

SEQ2SEQ Modeling

L9-1

SEQ2Label : $P(y^{(T)} | x^{(1)}, \dots, x^{(T+1)})$

SEQ2SEQ : $P(y^{(1)}, \dots, y^{(T_y)} | x^{(1)}, \dots, x^{(T_x)})$

↳ Applications

① NMT

INPUT	FRENCH SENT
OUTPUT	ENGLISH SENT

② TEXT GEN

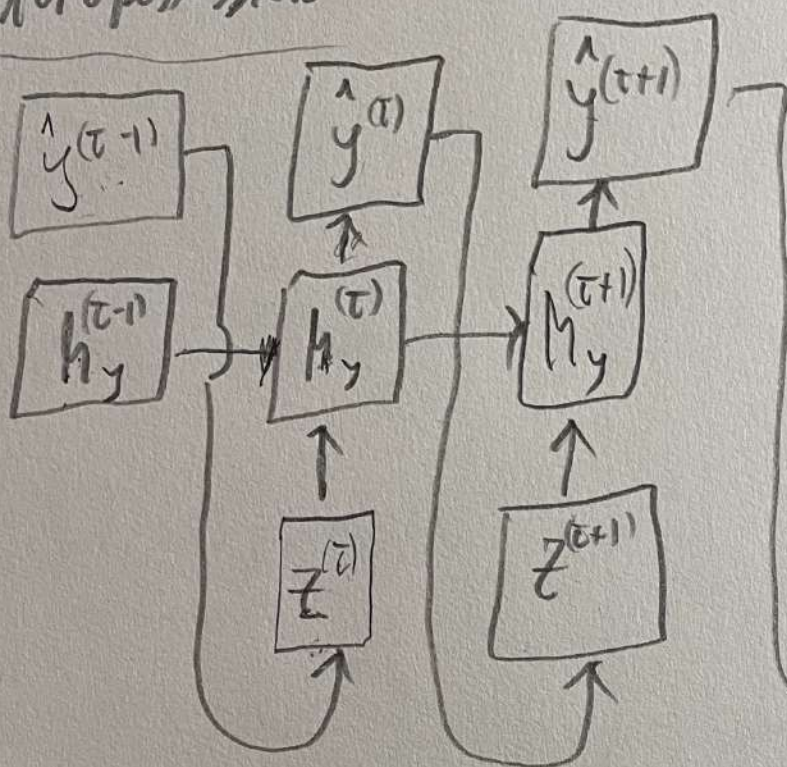
INPUT	PREFIX
OUTPUT	SUFFIX

↳ Factor the joint dist $P(y^{(1)} \dots y^{(T_y)} | x^{(1)} \dots x^{(T_x)})$
into $\prod_{t=1}^{T_y} P(y^{(t)} | x^{(1)}, \dots, x^{(T_x)}, y^{(1)}, \dots, y^{(t-1)})$

↳

Auto regression

L9-2



$$\hat{y}^{(0)} = \langle \text{START} \rangle$$

$$\hat{y}^{(T)} = \langle \text{STOP} \rangle$$

SEQ 2 SEQ ALGORITHM

$$① \quad h_y^{(0)} = h_x^{(T_x)} = f_h(x^{(1)}, \dots, x^{(T_x)})$$

$$② \quad \text{Set } T=1, \quad \hat{y}^{(0)} = \langle \text{START} \rangle$$

③ While TRUE:

$$h^{(t)} = f_h(h_y^{(t-1)}, y^{(t-1)}) \rightarrow \text{Computing hidden state}$$

$$\hat{y}^{(t)} = f_y(h^{(t)})$$

\rightarrow Predict T^m to next

$$\text{If } \hat{y}^{(t)} = \langle \text{STOP} \rangle ;$$

Break

$$T = T+1$$

SEQ 2 LABEL

$$h^{(t)} = f_h(h^{(t-1)}, x^{(t)})$$

Comes from the DATA!

SEQ 2 SEQ

$$h^{(t)} = f_h(h^{(t-1)}, y^{(t-1)})$$

Comes from the Model!

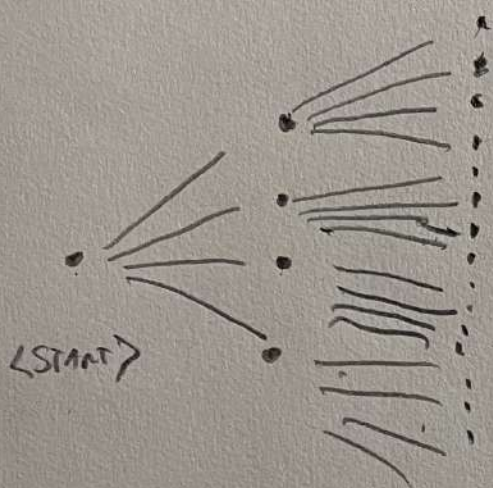
THE INFERENCE GAP

L9-3

INFERENCE TASK: $\hat{y}^{(1)} \dots \hat{y}^{(T_y)} = \underset{y^{(1)} \dots y^{(T_y)}}{\text{ARGMAX}} P(y^{(1)} \dots y^{(T_y)} | x^{(1)} \dots x^{(T_x)})$

Maximizing, $\hat{\theta} = \underset{\theta}{\text{ARGMAX}} P(y^{(1)} | f_{\theta}(h^{(1)}, y^{(1)}))$

SEARCH PROBLEM



$$N = 10^5$$

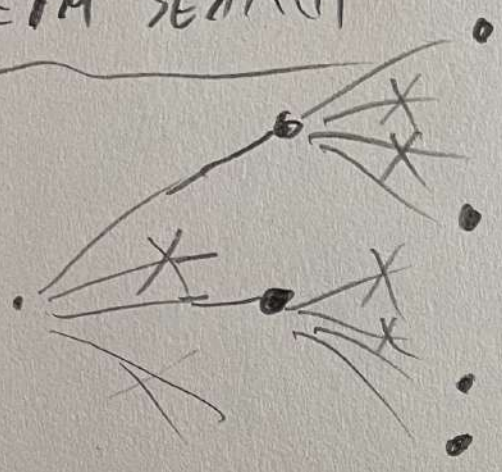
$$T_y = 5$$

$$P(y^{(1)}, \dots, y^{(T_y)}) = \prod_{t=1}^{T_y} P(y^{(t)} | y^{(1)} \dots y^{(t-1)}) \Rightarrow \text{MLE}$$

THE SEQUENCES: N^{T_y}

EX: $(10^5)^5 = 10^{25}$ evaluations

BEAM SEARCH



Reduce Branching factor from $N \rightarrow k$,
 where $k \ll N$.

$$N = 10^5, T_3 = 5 \Rightarrow 10^5$$

$$N \leq 10, T_3 = 5 \rightarrow 10^5$$

INFERENCE GAP

During training: $L_{CE}(y^{(t)}, P(y^{(t)} | \underbrace{y^{(1)} \dots y^{(t-1)}}_{\text{LABELS}}))$
 $\uparrow \quad \quad \uparrow$
 LABEL PRED
 "TEACHER FORCING"

During test: $P(y^{(t)} | \hat{y}^{(1)} \dots \hat{y}^{(t-1)})$

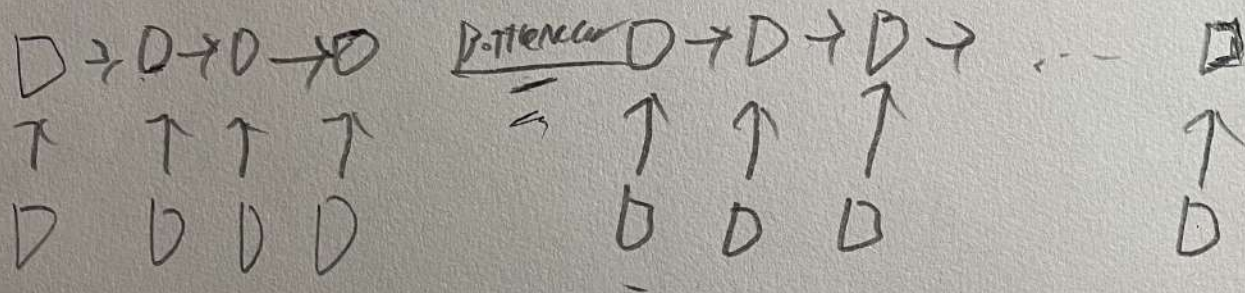
Stochastic Sampling

(L95)

$$L_{CE}(y^{(t)}, p(y^{(t)} | \tilde{y}^{(1)}, \dots, \tilde{y}^{(t-1)}))$$

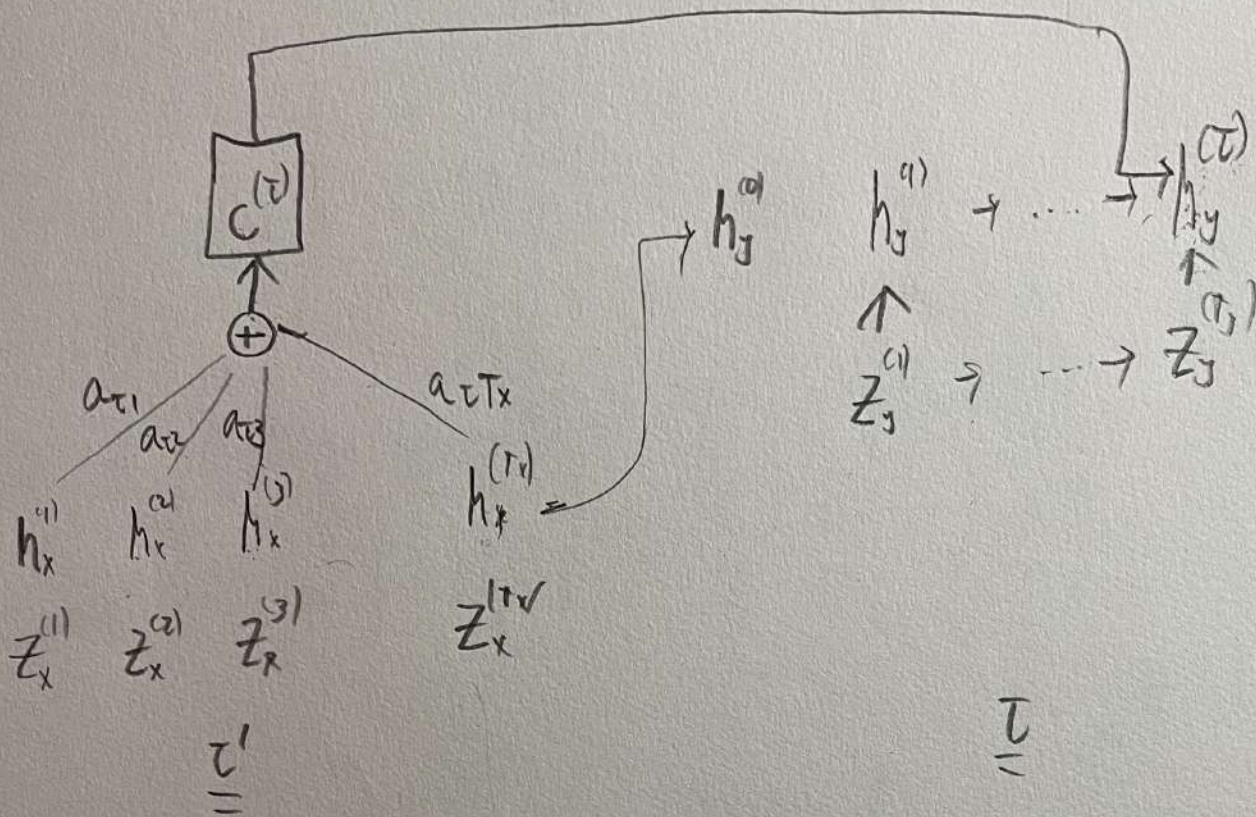
$$\tilde{y}^{(t)} = \begin{cases} \hat{y}^{(t)} & \text{with probability } p \\ y^{(t)} & \text{with probability } 1-p \end{cases}$$

Information Bottleneck



ATTENTION BASED SEQ2SEQ MODELS

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$$\sum_{\tau'=1}^{T_x} a_{\tau, \tau'} = 1$$

$$A \in [0, 1]^{T_y \times T_x}$$

$$c^{(\tau)} = \sum_{\tau'=1}^{T_x} a_{\tau, \tau'} h_x^{(\tau')}$$

$a_{\tau, \tau'}$ is the degree of attention that $h_y^{(\tau)}$ has on $h_x^{(\tau')}$.

$$a_{\tau, \tau'} = \frac{e^{\alpha_{\tau, \tau'}}}{\sum_{\tau''=1}^{T_x} e^{\alpha_{\tau, \tau''}}}$$

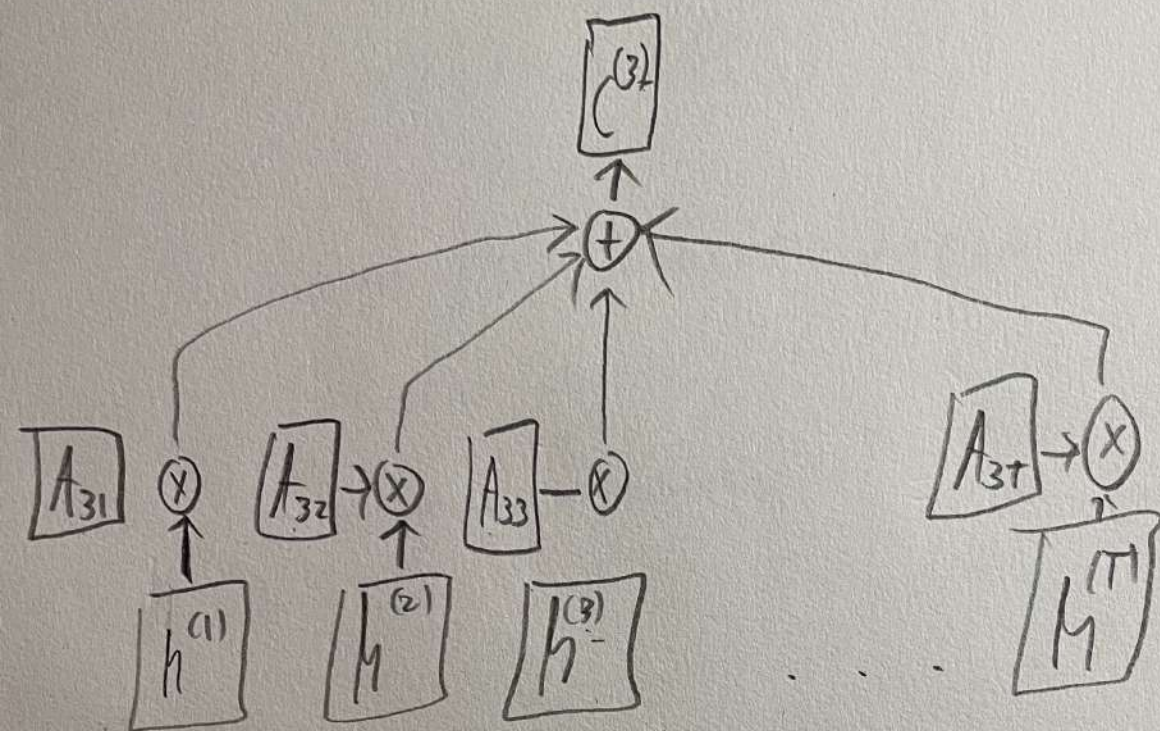
$$\alpha_{\tau, \tau'} = h_y^{(\tau)} \cdot h_x^{(\tau')}$$

$$\alpha_{\tau, \tau'} = f_{h_y}(h_y^{(\tau)}) \cdot f_{h_x}(h_x^{(\tau')})$$

$f = \text{NN}$

Self Attention

L9-7



$$c^{(i)} = \sum_{i'} A_{zi, z'} h^{(z')} \quad \text{where} \quad A_{zi, z'} = \frac{e^{h^{(z)} \cdot h^{(z')}}}{\sum_{z''} e^{h^{(z)} \cdot h^{(z'')}}}$$

$$\text{Each Row } \sum A_{\text{row}} = 1$$

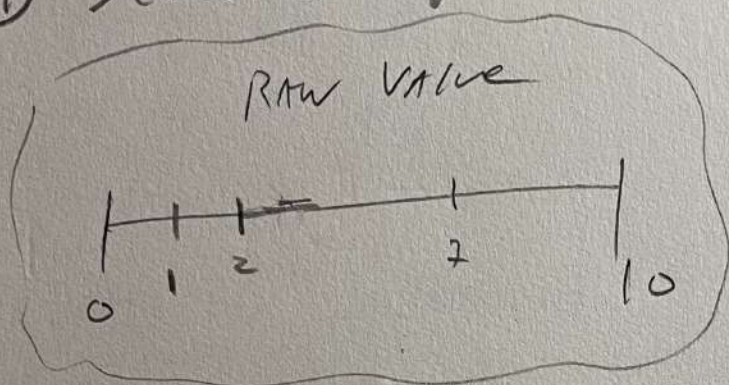
ATTENTION IS ALL YOU NEED

2017

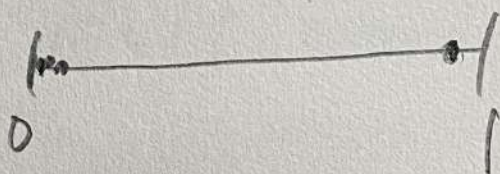
9-8

TRICKS INTRODUCED:

① Scaled Dot Product ATTENTION



SOFTMAX



$\mathbf{h} \in \mathbb{R}^D \Rightarrow \|\mathbf{h}\| \text{ vs } D$

$$D=2 \quad [1, 1] = \sqrt{2}$$

$$D=3 \quad [1, 1, 1] = \sqrt{3}$$

$$D=4 \quad [1, 1, 1, 1] = \sqrt{4}$$

\sqrt{D}

↳ Scaled Dot Product \rightarrow

$$\boxed{\frac{1}{\sqrt{D}}}$$

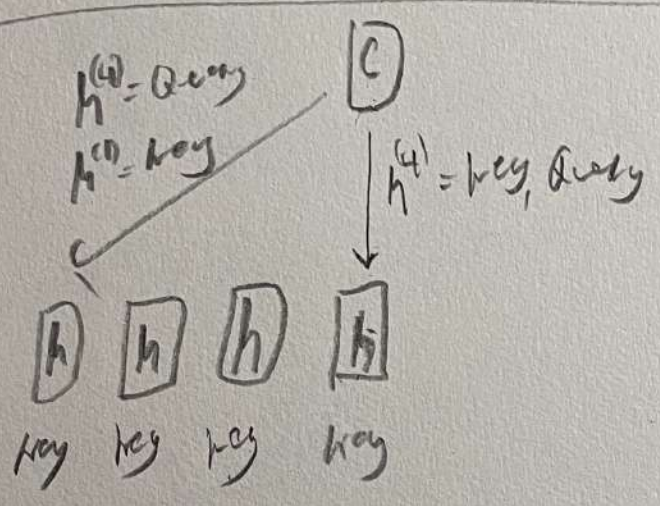
② ATTENTION IS LIKE A "SHIFT" LOOKUP TABLE

for $\mathbf{C}^{(T)} \Rightarrow$

$$\boxed{\mathbf{C}^{(T)}}$$

$$\boxed{\mathbf{h}^{(T)}}$$

③ Attention as a "Soft" Look up



hard
 $\text{Value} = f[\text{key}]$

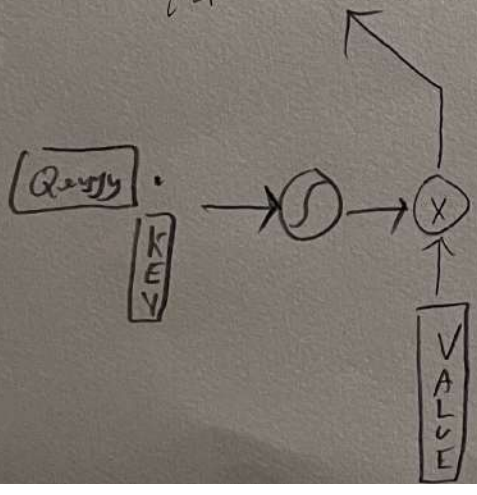
Soft

$\text{Value} = f[\text{Query, key}]$

for Every $C^{(t)}$ there is:

- ① A Query $h^{(t)}$
- ② T SEPARATE keys: $h^{(1)} \dots h^{(T)}$
- ③ T SEPARATE VALUES: $h^{(1)} \dots h^{(T)}$

$$\begin{aligned}
 C^{(t)} &= \text{VICT}[\text{Query}^{(t)}] \quad \leftarrow \text{"fuzzy" or "Soft" look up} \\
 &= \sum_{i=1}^T \text{Value}^{(i)} \cdot \sigma_{\text{softmax}}(\text{Query}^{(t)}, \text{key}^{(i)}) \\
 &= \sum_{i=1}^T h^{(i)} \cdot \sigma_{\text{softmax}}(h^{(t)}, h^{(i)})
 \end{aligned}$$



EACH INPUT H SERIES
 AS THE KEY, VALUE, QUERY
 DEPENDING ON WHICH POSITION
 WE ARE AT.

④ LEARNABLE SET OF KEYS, VALUES, QUERIES

$$\left. \begin{aligned} K_t &= K h^{(t)} + b_k \\ Q_t &= Q h^{(t)} + b_q \\ V_t &= V h^{(t)} + b_v \end{aligned} \right\} \Rightarrow \Theta = \{K, Q, V, b_k, b_q, b_v\}$$

⑤ MULTIHOP SA:

$$\begin{aligned} K &= \{K^{(1)} \dots K^{(n)}\} \\ Q &= \{Q^{(1)} \dots Q^{(n)}\} \\ V &= \{V^{(1)} \dots V^{(n)}\} \end{aligned}$$

n = NUMBER OF ATTENTION HEADS

$\hookrightarrow n$ CONTEXT VECTORS AT EACH POSITION IN THE SEQUENCE $\Rightarrow C^{(t)} = [C_1^{(t)}, \dots, C_n^{(t)}]$

$\hookrightarrow K, Q, V \in \mathbb{R}^{D \times n}$ SUCH THAT WE CAN CONCAT TO GET $C^{(t)} \in \mathbb{R}^D$