Transformers

CS 6384 Computer Vision
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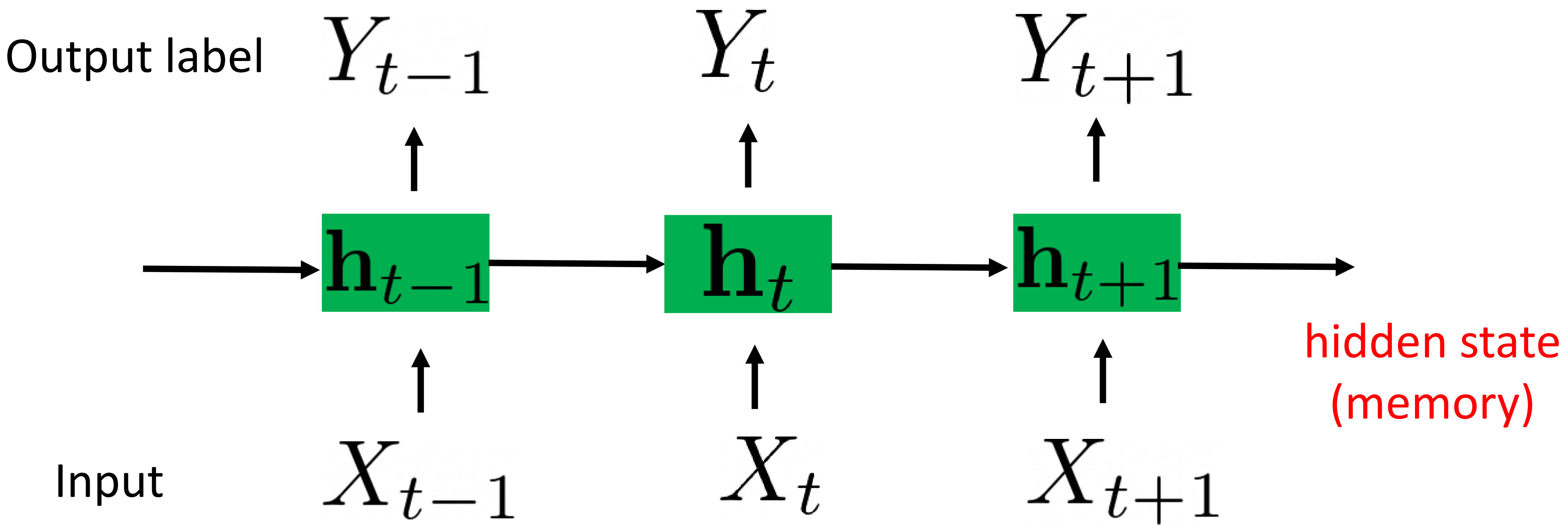
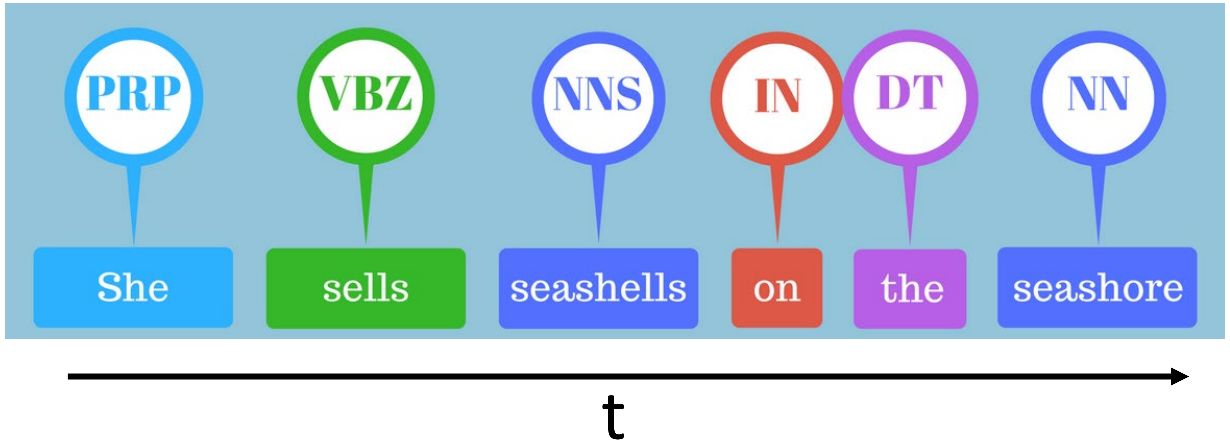
The University of Texas at Dallas

Recurrent Neural Networks



Sequential Data Labeling

- Part-of-speech tagging (grammatical tagging)



Tag	Meaning	English Examples
ADJ	adjective	*new, good, high, special, big, local*
ADP	adposition	*on, of, at, with, by, into, under*
ADV	adverb	*really, already, still, early, now*
CONJ	conjunction	*and, or, but, if, while, although*
DET	determiner, article	*the, a, some, most, every, no, which*
NOUN	noun	*year, home, costs, time, Africa*
NUM	numeral	*twenty-four, fourth, 1991, 14:24*
PRT	particle	*at, on, out, over per, that, up, with*
PRON	pronoun	*he, their, her, its, my, I, us*
VERB	verb	*is, say, told, given, playing, would*
.	punctuation marks	*. , ; !*
X	other	*ersatz, esprit, dunno, gr8, univeristy*

Machine Translation

- Translate a phrase from one language to anther
  - E.g., English phrase to French phrase

Google Translation

13 words

15 words

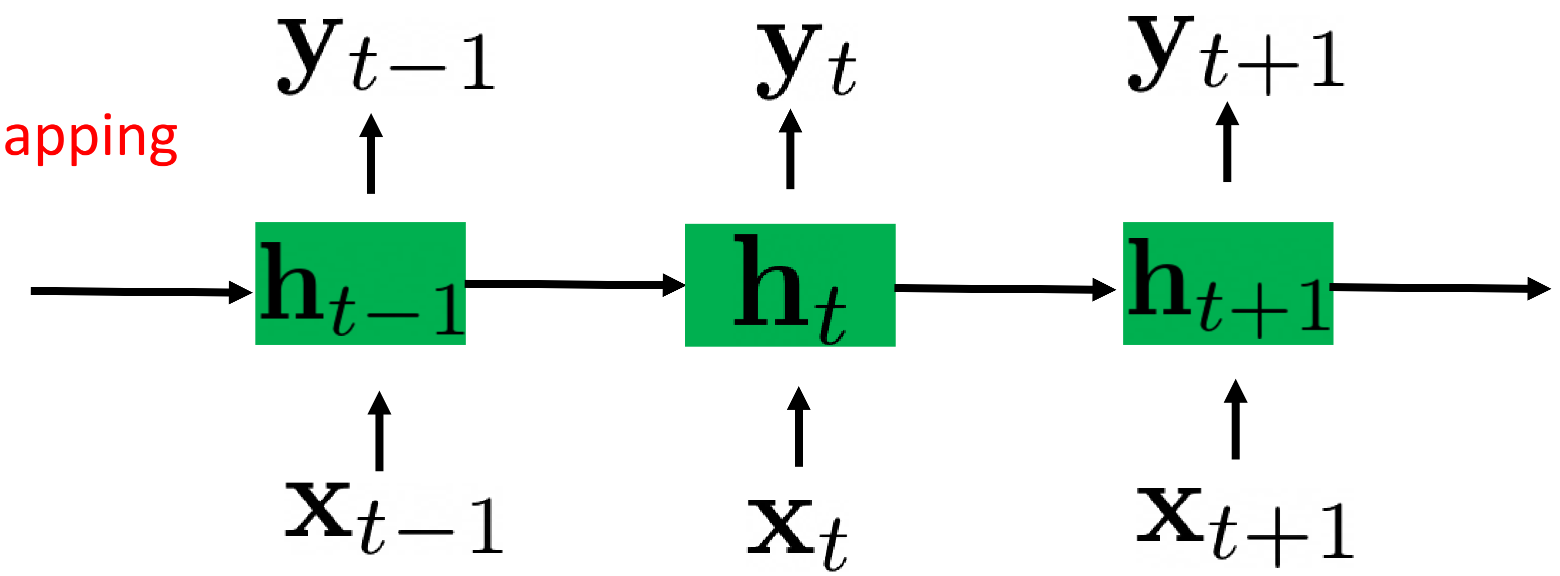
Machine Translation

- Input $\mathbf{x} = (\mathbf{x}_1, \mathbf{x}_2, \dots, \mathbf{x}_T)$
- Output $\mathbf{y} = (\mathbf{y}_1, \mathbf{y}_2, \dots, \mathbf{y}_{T'})$

$$T \neq T'$$

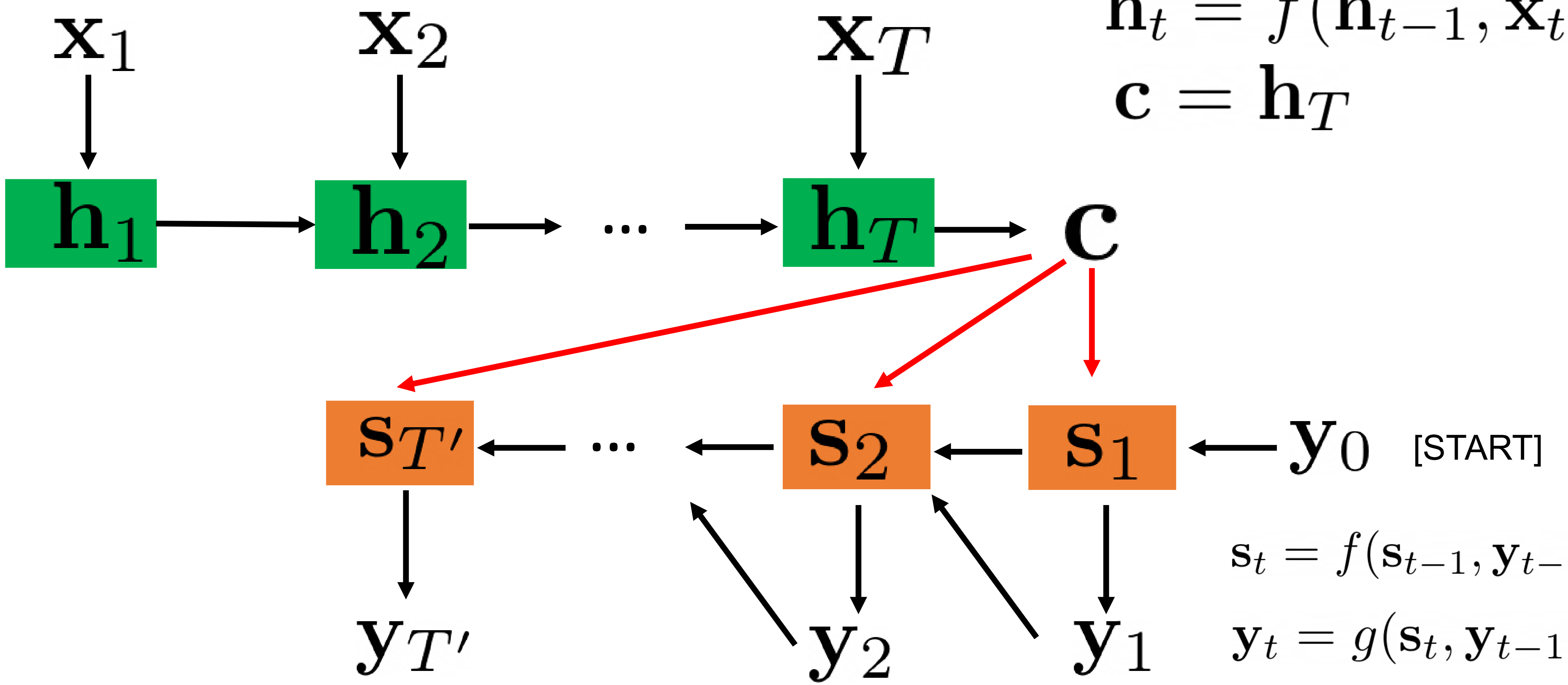
Not one to one mapping

RNN



RNN Encoder-Decoder

$$\mathbf{h}_t = f(\mathbf{h}_{t-1}, \mathbf{x}_t)$$
$$\mathbf{c} = \mathbf{h}_T$$



$$\mathbf{s}_t = f(\mathbf{s}_{t-1}, \mathbf{y}_{t-1}, \mathbf{c})$$
$$\mathbf{y}_t = g(\mathbf{s}_t, \mathbf{y}_{t-1}, \mathbf{c})$$

Learning Phrase Representations using RNN Encoder–Decoder for Statistical Machine Translation. Cho et al., EMNLP’14

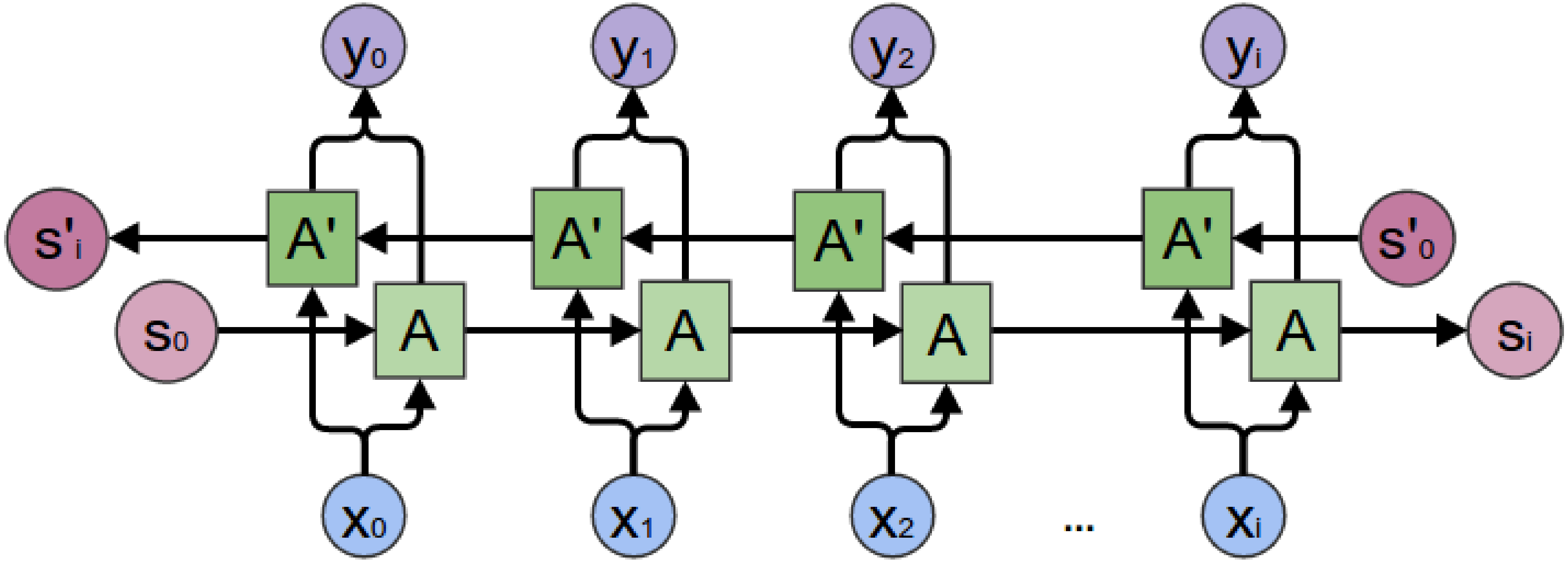
RNN Encoder-Decoder

- Encoder $\mathbf{h}_t = f(\mathbf{h}_{t-1}, \mathbf{x}_t) \quad \mathbf{c} = \mathbf{h}_T$
- Decoder $\mathbf{s}_t = f(\mathbf{s}_{t-1}, \mathbf{y}_{t-1}, \mathbf{c}) \quad \mathbf{y}_t = g(\mathbf{s}_t, \mathbf{y}_{t-1}, \mathbf{c})$

- Pros
  - Can deal with different input size and output size

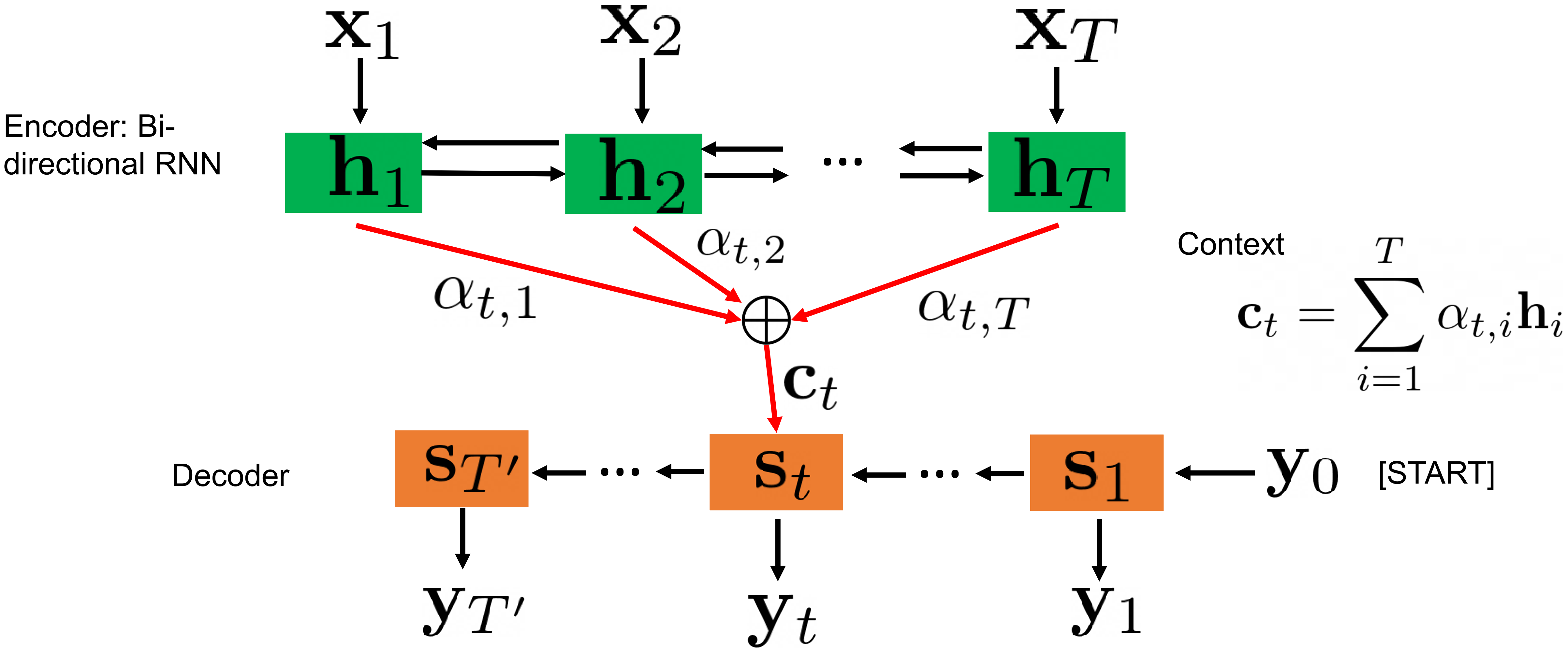
- Cons
  - The fixed length embedding $\mathbf{c}$ cannot handle long sentence well (long-distance dependencies)

Bi-directional RNNs



https://blog.paperspace.com/bidirectional-rnn-keras/

RNN Encoder-Decoder with Attentions



NEURAL MACHINE TRANSLATION BY JOINTLY LEARNING TO ALIGN AND TRANSLATE. Bahdanau et al., ICLR'15

RNN Encoder-Decoder with Attentions

- Alignment model (attention)

$$e_{ij} = a(\mathbf{s}_{i-1}, \mathbf{h}_j)$$

Feedforward network

Hidden state of output

Hidden state of input

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

Attending to different parts of the input

Context $\mathbf{c}_i = \sum_{j=1}^{T} \alpha_{ij} \mathbf{h}_j$

$$\mathbf{s}_i = f(\mathbf{s}_{i-1}, \mathbf{y}_{i-1}, \mathbf{c}_i)$$

Output $\mathbf{y}_i = g(\mathbf{s}_i, \mathbf{y}_{i-1}, \mathbf{c}_i)$

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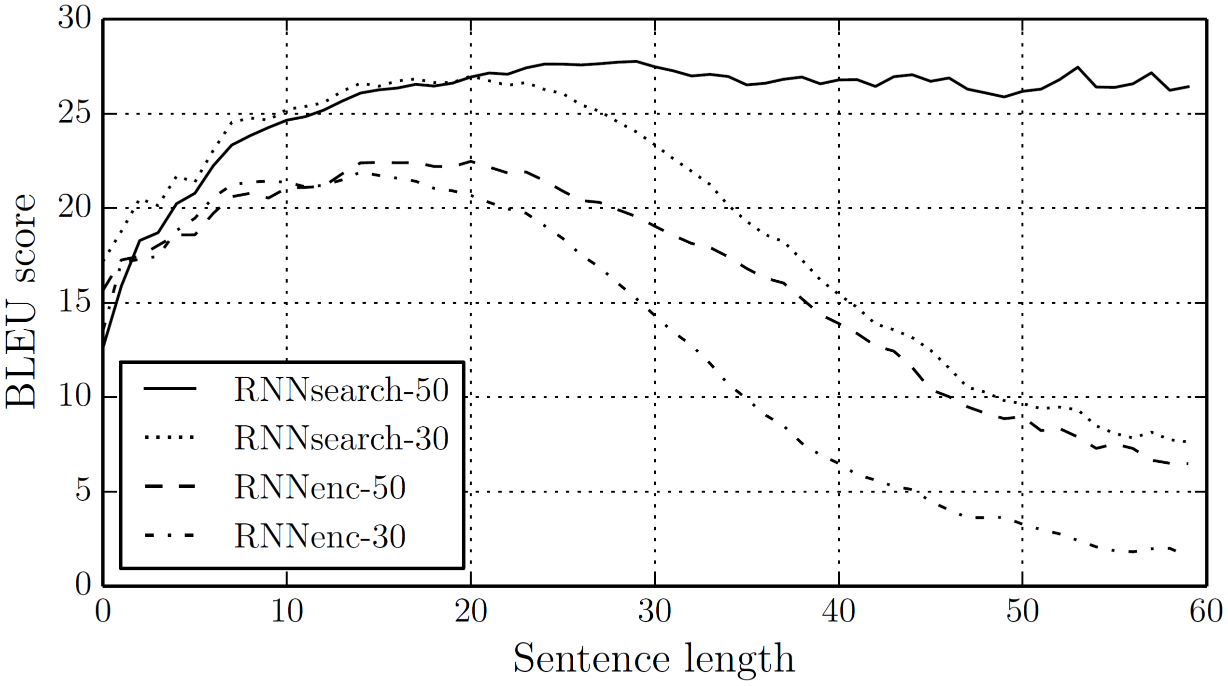
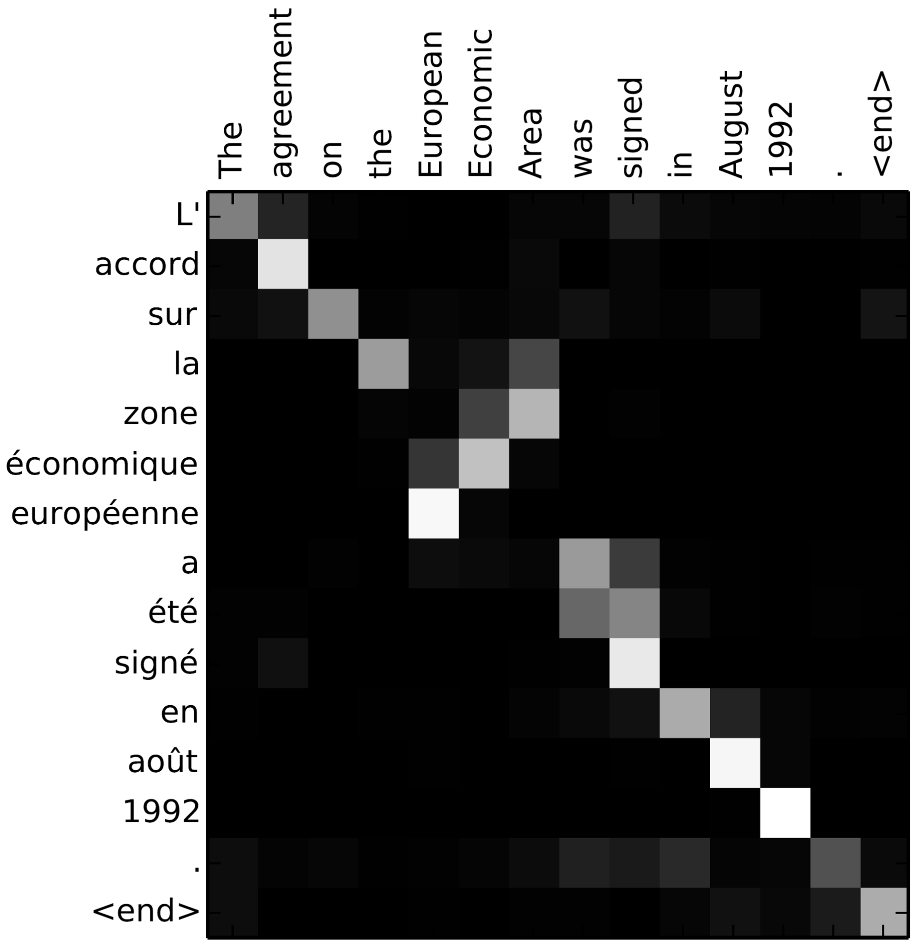
RNN Encoder-Decoder with Attentions





α_{ij}

NEURAL MACHINE TRANSLATION BY JOINTLY LEARNING TO ALIGN AND TRANSLATE. Bahdanau et al., ICLR'15

Limitations of RNNs

- The sequential computation of hidden states precludes parallelization within training examples

- Cannot handle long sequences well
  - Truncated back-propagation due to memory limits
  - Difficult to capture dependencies in long distances

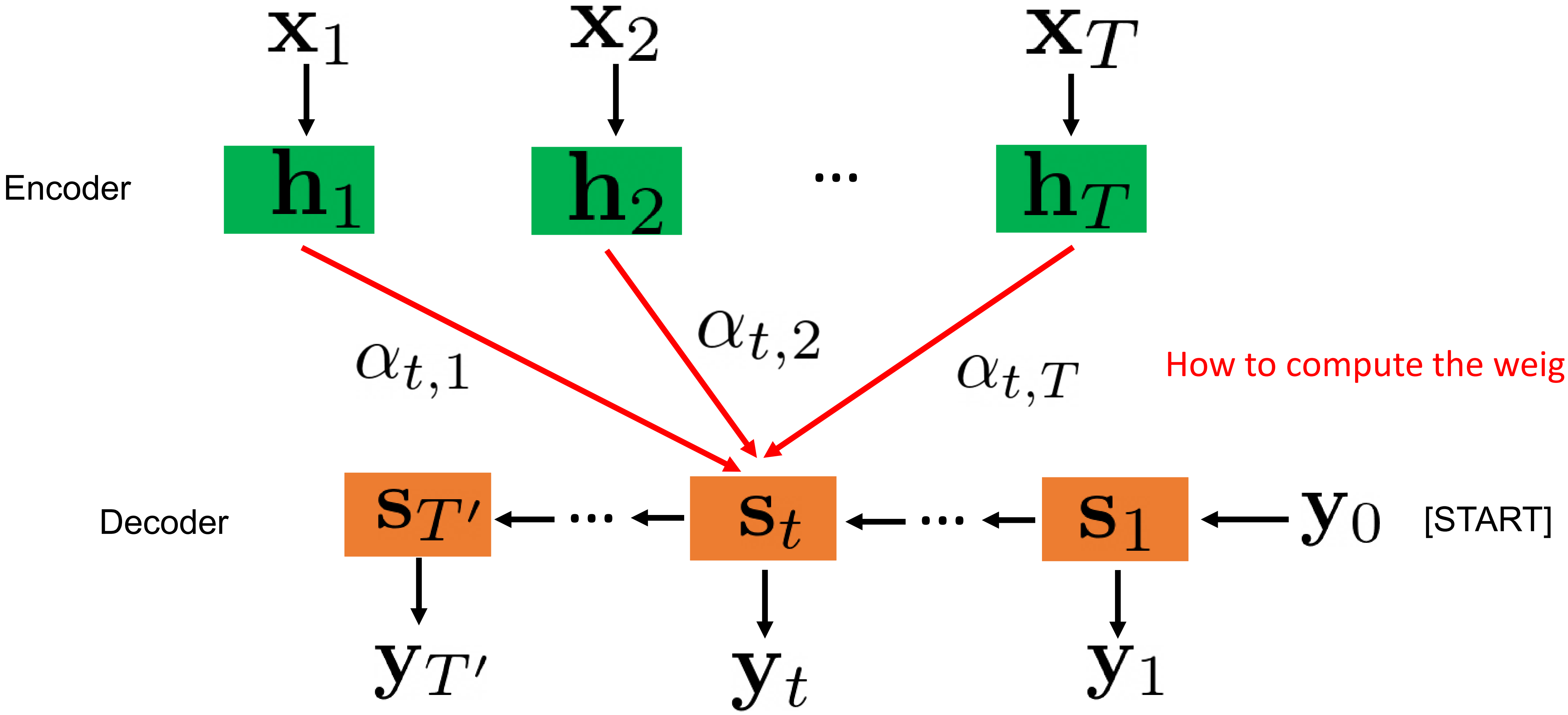
Transformer

- No recurrence

- Attention only
  - Global dependencies between input and output

  - More parallelization compared to RNNs

Transformer: Encoder-Decoder with Attention



How to compute the weights?

Transformer: Attention

- Input
  - (key, value) pairs (think about python dictionary)
  - A query

- Output
  - Compare the query to all the keys to compute weights
  - Weighted sum of the values

Attention is all you need. Vaswani et al., NeurIPS'17

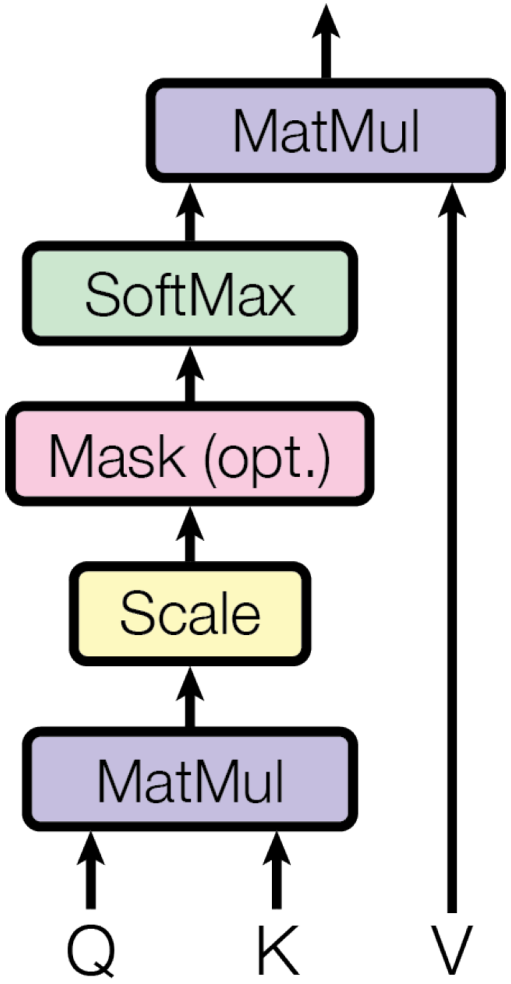
Transformer: Attention

- Scaled Dot-Product Attention
  - Keys $K : m \times d_k$
  - Values $V : m \times d_v$
  - n queries $Q : n \times d_k$

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

$$n \times d_v$$

weights



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Transformer: Attention

- Multi-Head Attention
  - Suppose the latent vector is with dimension d_{model}

$m \times d_{\text{model}}$ $\quad d_{\text{model}} \times d_k$

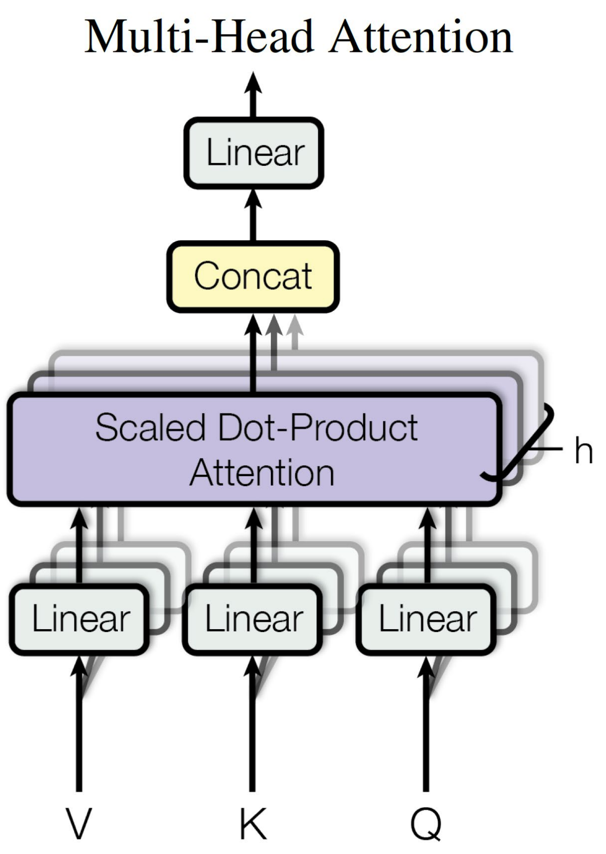
$$\text{head}_\text{i} = \text{Attention}(QW_i^Q, KW_i^K, VW_i^V)$$ Projection

$n \times d_v$

$n \times d_{\text{model}}$ $\quad d_{\text{model}} \times d_k$ $\quad m \times d_{\text{model}}$ $\quad d_{\text{model}} \times d_v$

$$\text{MultiHead}(Q, K, V) = \text{Concat}(\text{head}_1, ..., \text{head}_\text{h})W^O$$

$n \times d_{\text{model}}$ $\quad n \times hd_v$ $\quad hd_v \times d_{\text{model}}$



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Transformer: Encoder

- Self-attention
  - Keys, values and queries are all the same
  - n input tokens $n \times d_{\text{model}}$

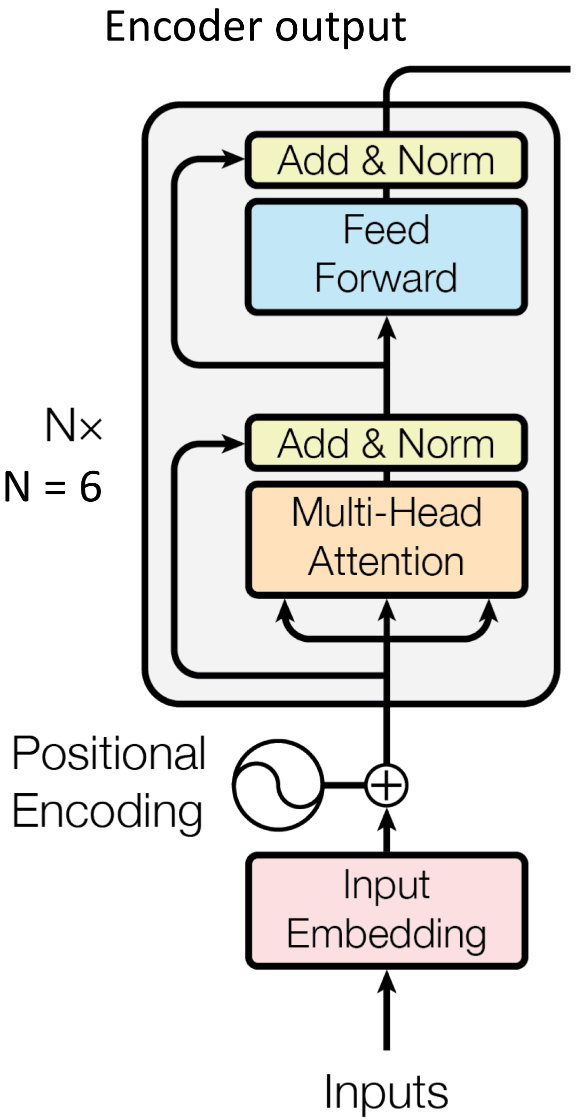
$$\text{MultiHead}(Q, K, V)$$

  - Residual connection

$$\text{LayerNorm}(x + \text{Sublayer}(x))$$

  - Layer normalization

$$\mu^l = \frac{1}{H}\sum_{i=1}^{H} a_i^l \qquad \sigma^l = \sqrt{\frac{1}{H}\sum_{i=1}^{H}\left(a_i^l - \mu^l\right)^2} \qquad \frac{a^l - \mu^l}{\sigma^l}$$



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Transformer: Encoder

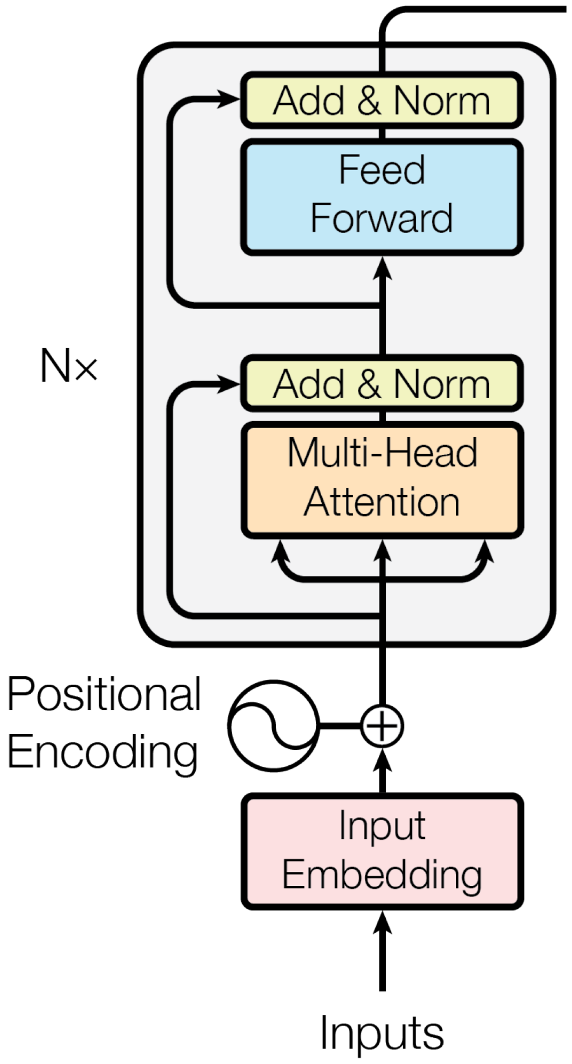
- Feed Forward Network

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

- Positional encoding
  - Make use the order of the sequence
  - With dimension d_{model} for each input

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

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



Attention is all you need. Vaswani et al., NeurIPS'17

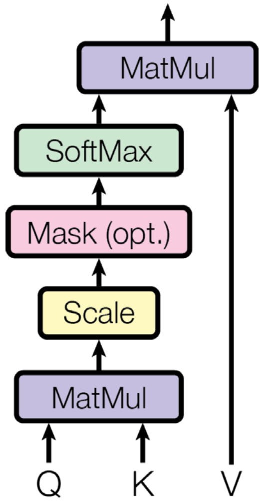
Transformer: Decoder

- Output embedding

[START]

$$\mathbf{y}_0 \ \mathbf{y}_1 \cdots \mathbf{y}_{t-1} \boxed{\mathbf{y}_t \ \ \mathbf{y}_{t+1} \cdots \ \mathbf{y}_{T'}}$$

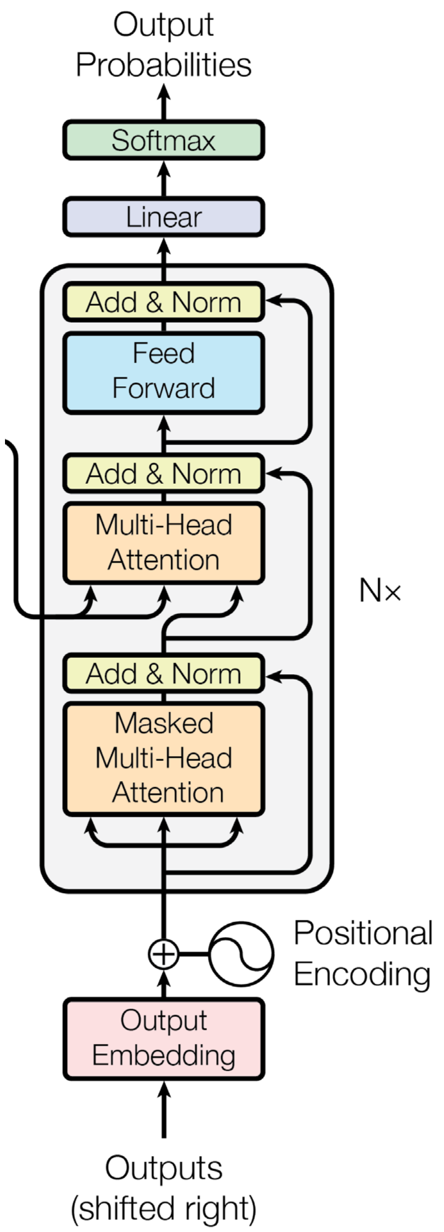
Shifted right by one position and insert the start token



Mask out current and future outputs during training (setting to $-\infty$)

Encoder output

$n \times d_{\text{model}}$

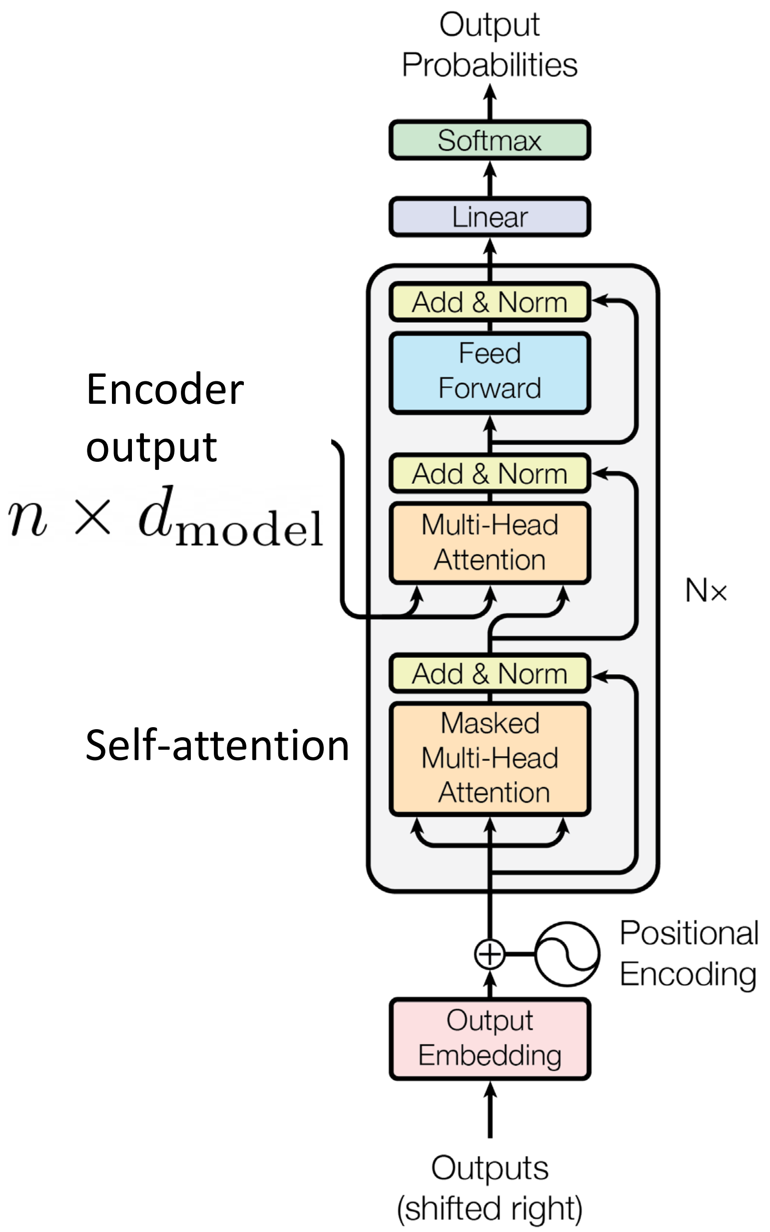


Attention is all you need. Vaswani et al., NeurIPS'17

Transformer: Decoder

- Encoder-decoder attention
  - (Key, value): encoder output
  - Queries: decoder output
  - Every position in the decoder attends to all positions in the input sequence

- Softmax
  - Predicts next-token probabilities



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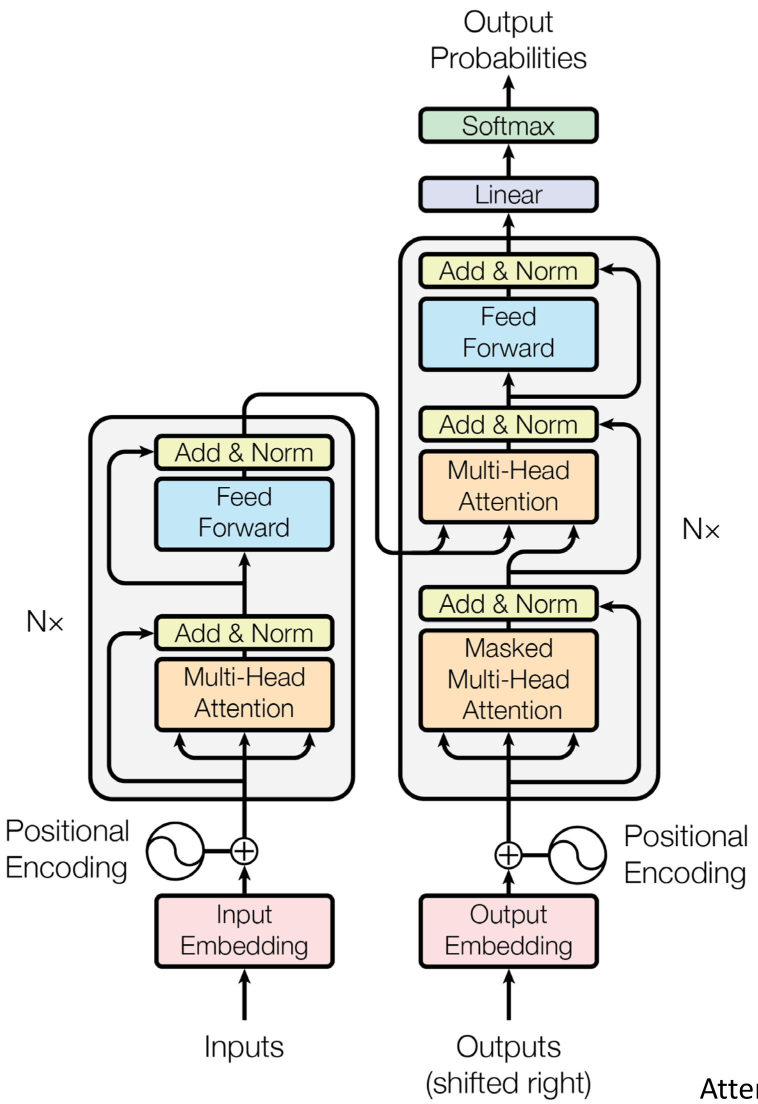
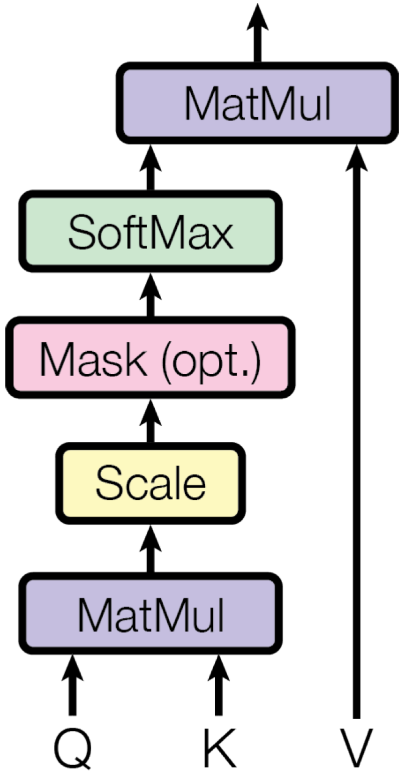
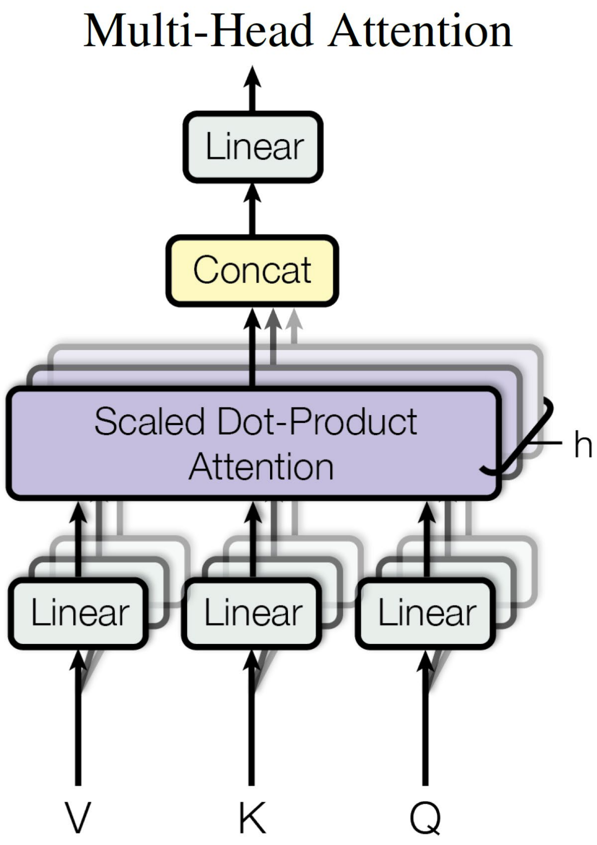
Transformer







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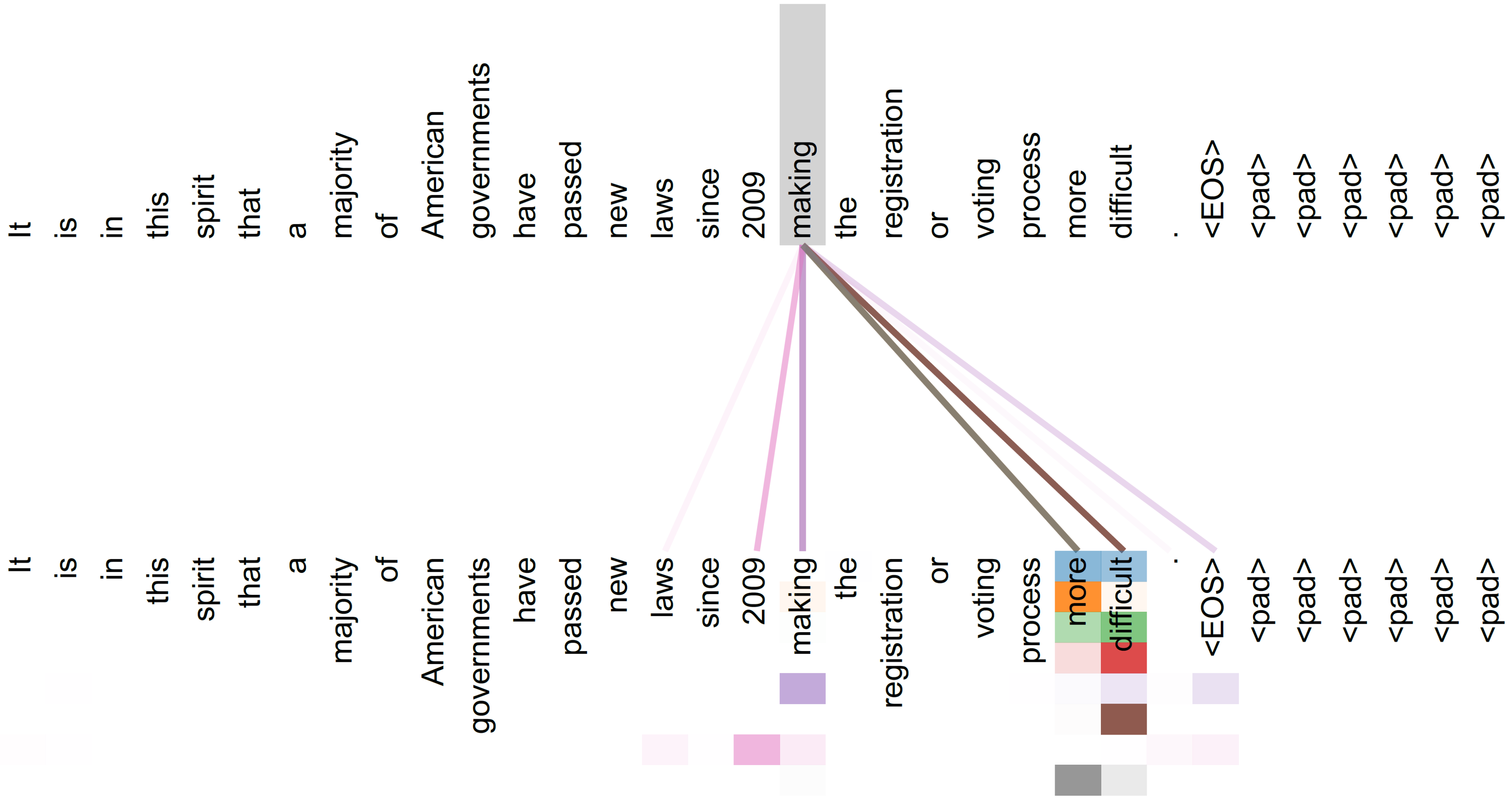
Transformer: Attention Visualization



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Vision Transformer

- Convert an image into a sequence of “token”

- Input embedding by linear projection

$$\mathbf{x}_p^1\mathbf{E};\ \mathbf{x}_p^2\mathbf{E};\cdots;\ \mathbf{x}_p^N\mathbf{E} \qquad \mathbf{E}\in\mathbb{R}^{(P^2\cdot C)\times D}$$

d_{model}

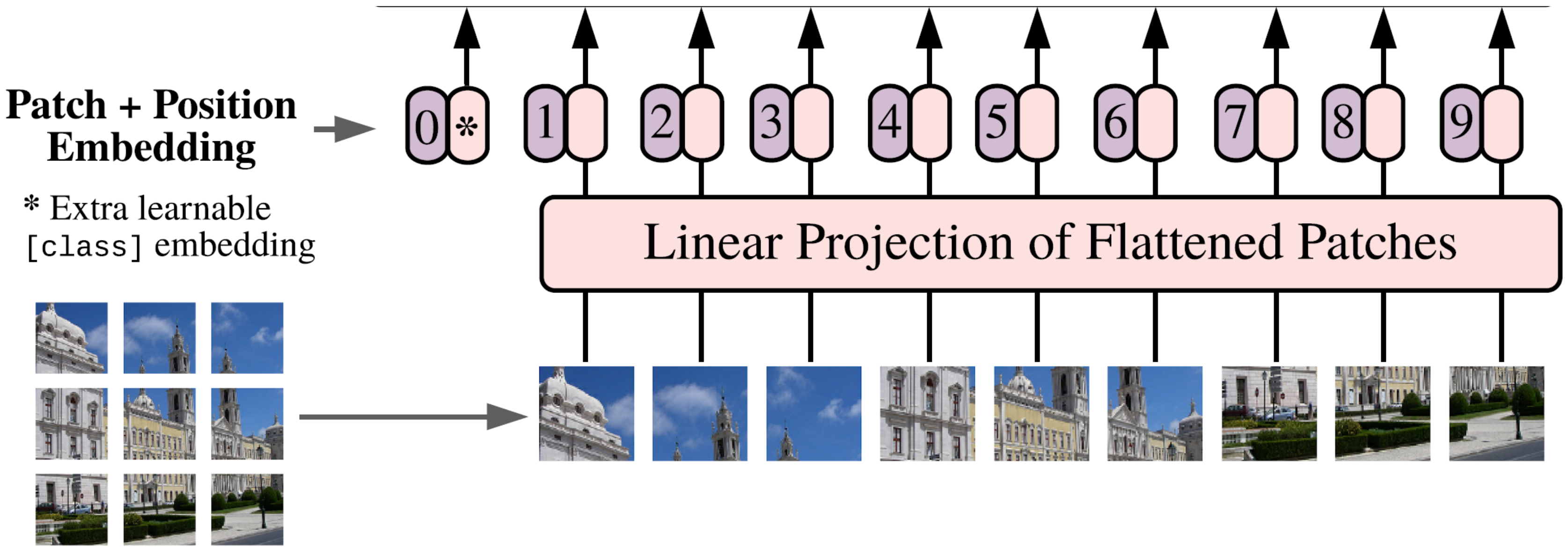
AN IMAGE IS WORTH 16X16 WORDS: TRANSFORMERS FOR IMAGE RECOGNITION AT SCALE. Dosovitskiy et al., ICLR’21

Vision Transformer

- Adding positional embedding
- Prepend a learnable embedding $\mathbf{z}_0^0$

$\mathbf{z}_L^0$ Will be used as the image representation

After L attention layers



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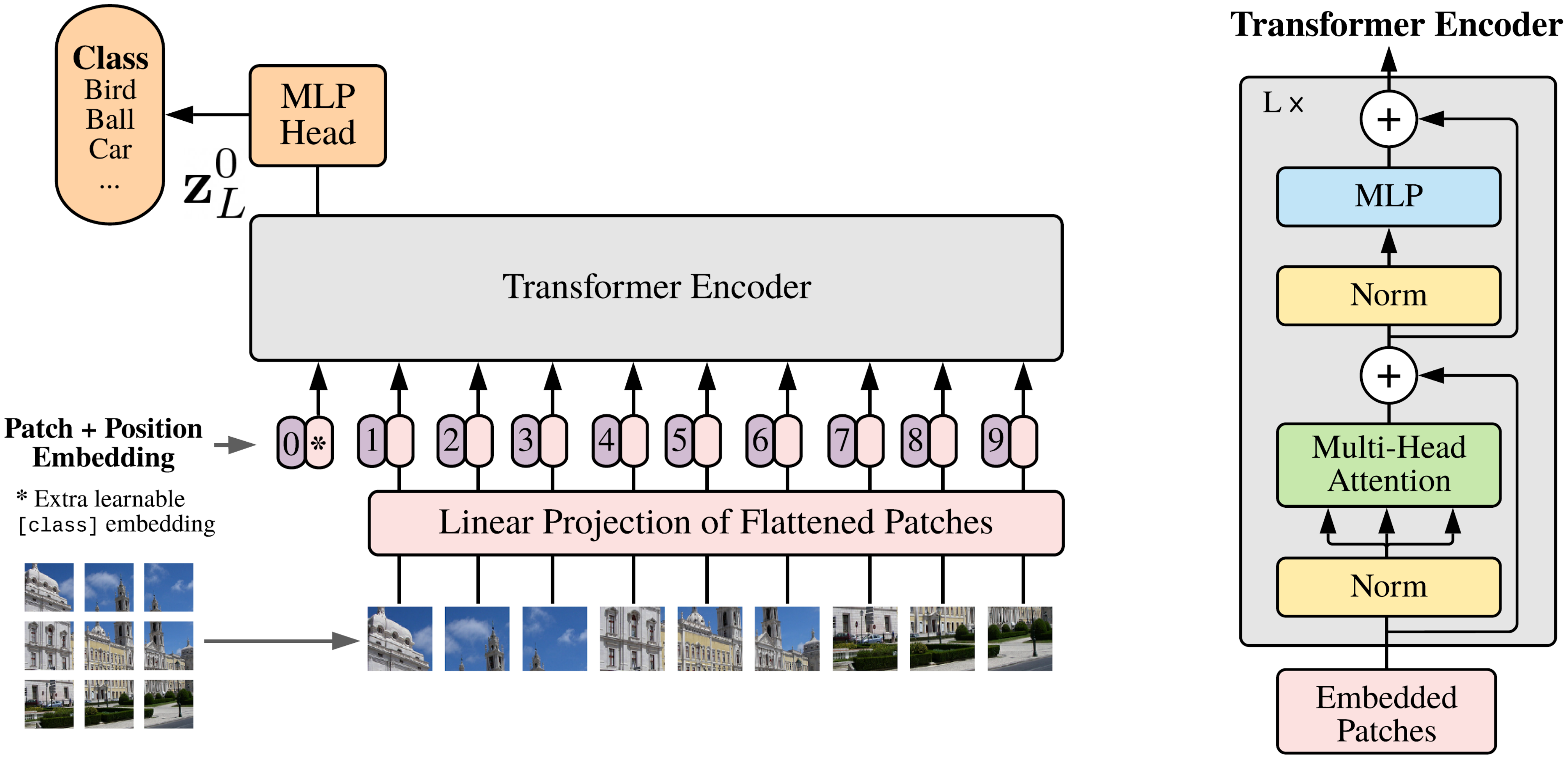
Vision Transformer



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Vision Transformer

- Pretrain on a large-scale dataset
- Fine-tune on different tasks

Model	Layers	Hidden size D	MLP size	Heads	Params
ViT-Base	12	768	3072	12	86M
ViT-Large	24	1024	4096	16	307M
ViT-Huge	32	1280	5120	16	632M

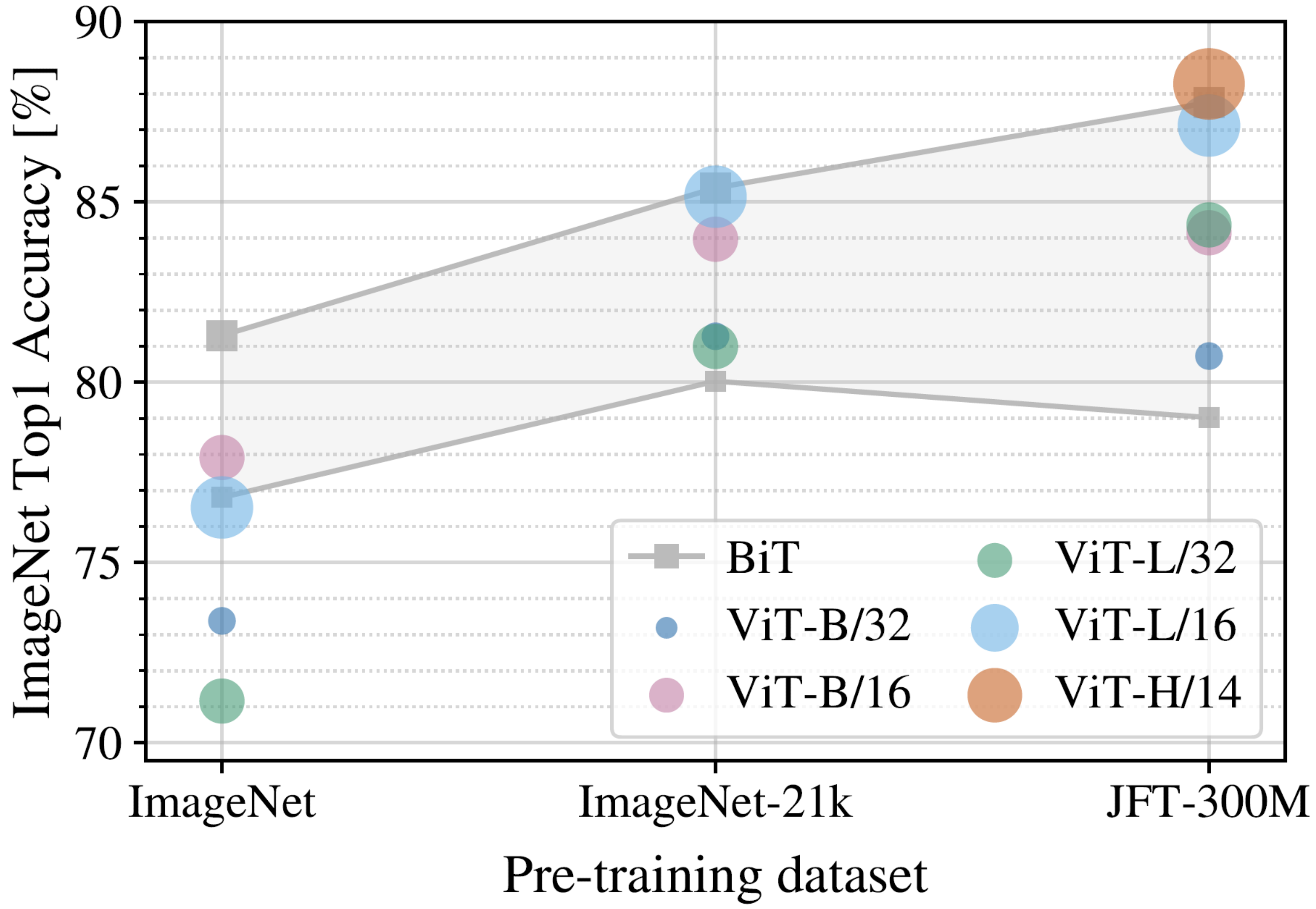
AN IMAGE IS WORTH 16X16 WORDS: TRANSFORMERS FOR IMAGE RECOGNITION AT SCALE. Dosovitskiy et al., ICLR'21

Vision Transformer

1k classes and 1.3M images

21k classes and 14M images

18k classes and 303M



Big Transfer (BiT)

- ResNets-based transfer

Vision transformer works better when pre-trained on large-scale dataset

AN IMAGE IS WORTH 16X16 WORDS: TRANSFORMERS FOR IMAGE RECOGNITION AT SCALE. Dosovitskiy et al., ICLR'21

Summary

- Transformers
  - Can capture long-distance dependencies (global attention)
  - Computationally efficient, more parallelizable
- Vision transformers
  - Works better when pre-trained on large scale datasets (e.g., 300M images)

Further Reading

- Learning Phrase Representations using RNN Encoder-Decoder for Statistical Machine Translation https://arxiv.org/abs/1406.1078
- Neural Machine Translation by Jointly Learning to Align and Translate https://arxiv.org/abs/1409.0473
- Transformer: Attention is all you need https://arxiv.org/abs/1706.03762
- Vision transformer: An Image is Worth 16x16 Words: Transformers for Image Recognition at Scale https://arxiv.org/abs/2010.11929