

LSTM  $(h_t, c_t)$   
 ↙ ↘  
 short long

① Outcome depends on short-term

$$o_t = \sigma \left( W_o \begin{pmatrix} h_{t-1} \\ x_t \end{pmatrix} + b_o \right) \quad \text{output gate}$$

$R^{d_c \times (d_h + d_x)}$   
 the same,

② short-term state depends on long term state

$$h_t = o_t * \tanh(c_t)$$

$\uparrow$   $\uparrow$   
 $R^{d_c}$   $IR^{d_c}$

$h_t \rightarrow$  produce a distribution on  $V$ .

(3) long-term states depend on short-term state & previous periods

$$C_t = f_t * C_{t-1} + \underbrace{i_t}_{\text{forget gate}} * \underbrace{\tilde{C}_t}_{\text{input gate}}$$

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$$(4) f_t = \sigma \left( W_f \cdot \begin{pmatrix} h_{t-1} \\ x_t \end{pmatrix} + b_f \right)$$

$$(5) \tilde{u}_t = \sigma \left( W_i \cdot \begin{pmatrix} h_{t-1} \\ x_t \end{pmatrix} + b_i \right)$$

$$\tilde{C}_t = \tanh \left( W_c \cdot \begin{pmatrix} h_{t-1} \\ x_t \end{pmatrix} + b_c \right)$$

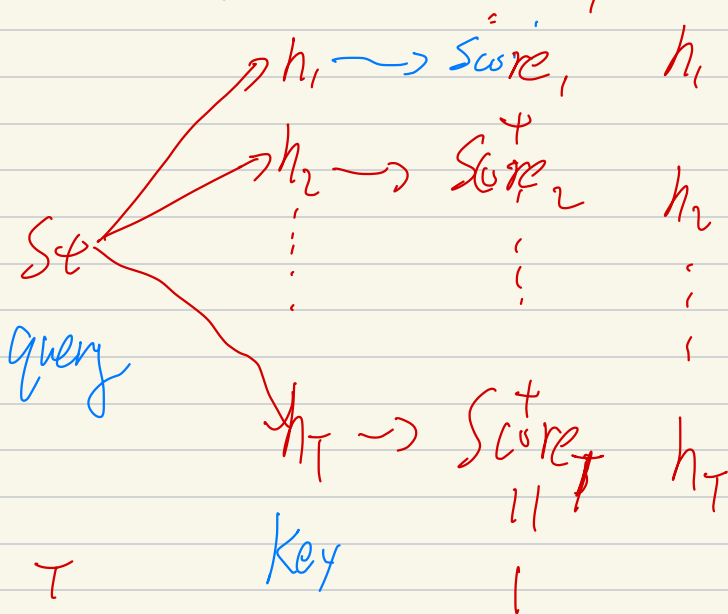
# Attention Mechanism

Decoder

Encoder

$h_1 \rightarrow h_2 \rightarrow h_3 \rightarrow \dots \rightarrow h_T$

Set



$$a_t = \sum_{j=1}^T \text{Score}_j \cdot h_j$$

$\uparrow$   
 $\mathbb{R}^d$

why is Attention  
greedy?

$$\text{Score} = \text{softmax}(e)$$

$\uparrow$   
 $\mathbb{R}^T$

$$e_i = h_i^T \cdot \text{Set GR}$$

$$\begin{pmatrix} a_t \\ \text{Set} \end{pmatrix}$$

$$x_1, x_2, \dots, x_n \in \mathbb{R}^d$$

$$W_q, W_k, W_v \in \mathbb{R}^{d \times d} \quad \in \mathbb{R}^d$$

$$q_i = w_q \cdot x_i, \quad k_i = w_k \cdot x_i, \quad v_i = w_v \cdot x_i$$

query                      key                      value  
w'

$$w_{ij}^1 = \frac{q_i^1 \cdot k_j}{\sqrt{d}} \quad i, j \in [n]$$

## Softmax

$$W_{ij} = \frac{\exp(w'_{ij})}{\sum_{j=1}^n \exp(w'_{ij})}$$

$$y_i = \sum_{j=1}^n w_{ij} v_j \in \mathbb{R}^d \quad \text{linear in } v_j$$



How can we do better?

① Better parallelization?

Multi-head attention.

② non-linear  $v$ ?

Add an MLP layer.

③ How to keep the sequence information?

Position encoding/embedding.

input =  $\vec{X} + \text{Position Encoding}$

④ No future information? / Auto-regressive

masked attention

(5) Can we pray to Optimizations  
God better?

(i) Skip-Connection.

$$f(x) + x$$

(2) Layer Normalization