$$\text{Head}_i = \text{Attention}(QW_i^Q, KW_i^K, VW_i^V)$$

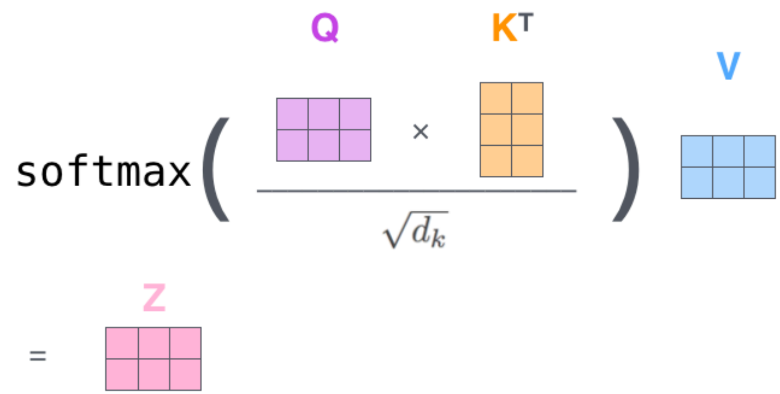
$$\text{MultiHead}(Q, K, V) = \text{Concat}(\text{Head}_1, \text{Head}_2, \ldots, \text{Head}_h)W^o$$



Multi-head Attention



sent len x sent len

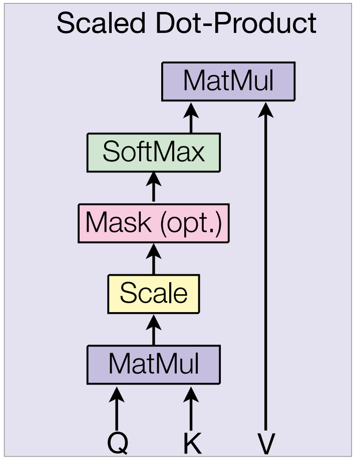


sent len x dim

Alammar, The Illustrated Transformer

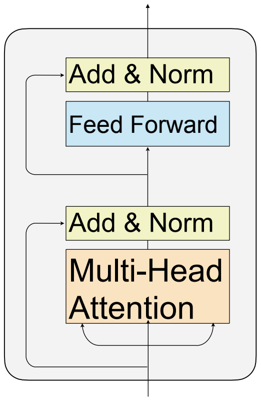
Self-Attention for Decoder

- Maskout right side before softmax (-inf)



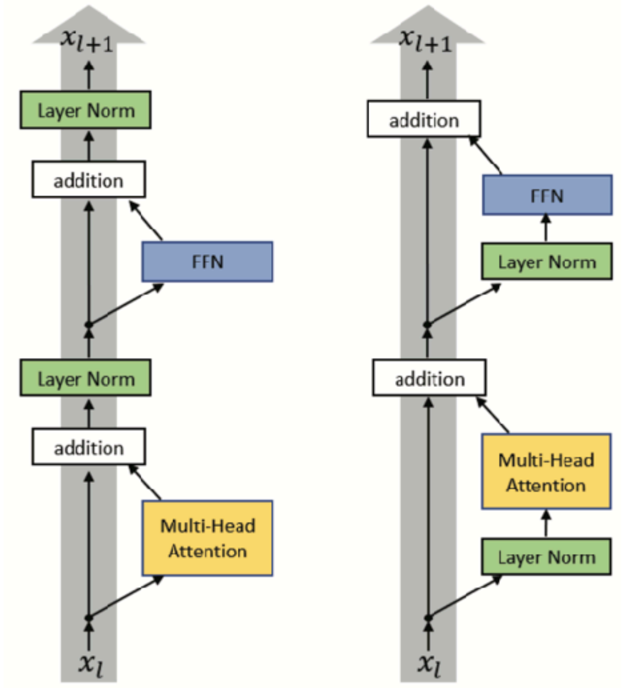
Feedforward Net

- $\mathrm{FFN}(x) = \max(0, x \cdot W_1 + b_1) \cdot W_2 + b_2$
- internal dimension size = 2048 (in Vaswani 2017)



Residual Connection and Layer Normalization

- Residual Connection
- Make it zero mean and unit variance within layer
- Post-norm
- Pre-norm

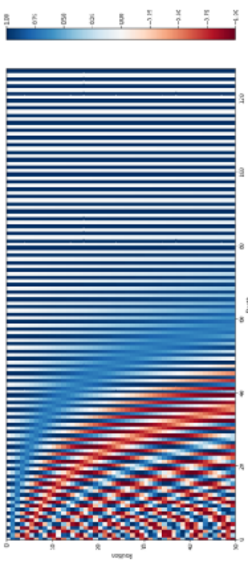


Embedding

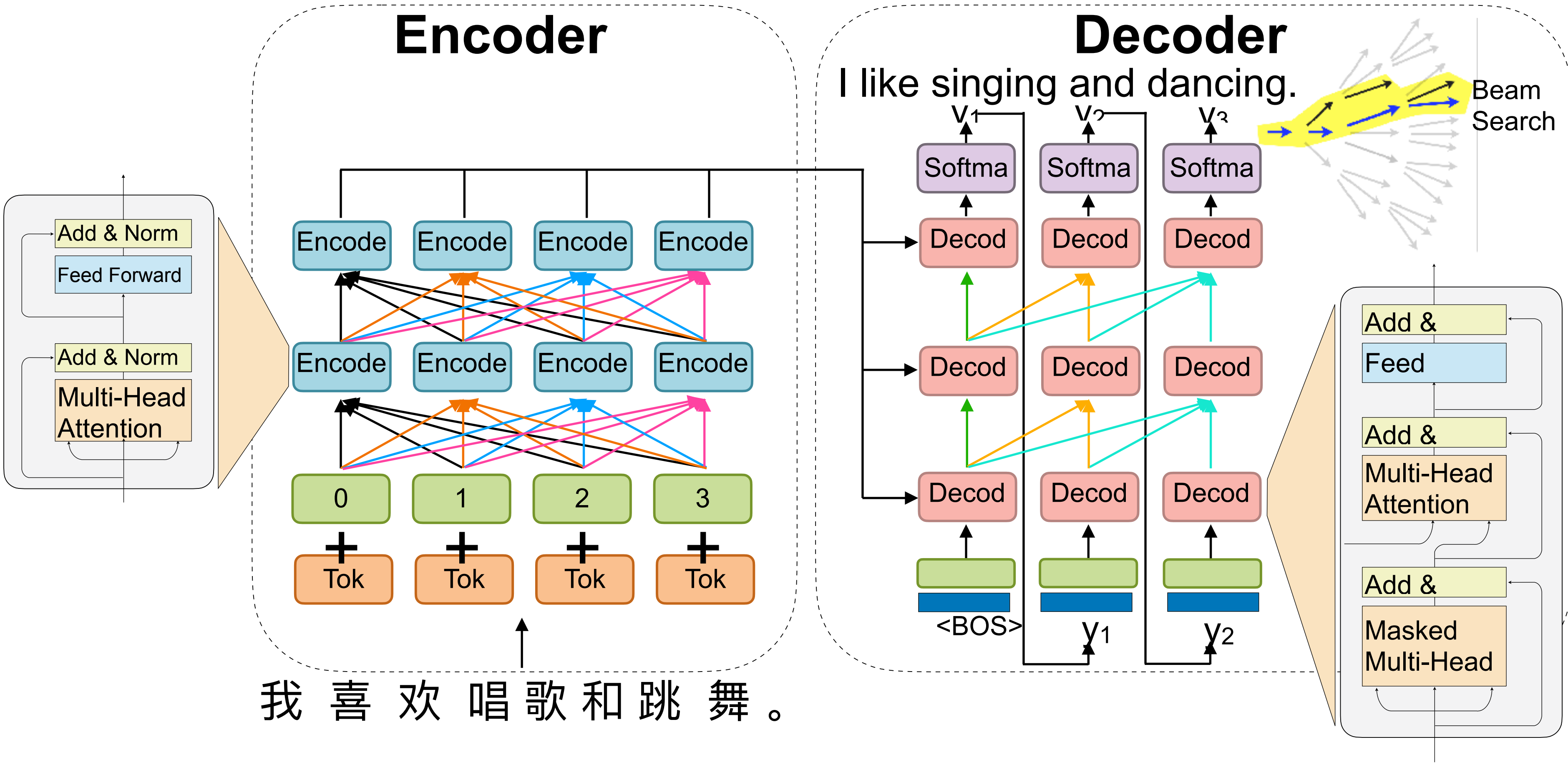
- Token Embedding: 512 (base), 1024 (large)
  - Shared (tied) input and output embedding
- Positional Embedding:
  - to distinguish words in different position, Map position labels to embedding, dimension is same as Tok Emb

$$PE_{pos,2i} = \sin\left(\frac{pos}{1000^{2i/d}}\right)$$

$$PE_{pos,2i+1} = \cos\left(\frac{pos}{1000^{2i/d}}\right)$$



Transformer



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Training Loss

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target:
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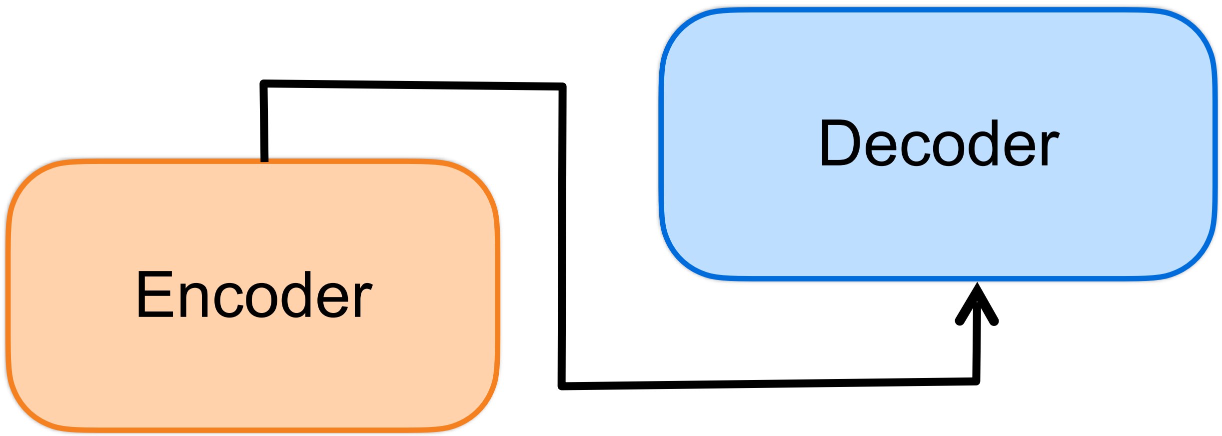


Source: 我喜欢唱歌和跳舞。

Training

- Dropout
  - Applied to before residual
  - and to embedding, pos emb.
  - p=0.1 ~ 0.3
- Label smoothing
  - 0.1 probability assigned to non-truth
- Vocabulary:
  - En-De: 37K using BPE
  - En-Fr: 32k word-piece (similar to BPE)

Label Smoothing

- Assume $\mathbf{y} \in \mathbb{R}^n$ is the one-hot encoding of label

$$y_i = \begin{cases} 1 & \text{if belongs to class } i \\ 0 & \text{otherwise} \end{cases}$$

- Approximating 0/1 values with softmax is hard
- The smoothed version

$$y_i = \begin{cases} 1 - \epsilon & \text{if belongs to class } i \\ \epsilon/(n-1) & \text{otherwise} \end{cases}$$

  – Commonly use $\epsilon = 0.1$

Training

- Batch
  - group by approximate sentence length
  - still need shuffling
- Hardware
  - one machine with 8 GPUs (in 2017 paper)
  - base model: 100k steps (12 hours)
  - large model: 300k steps (3.5 days)
- Adam Optimizer
  - increase learning rate during warmup, then decrease

$$\eta = \frac{1}{\sqrt{d}} \min\left(\frac{1}{\sqrt{t}}, \frac{t}{\sqrt{t_0^3}}\right)$$

ADAM

$$m_{t+1} = \beta_1 m_t - (1-\beta_1)\nabla \ell(x_t)$$
$$v_{t+1} = \beta_2 v_t + (1-\beta_2)(\nabla \ell(x_t))^2$$
$$\hat{m}_{t+1} = \frac{m_{t+1}}{1-\beta_1^{t+1}}$$
$$\hat{v}_{t+1} = \frac{v_{t+1}}{1-\beta_2^{t+1}}$$
$$x_{t+1} = x_t - \frac{\eta}{\sqrt{\hat{v}_{t+1}} + \epsilon}\hat{m}_{t+1}$$

Model Average

- A single model obtained by averaging the last 5 checkpoints, which were written at 10-minute interval (base)
- decoding length: within source length + 50

Evaluation for Machine Translation

Many possible translation, which is better?

SpaceX周三晚间进行了一次发射任务，将四名毫无航天经验的业余人士送入太空轨道。

SpaceX launched a mission Wednesday night to put four amateurs with no space experience into orbit.

SpaceX conducted a launch mission on Wednesday night, sending four amateurs with no aerospace experience into space orbit.

SpaceX conducted a launch mission Wednesday night that sent four amateurs with no spaceflight experience into orbit.

SpaceX carried out a launch mission on Wednesday night to put four amateurs without Aerospace experience into orbit.

BLEU

- Measuring the precision of n-grams
  - Precision of n-gram: percentage of tokens in output sentences

$$\_\, p_n = \frac{num\,.\,of\,.\,correct\,.\,token\,.\,ngram}{total\,.\,output\,.\,ngram}$$

- Penalize for brevity
  - if output is too short
  - $bp = min(1, e^{1-r/c})$
- BLEU=$bp \cdot (\prod p_i)^{\frac{1}{4}}$
- Notice BLEU is computed over the whole corpus, not on one sentence

Example

Ref: A SpaceX rocket was launched into a space orbit Wednesday evening.

System A: SpaceX launched a mission Wednesday evening into a space orbit.

System B: A rocket sent SpaceX into orbit Wednesday.

Example

Ref: A SpaceX rocket was launched into a space orbit Wednesday evening.

System A: SpaceX launched a mission Wednesday evening into a space orbit.

	Precision
Unigram	9/11
Bigram	4/10
Trigram	2/9
Four-gram	1/8

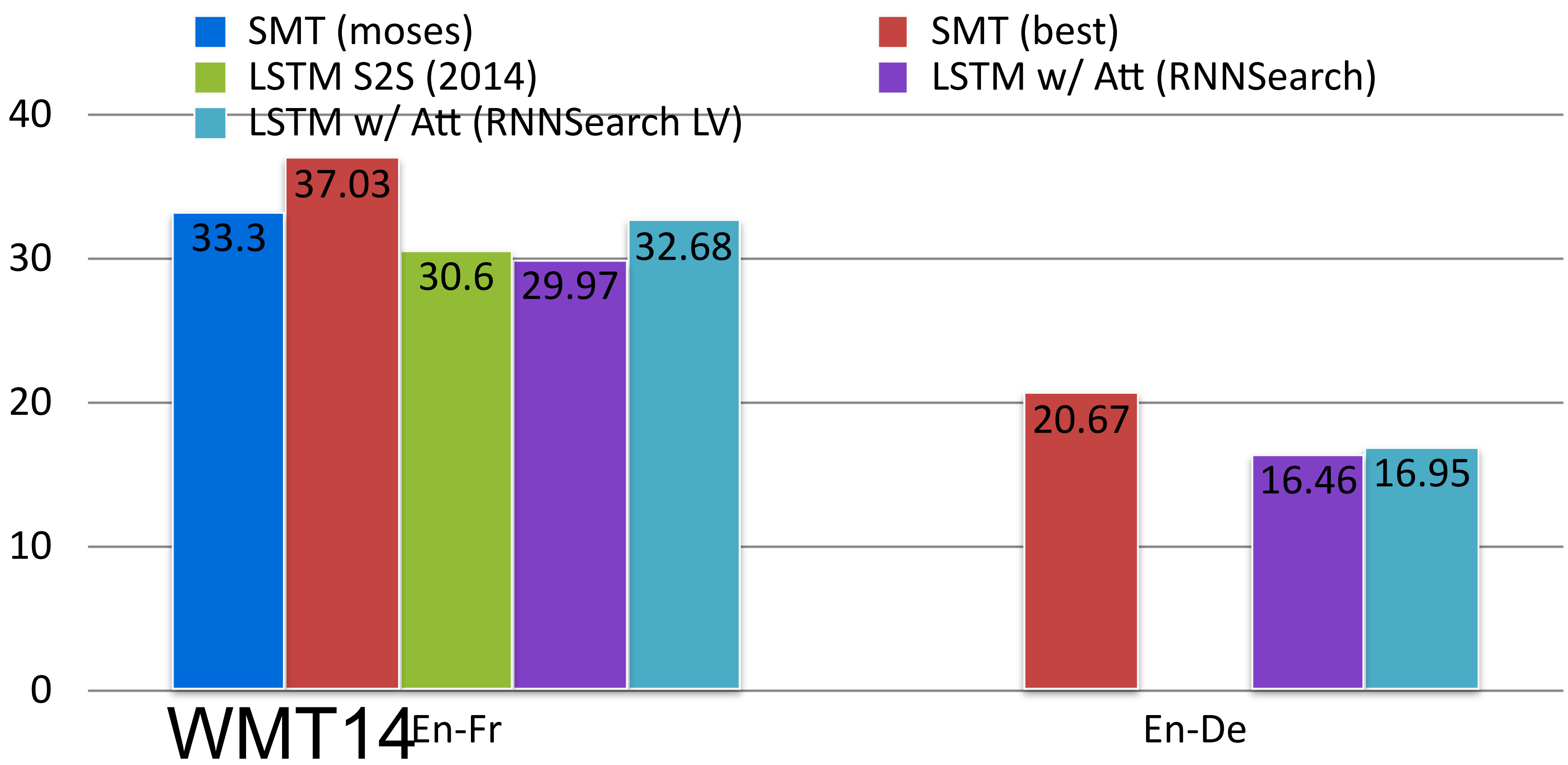
$$bp=e^{1-12/11}=0.91$$

$$BLEU=0.91*(9/11 * 4/10 * 2/9 * 1/8)^{1/4}$$

$$=28.1\%$$

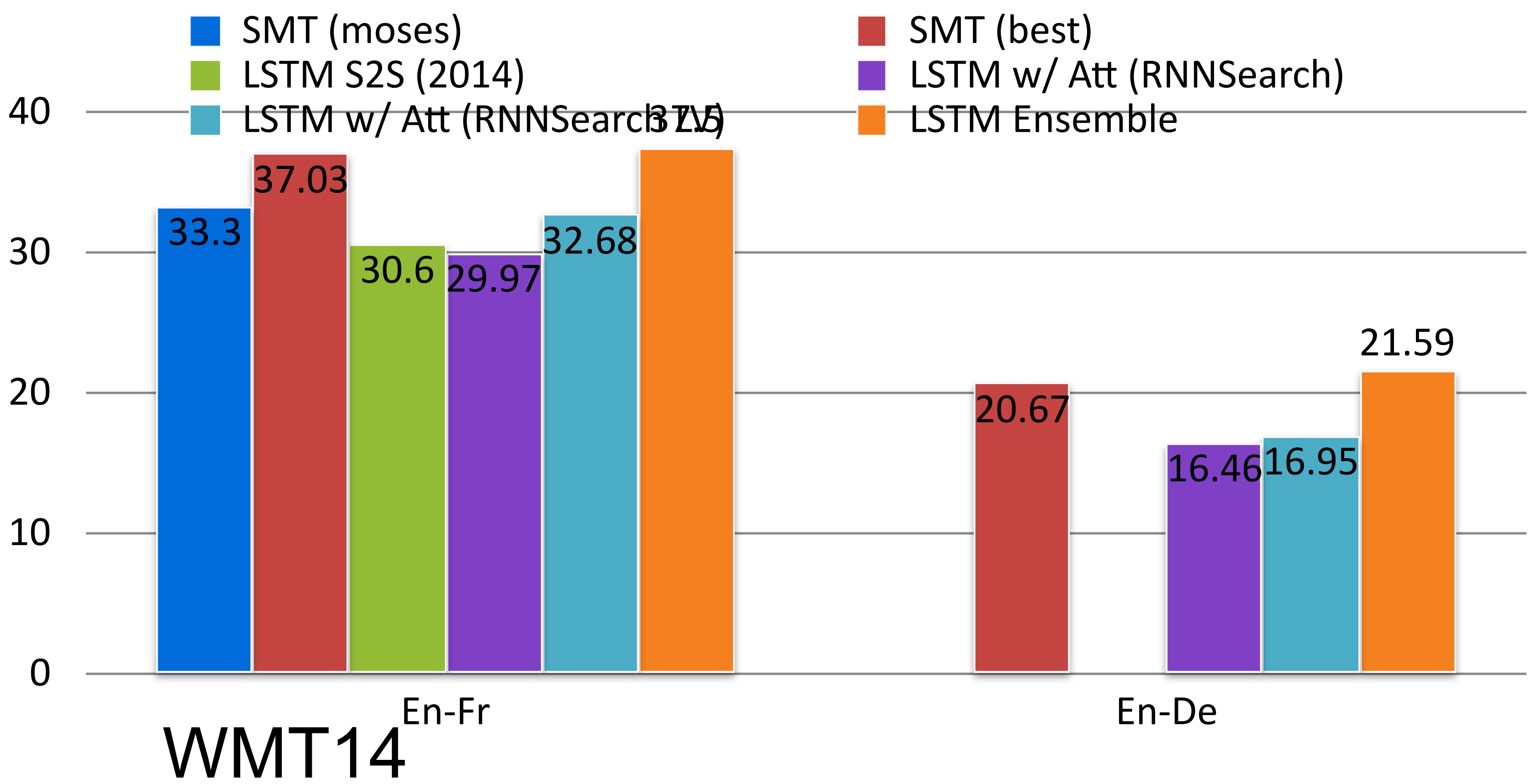
Machine Translation using Seq2seq and Transformer

LSTM Seq2Seq w/ Attention



Jean et al. On Using Very Large Target Vocabulary for Neural Machine Translation. 2015

Performance with Model Ensemble



Luong et al. Effective Approaches to Attention-based Neural Machine Translation. 2015

Results on WMT14

Model	BLEU		Training Cost (FLOPs)	
	EN-DE	EN-FR	EN-DE	EN-FR
ByteNet [15]	23.75			
Deep-Att + PosUnk [32]		39.2		$1.0 \cdot 10^{20}$
GNMT + RL [31]	24.6	39.92	$2.3 \cdot 10^{19}$	$1.4 \cdot 10^{20}$
ConvS2S [8]	25.16	40.46	$9.6 \cdot 10^{18}$	$1.5 \cdot 10^{20}$
MoE [26]	26.03	40.56	$2.0 \cdot 10^{19}$	$1.2 \cdot 10^{20}$
Deep-Att + PosUnk Ensemble [32]		40.4		$8.0 \cdot 10^{20}$
GNMT + RL Ensemble [31]	26.30	41.16	$1.8 \cdot 10^{20}$	$1.1 \cdot 10^{21}$
ConvS2S Ensemble [8]	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**	**41.0**	$2.3 \cdot 10^{19}$	

Effectiveness of Choices

- num. head
- dim of key
- num layers
- hid dim
- ffn dim
- dropout
- pos emb

	N	d_{model}	d_{ff}	h	d_k	d_v	P_{drop}	ϵ_{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

Deep Transformer

- 30 ~ 60 encoder
- 12 decoder
- dynamic linear combination of layers (DLCL)
  - or. deeply supervised
  - combine output from all layers

Wang et al. Learning Deep Transformer Models for Machine Translation, 2019.

Model		Param.	Batch (×4096)	Updates (×100k)	†Times	BLEU	Δ
Vaswani et al. (2017) (Base)		65M	1	1	reference	27.3	-
Bapna et al. (2018)-deep (Base, 16L)		137M	-	-	-	28.0	-
Vaswani et al. (2017) (Big)		213M	1	3	3x	28.4	-
Chen et al. (2018a) (Big)		379M	16	†0.075	1.2x	28.5	-
He et al. (2018) (Big)		†210M	1	-	-	29.0	-
Shaw et al. (2018) (Big)		†210M	1	3	3x	29.2	-
Dou et al. (2018) (Big)		356M	1	-	-	29.2	-
Ott et al. (2018) (Big)		210M	14	0.25	3.5x	29.3	-
post-norm	Transformer (Base)	62M	1	1	1x	27.5	reference
	Transformer (Big)	211M	1	3	3x	28.8	+1.3
	Transformer-deep (Base, 20L)	106M	2	0.5	1x	failed	failed
	DLCL (Base)	62M	1	1	1x	27.6	+0.1
	DLCL-deep (Base, 25L)	121M	2	0.5	1x	29.2	+1.7
pre-norm	Transformer (Base)	62M	1	1	1x	27.1	reference
	Transformer (Big)	211M	1	3	3x	28.7	+1.6
	Transformer-deep (Base, 20L)	106M	2	0.5	1x	28.9	+1.8
	DLCL (Base)	62M	1	1	1x	27.3	+0.2
	DLCL-deep (Base, 30L)	137M	2	0.5	1x	**29.3**	**+2.2**

Wang et al. Learning Deep Transformer Models for Machine Translation, 2019.

Model	Param.	newstest17	newstest18	$\Delta_{avg.}$
Wang et al. (2018a) (post-norm, Base)	102.1M	25.9	-	-
pre-norm Transformer (Base)	102.1M	25.8	25.9	reference
pre-norm Transformer (Big)	292.4M	26.4	27.0	+0.9
pre-norm DLCL-deep (Base, 25L)	161.5M	26.7	27.1	+1.0
pre-norm DLCL-deep (Base, 30L)	177.2M	**26.9**	**27.4**	**+1.3**

Table 4: BLEU scores [%] on WMT'18 Chinese-English translation.

Wang et al. Learning Deep Transformer Models for Machine Translation, 2019.

Summary

- Key components in Transformer
  - Positional Embedding (to distinguish tokens at different pos)
  - Multihead attention
  - Residual connection
  - layer norm
- Transformer is effective for machine translation, and many other tasks

Next Up

- Pretraining for NLP