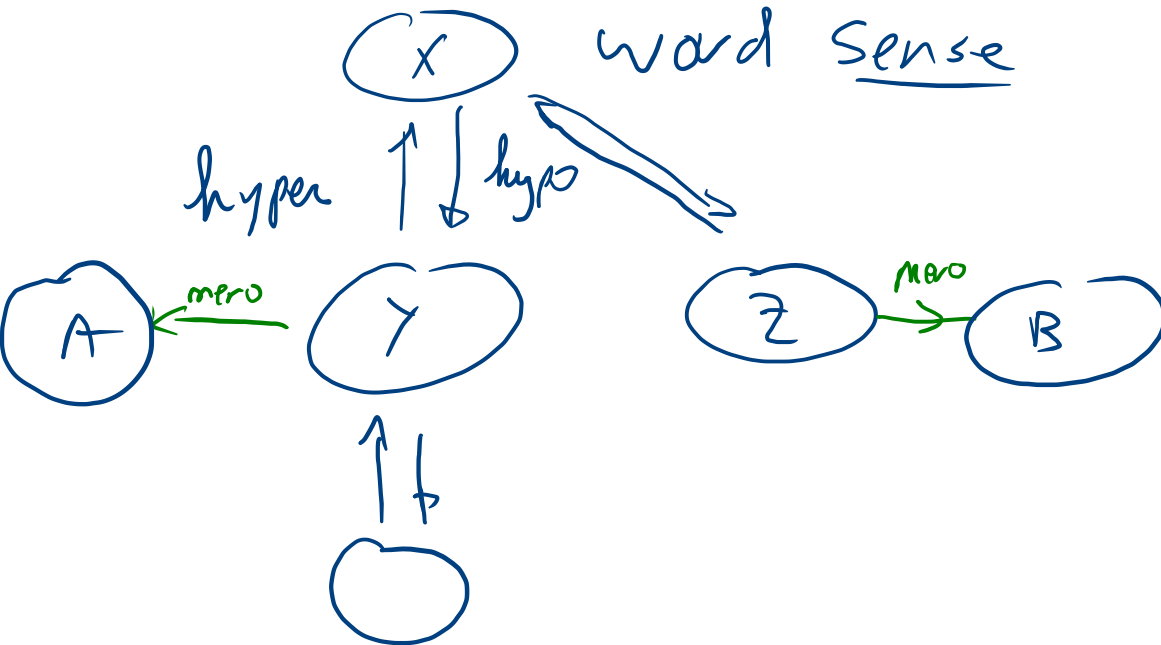


Semantics



RNN

$$h^d = \sum_i a_i h^e$$

$$a = \text{softmax}(\text{Attention}(h_i, h^d))$$

$$\sum_i a_i = 1$$

$14 \cdot 10 + 5 \cdot 10 + 2.5 \times 6 \rightarrow \alpha$
$14 \cdot 10 + 5 \cdot 10 + 2.6 \times 6 \rightarrow \beta$

30%	40%	60-70%
$\frac{e^\alpha}{5}$	$\frac{e^\beta}{5}$	

HMM

$$\operatorname{Argmax}_{t_1 \dots t_n} P(t_1 \dots t_n | w_1 \dots w_n)$$

$$P(t_1 \dots t_n) = P(t_1) P(t_2 | t_1) P(t_3 | t_2) \dots P(t_n | t_{n-1})$$

transformers

~

$$f_l = \text{softmax} \left(\frac{1}{\sqrt{d_k}} (Q W^Q) \cdot (K W^K) \right) \cdot (V W^V)$$

attention

self-attention: $Q = K = H$

CBow

$P(\text{word} | \text{context})$

$$\text{Softmax} \left(U \cdot \sum_{\text{Context}} \text{embed}(w) \right)$$

④ [5 pt] Considering the probability of a **word** sequence $w_1 \dots w_n$, what is the fundamental difference between a 2-gram language model and an order-1 HMM Part-of-Speech tagger?

Support your claim by providing the formula of $P(w_1, \dots, w_n)$ in both cases.

⑤ [12 pt] Consider the following sentence:

the quick fox jumps over the lazy dog

and an order-1 HMM for Part-of-Speech tagging with the following parameters (not exhaustive, but no missing information to solve the question):

the: Det
 quick: Adj: $2 \cdot 10^{-4}$, Adv: $9 \cdot 10^{-4}$, N: $4 \cdot 10^{-4}$
 fox: N: $2 \cdot 10^{-4}$, V: $8 \cdot 10^{-4}$
 jumps: N: 10^{-4} , V: $3 \cdot 10^{-4}$
 over: Prep
 lazy: Adj
 dog: N: $6 \cdot 10^{-4}$, V: $7 \cdot 10^{-4}$

	Adj	Adv	Det	N	V	Prep
Adj	0.15	0.1	0.3	0.2	0.05	0.25
Adv	0.05	0.2	0	0.1	0.15	0
Det	0.02	0.1	0	0.04	0.05	0.3
N	0.4	0.1	0.7	0.3	0.45	r
V	0.3	0.4	0	0.25	0.1	s
Prep	0.02	0.1	0	p	q	0

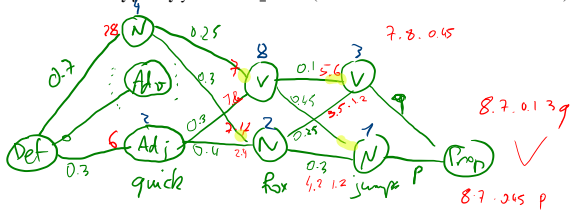
$\sum_x P(x|y) = 1$

(a) [8 pt] Provide the tightest possible condition(s) between p , q , r and s so that the tag of "jumps" in the most probable sequence of tags for the above sentence is V.

(b) [4 pt] If these conditions are fulfilled, what is the most probable sequence of tags for the above sentence?

Fully justify your answers. (There is also room for answer at the back.)

$\left. \begin{array}{l} \text{Adj} \rightarrow \text{N} \cdot \text{N dog} \\ \text{Adj} \rightarrow \text{V} \cdot \text{V dog} \end{array} \right\} \begin{array}{l} 0.4 \quad 6 \\ 0.3 \quad 7 \end{array}$



You decide to use the continuous bag of words algorithm to train your word embeddings. To test whether your training algorithm works correctly, you test it with a small vocabulary of five words and provide it the sequence of words "what day is the exam" with the following embeddings:

$$\begin{aligned} \text{what} &= [\ln 2, \ln 0.5] \\ \text{day} &= [\ln 0.5, \ln 2] \\ \text{is} &= [\ln 0.5, \ln 0.5] \\ \text{the} &= [\ln 1.5, \ln 0.5] \\ \text{exam} &= [\ln 2, \ln 2] \end{aligned}$$

1st
 $\ln 2 + \ln 0.5 + \ln 1.5 + \ln 2$
 $- \ln 3$

2nd
 $\ln 0.5 + \ln 2 + \ln 0.5 + \ln 2$
 $= 0$
 $= \ln 3 \cdot U_1$

(where \ln is the natural logarithm function of base e);

and output vocabulary projection U :

$$U = \begin{pmatrix} 0 & 1 & 2 & 1 & 0 \\ 1 & 2 & 3 & 2 & 1 \end{pmatrix} \begin{pmatrix} \ln 3 \\ 0 \end{pmatrix} = \ln 3 \cdot U_1$$

You can assume each column of U corresponds to the following vocabulary items: what, day, is, the, exam.

- ④ [6 pt] Using a window size of 2, what is the probability of the word "is" according to the continuous bag of words network?
Justify your answer.

- ⑤ [2 pt] Using a window size of 1, what is the probability of the word "the" according to the continuous bag of words network?
Justify your answer.



Now that your embeddings are pretrained, you train your transformer language model. For the following questions, assume a single-headed attention function and use the following input embeddings as key vectors:

$$\left. \begin{aligned} \text{what} &= [2, 0.5] \\ \text{day} &= [0.5, 2] \\ \text{is} &= [0.5, 0.5] \\ \text{the} &= [2, -2] \\ \text{exam} &= [1, 1] \end{aligned} \right\} \Rightarrow K$$

- ⑥ [6 pt] Using scaled dot product attention, what is the attention distribution over key vectors for the word “exam” as the query in the first attention layer? You can ignore position embeddings. Assume that W^K, W^V are identity matrices and

$$W^Q = \begin{pmatrix} \sqrt{2} \ln(4) & 0 \\ 0 & \sqrt{2} \ln(4) \end{pmatrix} = \sqrt{2} \ln(4) I_2$$

Justify your answer and provide all the steps of your computation.

$$\frac{1}{\sqrt{2}} \sqrt{2} \ln(4) h \cdot K$$

$$[1, 1]$$

Softmax
 $\hookrightarrow 4$

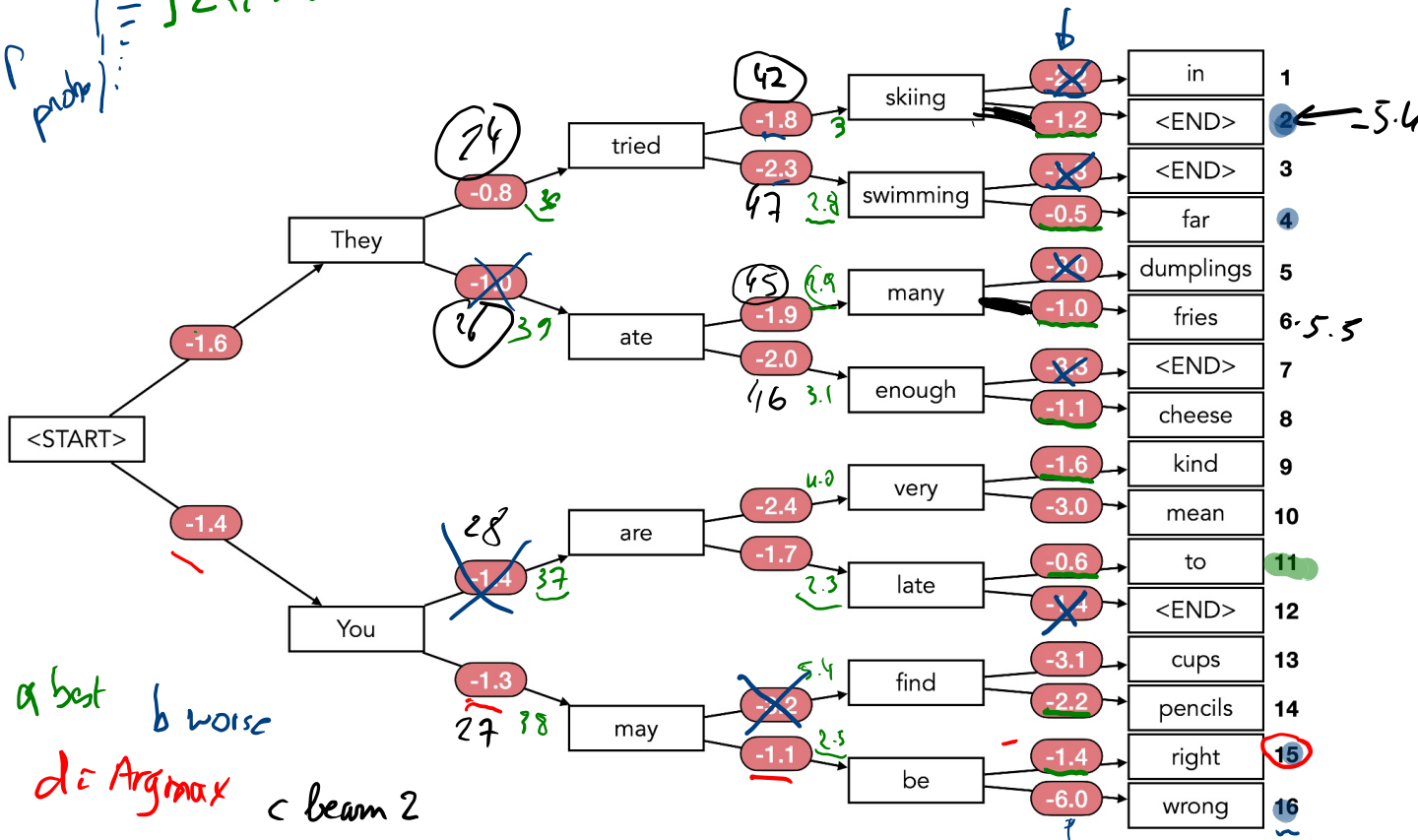
what	day	is	the	exam
2.5	2.5	1	0	2
32	32	4	1	16 $\rightarrow 5$
				5

- ⑦ [2 pt] What is the attention distribution if the position embedding in the first position is $[-1, 0.5]$ and the others are $[0, 0]$?

Justify your answer.



top-p
 $\sum p_i > \text{threshold}$



a best b worse

d = Argmax c beam 2

top p lmp - 1.3

top - p



⋮
⋮

Special

Order \Downarrow
↘

X don't take it
if $P_1 \geq \theta$

k best

