Paragraph Embeddings & Attention

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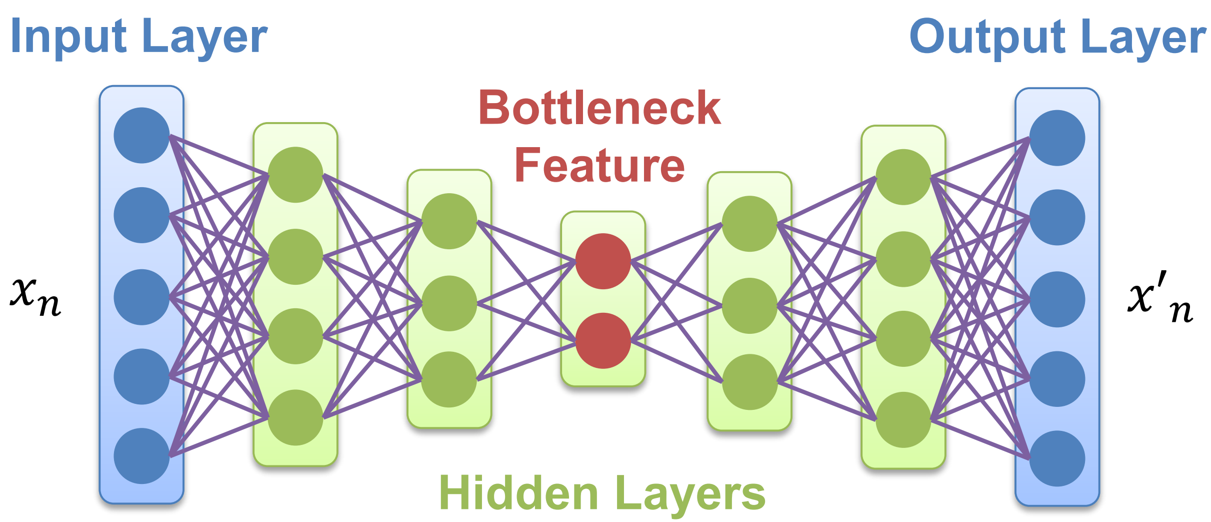
Autoencoder.

- An autoencoder is a DNN-based **unsupervised learning** of efficient codings
  - The training objective is to minimize the reconstructed errors

$$\min \frac{1}{N}\sum_{n=1}^{N}(x_n - x'_n)^2$$

$$\min -\sum_{n=1}^{N} x_n log(x'_n)$$



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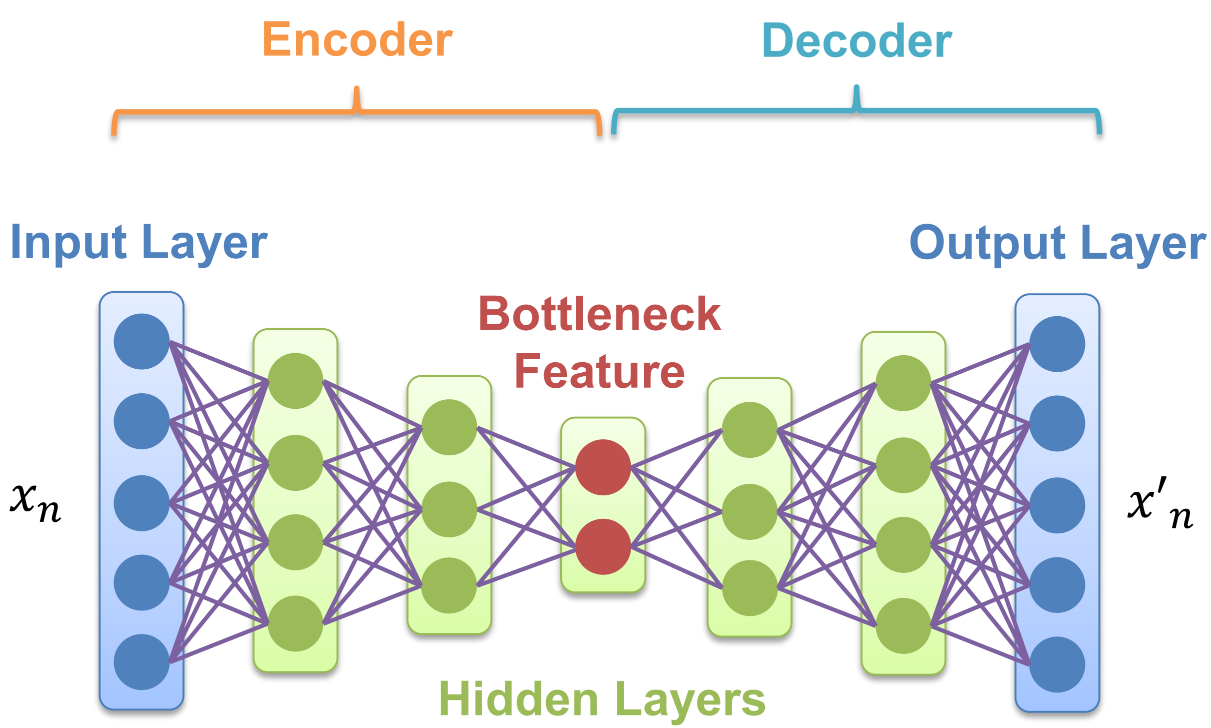
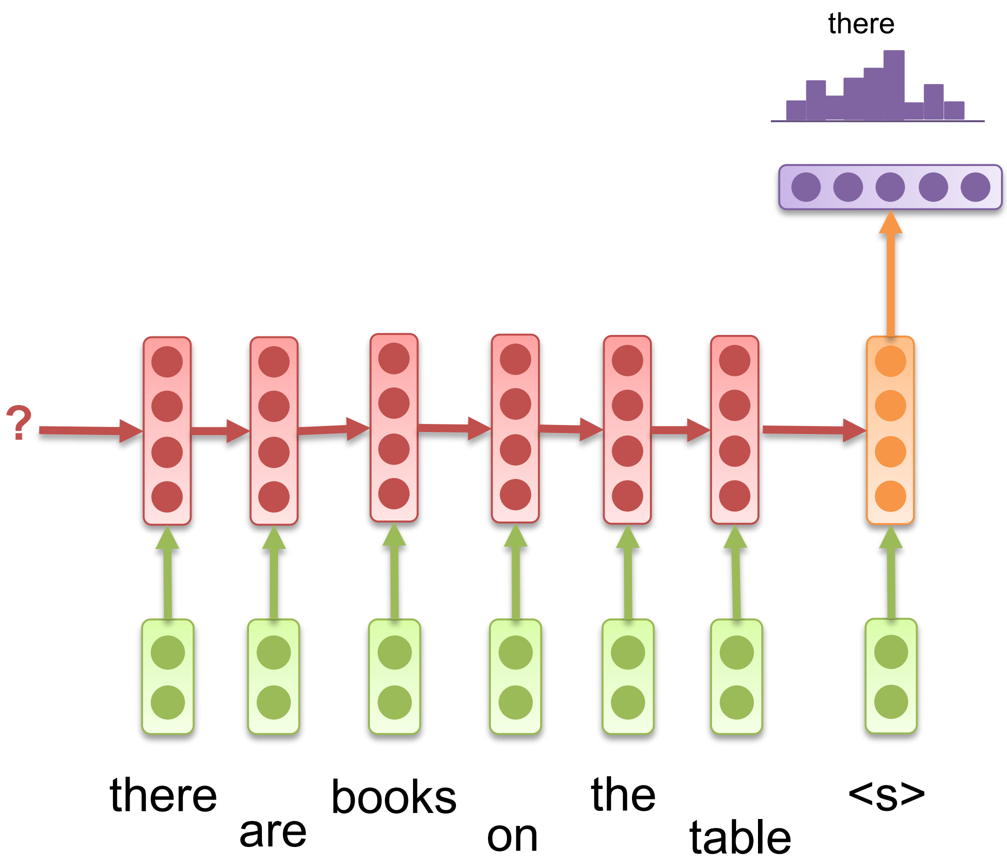


RNN-based Autoencoder.

- RNN can also be used to construct an autoencoder



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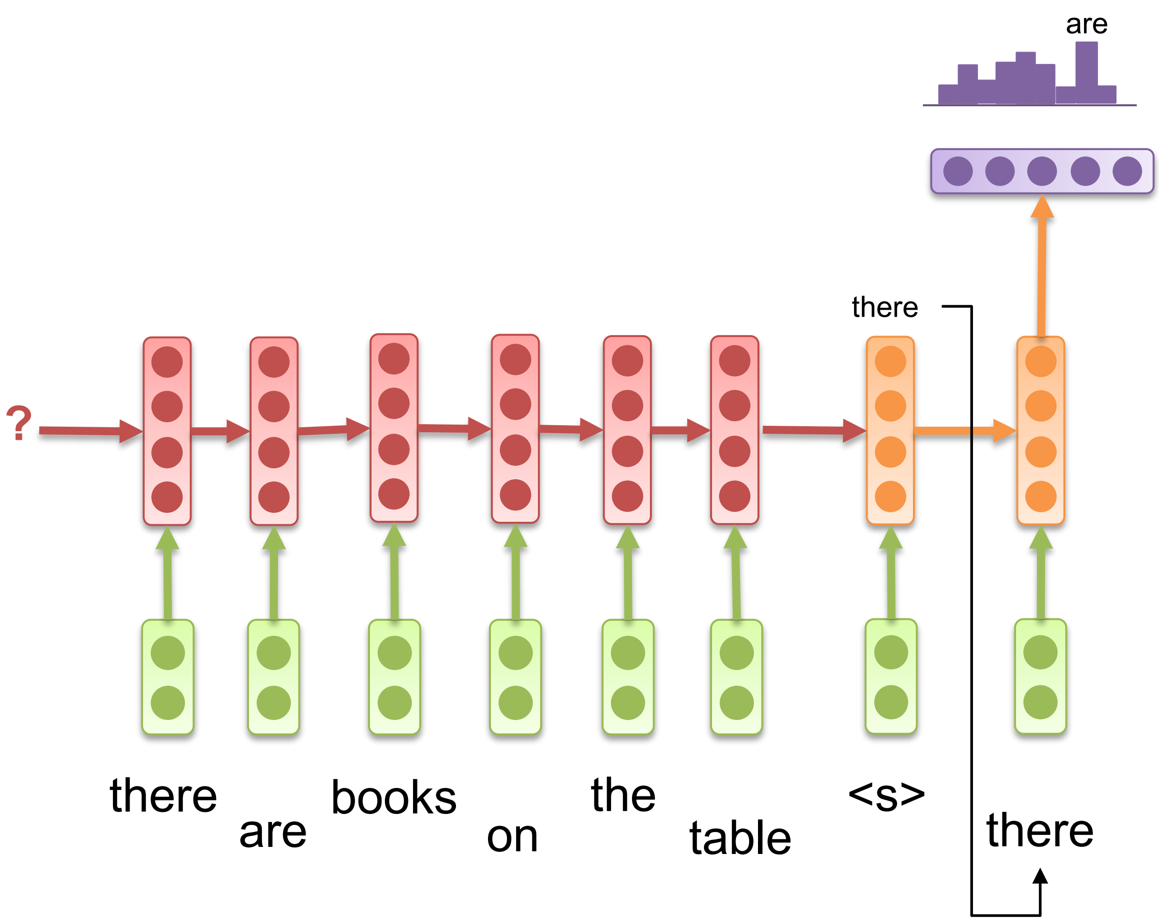

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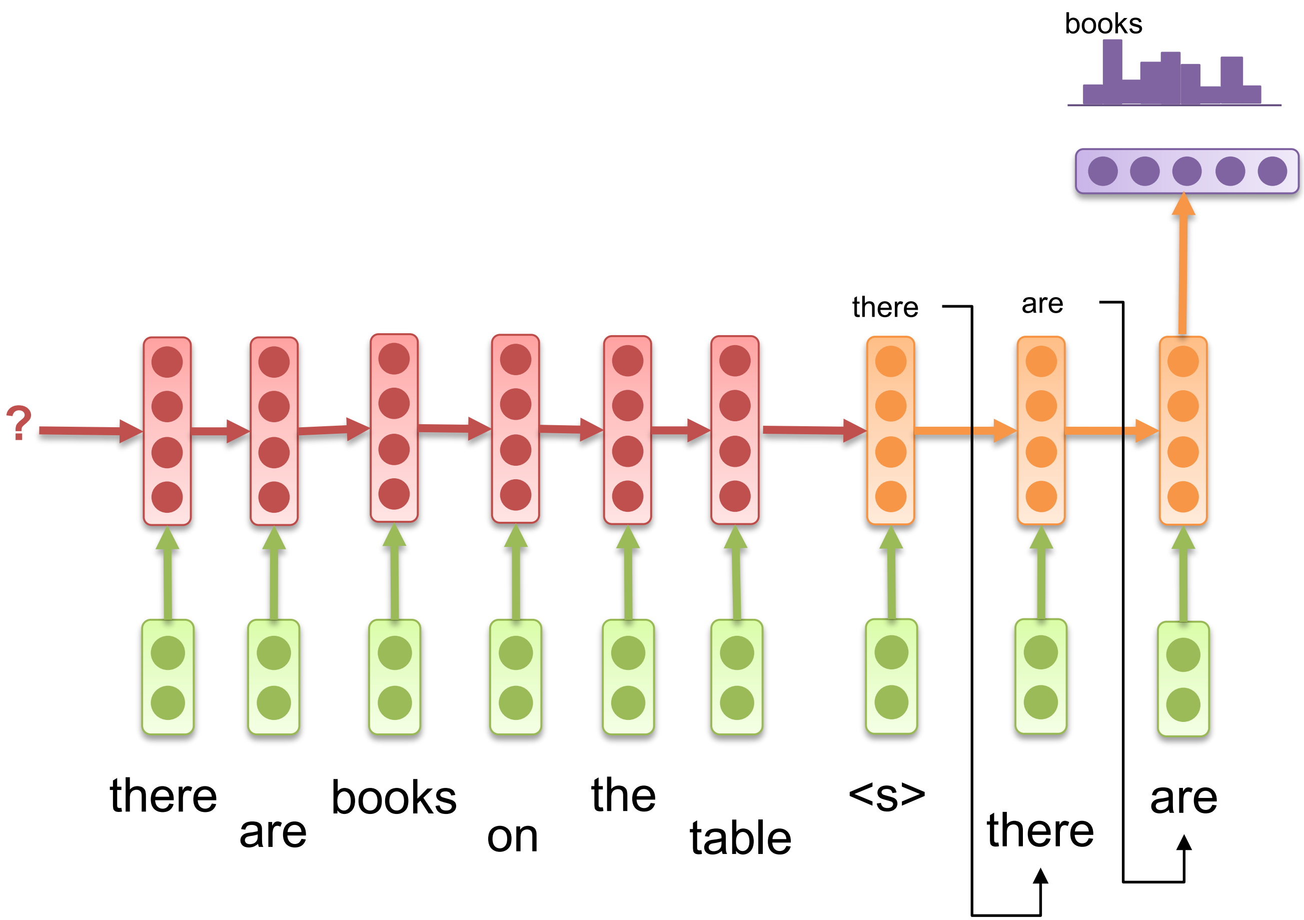

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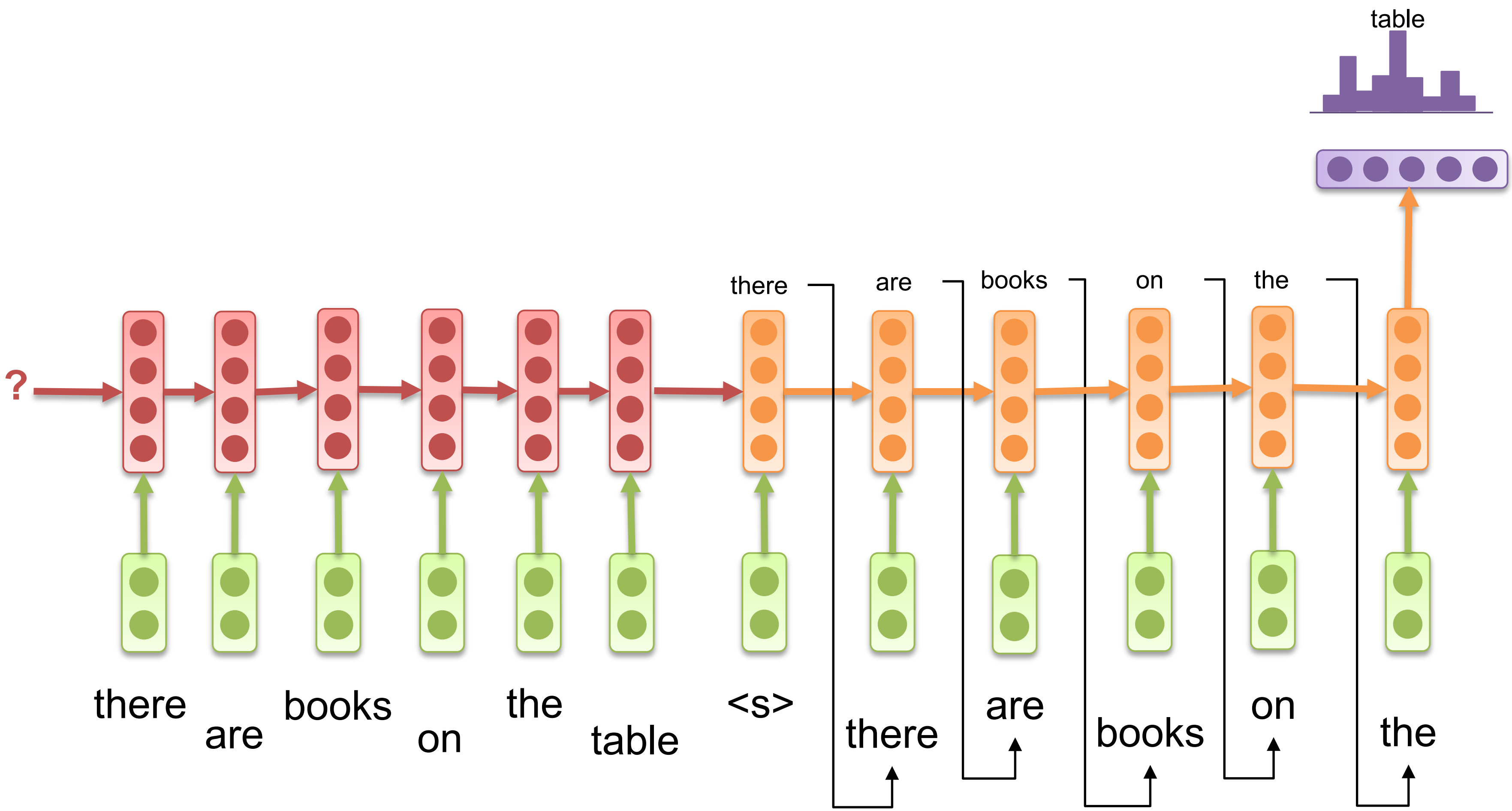

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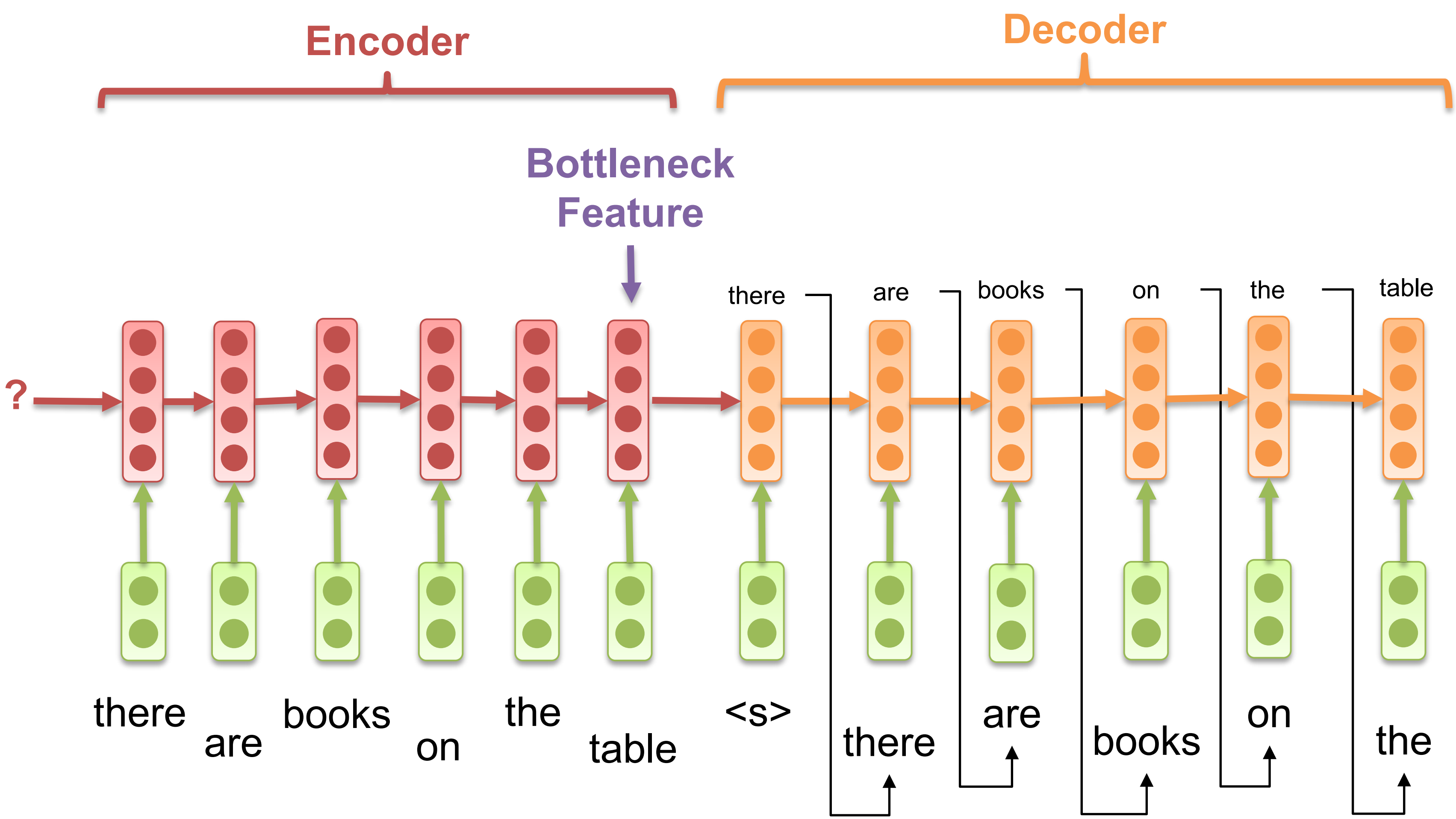
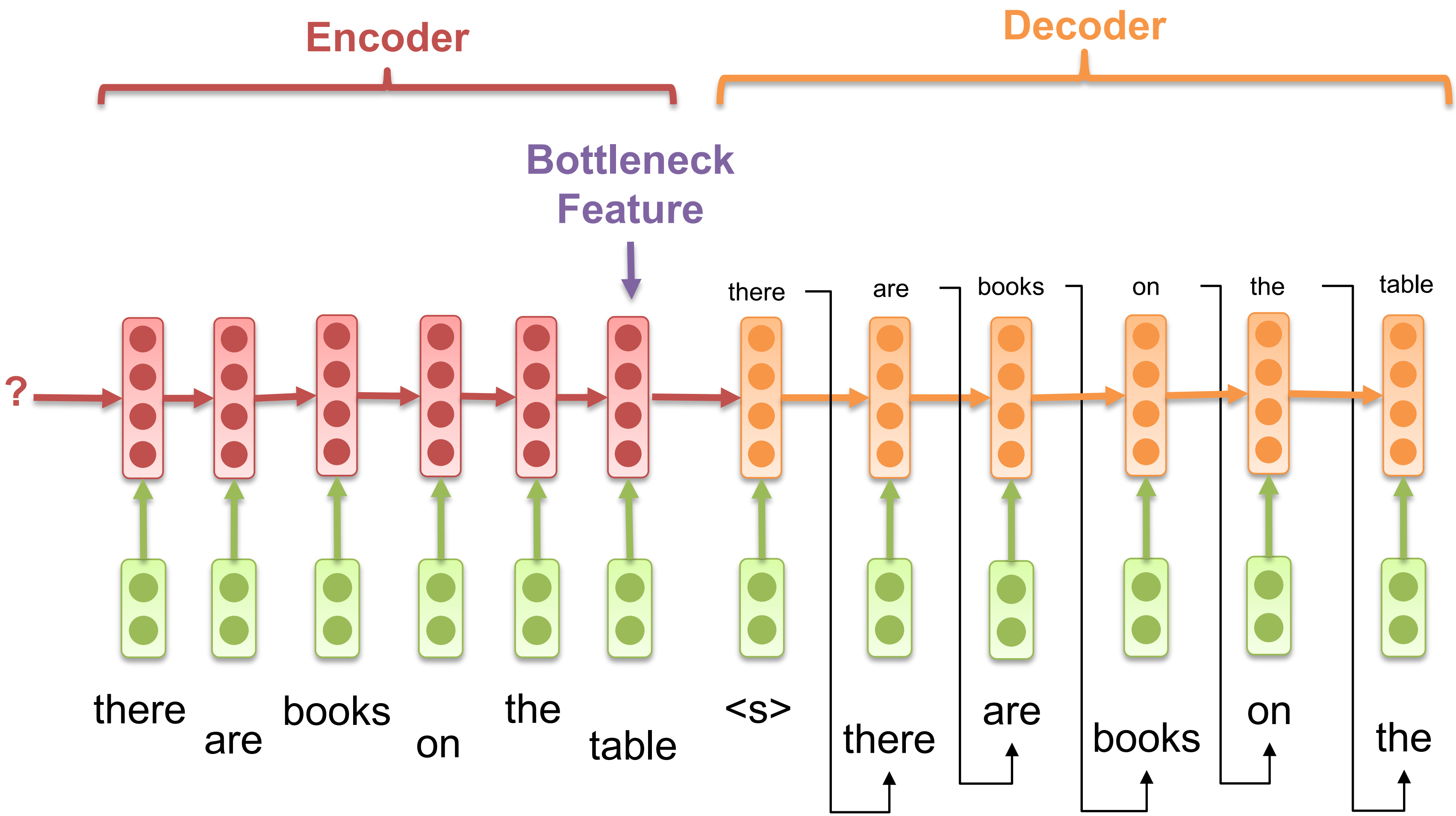


Sequence-to-sequence Learning

- Such a methodology also calls sequence-to-sequence (seq2seq) learning

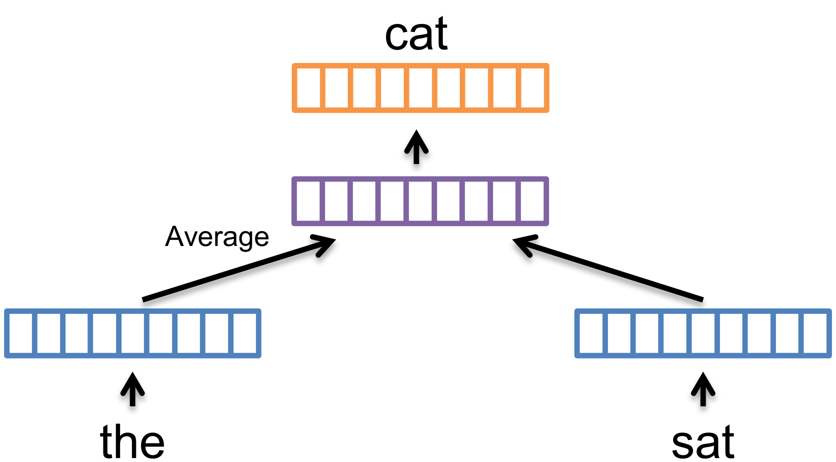


Revisiting Classic Word Embeddings

- CBOW and Skip-gram models are two representative word embedding methods

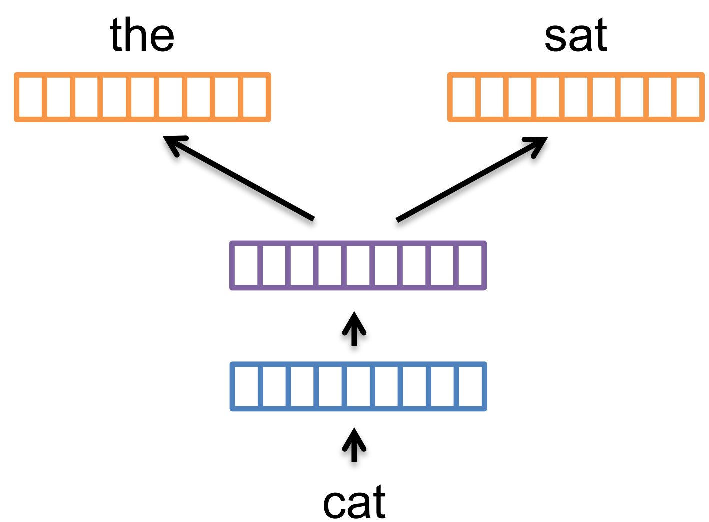
CBOW

$$\prod_{t=1}^{T} P(w_t | w_{t-c}, \dots, w_{t-1}, w_{t+1}, \dots, w_{t+c})$$



Skip-gram

$$\prod_{t=1}^{T} P(w_{t-c}, \dots, w_{t-1}, w_{t+1}, \dots, w_{t+c} | w_t)$$



Paragraph Embeddings

- Learning of paragraph representations is more reasonable and suitable for some tasks
  - Summarization, Retrieval, and Sentiment Analysis

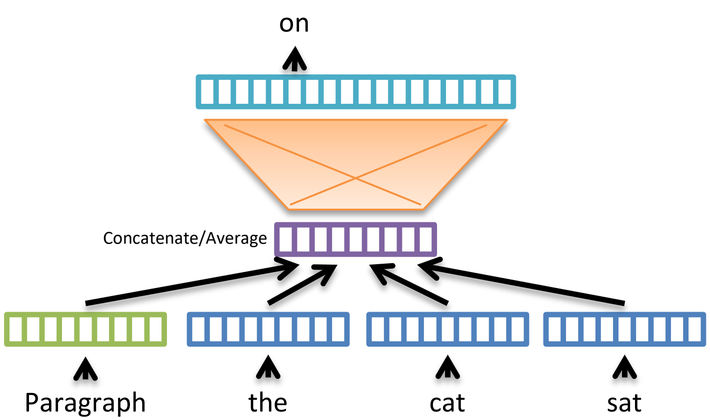
- A straightforward method is to represent a paragraph by averaging the vector representations of words occurring in the paragraph

$$\vec{d} = \sum_{w \in d} \frac{c(w,d)}{|d|} v_w$$

Distributed Memory (DM) Model

- Learning of paragraph representations is more reasonable and suitable for some tasks
  - The distributed memory model, the distributed bag-of-words model, and the thought vector model

- The DM model is inspired from the CBOW model

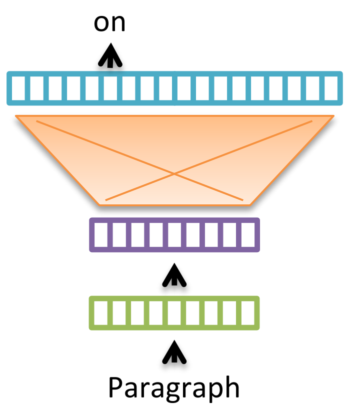


$$\prod_{t=1}^{T} P(w_t | w_{t-c}, \dots, w_{t-1}, w_{t+1}, \dots, w_{t+c}, d)$$

  - The idea is that a given paragraph also contributes to the prediction of a next word

Distributed Bag-of-words (DBOW) Model

- Opposite to the DM model, a simplified version is to only leverage the paragraph representation to predict all of the words occurring in the paragraph

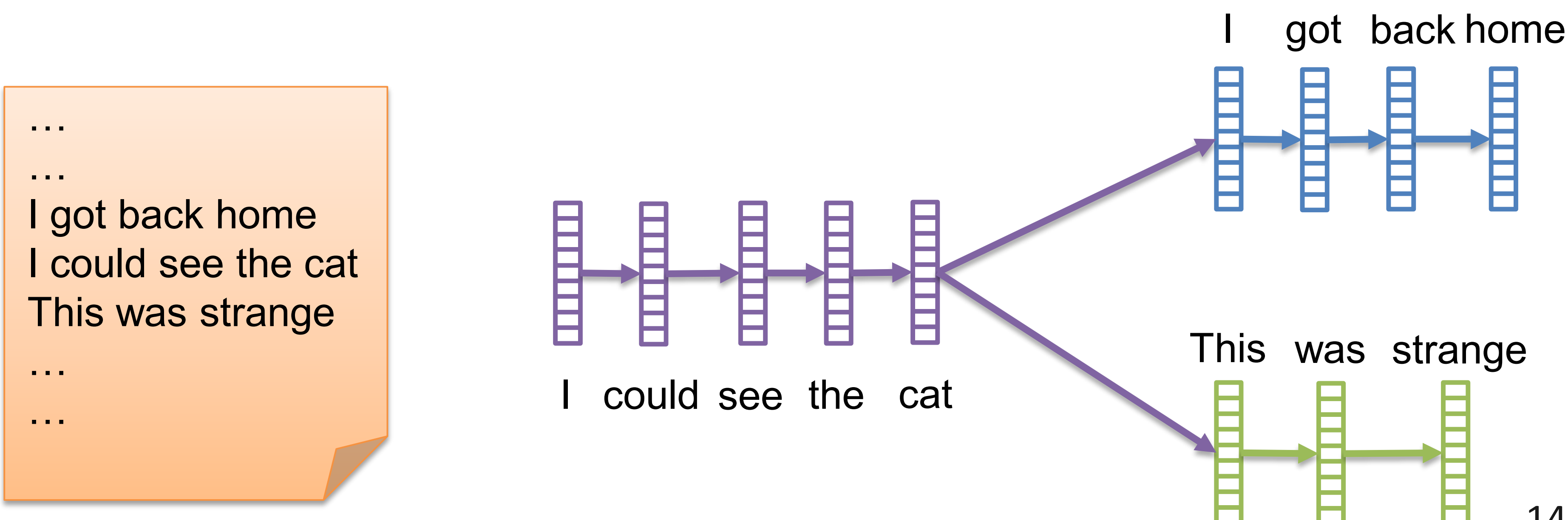


$$\prod_{t=1}^{T} P(w_t|d)$$

- Since the model ignores the contextual words at the input layer, it is named the distributed bag-of-words (DBOW) model

Skip-Thought Vector Model

- The skip-thought vector model presents an objective function that abstracts the **skip-gram** model to the sentence level
  - Instead of using a word to predict its surrounding context, thought vector encodes a sentence to predict the sentences around it



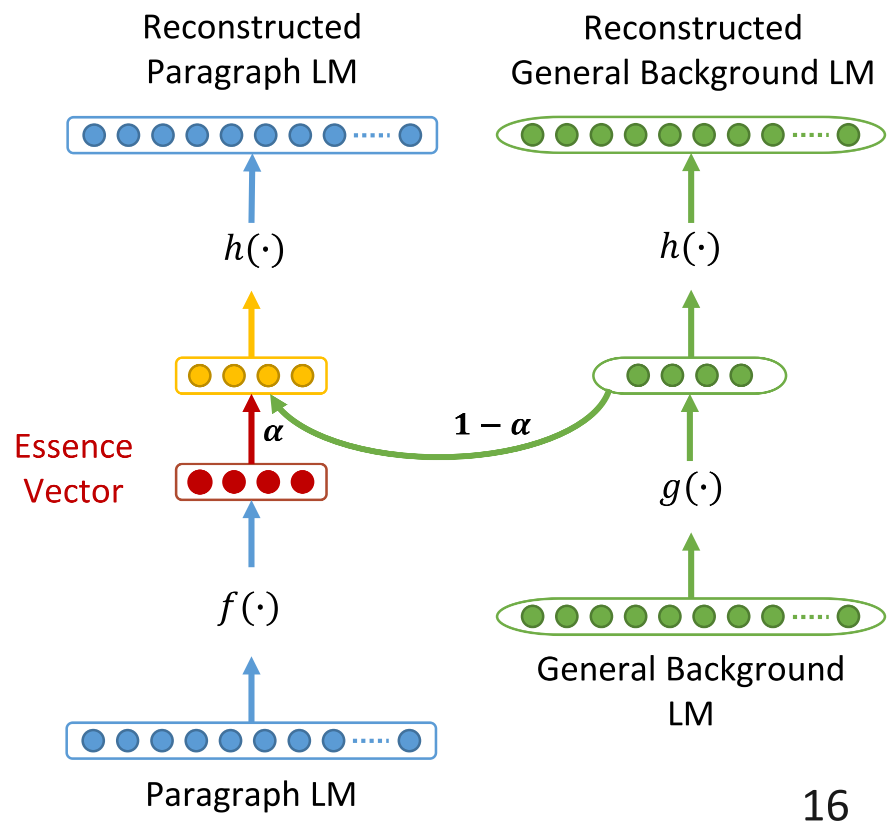
Classic Paragraph Embedding Methods

- Classic paragraph embedding methods infer the representation of a given paragraph by **considering all of the words** occurring in the paragraph
  - Such as the Distributed Memory model, the Distributed Bag-of-words model, and the skip-though vector model

- The **stop** or **function words** that occur frequently may mislead the embedding learning process
  - The learned representation for the paragraph might be undesired
  - The performance is limited
  - Our goal is to
    - Distill the most representative information from a given paragraph
    - Get rid of the general background information

Learning to Distill

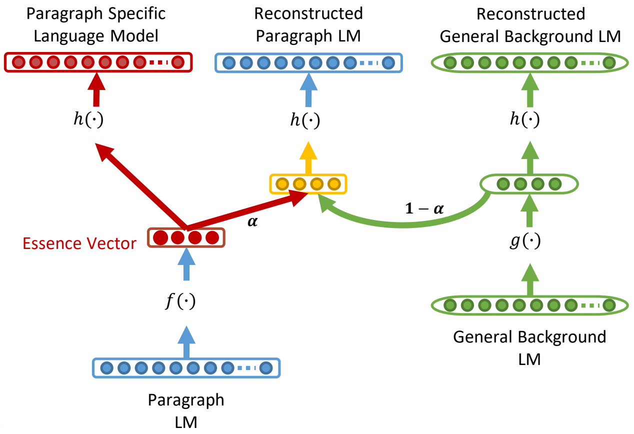
- We assume that each paragraph can be assembled by the **paragraph specific information** and the **general background information**
  - This assumption also holds in the low-dimensional representation space
  - Three modules
    - Paragraph encoder $f(\cdot)$
    - Background encoder $g(\cdot)$
    - Decoder $h(\cdot)$



Essence Vector-based Language Model

- A brilliant property inherits in the EV model is that it can be readily inferred a "paragraph" specific language model

$$\hat{P}(w) \equiv h\left(f\left(P_{D_t}\right)\right)$$



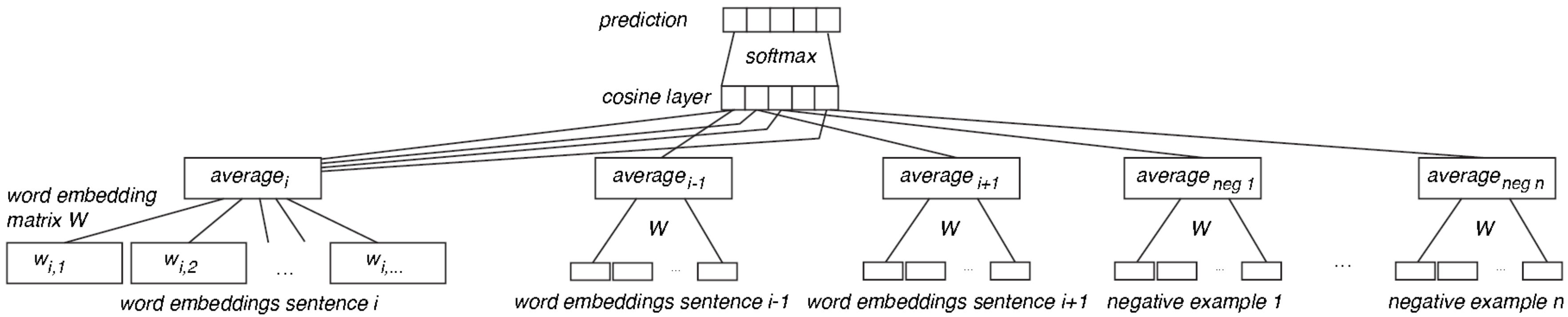
Paragraph Specific Language Model

Original Paragraph Language Model

Background Language Model

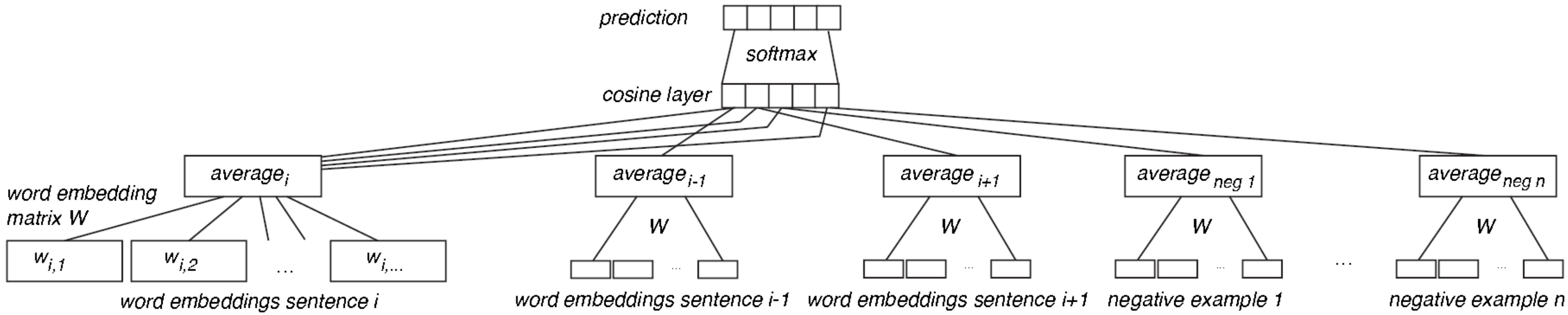
Siamese CBOW.

- Siamese CBOW model aims at learning a set of word embeddings which can be directly used for the purpose of being averaged



K.Y. Chen, *et al.*, “Learning to distill: the essence vector modeling framework,” in *Proc. of Coling*, 2016.

Siamese CBOW..



$$L = -\sum_{s_j \in \{S^+, S^-\}} P(s_i, s_j) \log P'(s_i, s_j)$$

sentences that occur next to the target sentence

$$P(s_i, s_j) = \begin{cases} \dfrac{1}{|S^+|}, & if\ s_j \in S^+ \\ 0, & if\ s_j \in S^- \end{cases}$$

randomly chosen sentences that do not occur next to the target sentence

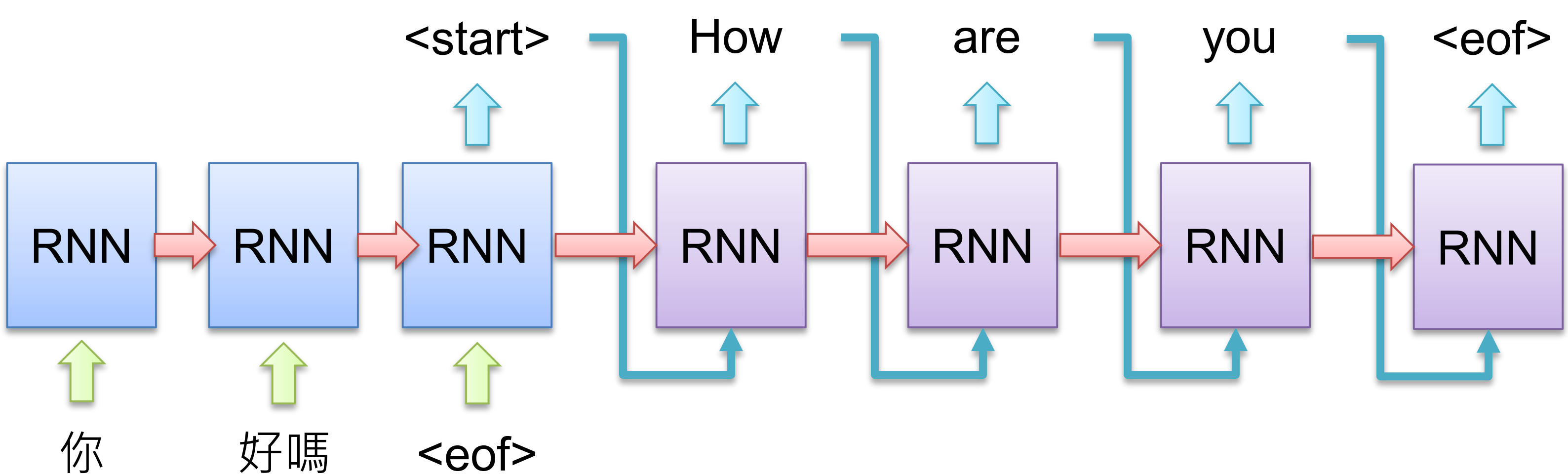
…
…
I got back home
I could see the cat
This was strange
…
…

$$P'(s_i, s_j) = \frac{e^{\cos(\vec{s_i}, \vec{s_j})}}{\sum_{s_k \in \{S^+, S^-\}} e^{\cos(\vec{s_i}, \vec{s_k})}}$$

sentence representations

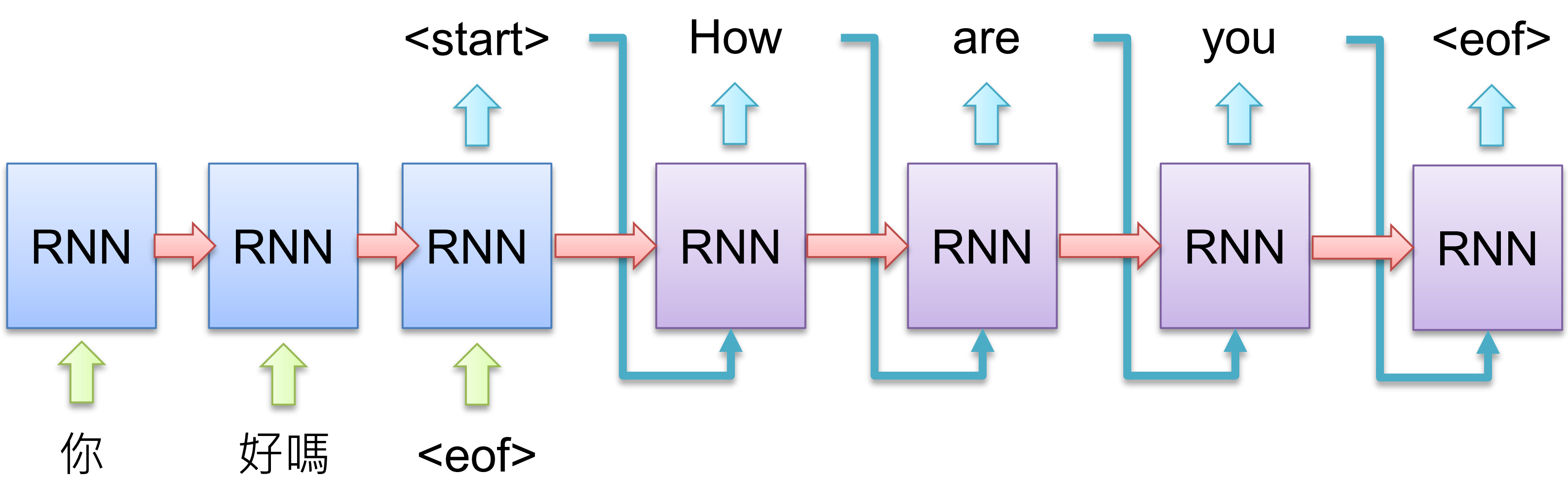
Machine Translation.

- RNN can be used to encode a variable-length source sentence, and then a variable-length target sentence will be generated by considering the encoded information
  - RNN Encoder-Decoder
  - Seq2seq
  - It is suitable for machine translation task



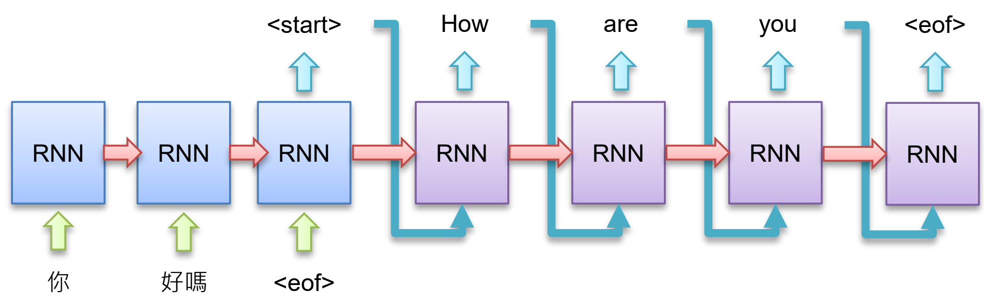
Machine Translation..

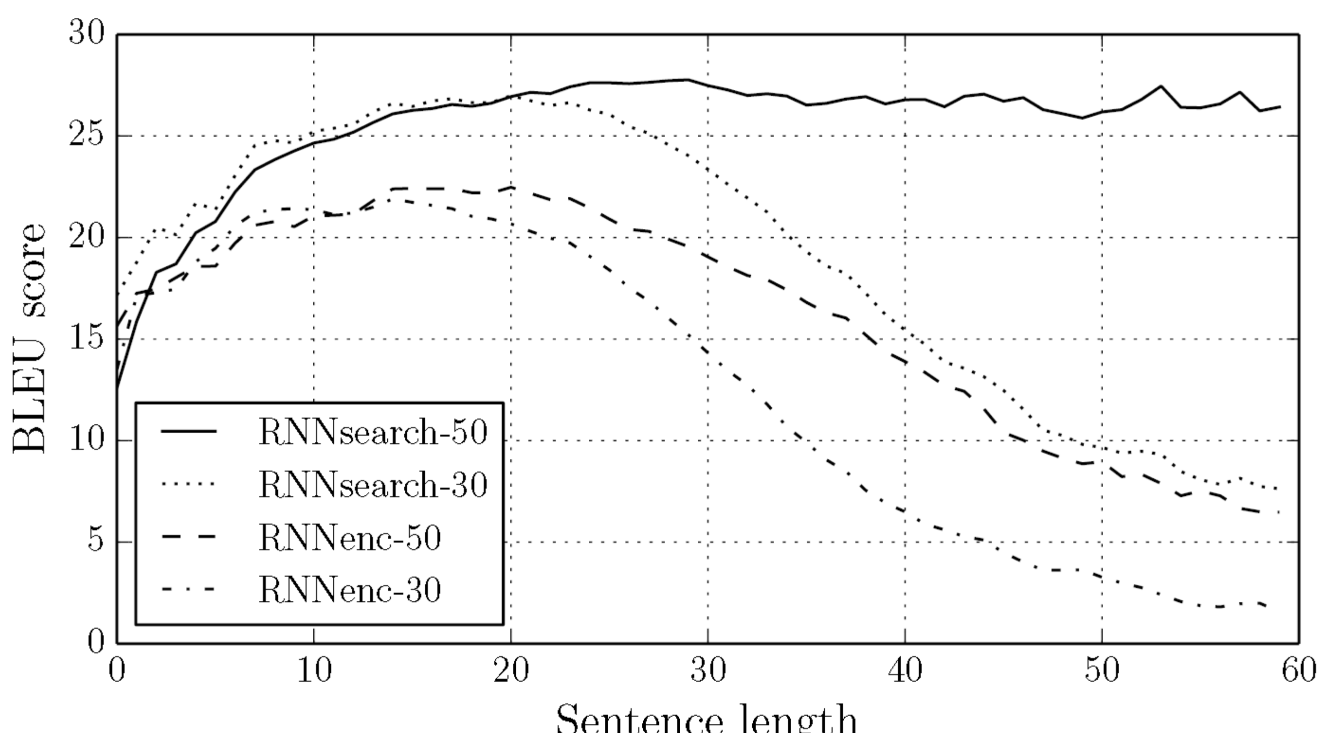
- A potential issue with this encoder–decoder approach is that a neural network needs to be able to compress all the necessary information of a source sentence into a fixed-length vector



Machine Translation…

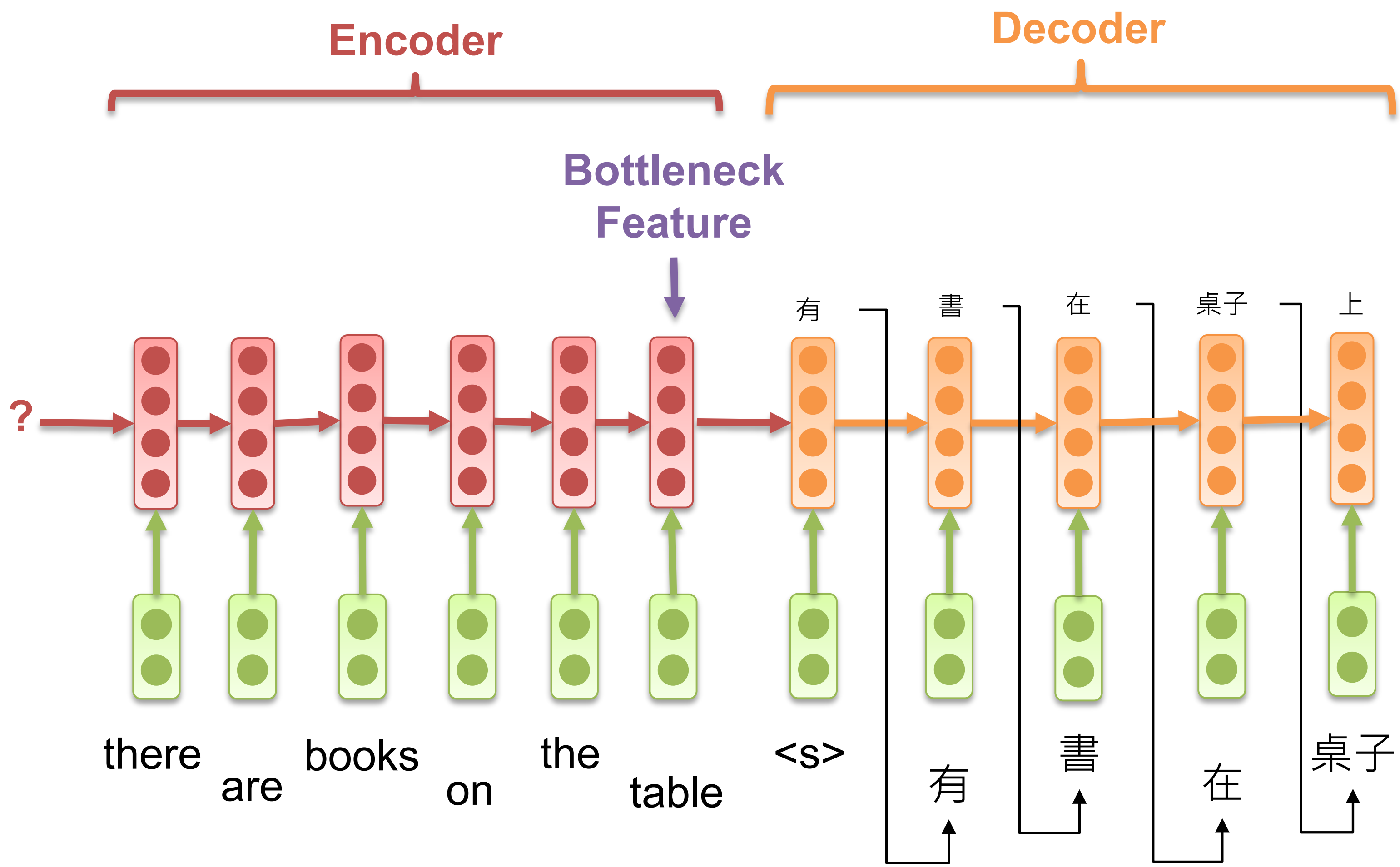
- The performance will drop when the sentence being longer!



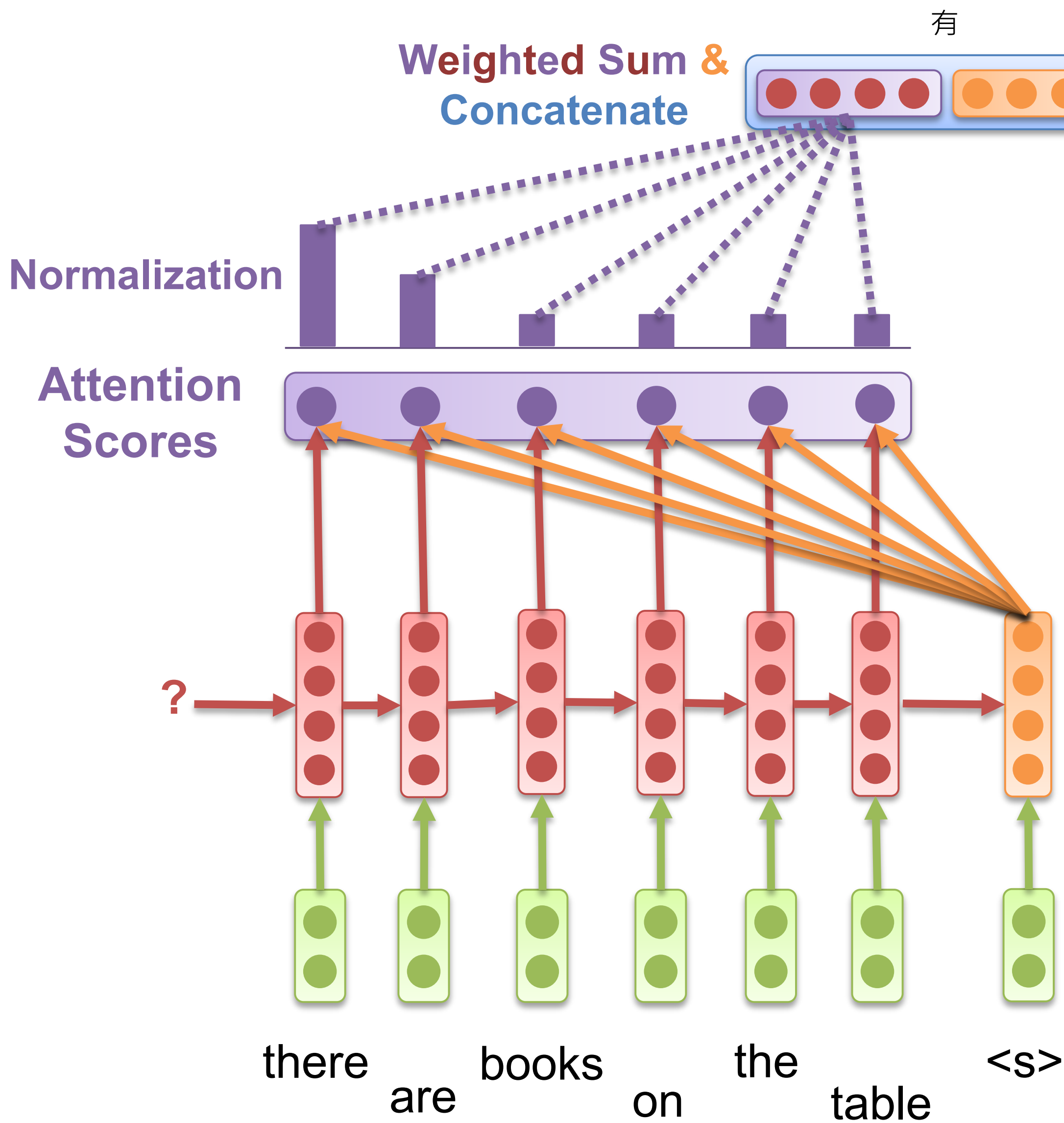


The Bottleneck Problem

- The bottleneck feature needs to capture all information about the source sentence
  - Information bottleneck!



Attention Mechanism.



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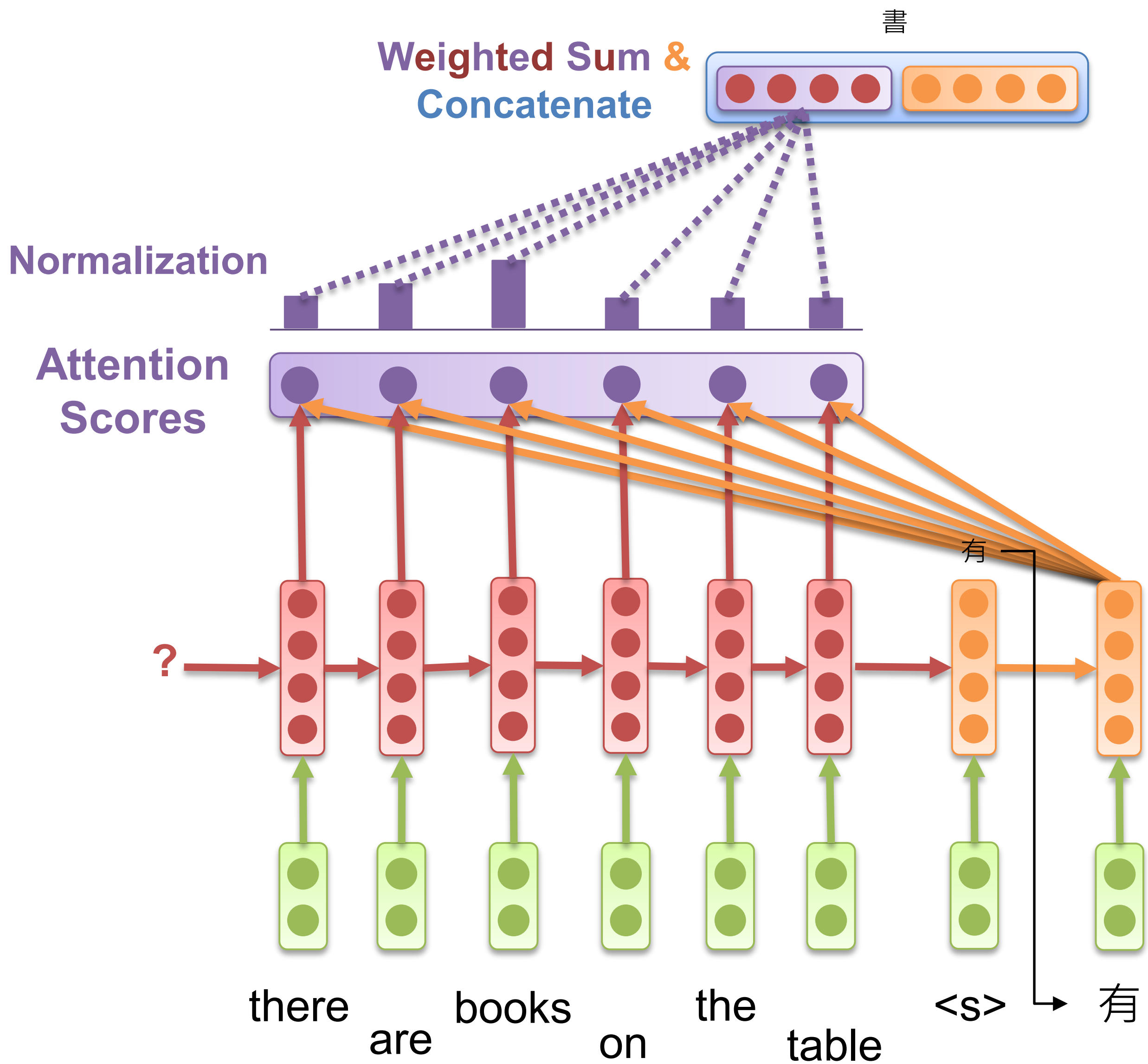

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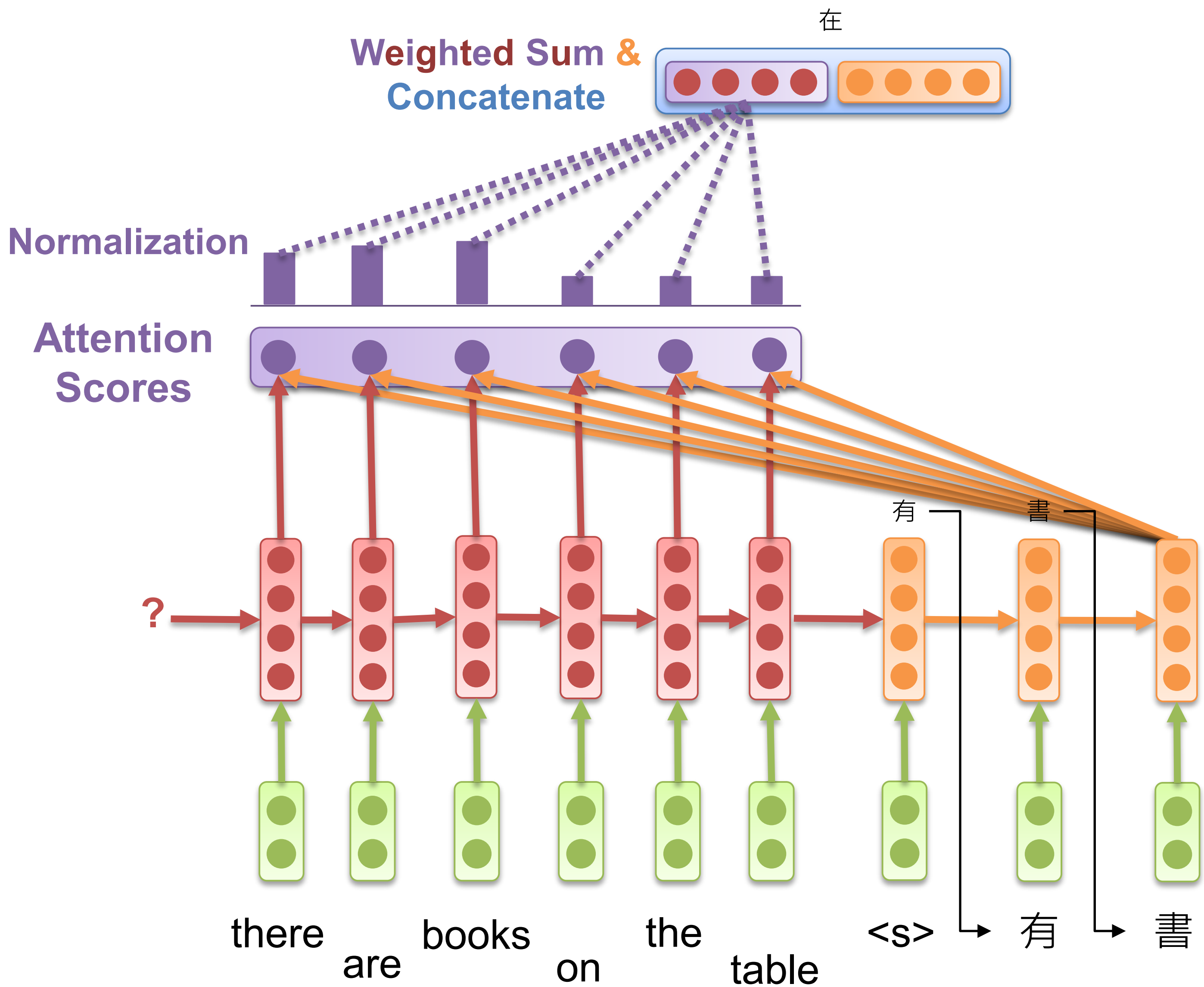

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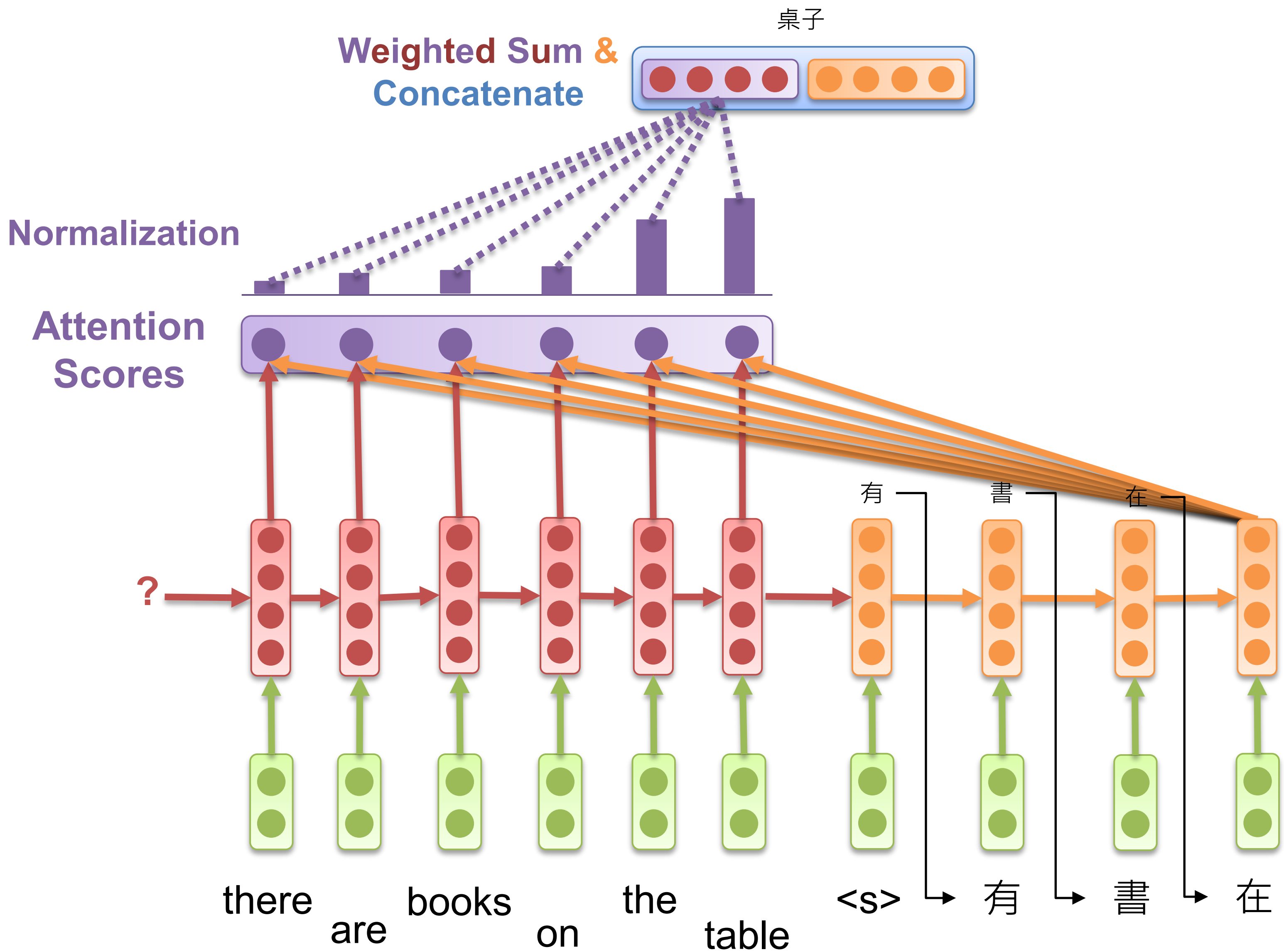

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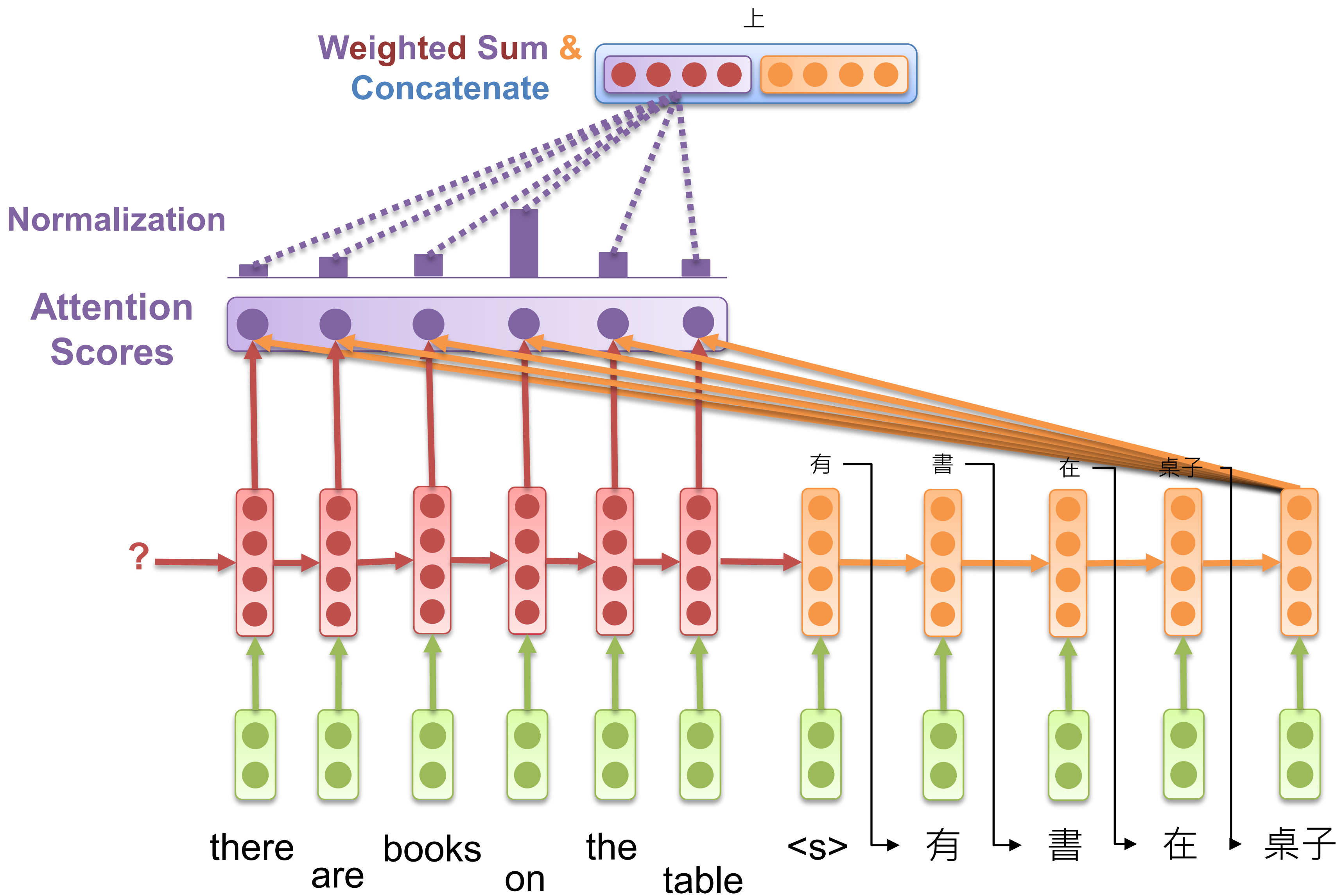
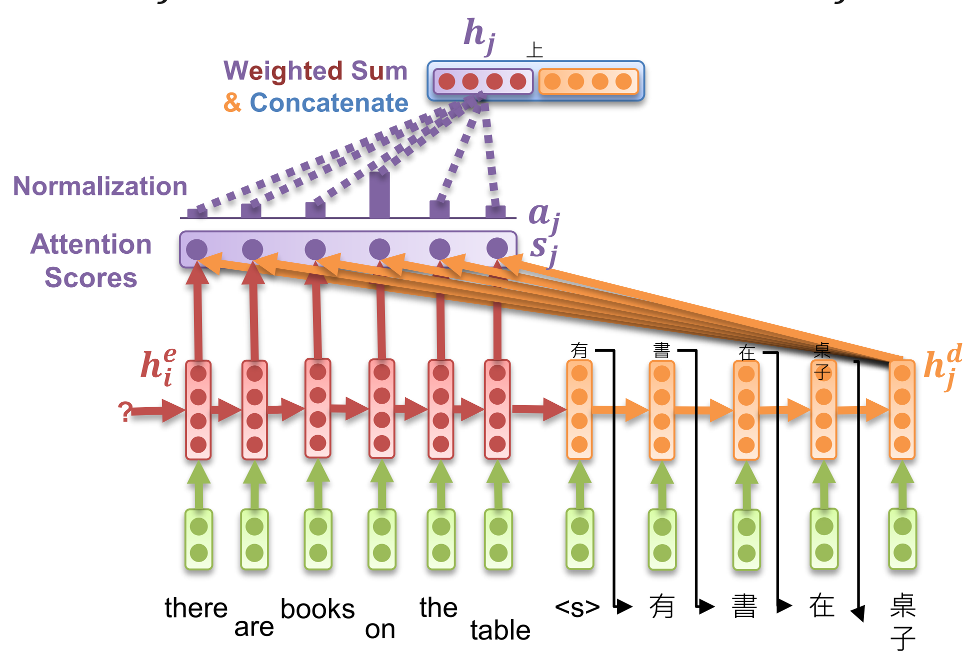


Descriptions

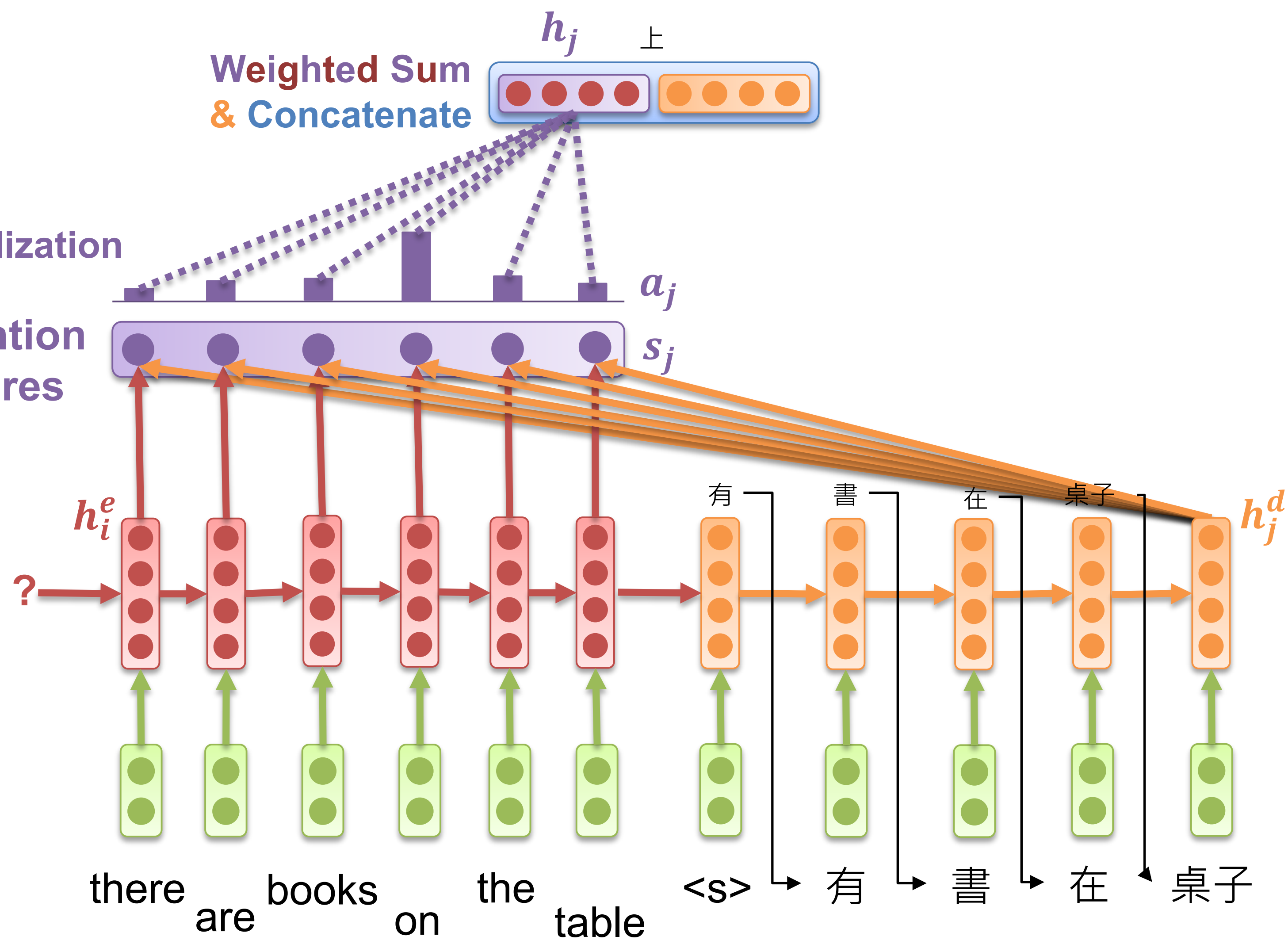
- The attention mechanism
  - The encoder states $h_1^e, h_2^e, \cdots, h_i^e, \cdots, h_I^e \in \mathbb{R}^{d_1}$
  - The decoder states $h_1^d, h_2^d, \cdots, h_j^d, \cdots, h_J^d \in \mathbb{R}^{d_2}$
  - The attention score vector at time j is $s_j \in \mathbb{R}^I$
  - Softmax is taken on s_j to get the attention distribution $a_j \in \mathbb{R}^I$
  - A new vector representation h_j is derived by referring to a_j and the encoder states

$$h_j = \sum_{i=1}^{I} a_j^i \, h_i^e$$



The Attention Scores.

- There are several ways for us to compute the attention scores



The Attention Scores..

- Basic dot-product Attention
  - Assume $d_1 = d_2$

$$s^i = h_i^e \cdot h_j^d$$

- Multiplicative Attention
  - $W \in \mathbb{R}^{d_1 \times d_2}$ is a learned parameter

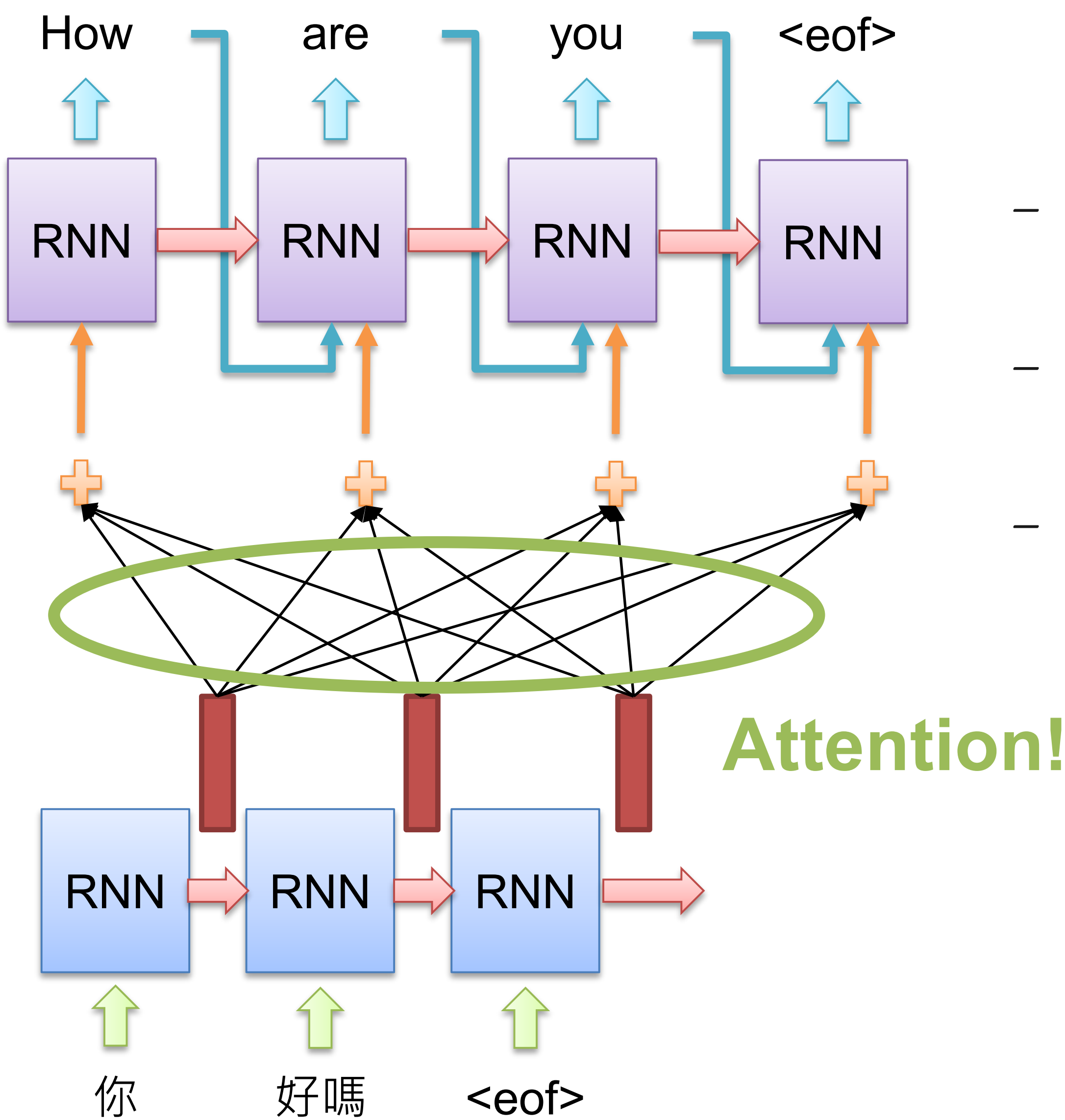
$$s^i = (h_i^e)^{\mathrm{T}} W h_j^d$$

- Additive Attention
  - $W_1 \in \mathbb{R}^{d_3 \times d_1}$, $W_2 \in \mathbb{R}^{d_3 \times d_2}$, and $W_3 \in \mathbb{R}^{d_3}$ are learned parameters

$$s^i = W_3^{\mathrm{T}} \tanh(W_1 h_i^e + W_2 h_j^d)$$

The encoder states $h_1^e, h_2^e, \cdots, h_i^e, \cdots, h_I^e \in \mathbb{R}^{d_1}$
The decoder states $h_1^d, h_2^d, \cdots, h_j^d, \cdots, h_J^d \in \mathbb{R}^{d_2}$

Attention-based Modeling

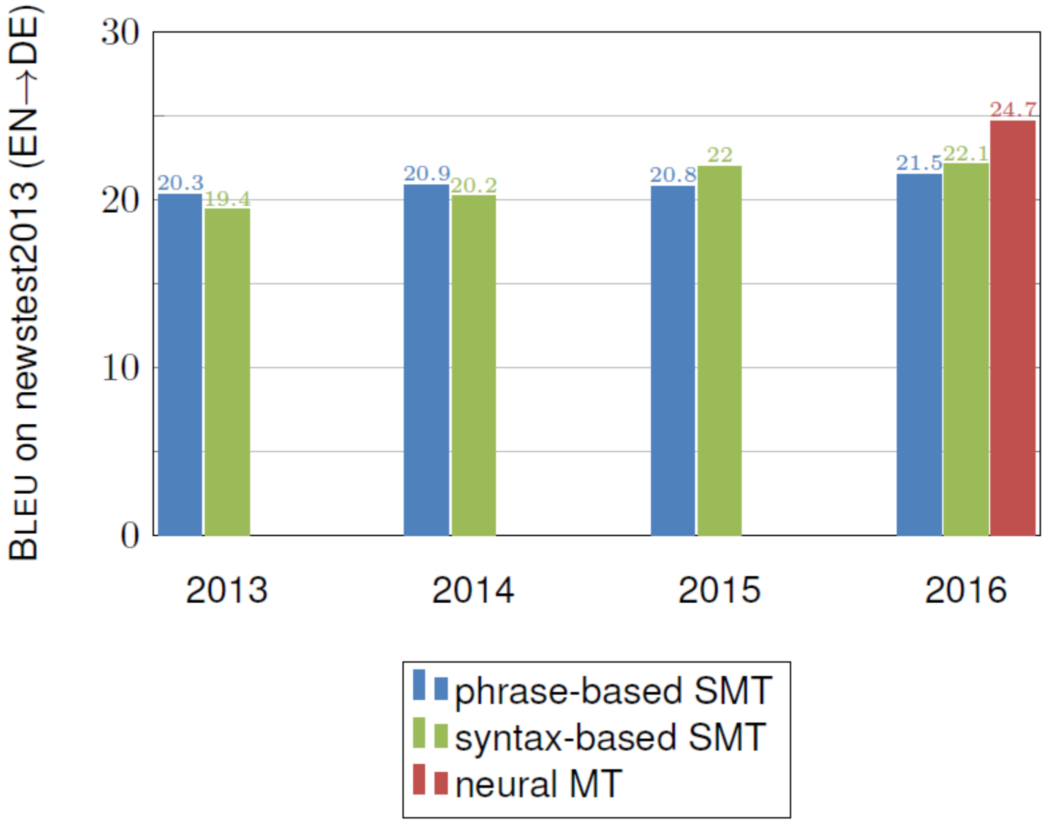


- Location-based Modeling
  - Handwriting synthesis
- Content-based Modeling
  - Machine Translation
- Hybrid Attention Modeling
  - Speech Recognition

Amazing!

- Neural Machine Translation went from a fringe research activity in 2014 to the leading standard method in 2016
  - 2014: First seq2seq paper published
  - 2016: Google Translate switches from SMT to NMT

- This is amazing!
  - SMT systems, built by hundreds of engineers over many years, outperformed by NMT systems trained by a handful of engineers in a few months



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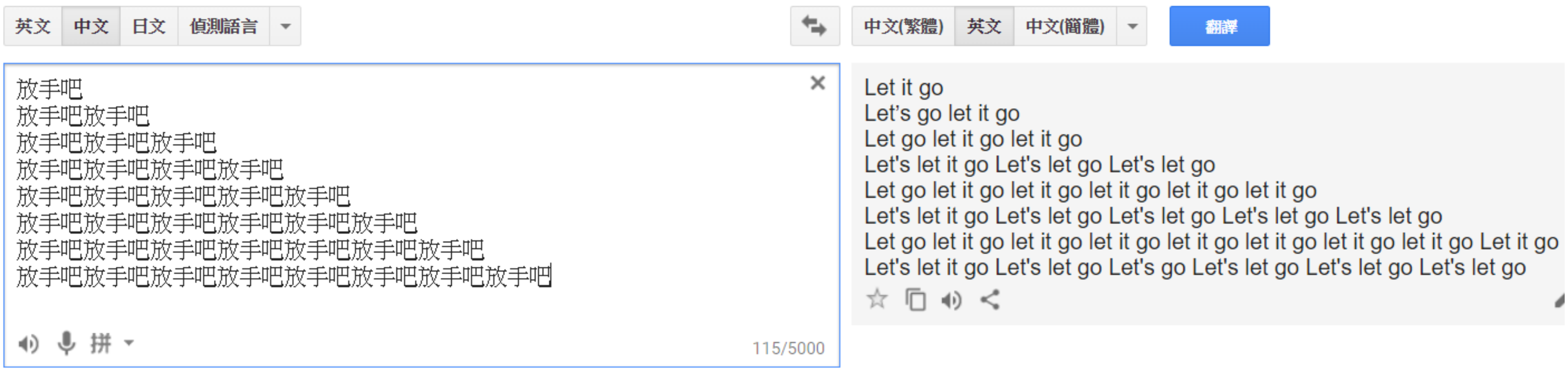
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Questions?

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