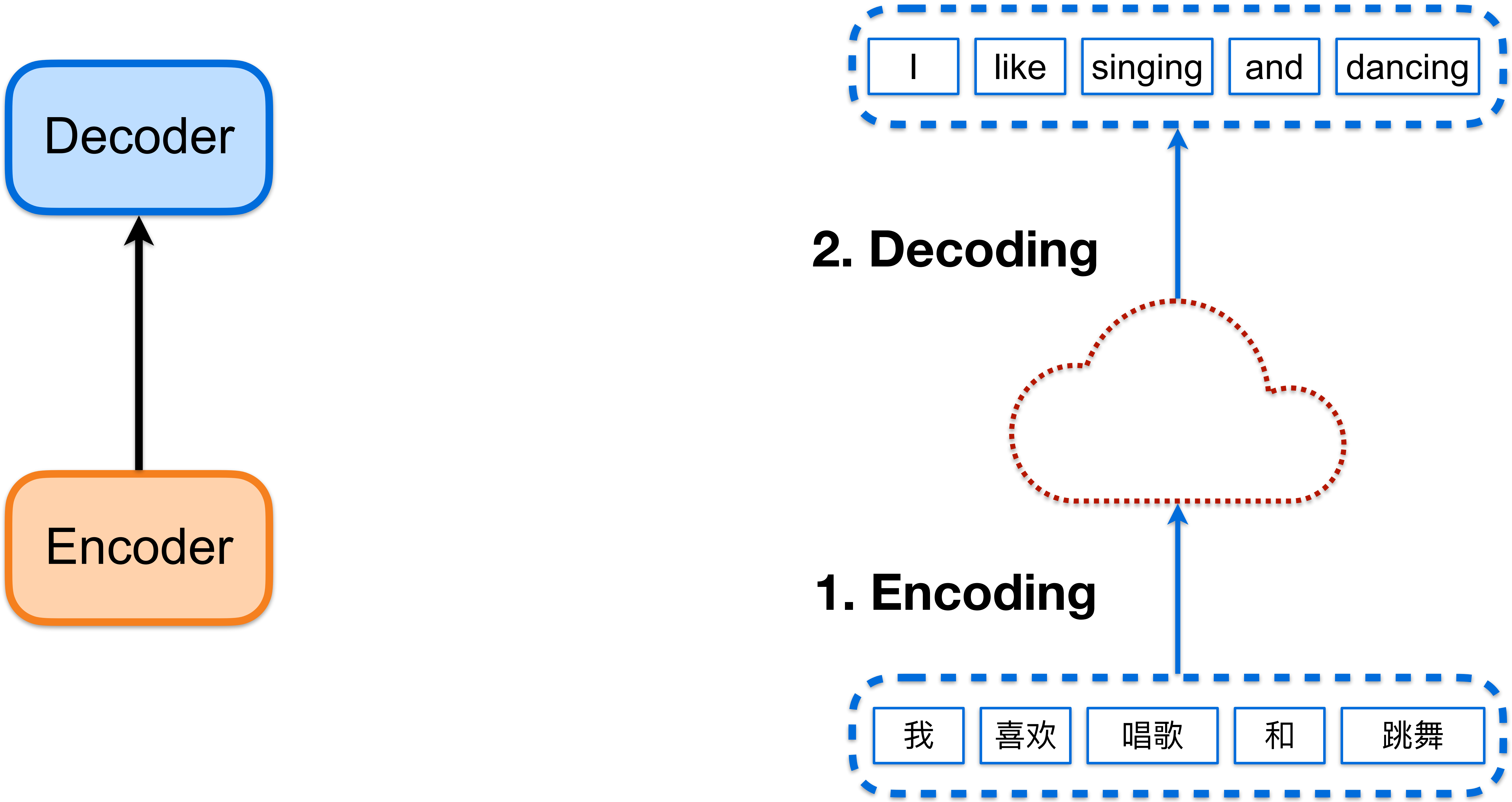
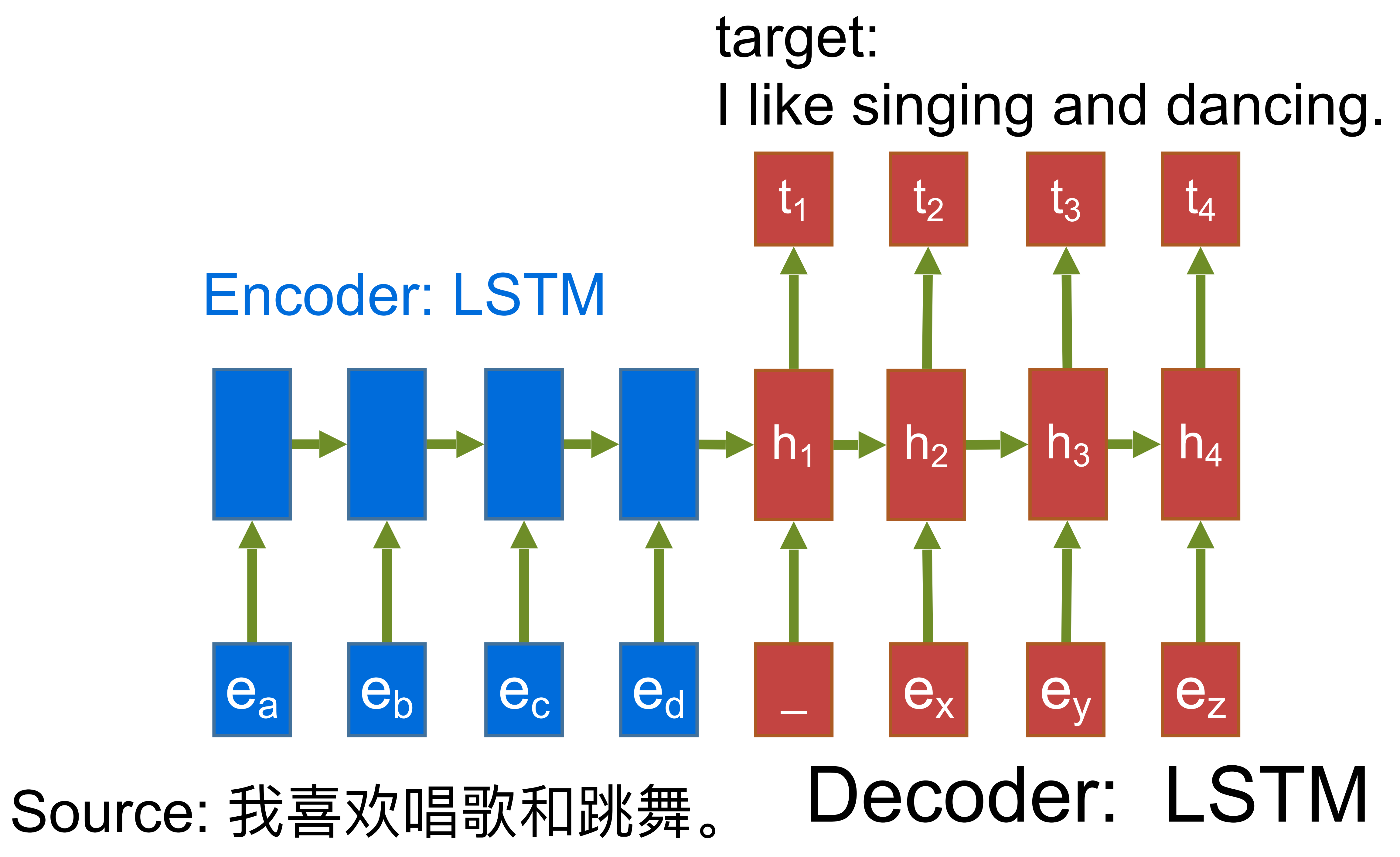
291K
Deep Learning for Machine Translation
Transformer

Lei Li
UCSB
10/13/2021

Encoder-Decoder Paradigm



Seq2Seq



- Directly learning a function mapping from source sequence to target sequence

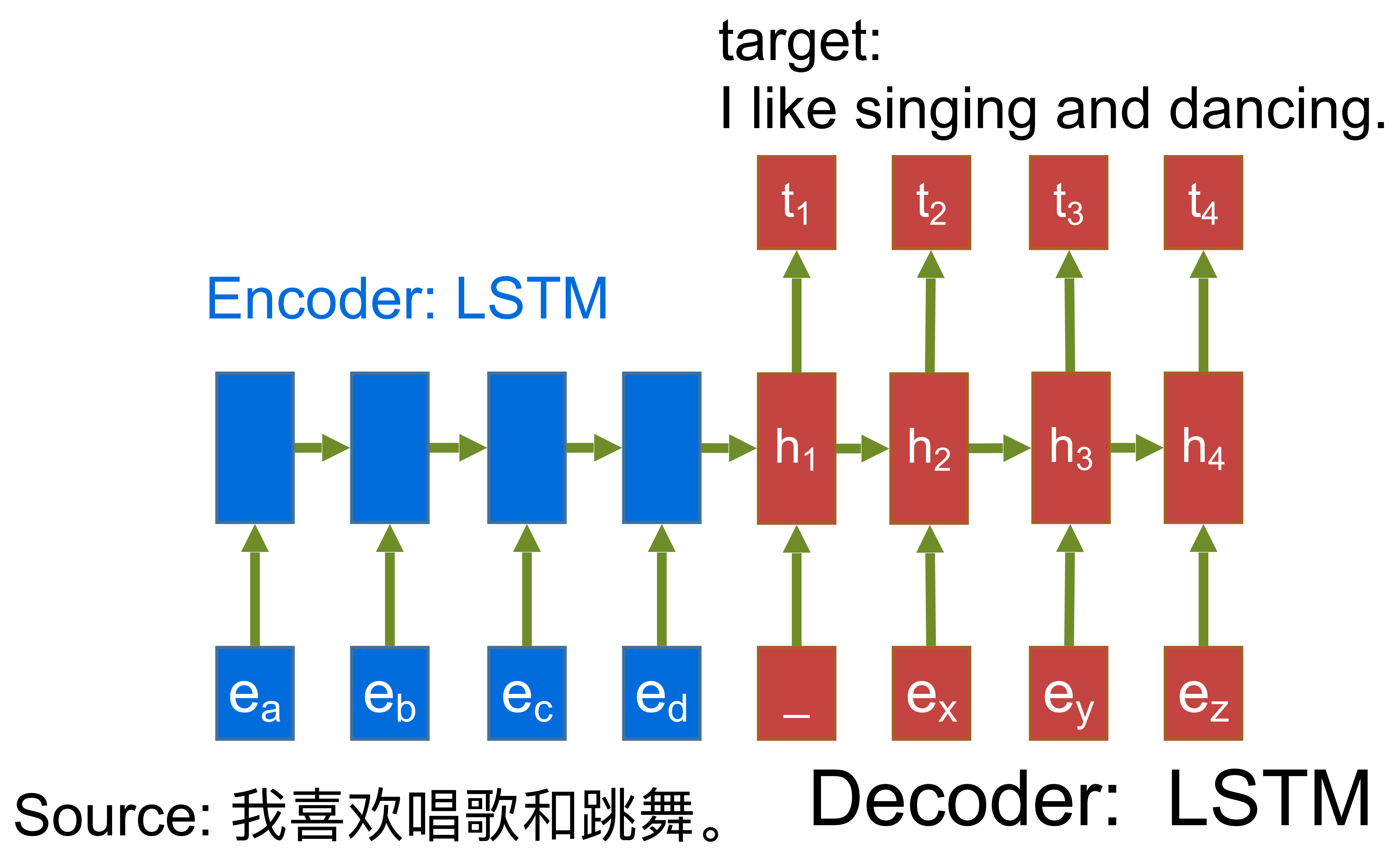
$$P(Y|X) = \prod P(y_t | y_{<t}, x)$$

$$P(y_t | y_{<t}, x) = f_\theta(x_{1\ldots k}, y_{1\ldots t-1})$$

Training loss: Cross-Entropy

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

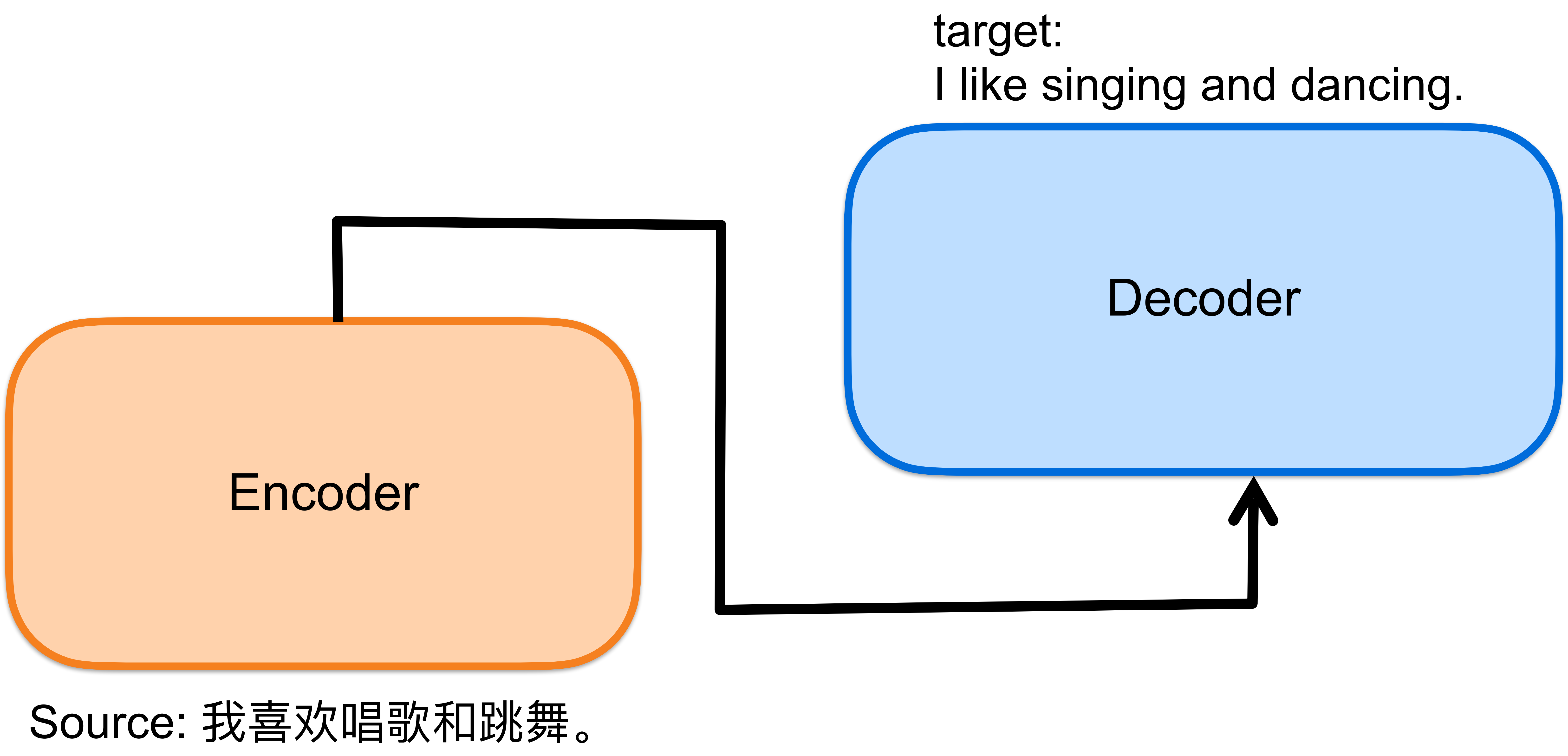
Limitation of RNN/LSTM



- 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

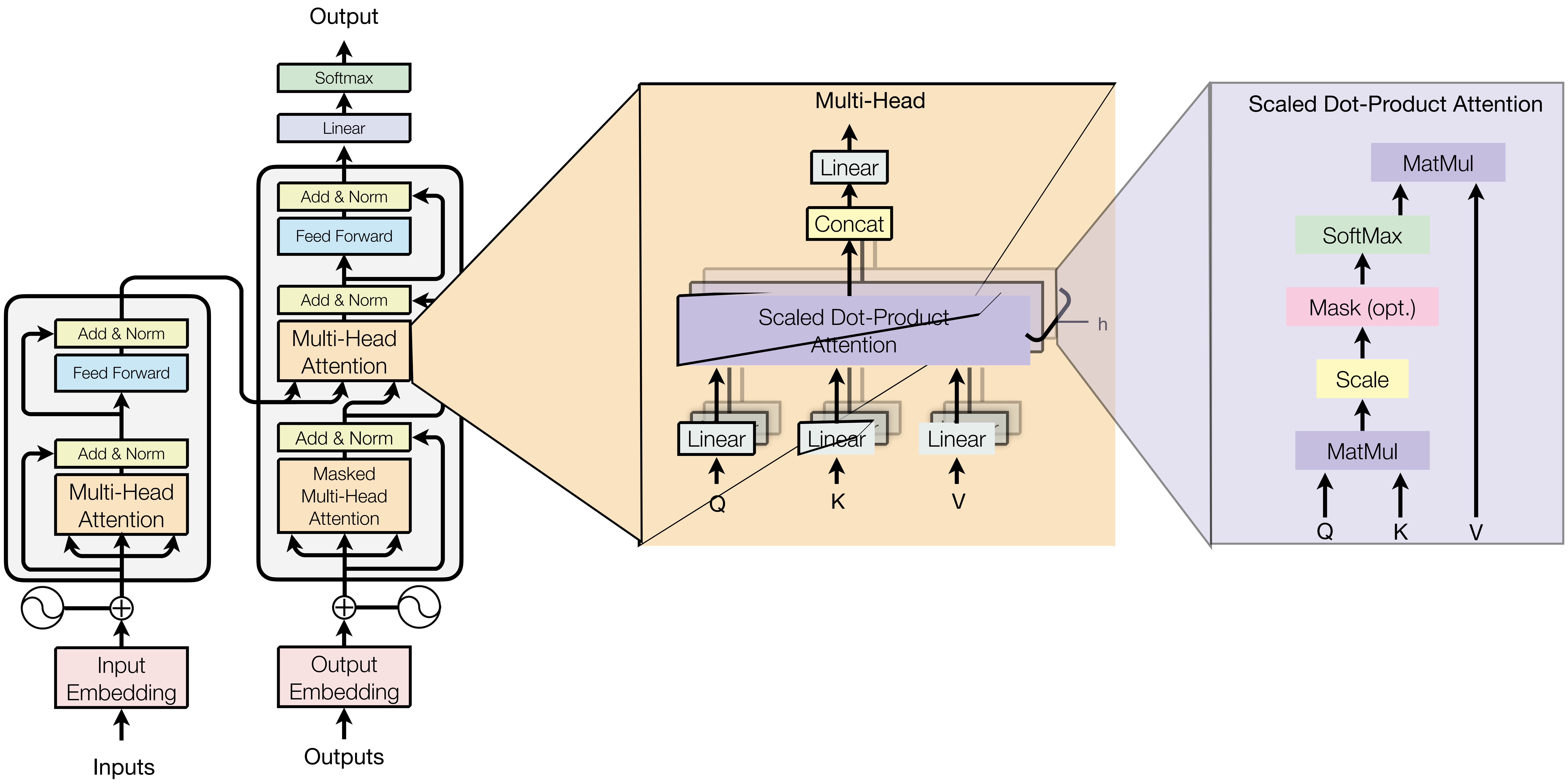


Transformer

Vaswani et al. Attention is All You Need. 2017

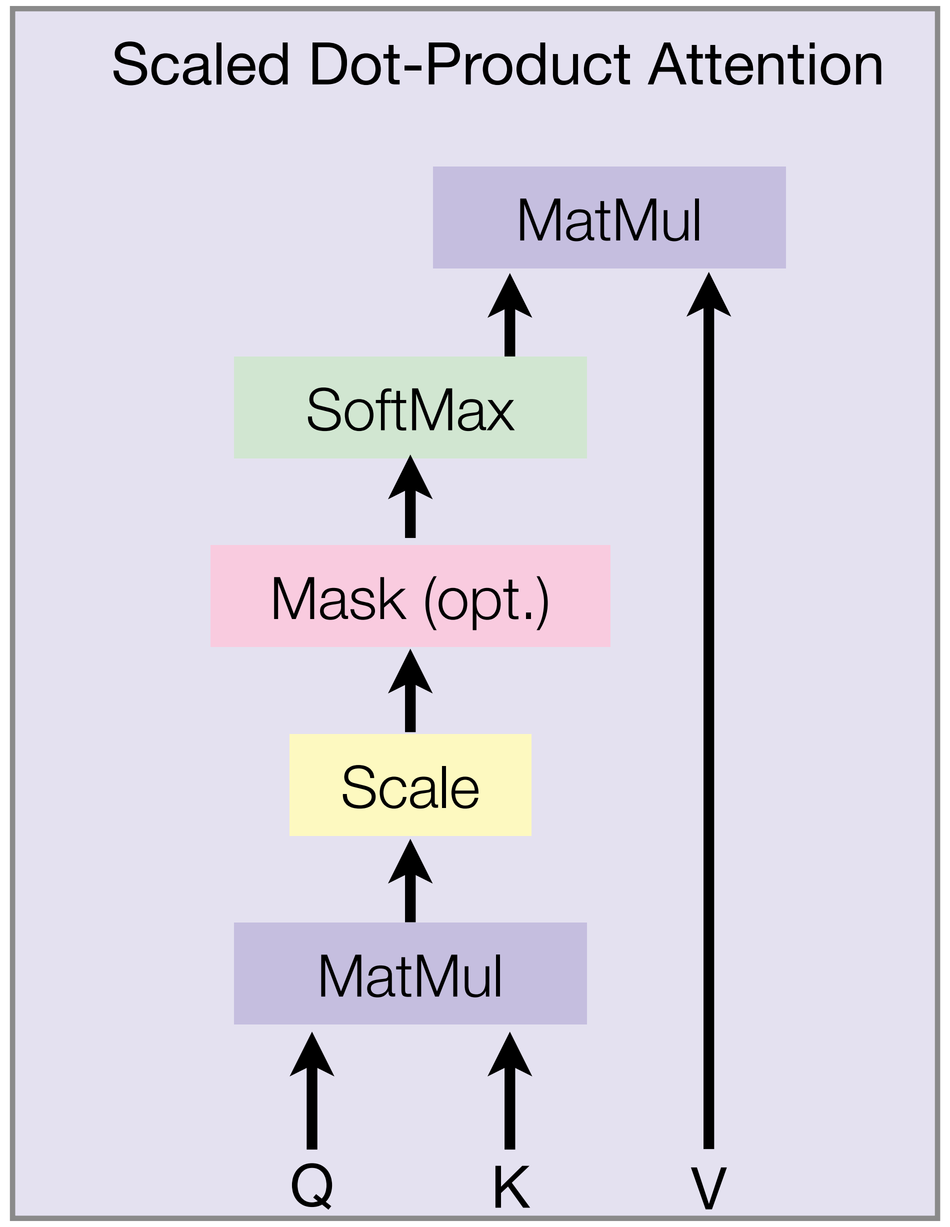
Transformer Multi-head Attention

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



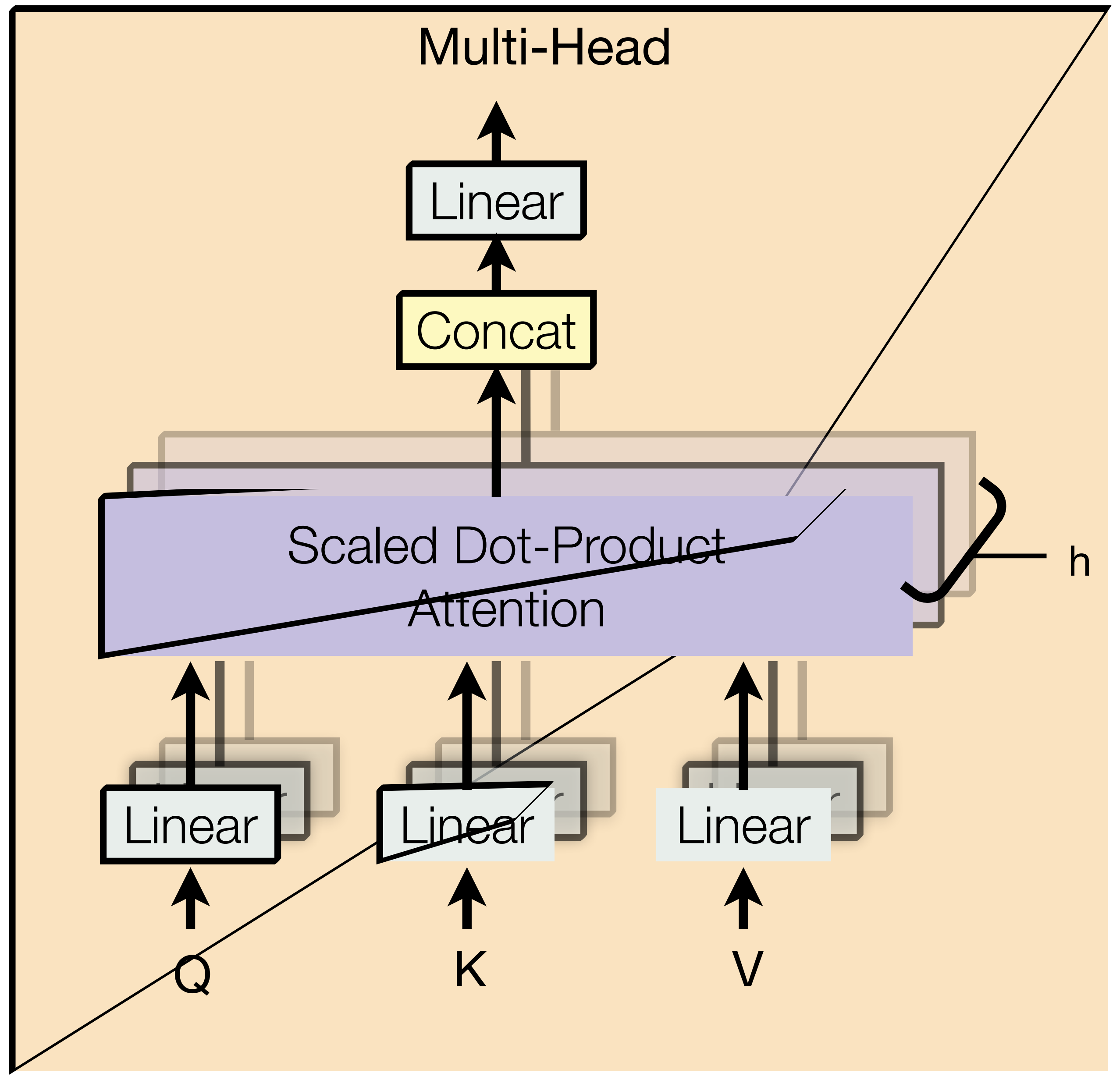
Scaled Dot-Product Attention

- Scale by $\dfrac{1}{\sqrt{d_k}}$
- why?
- What are Q, K, V



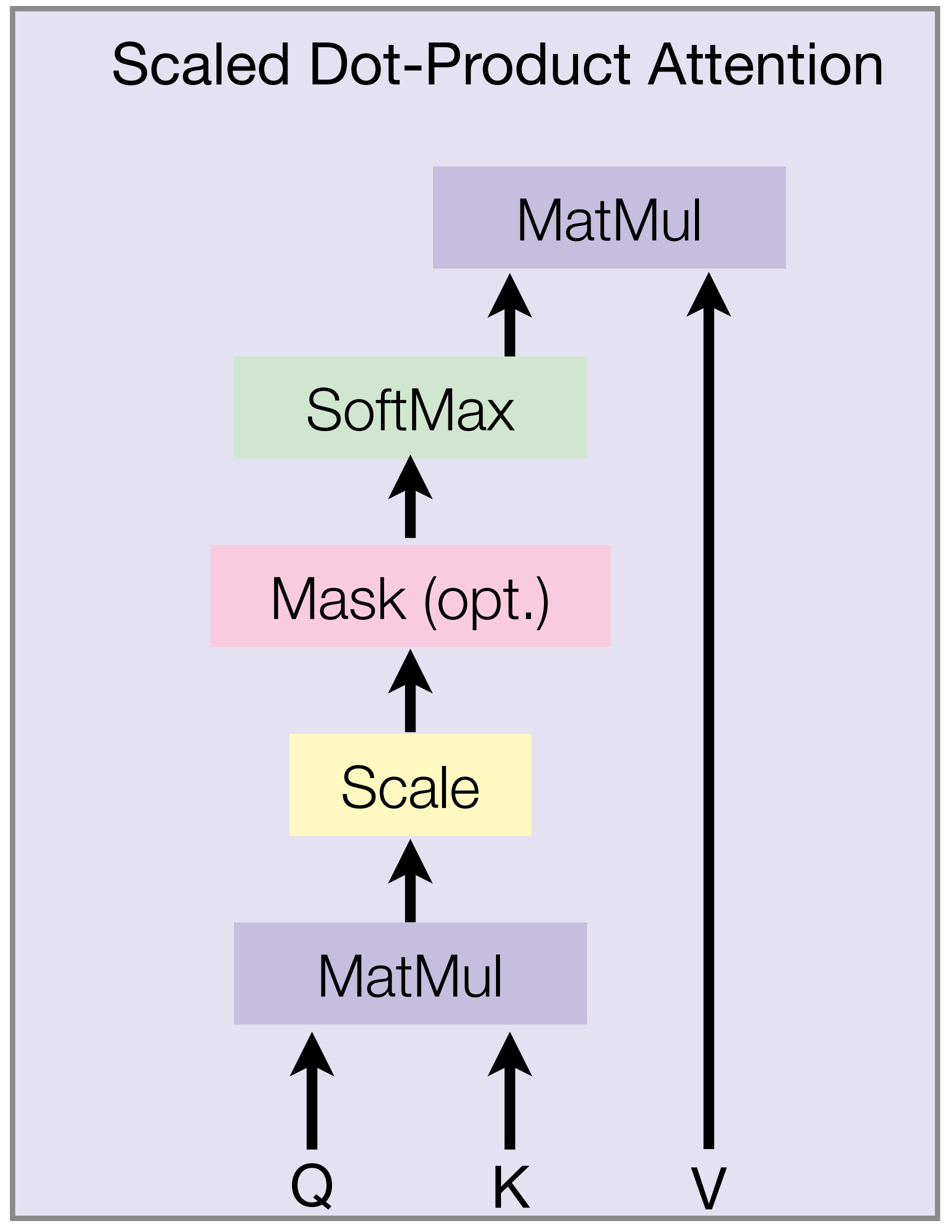
Multi-head Attention

- Benefits?



Self-Attention for Decoder

- Maskout right side before softmax (-inf)

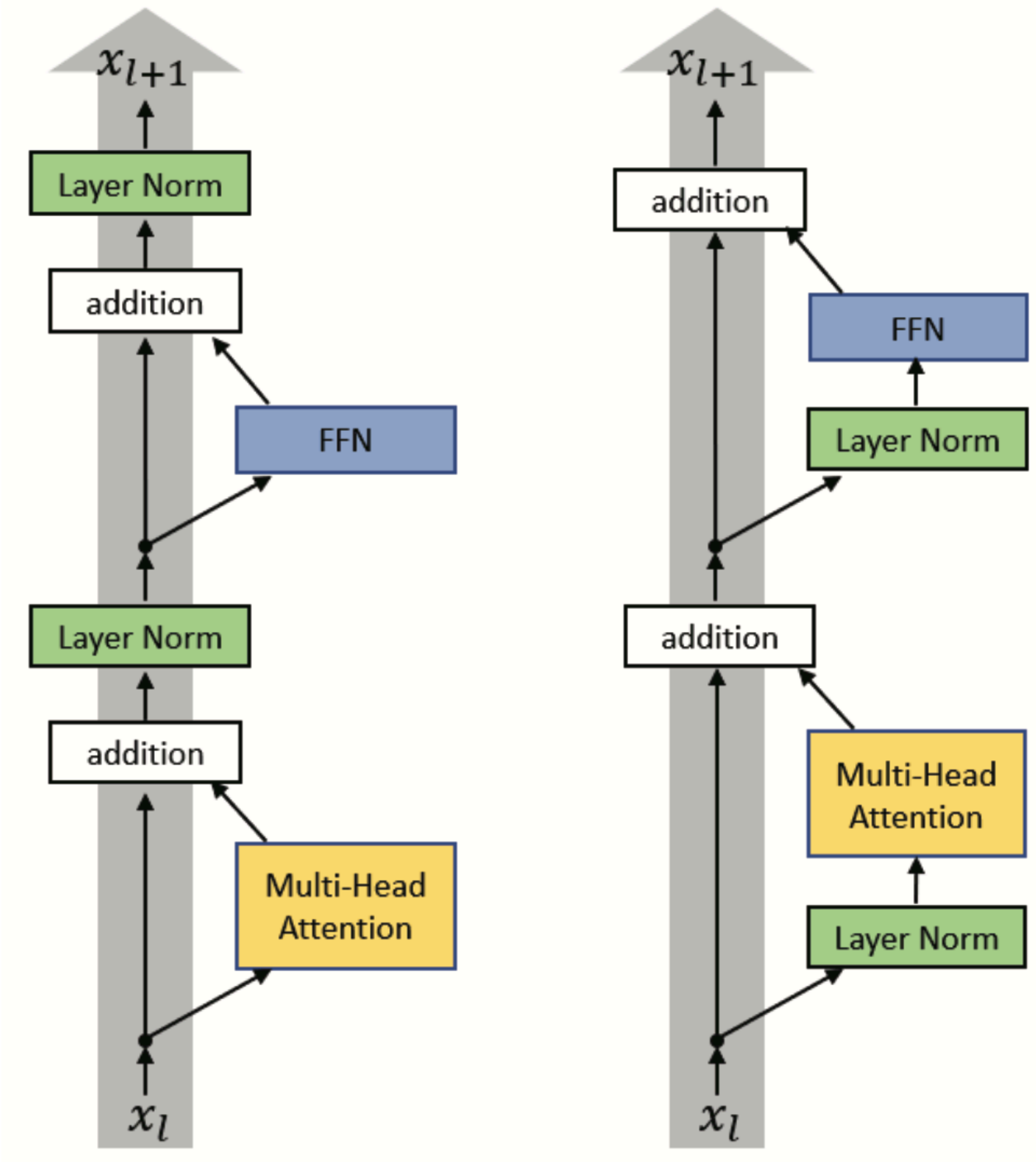


Feedforward Net

- $\mathrm{FFN}(x) = \max(0, x \cdot W_1 + b_1) \cdot W_2 + b_2$
- 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

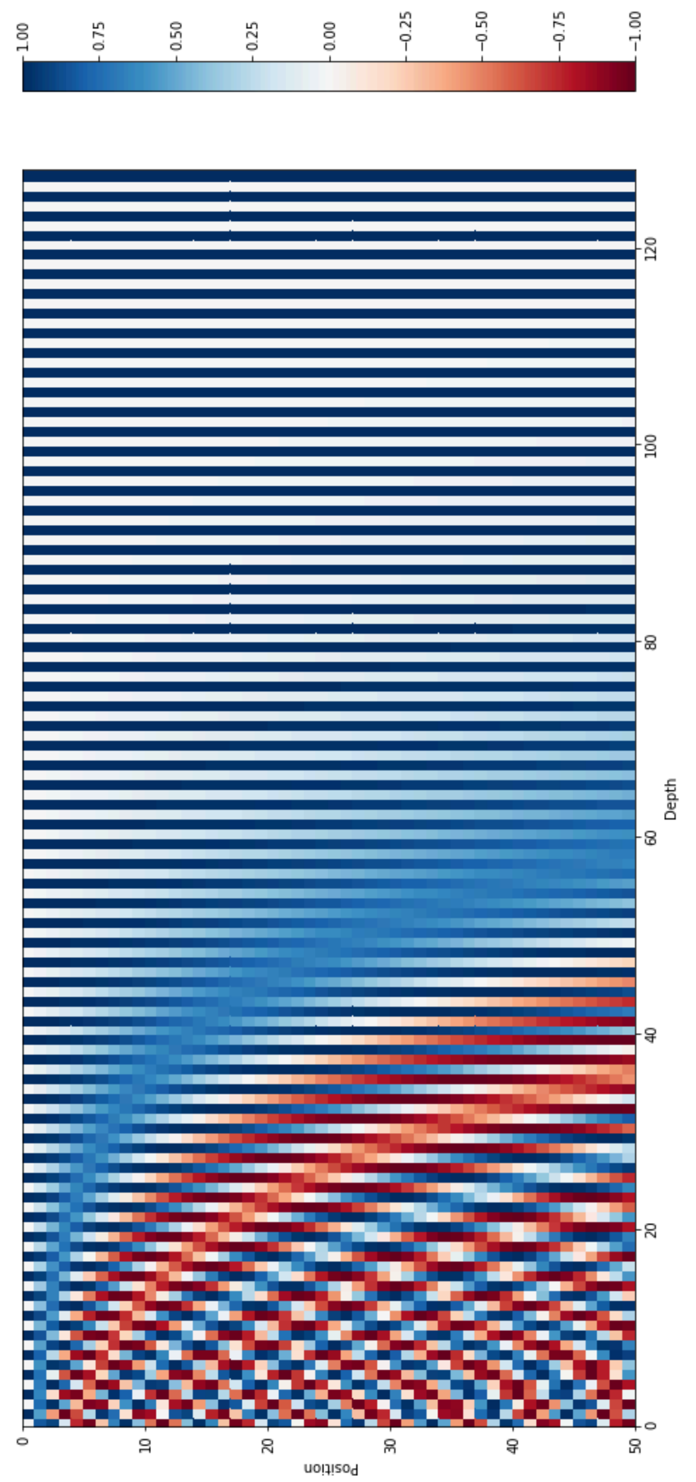


Embedding

- 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

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

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



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)

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

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

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

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. heads
- 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.

Language Presentation - Two today

- Please signup by EOB today if not already
- Turn in your slides and your report (<= 4 pages) on the day of presentation

Reading

- Vaswani et al. Attention is All You Need. 2017