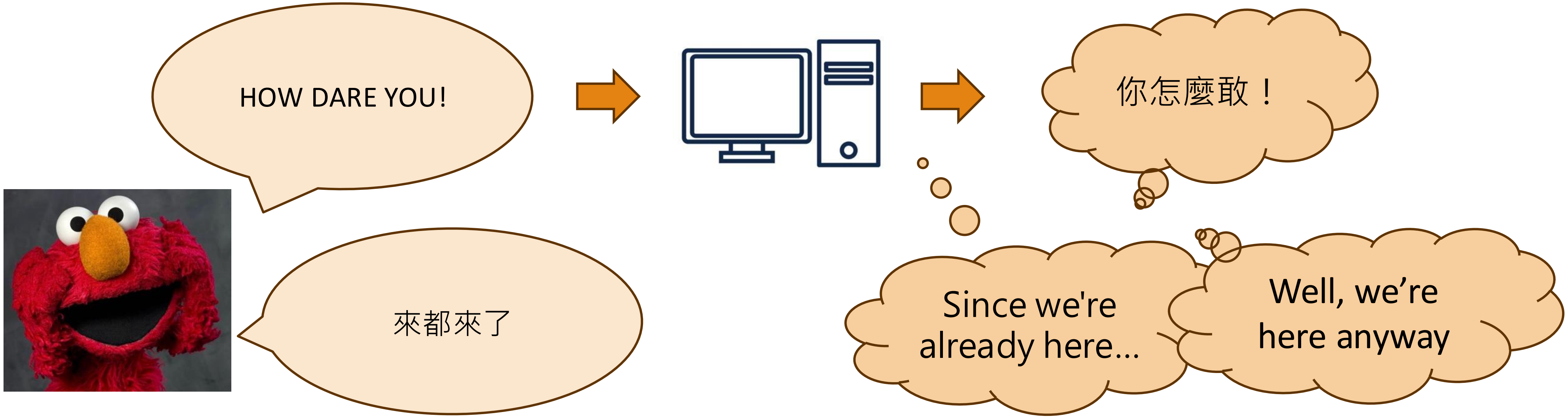
Natural Language Processing

Sequence-to-sequence Models and Attention Mechanisms

Machine Translation

Machine translation plays a pivotal role in the development of NLP.

- Many advancements in NLP language models were initially motivated by the need to address translation challenges.



Challenges of Machine Translation

Unlike the other tasks like classification, the input and output of machine translation are **in different lengths**.

Look over there	←	請看那邊	→	あそこを見てください
English Short (3 tokens)		Chinese (4 tokens)		Japanese Long (12 tokens)

× We cannot just add an FFN at the end.

√ The hidden state should be utilized to encode the original sequence and it should be passed to the generation process.

Sequence to sequence Model

Sequence to Sequence (Seq2Seq) model

The core idea of the Seq2Seq model is to map **variable-length input sequences to variable-length output sequences**.

This flexibility enables its wide application across various tasks, such as:

- Machine Translation: Translating a sentence from one language to another.
- Text Summarization: Condensing long articles into shorter summaries.
- Dialogue Generation: Generating appropriate responses based on input contexts.

Sequential Models

Sequence models, also known as time series models, are a class of neural network architectures designed to model sequences of data.

- **RNN**
- **LSTM**

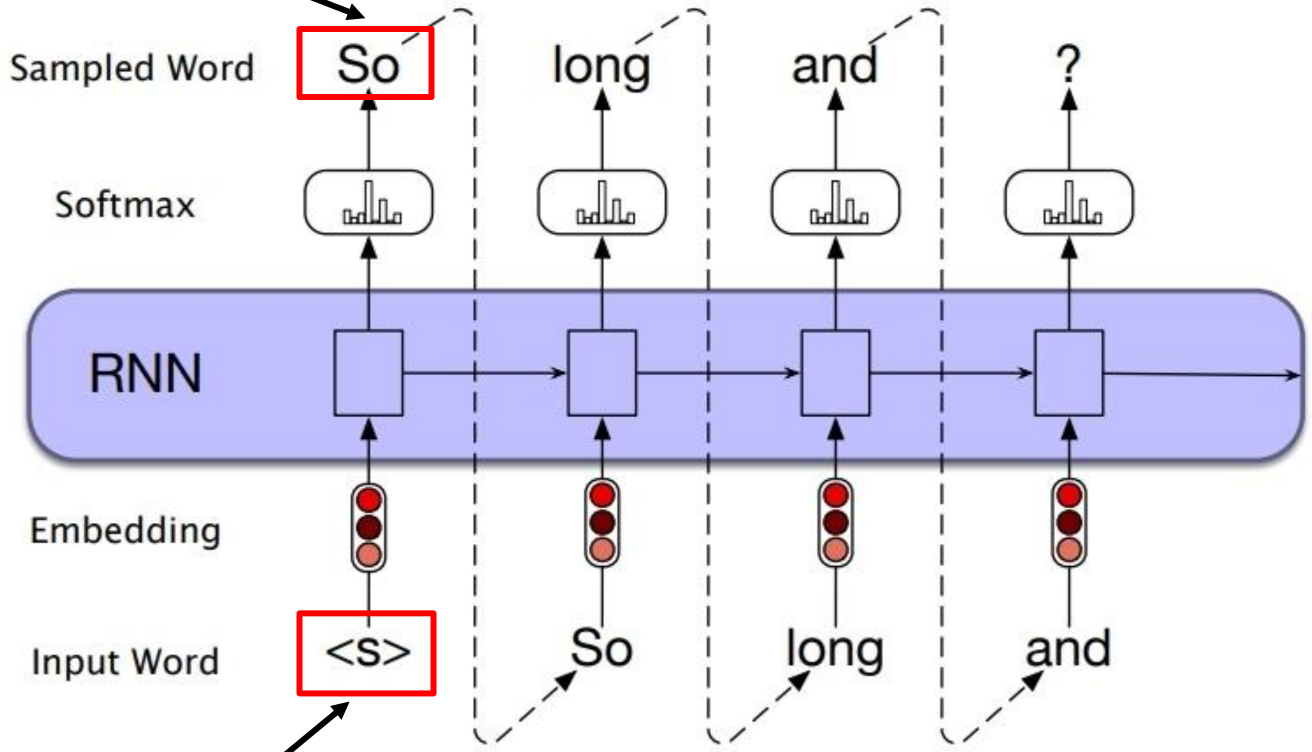
Each output of a sequential model depends on the hidden state variable provided by the previous step.

RNN for Sequence Generation

1. **Input Encoding:**
   - The input sequence is fed into the RNN one element at a time.
2. **Hidden State Update:**
   - The RNN updates its hidden state at each time step based on the current input element and the previous hidden state.
3. **Output Generation:**
   - Using the hidden states at each time step, the RNN generates the output sequence one element at a time.
4. **Iteration:**
   - Steps 2-3 are iterated until the desired length of the output sequence is reached or until a specific termination condition is met (e.g., generating an end-of-sequence token).

RNN for Sequence Generation

Predict the next token.

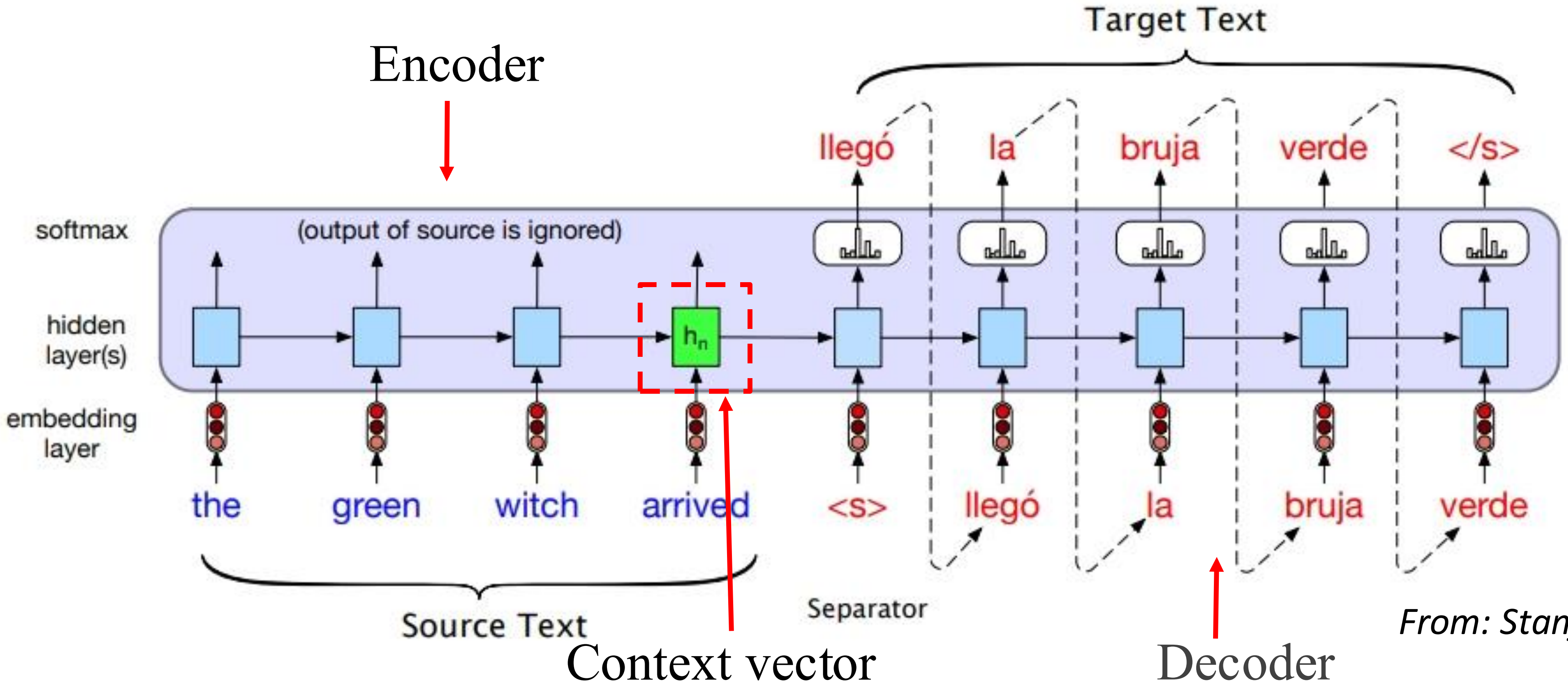


The sequence generation begin with a special token.

From: Stanford NLP

RNN for Machine Translation

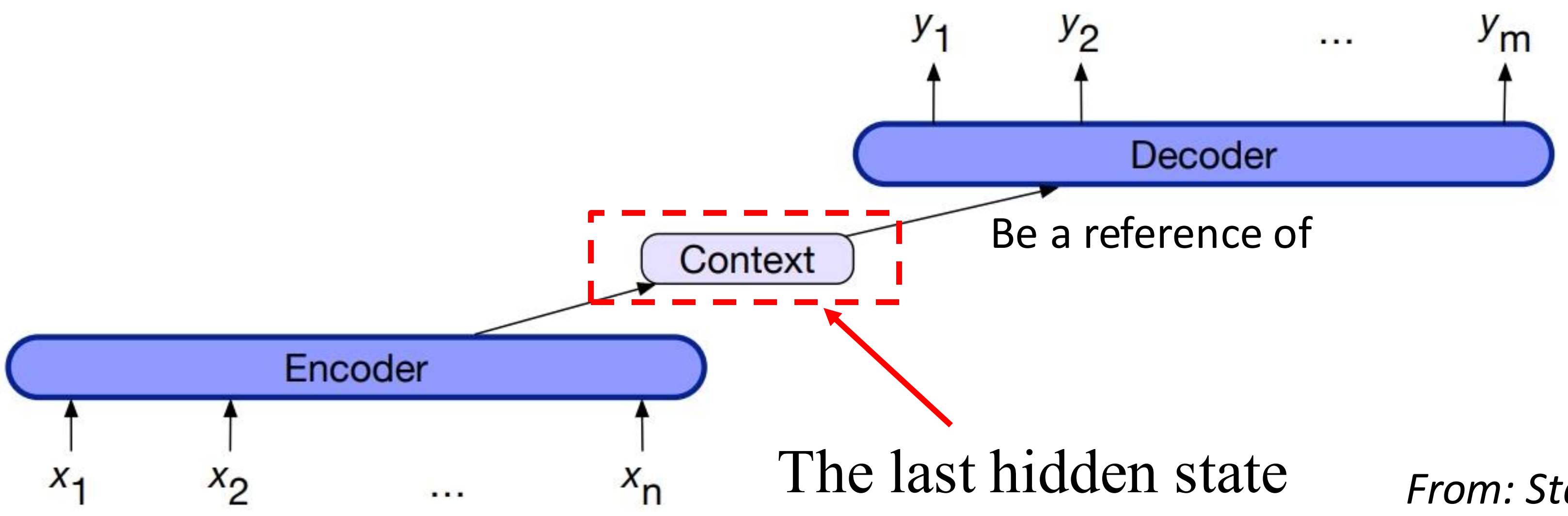
- Machine translation is a classic application of encoder-decoder architecture.



From: Stanford NLP

RNN for Machine Translation

- The context vector is the last hidden state of the encoder and it contains all the information of the input.



From: Stanford NLP

Encoder-decoder RNN

Encoder-decoder networks consist of three conceptual components:

- **An encoder** that accepts an input sequence, $x_{1:n}$, and generates a corresponding sequence of *contextualized representations*, $h_{1:n}$.
- **A context vector**, which is a function of $h_{1:n}$, and conveys the essence of the input to the decoder.
- **A decoder**, which accepts the context vector as input and generates an arbitrary length sequence of hidden states $h_{1:m}$, from which a corresponding sequence of output states $y_{1:m}$, can be obtained.

Gradient Vanishing/Exploding Problem of RNN

- During backpropagation, gradients are computed with respect to the hidden states through the loss function at each time step.

$$y_t = g(Vh_t)$$

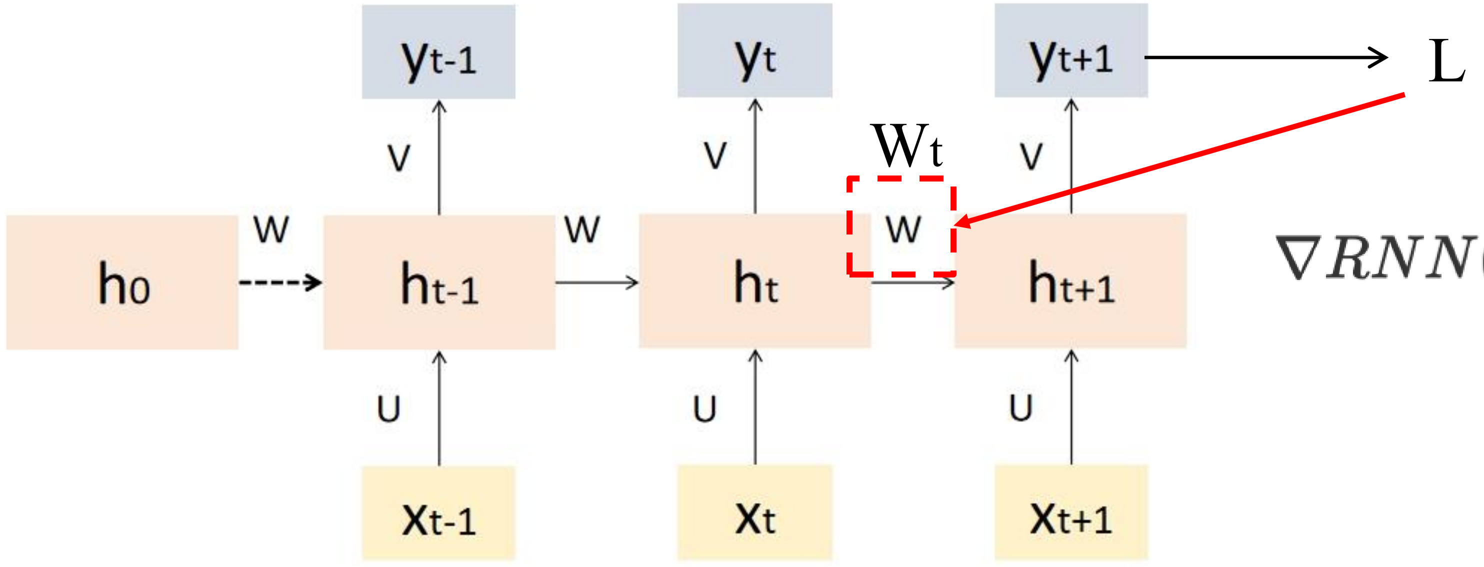
$$h_t = f(Ux_t + Wh_{t-1})$$

- Compute the gradient (use the parameter W as an example):

$$\frac{\partial L}{\partial W} = \sum_{t=1}^{T} \frac{\partial L}{\partial h_T} \cdot \boxed{\frac{\partial h_T}{\partial h_{T-1}}} \cdots \frac{\partial h_t}{\partial W}$$

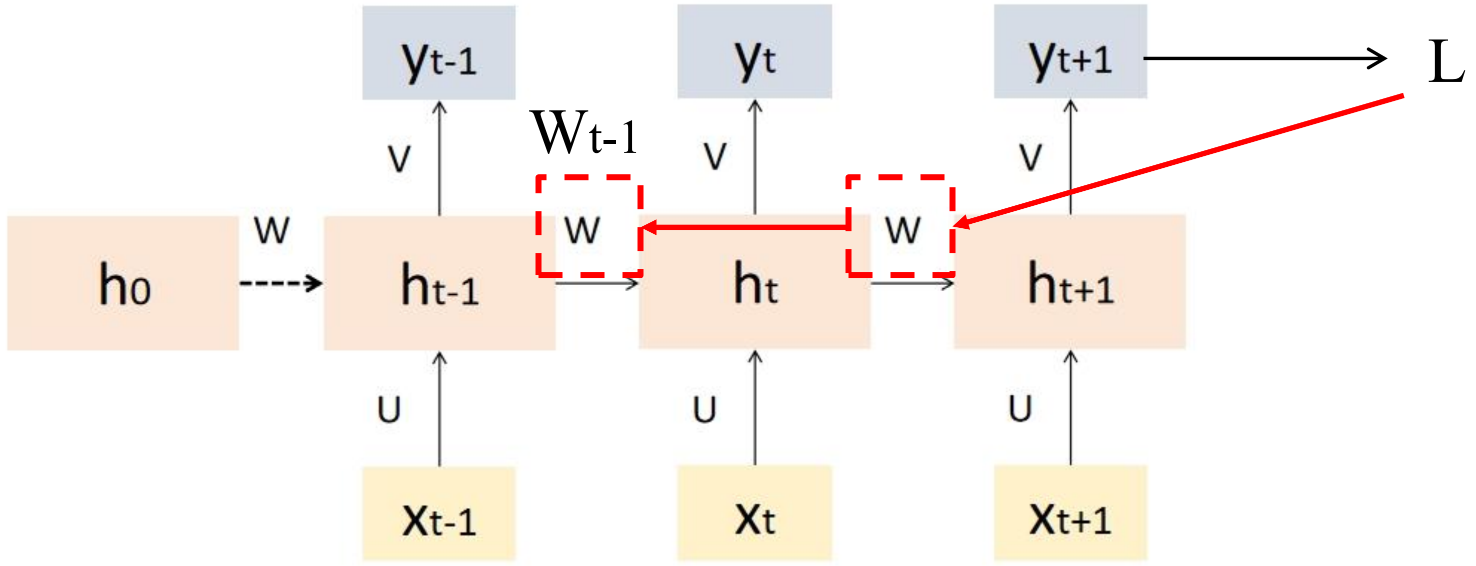
The further back in time an input is, the more factors it needs to be multiplied by.

Gradient Vanishing/Exploding Problem of RNN



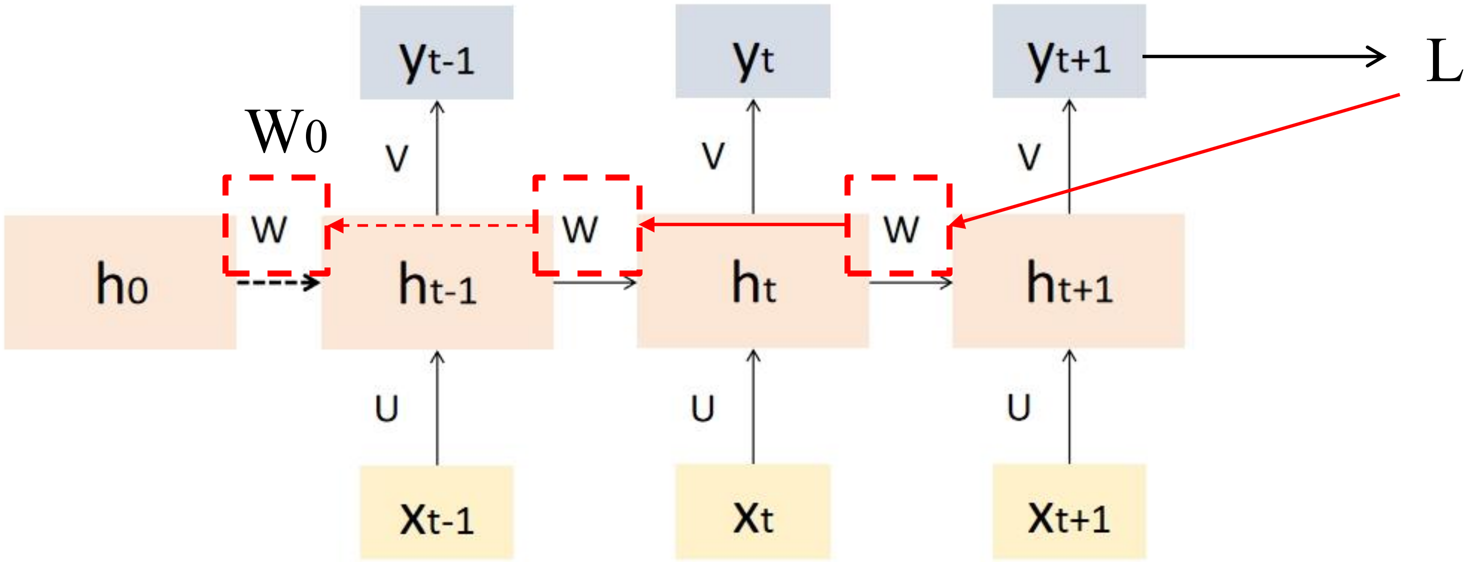
$$\nabla RNN(W_t) = \frac{\partial L}{\partial W_t}$$

Gradient Vanishing/Exploding Problem of RNN



$$\nabla RNN(W_{t-1}) = \frac{\partial L}{\partial W_{t-1}} = \frac{\partial L}{\partial W_t}\frac{\partial W_t}{\partial W_{t-1}}$$

Gradient Vanishing/Exploding Problem of RNN



$$\nabla RNN(W_0) = \frac{\partial L}{\partial W_0} = \underbrace{\frac{\partial L}{\partial W_t} \frac{\partial W_t}{\partial W_{t-1}} \frac{\partial W_{t-1}}{\partial W_{t-2}} \cdots \frac{\partial W_1}{\partial W_0}}$$

If these terms <1, the gradient decays exponentially (gradient vanishing)

If these terms >1, the gradient grows rapidly (gradient exploding)

Gradient Vanishing Problem of RNN

Gradient vanishing results in ：

- **Information Loss:**

  As the number of time steps increases, gradient vanishing prevents RNNs from retaining important information from earlier time steps.

- **Training Instability:**

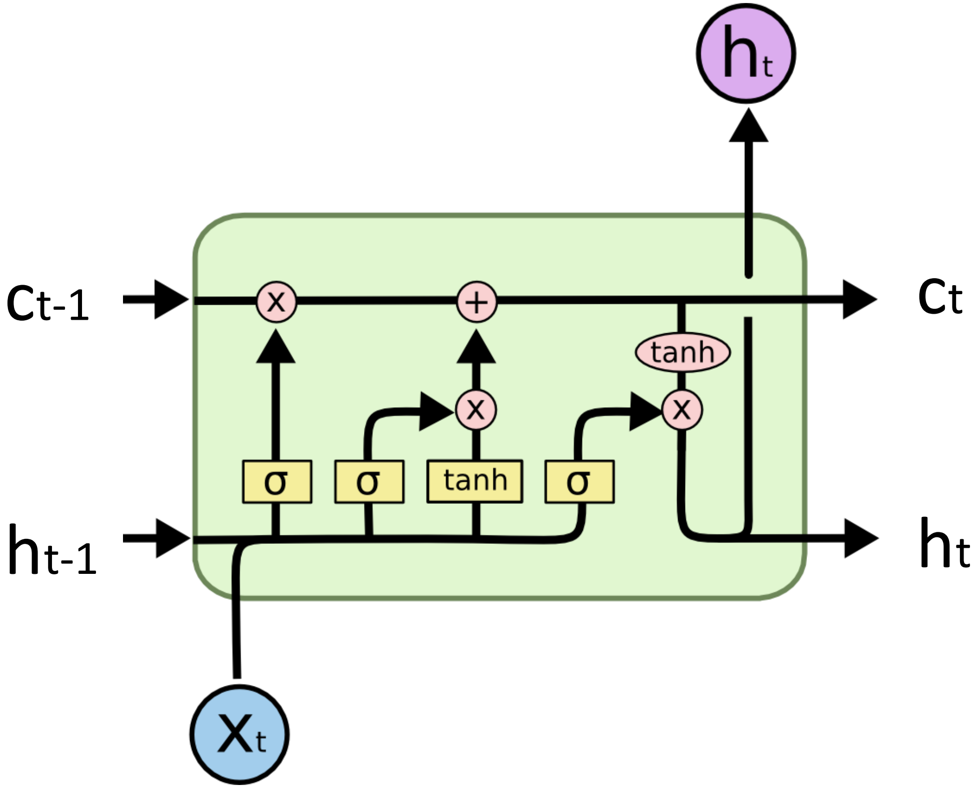
  With the disappearance of gradients in early time steps, the update of network parameters becomes slow or even stagnates.

- **Difficulty in Generating Long Sequences:**

  RNNs perform poorly in generating long sequences. Generated sequences may become incoherent or meaningless.

Long Short-Term Memory

Long Short-Term Memory (LSTM) is proposed to solve Gradient Vanishing problem of RNNs.



$$R_t = \sigma_r(W_r x_t + U_r h_{t-1} + b_r)$$ Forget gate

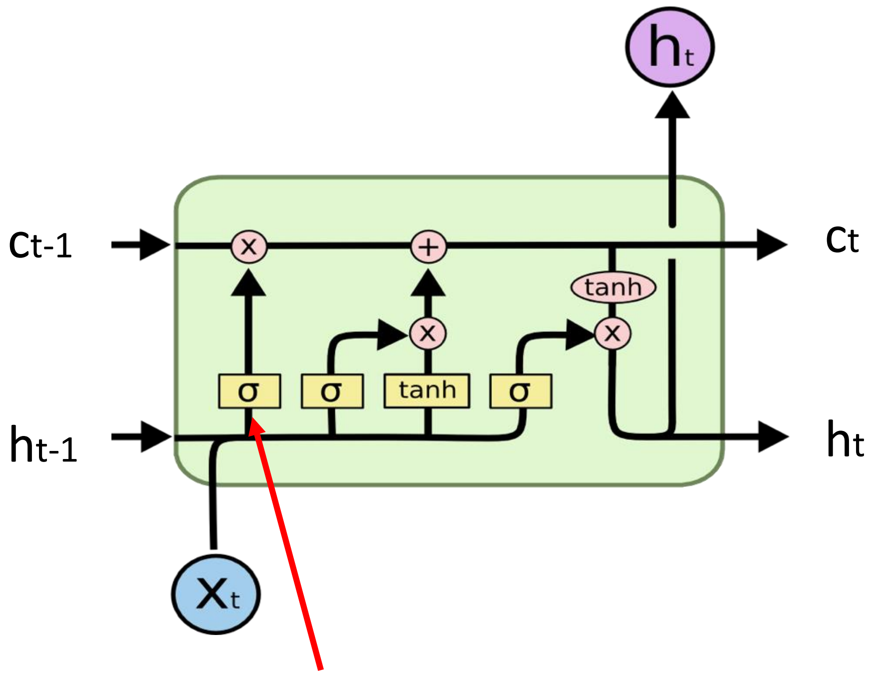
$$K_t = \sigma_r(W_k x_t + U_k h_{t-1} + b_k)$$ Input gate

$$V_t = \sigma_r(W_v x_t + U_v h_{t-1} + b_v)$$ Output gate

$$c_t = R_t \cdot c_{t-1} + K_t \cdot \sigma_c(W_c x_t + U_c h_{t-1} + b_c)$$

$$h_t = V_t \sigma_h(c_t)$$

Long Short-Term Memory

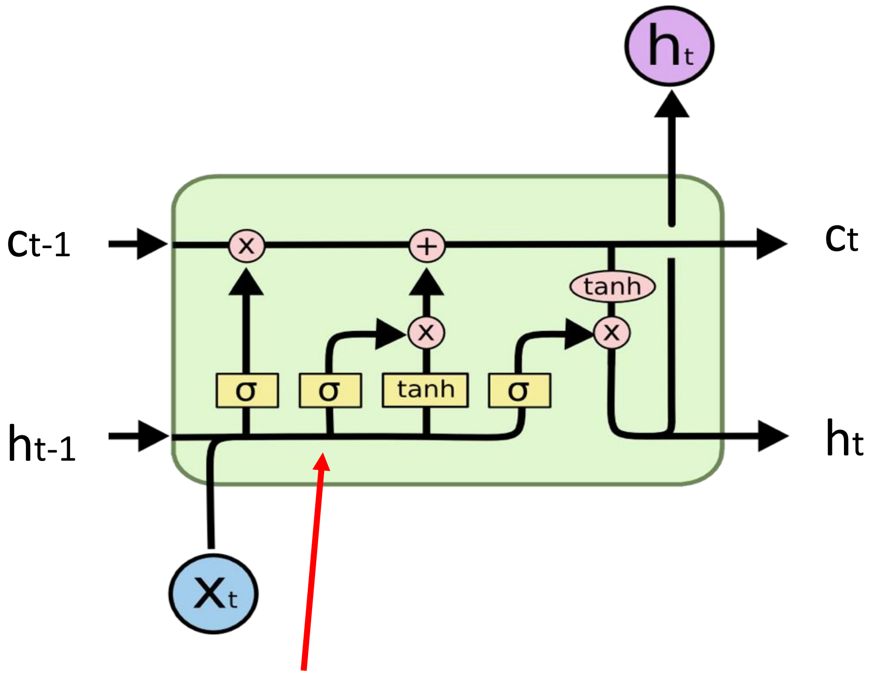


Forget gate

$$R_t = \sigma_r(W_r x_t + U_r h_{t-1} + b_r)$$

- **Forget Gate:** It uses a sigmoid function to determines which information from past memory should be forgotten or discarded.

Long Short-Term Memory

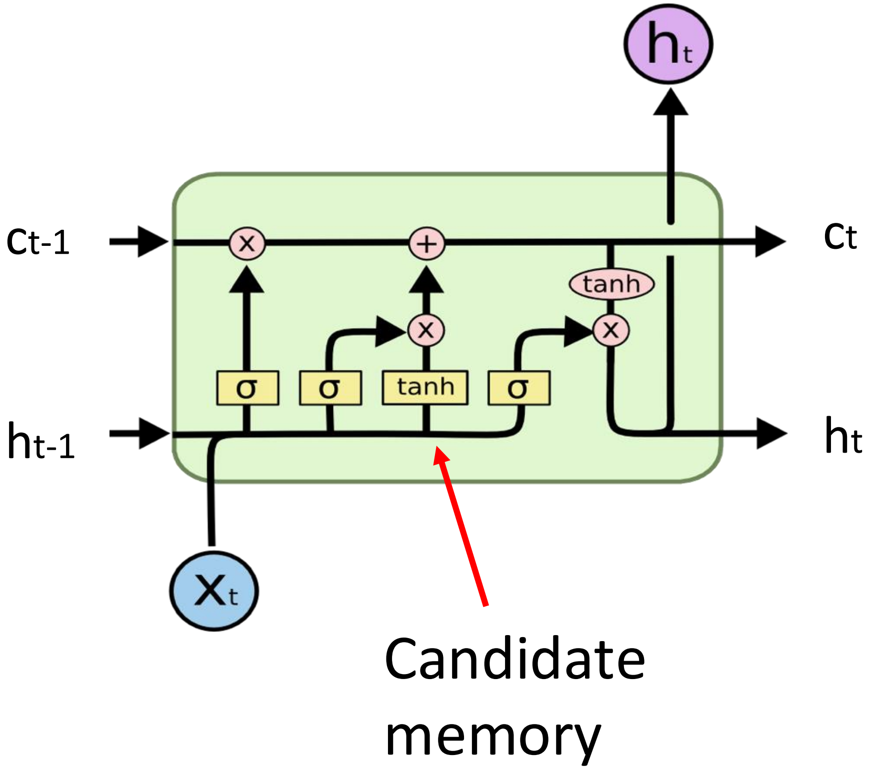


Input gate

$$K_t = \sigma_r(W_k x_t + U_k h_{t-1} + b_k)$$

- **Input Gate:** It uses a sigmoid function to determine which information should be added to the cell state.

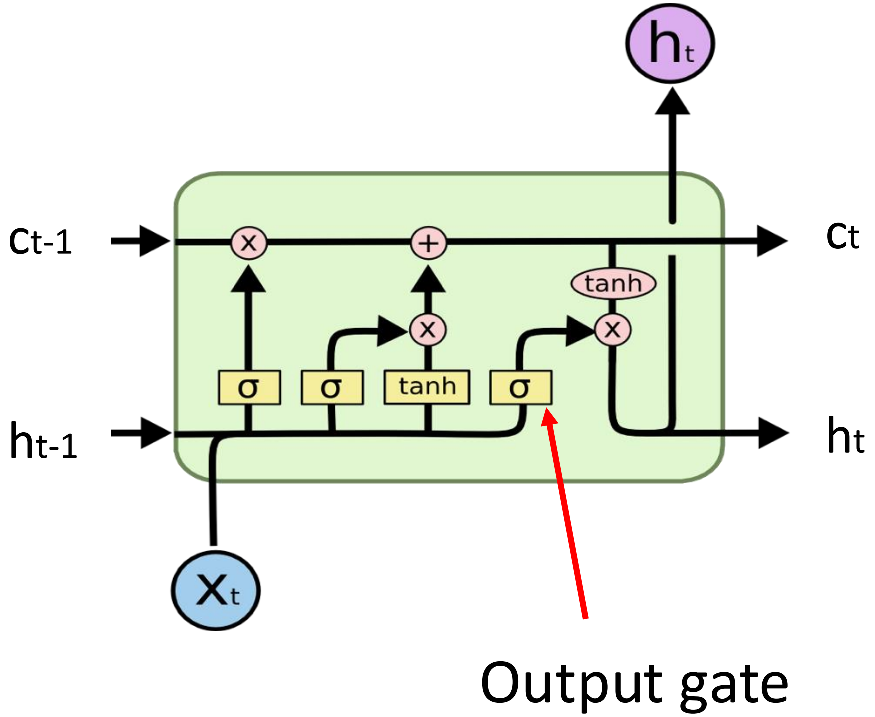
Long Short-Term Memory



$$V_t = \sigma_r(W_v x_t + U_v h_{t-1} + b_v)$$

- **Candidate Memory:** The candidate memory represents potential new information that could be added to the cell state. It is generated by a tanh which is relatively closer to binary than sigmoid.

Long Short-Term Memory



$$c_t = R_t \cdot c_{t-1} + K_t \cdot \sigma_c(W_c x_t + U_c h_{t-1} + b_c)$$

$$h_t = V_t \sigma_h(c_t)$$

- **Output Gate:** The output gate controls the flow of information from the cell state to the hidden state.

How does LSTM work?

Summary in plain words:
•**Forget gate** → drop “chasing” details.
•**Input gate** → add “climbing” action.
•**Candidate memory** → encode “climb + object.”
•**Output gate** → release “tree” at the right time.

“The cat chased the mouse, and then it climbed a tree.”

LSTM gate interpretations (language perspective)

Forget Gate

- When the model reaches “climbed a tree,” it **reduces the importance of older context like “chased the mouse”** because the focus shifts to a new action.
- **Meaning**: drop past context that is less relevant for the current prediction.

Input Gate

- At “climbed,” the model needs to **store this new action (climb) into the memory** since it defines what happens next.
- **Meaning**: decide which new information is worth adding to memory.

Candidate Memory

- Here, the candidate representation encodes the semantics of “climb + tree.”
- **Meaning**: generate potential new content that could be added to the cell state.

Output Gate

- When producing the word “tree,” the model **selects from memory the relevant semantic content (the location being climbed)** to expose as output.
- **Meaning**: choose which part of the memory should influence the current word generation.

Long Short-Term Memory

LSTM can partially avoid the vanishing gradient problem due to ：

- gating mechanisms & memory cells.
    - These components enable LSTM to **selectively retain or discard information** over time。
    - It maintains stable gradient flow during training and capture long-term dependencies more effectively compared to traditional RNNs.

Problems of time-series

Traditional sequential models, such as simple RNNs, suffer from the following issues:

- **Vanishing/Exploding Gradients:** although LSTM alleviate this problem, it is still existed.
- **Difficulty in Parallelization:** Because sequential models rely on the previous time step's hidden state, they are challenging to parallelize effectively, limiting their training efficiency on large-scale datasets and the size-growth of language models.

Attention Mechanisms

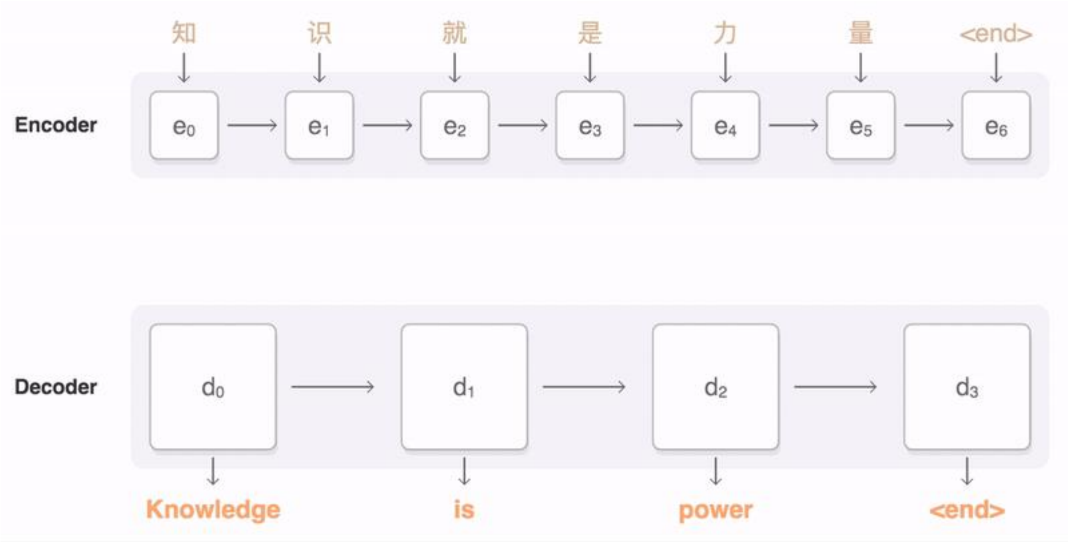
The attention mechanism solve the gradient problems and provided a parallelizable solution of LMs.

Core Idea: To enable a model to **focus on the most relevant parts** of the input sequence when making predictions or generating outputs.

- **Attention**

  Attention with RNNs

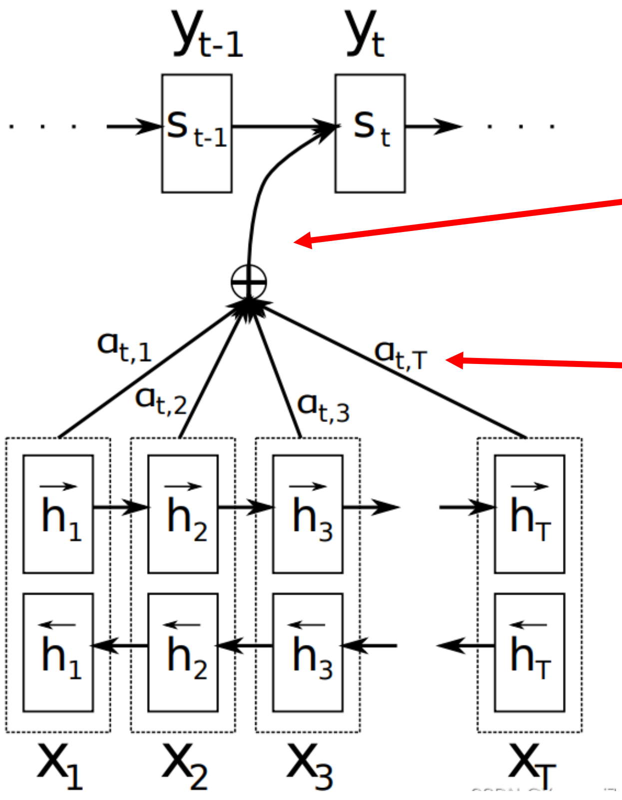
  Attention without RNNs



From Google Seq2seq

Attention

At the beginning the attention is associated with RNNs.



From: Attention 2015

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

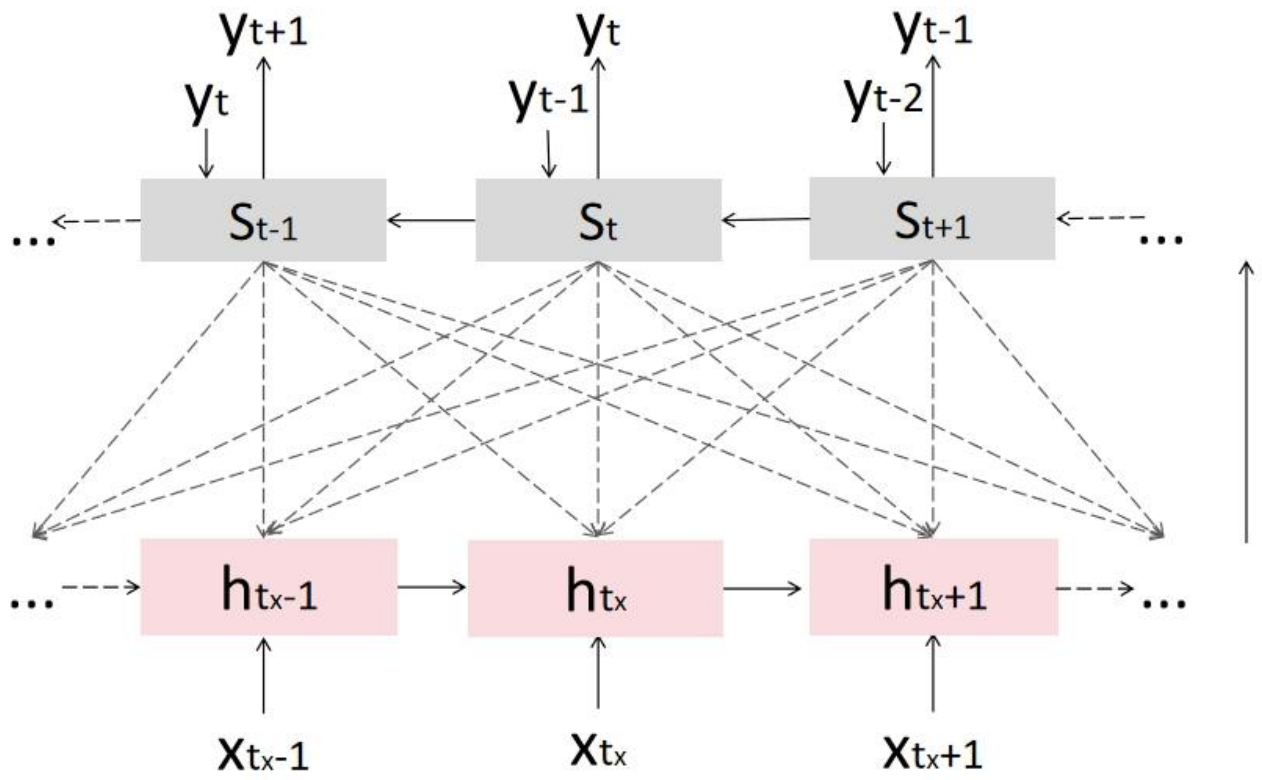
$$\alpha_{ij} = \frac{\exp(e_{ij})}{\sum_{k=1}^{T_x} \exp(e_{ik})}$$

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

a is an alignment model which scores how well the inputs around position j and the output at position i match

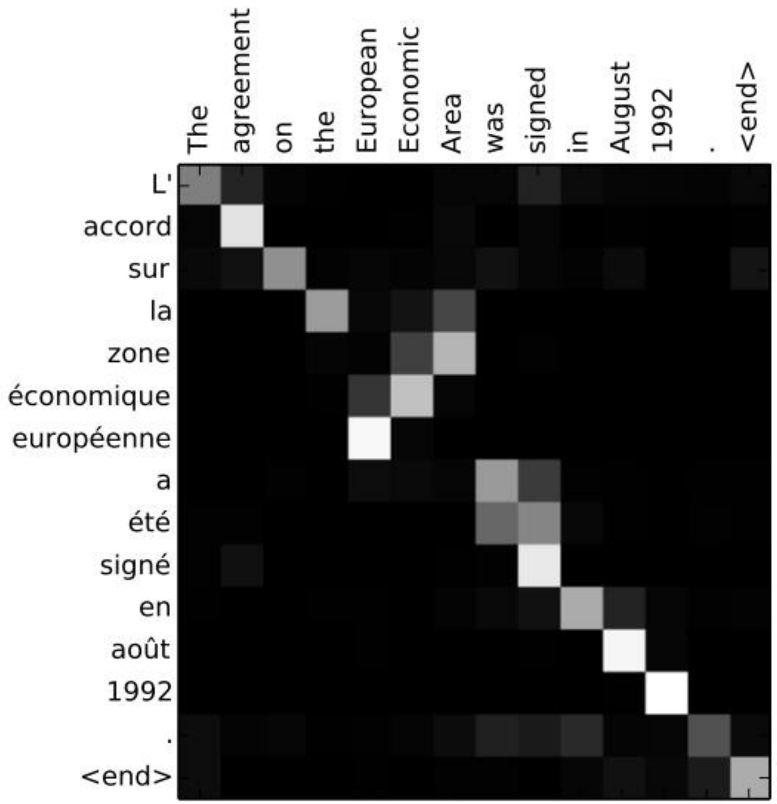
Attention

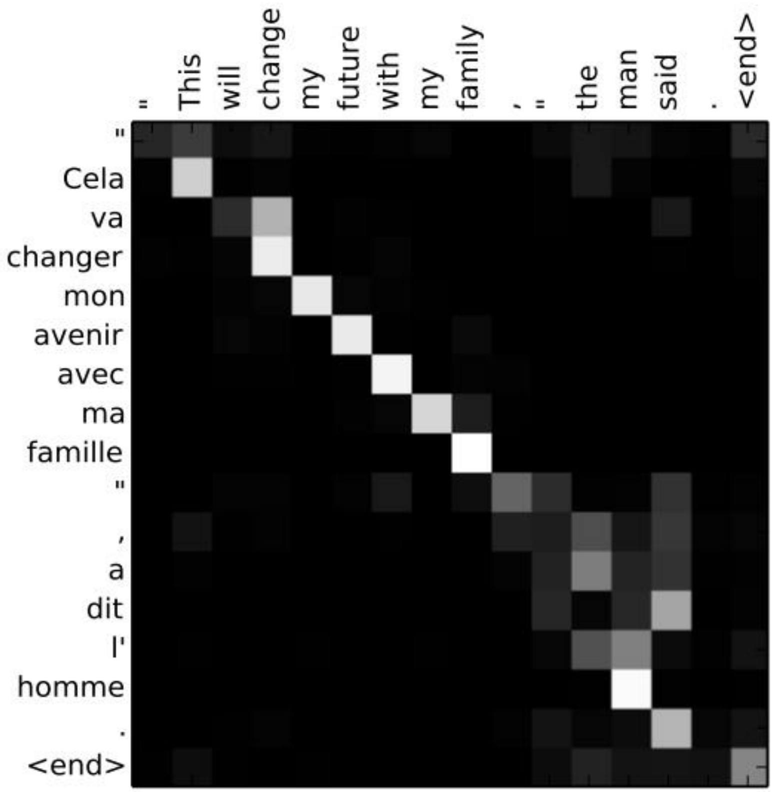
When computing the new hidden state s_t, attention mechanism compute attention scores with all the input tokens (from a bidirectional RNN).



Attention

An example of machine translation.





From: Attention 2015

Attention without RNNs

It has been proposed to eliminate the RNN component due to:

- The primary function of the RNN is to extract and process sequential features. However, this functionality can be achieved using simpler methods, leading to **reduced computational complexity**.
- RNNs are **not parallelizable**, meaning they cannot efficiently process multiple input sequences simultaneously, which limits their scalability and efficiency in large-scale applications.

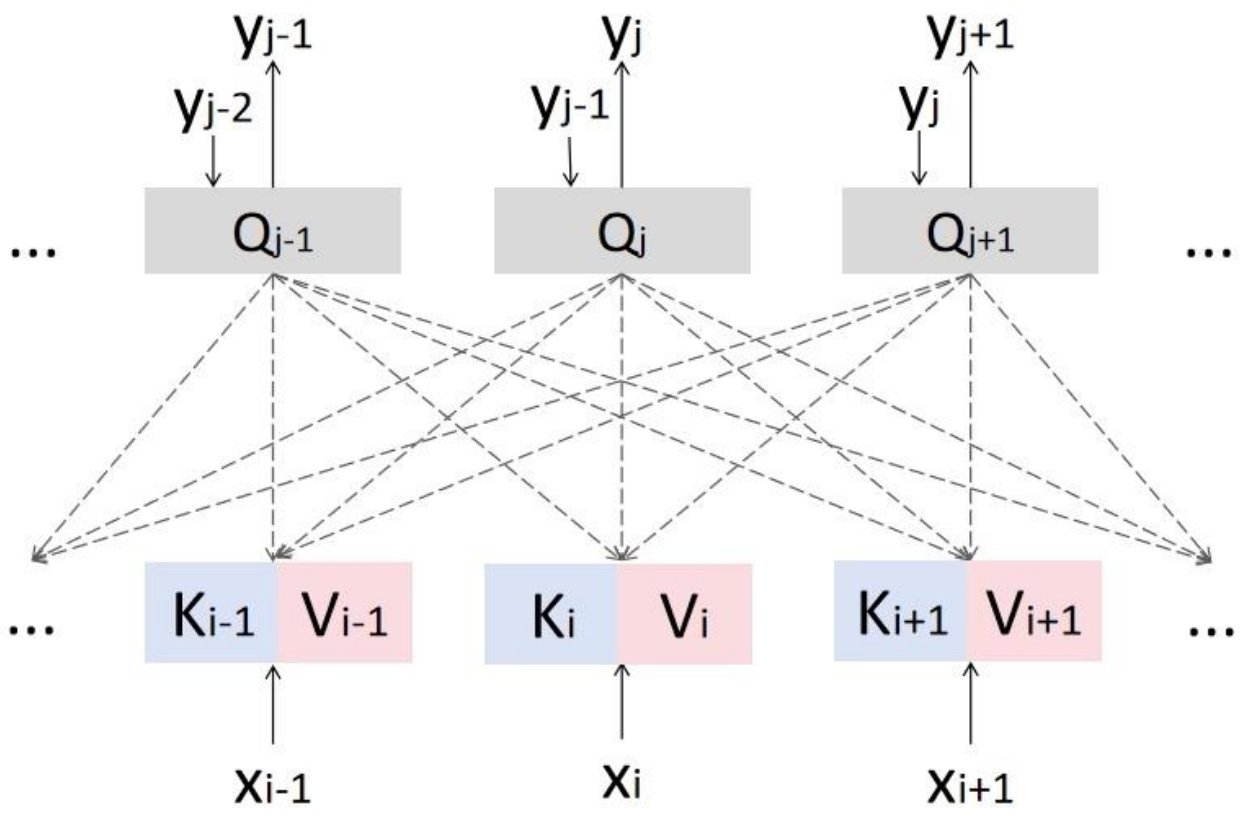
Attention without RNNs

$x, y \in \mathbb{R}^{d_{model} \times N}$

$W_Q, W_K \in \mathbb{R}^{d_k \times d_{model}}$

$W_V \in \mathbb{R}^{d_v \times d_{model}}$

N *is text length*, d_{model} *is the size of embedding*



Learnable weight matrix

$$Q = \boxed{W_Q} \boxed{y}$$ output

$$K = W_K \cdot x$$ input

$$V = W_V \cdot x$$

$Q^T K \in \mathbb{R}^{N \times N}$

Attention score:

$$\alpha_i = Softmax\left(\frac{Q^\top K}{\sqrt{d}}\right)$$

$$y_{output} = \sum_{i=1}^{N} \alpha_i v_i$$

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

eq in the original paper

Why $\sqrt{d}$

The model's parameters should undergo normalization, ensuring their average is 0 and variance is 1.

Assume that q_i and k_i are random variable with average 0 and variance 1:

$$
\begin{aligned}
E(q_i k_i) &= E(q_i)E(k_i) = 0 \\
Var(q_i k_i) &= E(q_i^2 k_i^2) - E(q_i k_i)^2 \\
&= E(q_i^2 - 0^2)E(k_i^2 - 0^2) \\
&= E(q_i^2 - E(q_i)^2)E(k_i^2 - E(k_i)^2) \\
&= Var(q_i)Var(k_i) = 1
\end{aligned}
$$

Why $\sqrt{d}$

However, after we multiply Q and K, the variance becomes d:

$$Var(Q^\top K) = Var(\sum_{i=0}^{d} q_i k_i) = d \cdot 1 = d$$

So it should be divided by $\sqrt{d}$:

$$Var(\frac{Q^\top K}{\sqrt{d}}) = \frac{d}{(\sqrt{d})^2} = 1$$

Summary

Sequential Models:

RNN: Recurrent Neural Network, the fundamental NN in NLP tasks.

LSTM: A modification of RNNs designed to alleviate gradient issues.

Attentions:

Attention with RNN: Avoid gradient vanishing in RNNs.

Attention without RNN: Parallelizable and simpler.

Reference

Stanford NLP:

- https://web.stanford.edu/~jurafsky/slp3/

Attention 2015:

- Bahdanau, D., Cho, K., & Bengio, Y. (2014). Neural machine translation by jointly learning to align and translate. arXiv preprint arXiv:1409.0473.