

الشبكات العصبية

محاضرة 6

## NLP and Word Embeddings

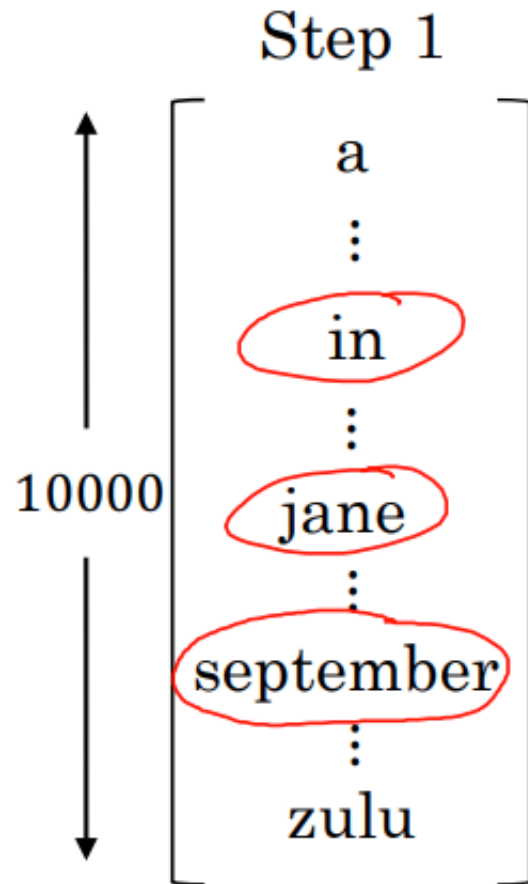
د. فادي متوج

# Sequence to sequence models

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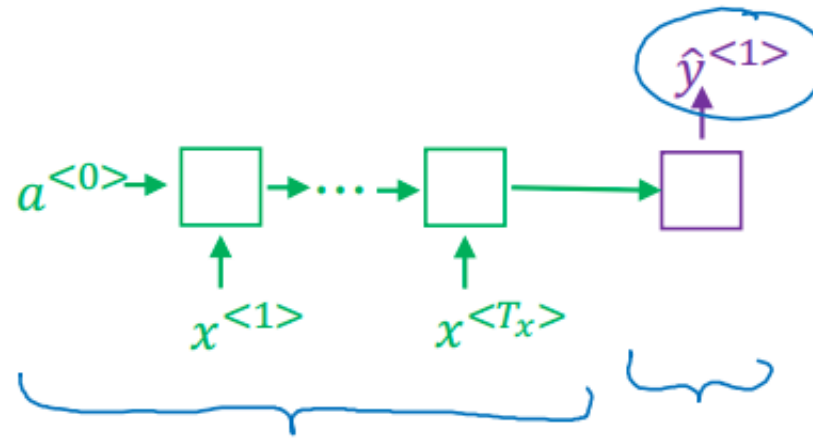
## Beam search

# Beam search algorithm

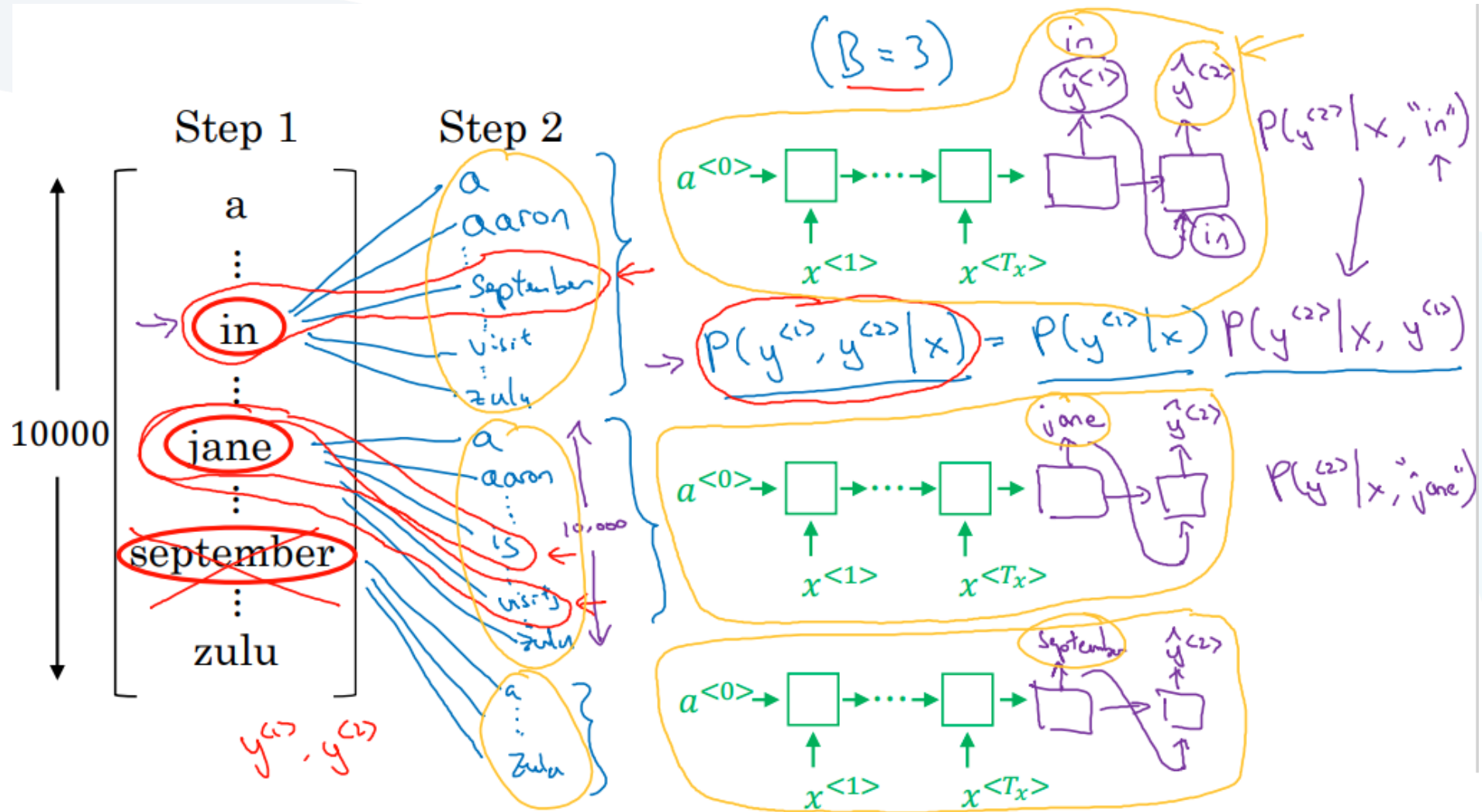


$B = 3$  (beam width)

$\rightarrow P(y^{<1>} | x)$

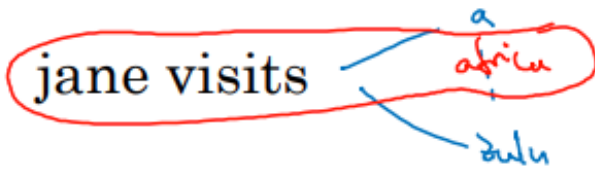
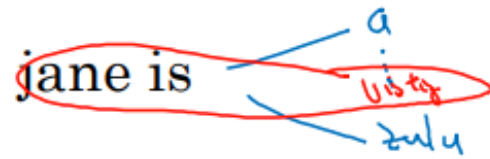
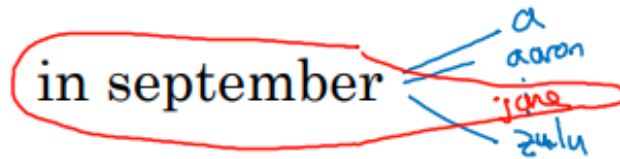


# Beam search algorithm



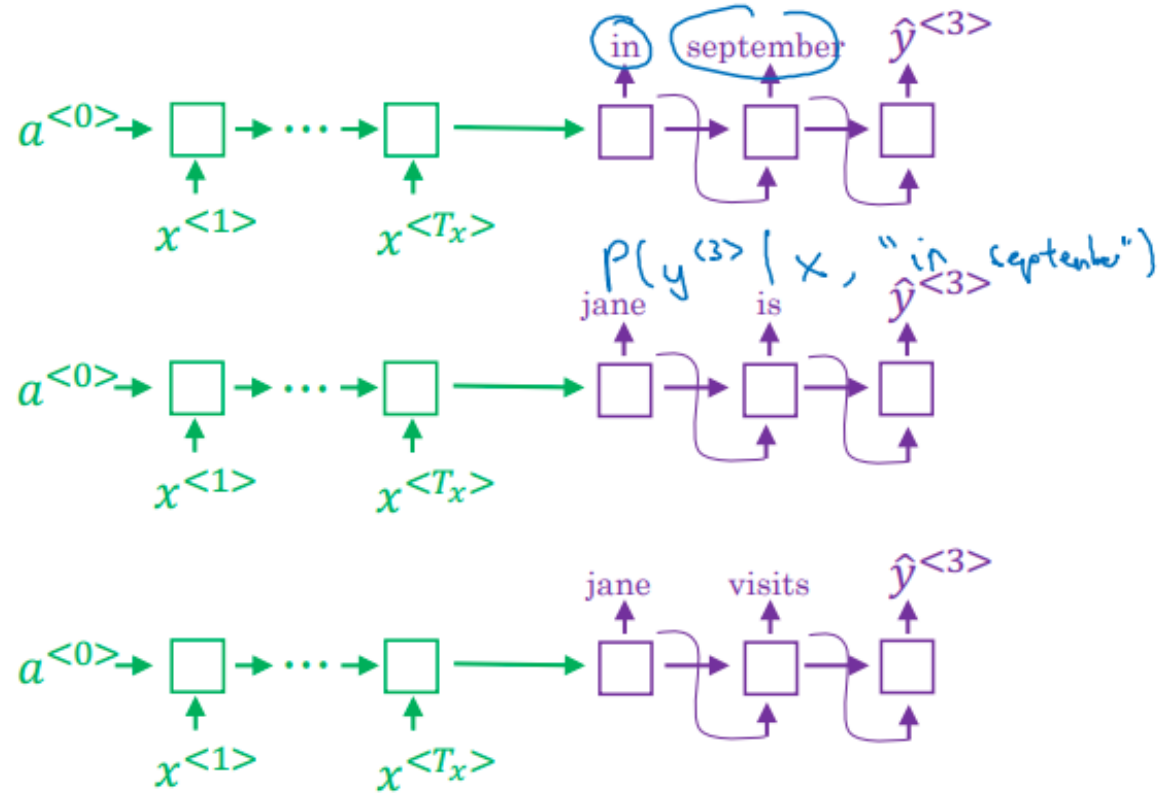
# Beam search (4 = 3)

$B=1 \rightsquigarrow$  greedy search



$$P(y^{<1>}, y^{<2>} | x)$$

jane visits africa in september. <EOS>



# Sequence to sequence models

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## Refinements to Beam search

# Length normalization

$$p(y^{(1)} \dots y^{(T_y)} | x) = \frac{P(y^{(1)} | x) P(y^{(2)} | x, y^{(1)}) \dots}{P(y^{(T_y)} | x, y^{(1)}, \dots, y^{(T_y-1)})}$$

$$\arg \max_y \prod_{t=1}^{T_y} P(y^{(t)} | x, y^{(1)}, \dots, y^{(t-1)})$$

log

$$\arg \max_y \sum_{t=1}^{T_y} \log P(y^{(t)} | x, y^{(1)}, \dots, y^{(t-1)}) \leftarrow$$

$T_y = 1, 2, 3, \dots, 30.$

$$\rightarrow \frac{1}{T_y^\alpha} \sum_{t=1}^{T_y} \log P(y^{(t)} | x, y^{(1)}, \dots, y^{(t-1)})$$

$\alpha = 0.7$        $\frac{\alpha = 1}{\alpha = 0}$

# Beam search discussion



Beam width B?

1 → 3 → 10, 100, 1000, → 3000

large B: better result, slower  
Small B: worse result, faster

Unlike exact search algorithms like BFS (Breadth First Search) or DFS (Depth First Search), Beam Search runs faster but is not guaranteed to find exact maximum for  $\arg \max P(y/x)$



# Sequence to sequence models

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## Error analysis on beam search

# Example



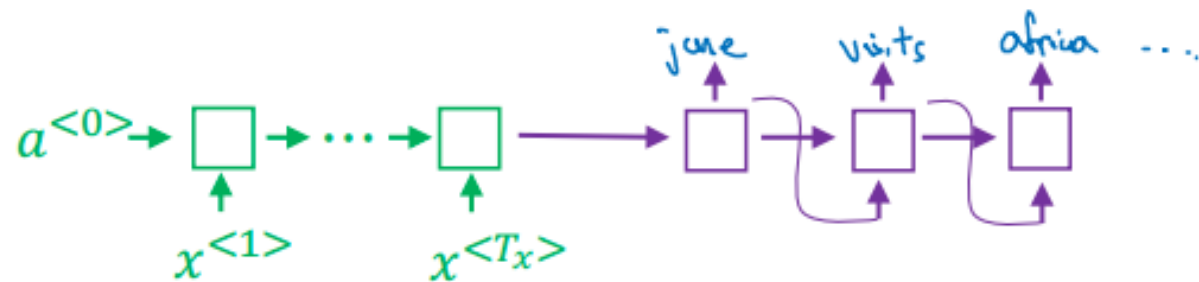
→ RNN  
→ Beam Search

Jane visite l'Afrique en septembre.

Human: Jane visits Africa in September. ( $y^*$ )

Algorithm: Jane visited Africa last September. ( $\hat{y}$ ) ←

RNN computes  $P(y^*|x) \gtrless P(\hat{y}|x)$



# Error analysis on beam search



Human: Jane visits Africa in September. ( $y^*$ )

$$P(y^*|x)$$

Algorithm: Jane visited Africa last September. ( $\hat{y}$ )

$$P(\hat{y}|x)$$

Case 1:  $P(y^*|x) > P(\hat{y}|x)$  ←

$$\arg \max_y P(y|x)$$

Beam search chose  $\hat{y}$ . But  $y^*$  attains higher  $P(y|x)$ .

Conclusion: Beam search is at fault.

Case 2:  $P(y^*|x) \leq P(\hat{y}|x)$  ←

$y^*$  is a better translation than  $\hat{y}$ . But RNN predicted  $P(y^*|x) < P(\hat{y}|x)$ .

Conclusion: RNN model is at fault.

# Error analysis process

Human	Algorithm	$P(y^* x)$	$P(\hat{y} x)$	At fault?
Jane visits Africa in September. ... ...	Jane visited Africa last September. ... ...	$\frac{2 \times 10^{-10}}{\text{---}}$ ---	$\frac{1 \times 10^{-10}}{\text{---}}$ ---	(B) (R) ... R R R ...

Figures out what fraction of errors are “due to” beam search vs. RNN model

# Sequence to sequence models

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## BLUE (Bilingual Evaluation Understudy)

# Evaluating machine translation



French: Le chat est sur le tapis.

Reference 1: The cat is on the mat.

Reference 2: There is a cat on the mat.

MT output: the the the the the the the.

[Papineni et. al., 2002. Bleu: A method for automatic evaluation of machine translation]

# Bleu score on bigrams

French: Le chat est sur le tapis.

Reference 1: The cat is on the mat.

Reference 2: There is a cat on the mat.

MT output: the the the the the the the.

	Count	Count <sub>clip</sub>	
the cat	2 ←	1 ←	$\frac{4}{6}$
cat the	1 ←	0	
cat on	1 ←	1 ←	
on the	1 ←	1 ←	
the mat	1 ← ↑	1 ←	

[Papineni et. al., 2002. Bleu: A method for automatic evaluation of machine translation]

# Bleu score on unigrams

Example: Reference 1: The cat is on the mat.

Reference 2: There is a cat on the mat.

MT output: The cat the cat on the mat.

$$P_1 = \frac{\sum_{\text{unigrams} \in \hat{y}} \text{Count}_{\text{ref}}(\text{unigram})}{\sum_{\text{unigram} \in \hat{y}} \text{Count}(\text{unigram})}$$

unigram ↑

$$P_n = \frac{\sum_{\text{n-grams} \in \hat{y}} \text{Count}_{\text{ref}}(\text{n-gram})}{\sum_{\text{n-grams} \in \hat{y}} \text{Count}(\text{n-gram})}$$

n-gram ↑

$$P_1, P_2 = 1.0$$

[Papineni et. al., 2002. Bleu: A method for automatic evaluation of machine translation]



# Bleu details



$p_n$  = Bleu score on n-grams only

$p_1, p_2, p_3, p_4$

Combined Bleu score =  $BP \cdot \exp\left(\frac{1}{4} \sum_{n=1}^4 p_n\right)$

**BP: Brevity Penalty**

$$BP = \begin{cases} 1 & \text{if MT\_output\_length} > \text{reference\_output\_length} \\ \exp(1 - \text{MT\_output\_length}/\text{reference\_output\_length}) & \text{otherwise} \end{cases}$$

[Papineni et. al., 2002. Bleu: A method for automatic evaluation of machine translation]