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Seq2Seq model for NMT

Outline

- Introduction to Neural Machine Translation
- Seq2Seq model and its shortcomings
- Solution for the information bottleneck

Neural Machine Translation

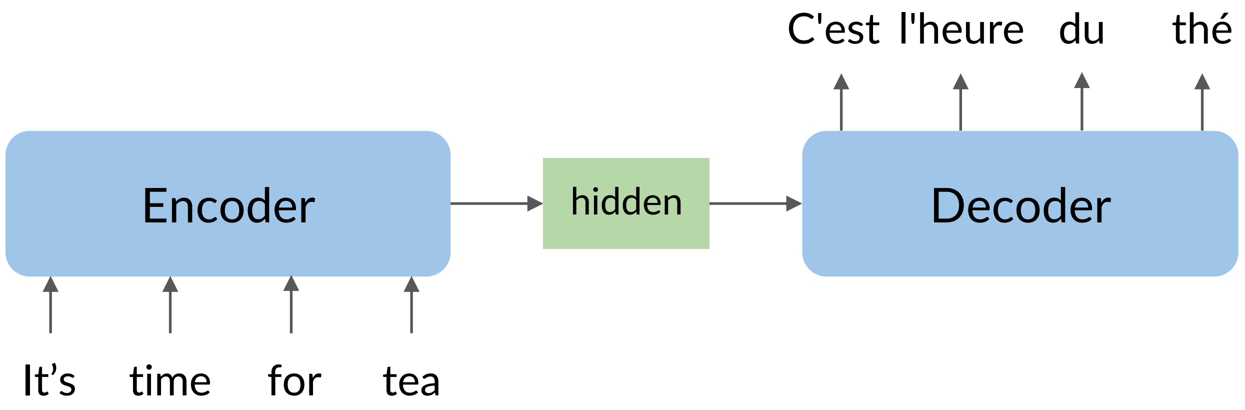
It’s time for tea → C'est l'heure du thé

U F

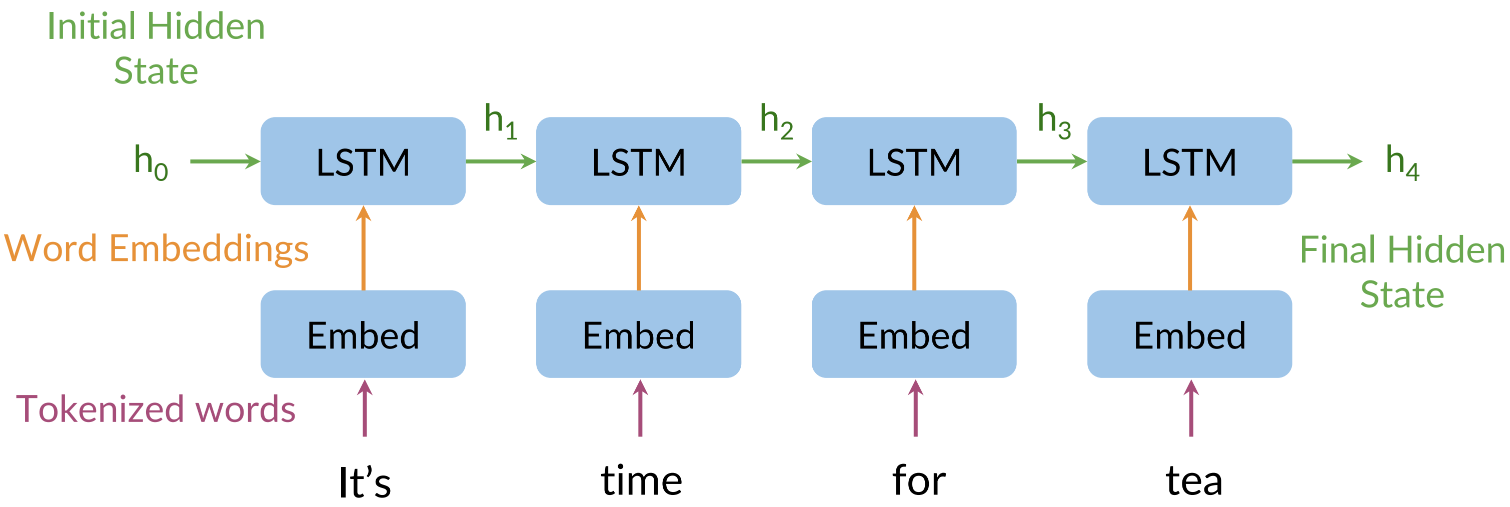
Seq2Seq model

- Introduced by Google in 2014
- Maps variable-length sequences to fixed-length memory
- Inputs and outputs can have different lengths
- LSTMs and GRUs to avoid vanishing and exploding gradient problems

Seq2Seq model

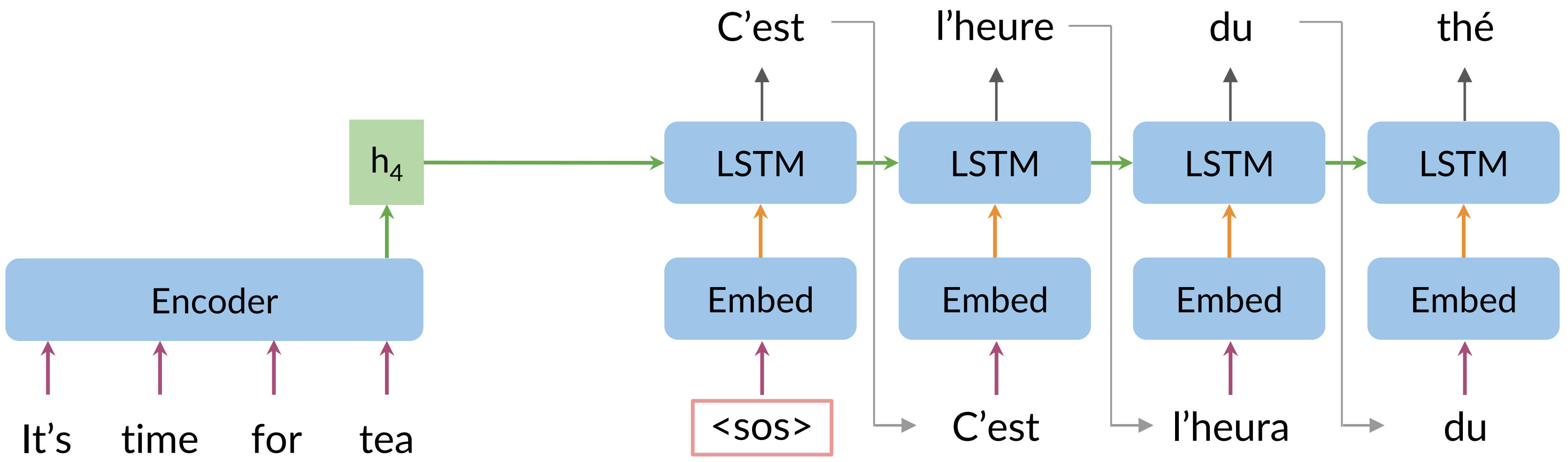


Seq2Seq encoder

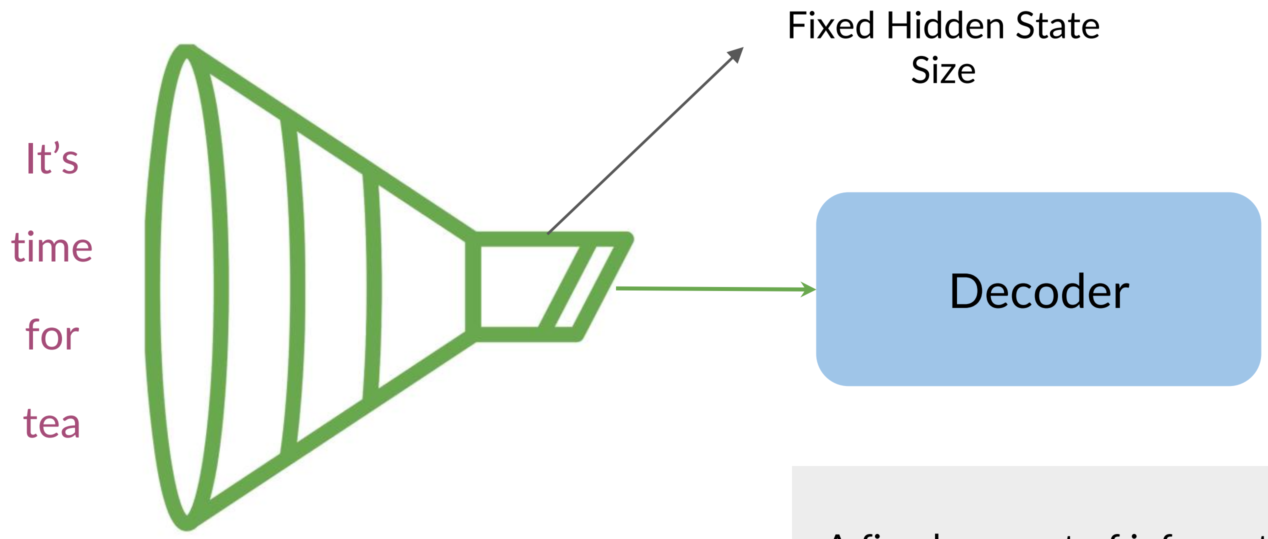


Encodes the overall meaning of the sentence

Seq2Seq decoder



The information bottleneck



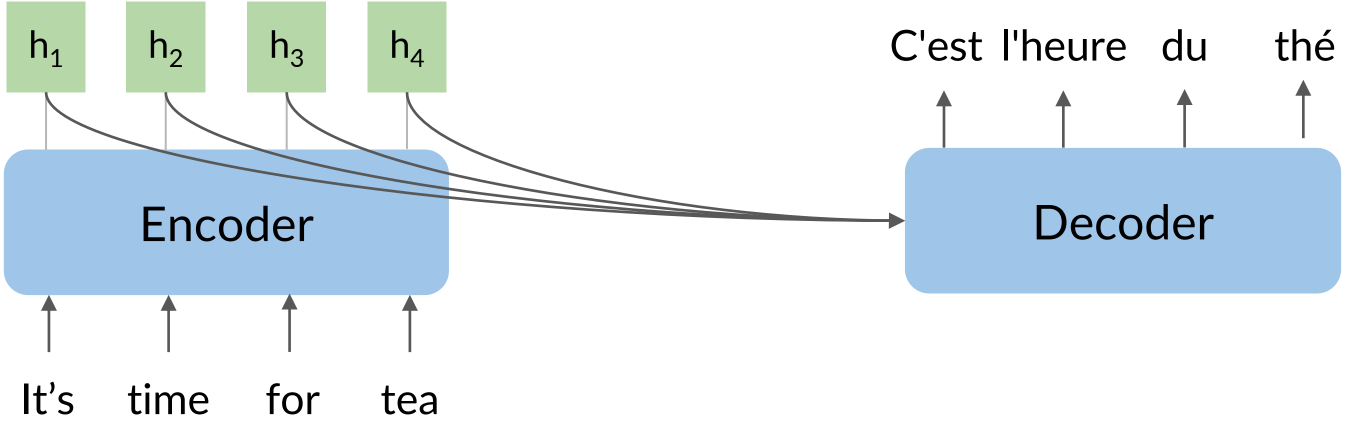
A fixed amount of informations goes from the encoder to the decoder

Seq2Seq shortcomings

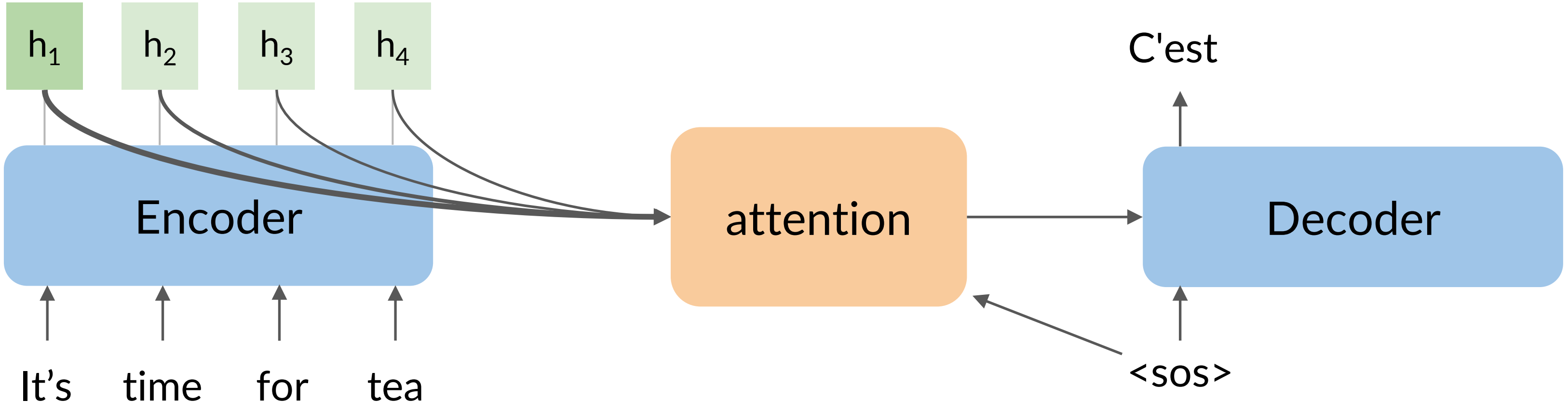
- Variable-length sentences + fixed-length memory =

- As sequence size increases, model performance decreases

Use all the encoder hidden states?



Solution: focus attention in the right place



The model can focus on specific hidden states at every step

Seq2Seq model with attention

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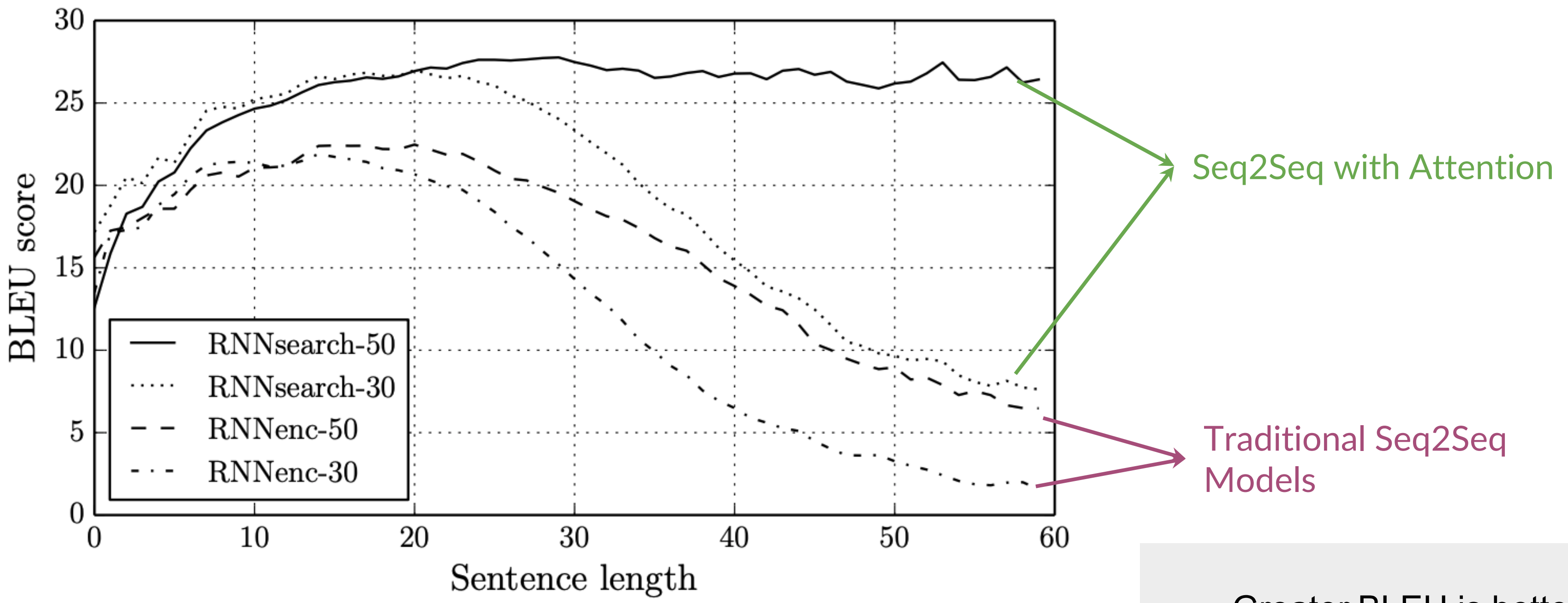
NEURAL MACHINE TRANSLATION BY JOINTLY LEARNING TO ALIGN AND TRANSLATE

Dzmitry Bahdanau
Jacobs University Bremen, Germany

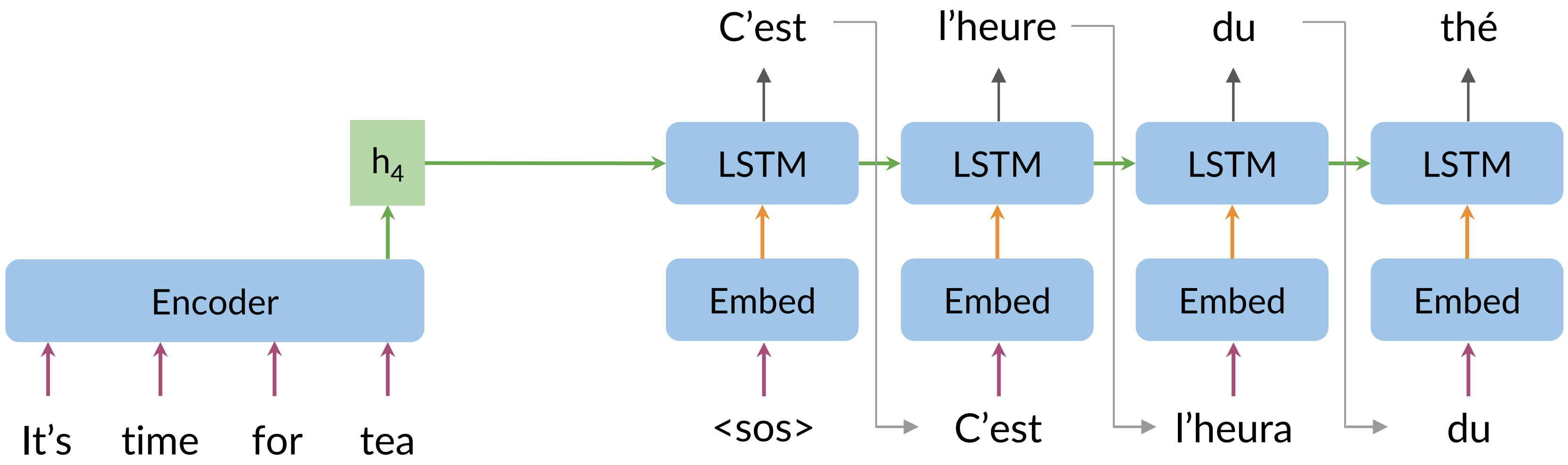
KyungHyun Cho **Yoshua Bengio***
Université de Montréal

Performance

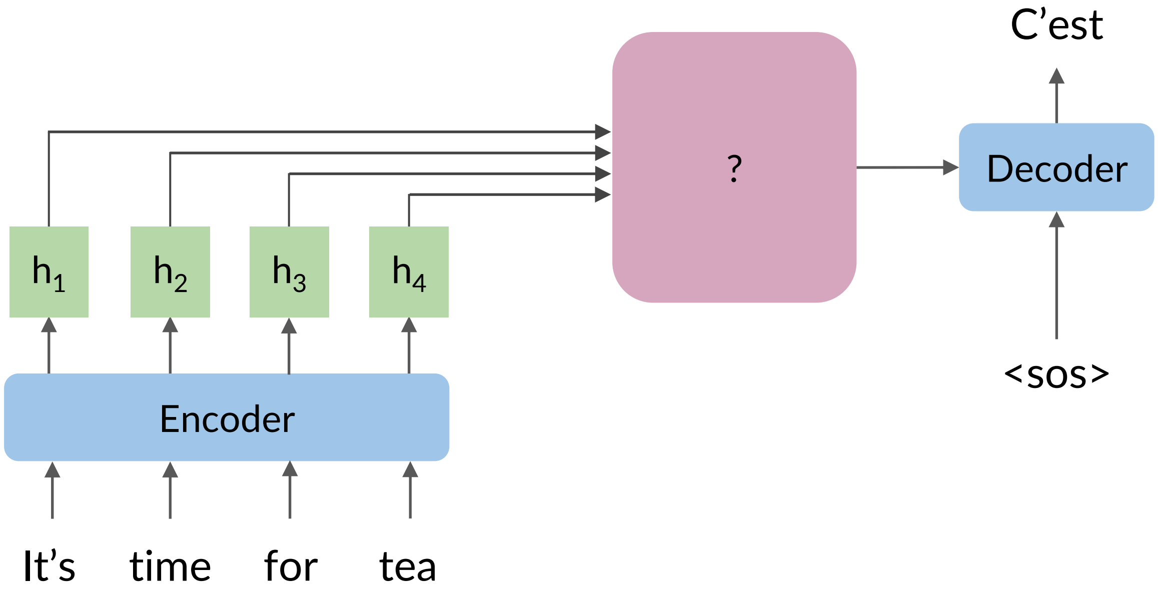


Greater BLEU is better

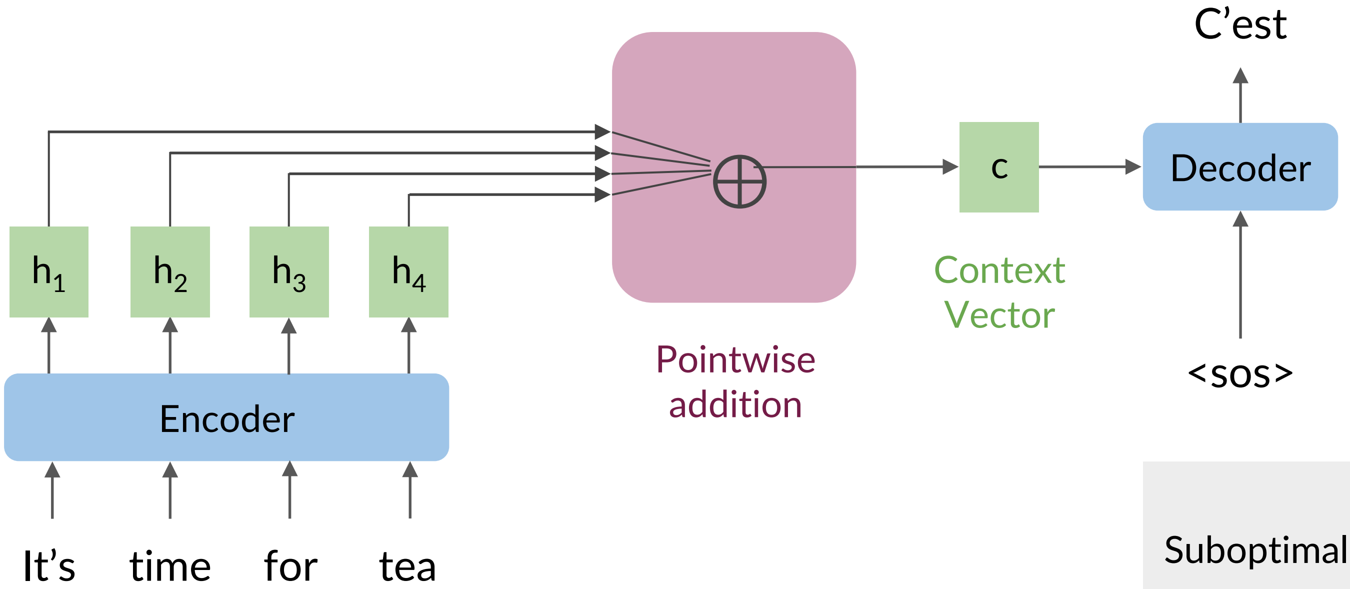
Traditional seq2seq models



How to use all the hidden states?

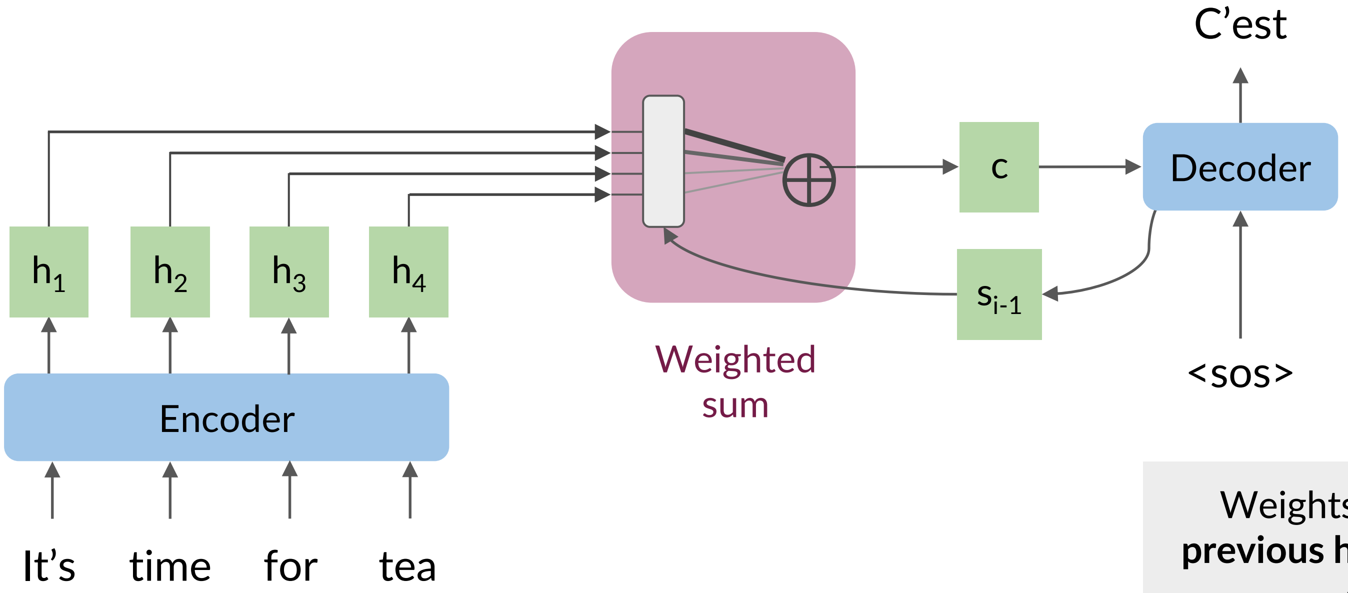


How to use all the hidden states?



Suboptimal use of information

How to use all the hidden states?



Weights depend on the **previous hidden state** in the decoder

The attention layer in more depth

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

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

h_j, s_{i-1} → Feedforward Network → e_{ij} → Softmax → α_{ij}

Learnable parameters

Weights used for the sum of hidden states

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

$$\alpha_{i1}h_1 + \alpha_{i2}h_2 + \alpha_{i3}h_3 + \cdots + \alpha_{iM}h_M \longrightarrow c_i$$

Context Vector is an expected value

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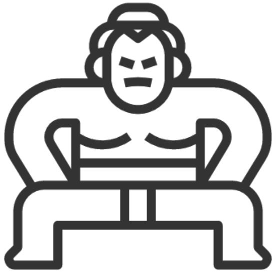
Queries, Keys, Values and Attention

Outline

- Queries, Keys, and Values
- Alignment



Queries, Keys, Values

Query	Key	Value
l'heure	It's	[0.5, 0.2, -1.2, ...,]
	time	[0.2, -0.7, 0.9, ...,]
	for	[1.3, 0.3, 0.8, ...,]
	tea	[-0.4, 0.6, -1.1, ...,]

Queries, Keys, Values

Query

l’heure

Key	Value
It’s	[0.5, 0.2, -1.2, …,]
time	[0.2, -0.7, 0.9, …,]
for	[1.3, 0.3, 0.8, …,]
tea	[-0.4, 0.6, -1.1, …,]

Queries, Keys, Values

Query

l'heure

Key	Value
It's	[0.5, 0.2, -1.2, ...,]
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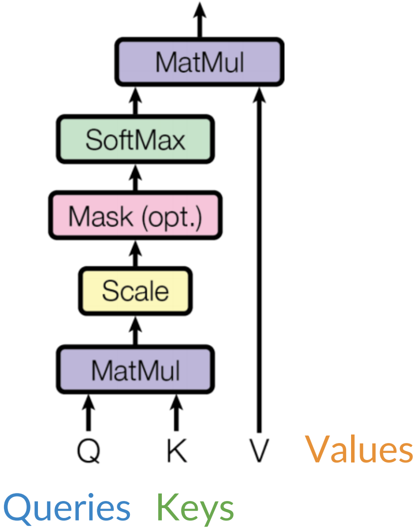
for	[1.3, 0.3, 0.8, ...,]
tea	[-0.4, 0.6, -1.1, ...,]

Similarity is used in for weighted sum

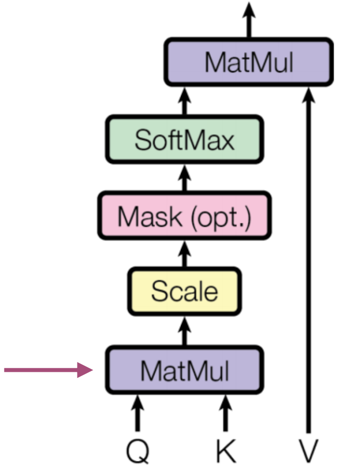
Scaled dot-product attention



(Vaswani et al., 2017)

$$\mathrm{softmax}\left(\frac{QK^\top}{\sqrt{d_k}}\right)V$$

Scaled dot-product attention

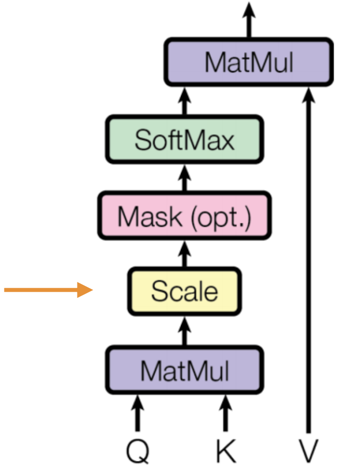


(Vaswani et al., 2017)

Similarity Between
Q and K

$$\mathrm{softmax}\left(\frac{\boxed{QK^\top}}{\sqrt{d_k}}\right)V$$

Scaled dot-product attention

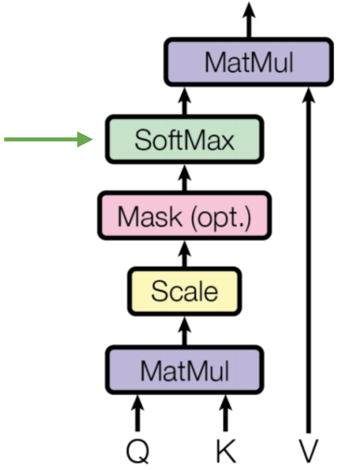


(Vaswani et al., 2017)

$$\mathrm{softmax}\left(\frac{QK^\top}{\sqrt{d_k}}\right)V$$

Scale using the root of the key vector size

Scaled dot-product attention

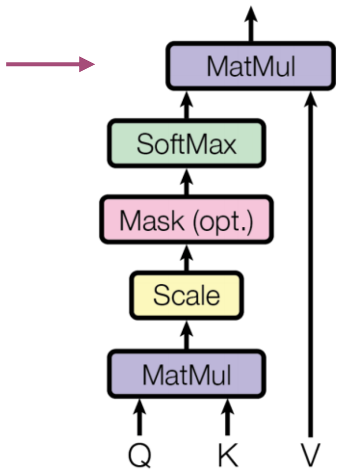


(Vaswani et al., 2017)

$$\mathrm{softmax}\left(\frac{QK^\top}{\sqrt{d_k}}\right)V$$

Weights for the weighted sum

Scaled dot-product attention



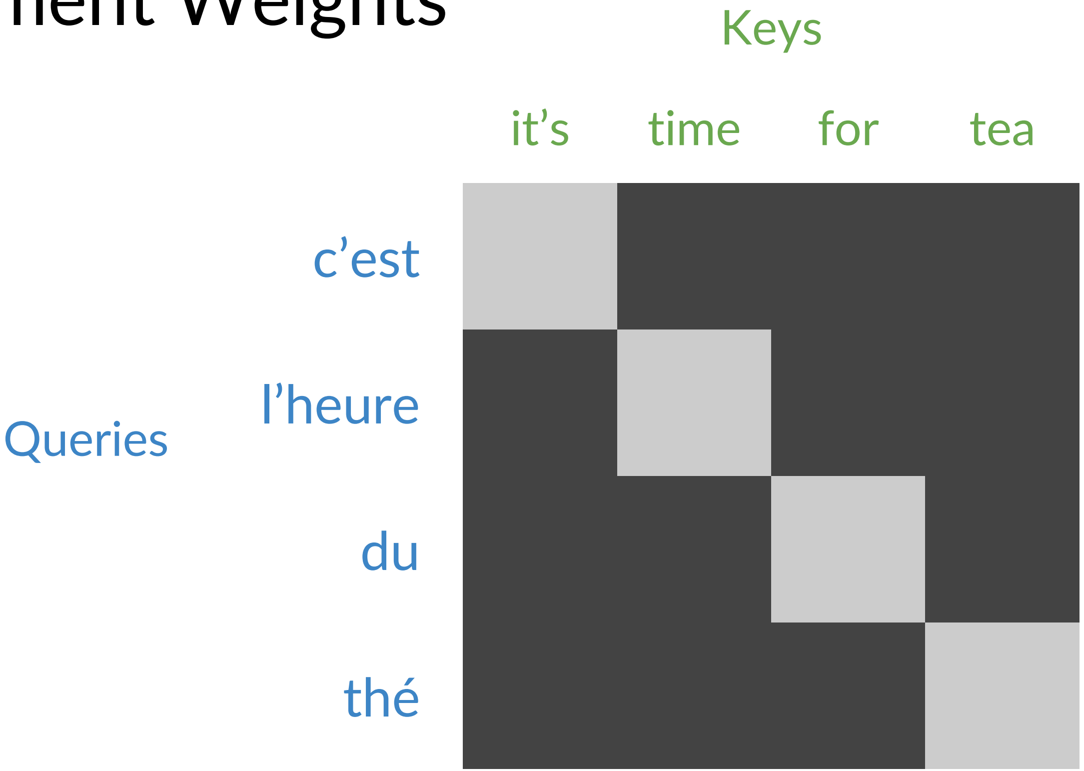
(Vaswani et al., 2017)

$$\mathrm{softmax}\left(\frac{QK^{\top}}{\sqrt{d_k}}\right)V$$

Weighted sum of values V

Just two matrix multiplications and a Softmax!

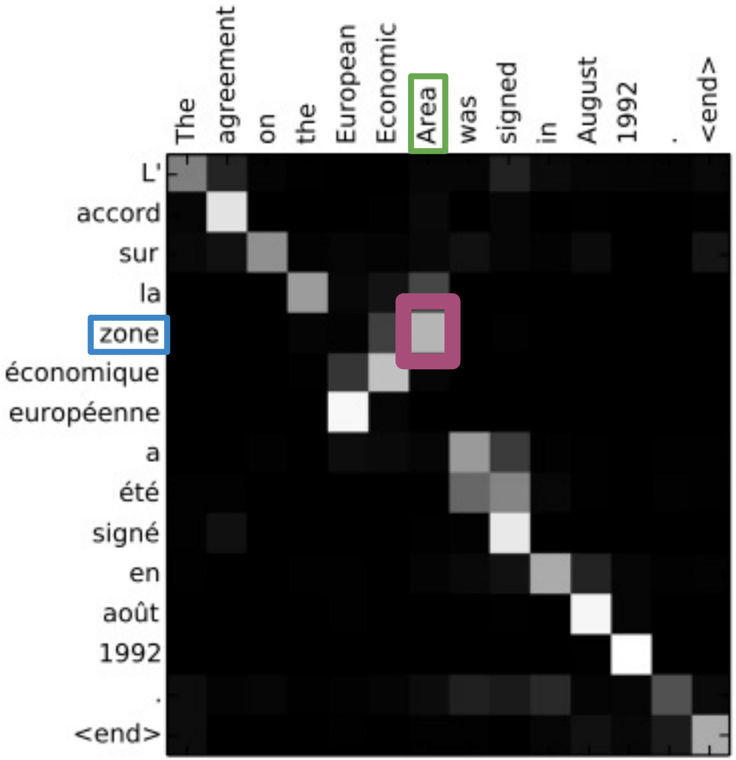
Alignment Weights



Similar words have large weights

Flexible attention

Works for languages with different grammar structures!



Bahdanau et al., 2015

Summary

- Attention is a layer that lets a model focus on what's important
- Queries, Values, and Keys are used for information retrieval inside the Attention layer
- Works for languages with very different grammatical structures

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Setup for machine translation

Data in machine translation

English	French
I am hungry!	J'ai faim!
...	...
I watched the soccer game.	J'ai regardé le match de football.

Attention! (pun intended) Assignment dataset is not as squeaky-clean as this example and contains some Spanish translations.

Machine translation setup

- Use pre-trained vector embeddings
- Otherwise, initially represent words with a one-hot vectors
- Keep track of index mappings with word2ind and ind2word dictionaries
- Add end of sequence tokens: <EOS>
- Pad the token vectors with zeros

Preparing to Translate to English

ENGLISH SENTENCE:

Both the ballpoint and the mechanical pencil in the series are equipped with a special mechanism: when the twist mechanism is activated, the lead is pushed forward.

TOKENIZED VERSION OF THE ENGLISH SENTENCE:

[4546 4 11358 362 8 4 23326 20104 1745 8210 9641 5 6
4 3103 31 2767 30 13 914 4797 64 196 4 22474 5 4797 16
24864 86 2 4 1060 16 6413 1138 3 1 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]

<EOS>

Padding

English to French

FRENCH TRANSLATION:

Le stylo à bille et le porte-mine de la série sont équipés d'un mécanisme spécial: lorsque le mécanisme de torsion est activé, le plomb est poussé vers l'avant.

TOKENIZED VERSION OF THE FRENCH TRANSLATION:

[7 29587 9 18240 8 7 420 5 3440 2 6 156 39 7941 14 19
5548 2648 562 7 5548 2 23194 18 20114 1 7 5695 18 8865 149
12 137 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0]

Padding

<EOS>

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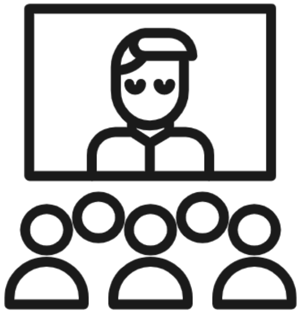
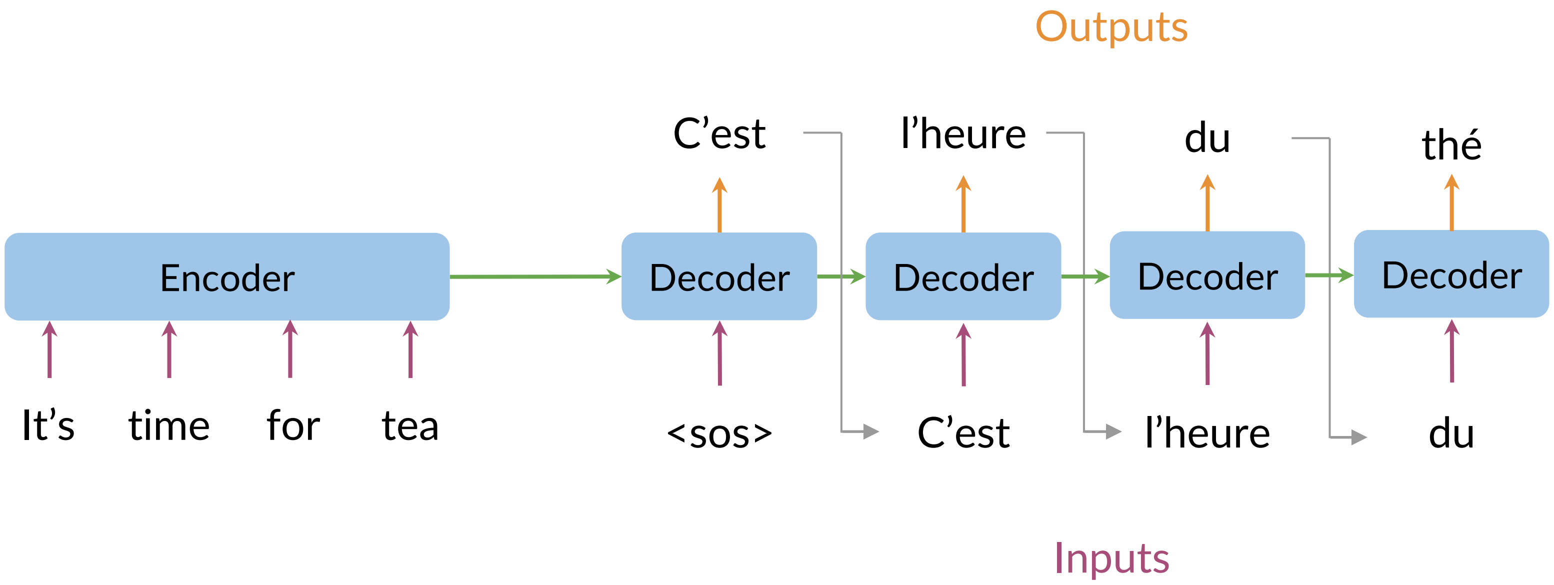
Teacher Forcing

Outline

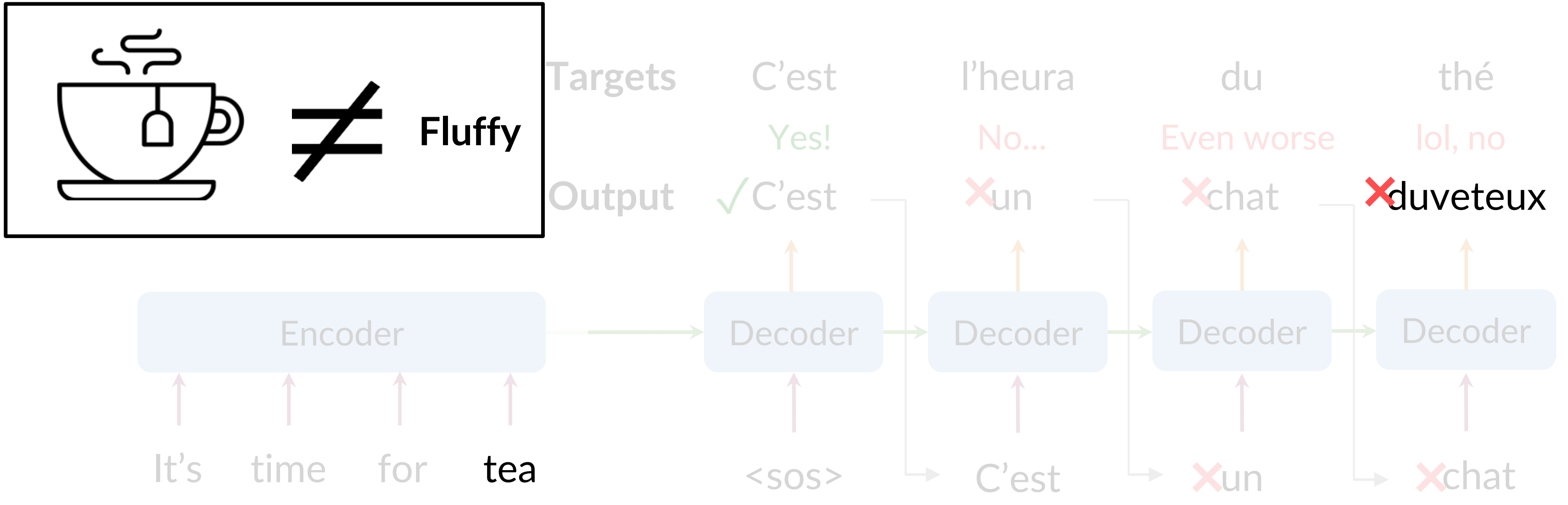
- Training for NMT
- Teacher forcing



Traditional seq2seq models



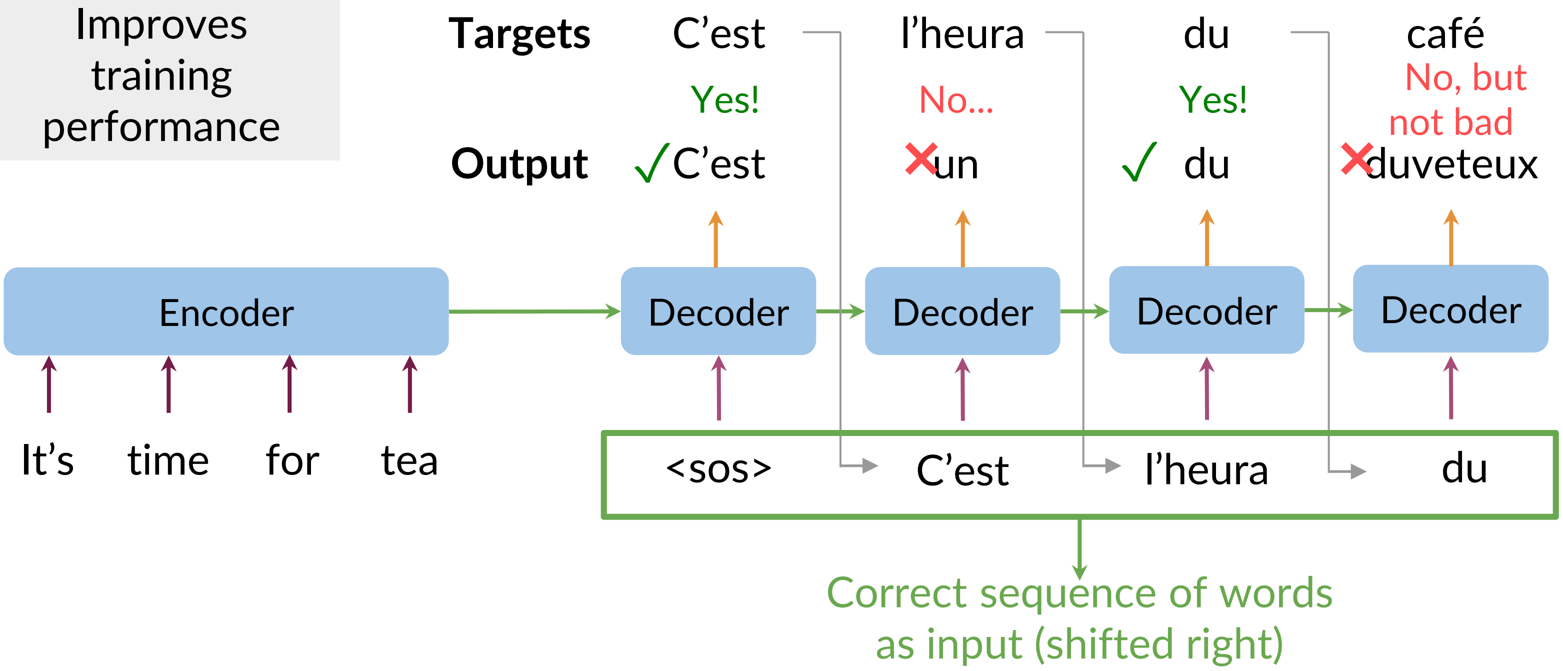
Training seq2seq models



Errors from early steps propagate

Teacher Forcing

Improves training performance



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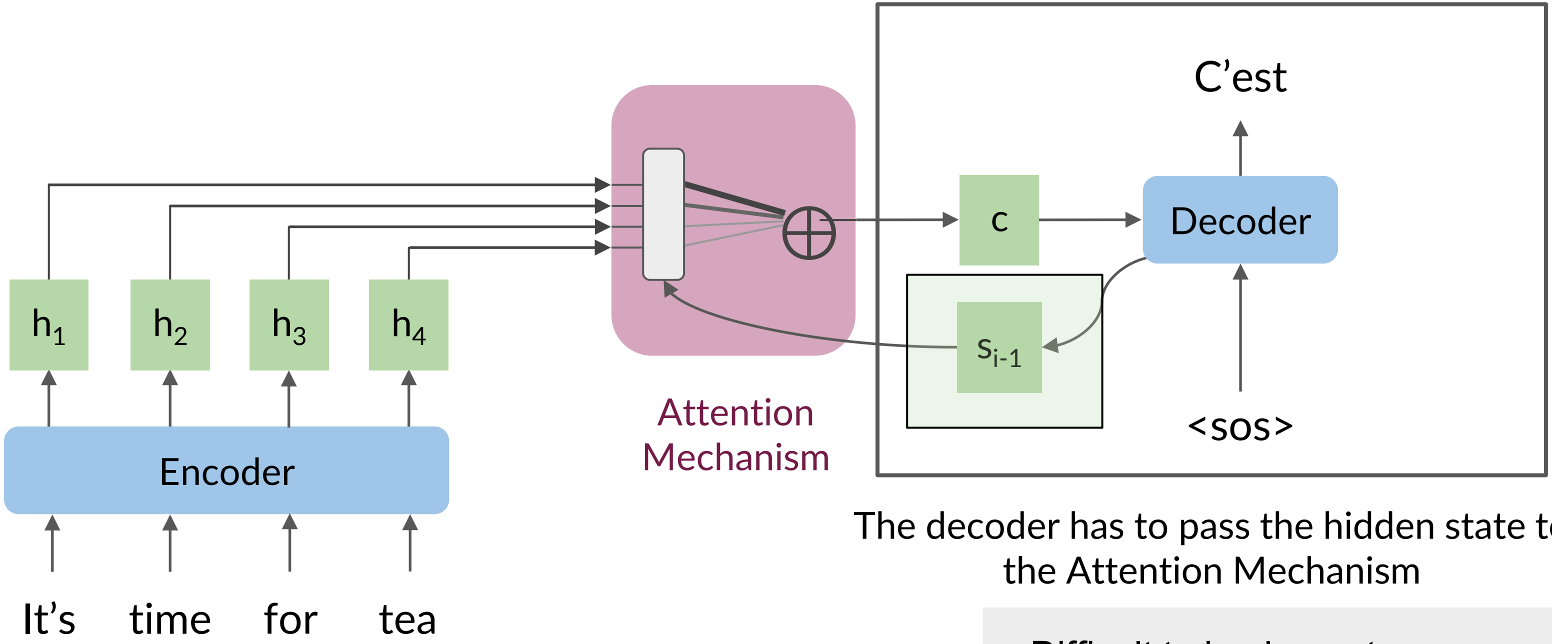
NMT Model with Attention

Outline

- How everything fits together
- NMT model in detail

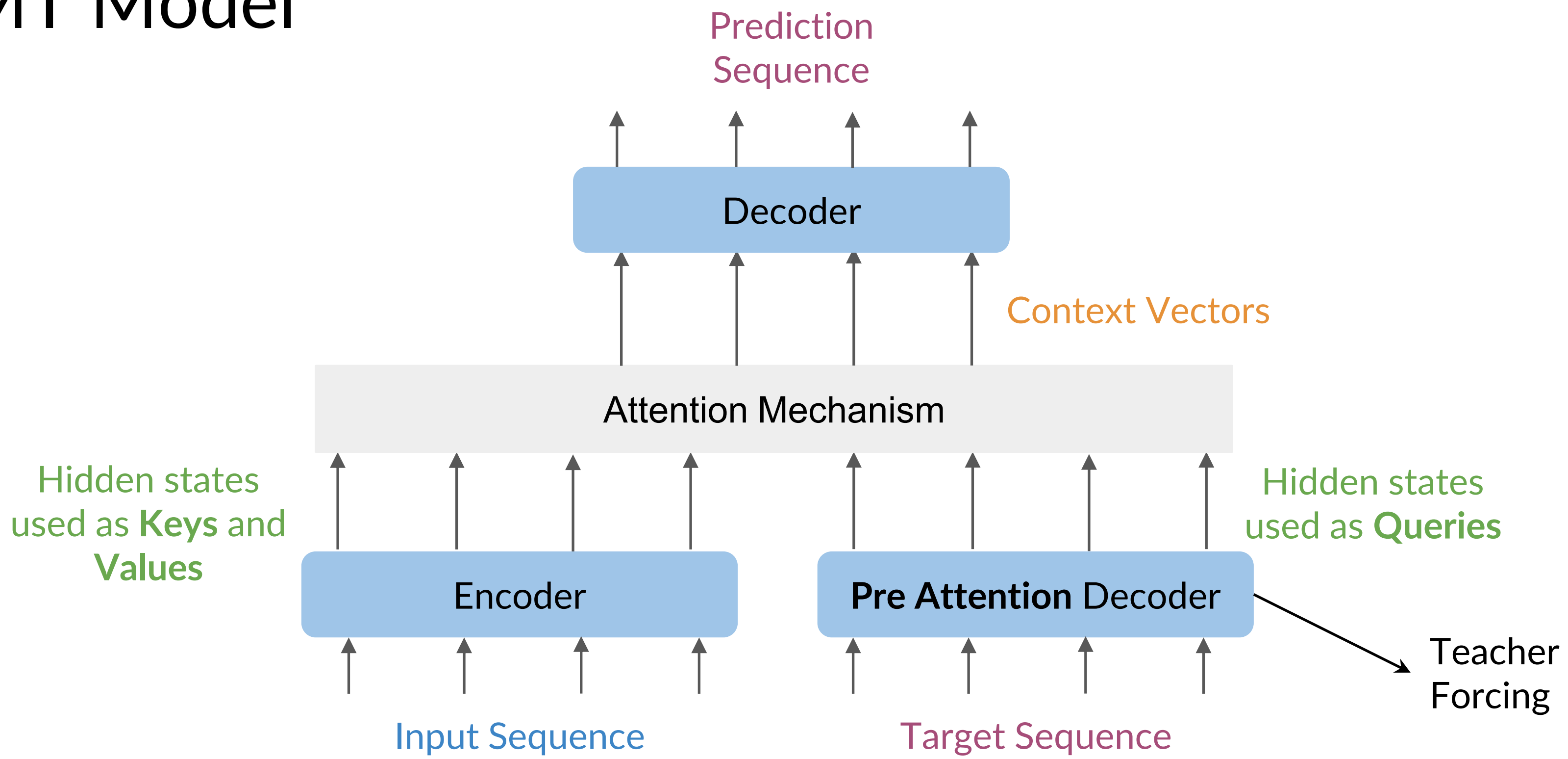
NMT Model



The decoder has to pass the hidden state to the Attention Mechanism

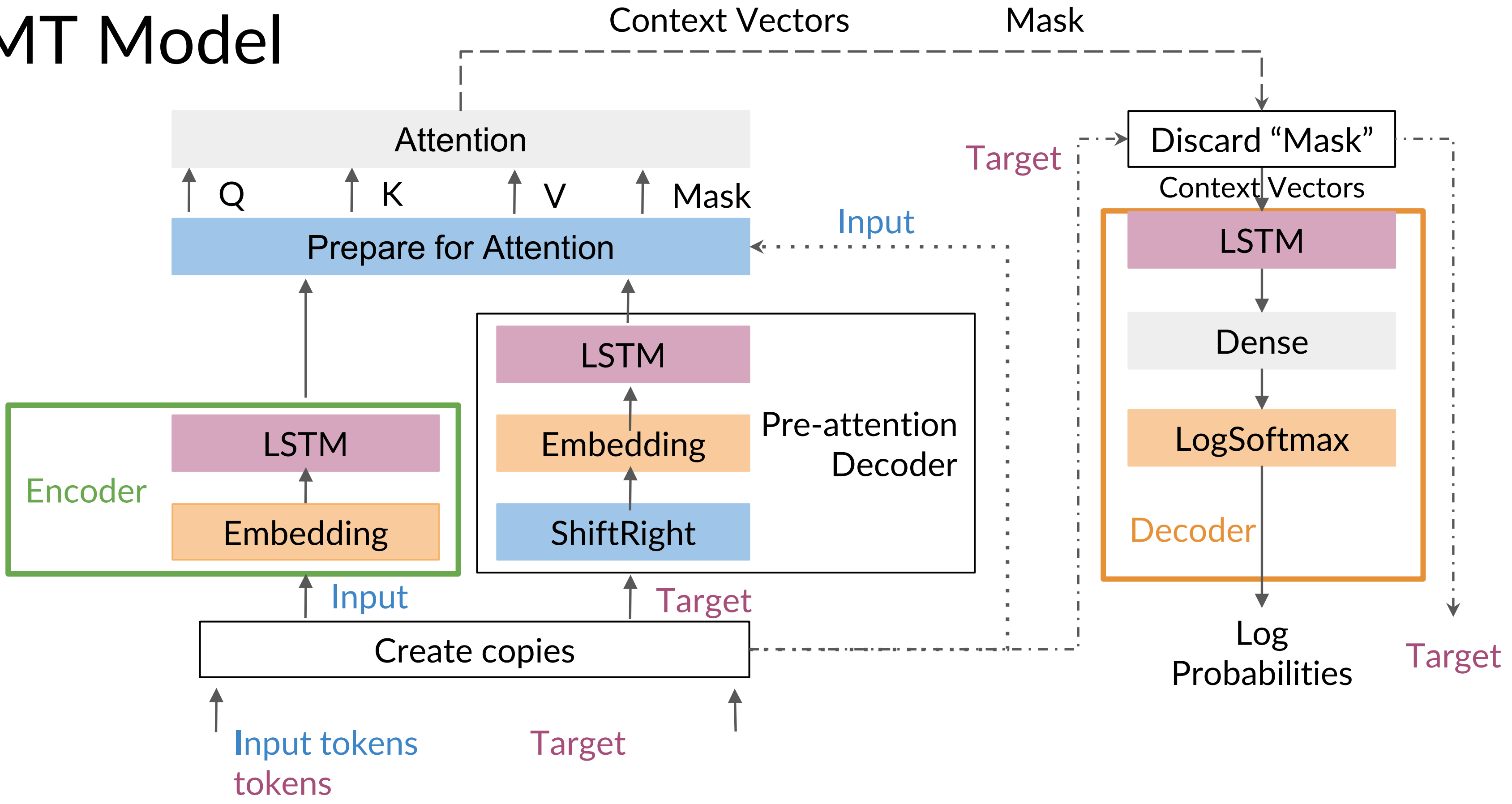
Difficult to implement, so a **pre-attention decoder** is introduced.

NMT Model



Prediction Sequence
Decoder
Context Vectors
Attention Mechanism
Hidden states used as **Keys** and **Values**
Hidden states used as **Queries**
Encoder
Pre Attention Decoder
Teacher Forcing
Input Sequence
Target Sequence

NMT Model


Context Vectors
Mask
Attention
Q
K
V
Mask
Prepare for Attention
Target
Discard "Mask"
Context Vectors
Input
LSTM
Dense
LogSoftmax
Decoder
LSTM
Embedding
ShiftRight
Pre-attention Decoder
Encoder
LSTM
Embedding
Input
Target
Create copies
Log Probabilities
Target
Input tokens
tokens
Target

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BLEU Score

BLEU Score

Bi**L**ingual **E**valuation **U**nderstudy

Compares candidate translations to reference (human) translations

The closer to 1, the better

BLEU Score

Candidate	I	I	am	I	
Reference 1	Younes	said	I	am	hungry
Reference 2	He	said	I	am	hungry

How many words from the candidate appear in the reference translations?

BLEU Score

Candidate	$\boxed{\text{I}}$	$\boxed{\text{I}}$	$\boxed{\text{am}}$	$\boxed{\text{I}}$	
Reference 1	Younes	said	<u>I</u>	<u>am</u>	hungry
Reference 2	He	said	<u>I</u>	<u>am</u>	hungry

Count: $\frac{1+1+1+1}{4} = 1$

A model that always outputs common words will do great!

BLEU Score (Modified)

Candidate	$\boxed{\text{I}}$	$\boxed{\text{I}}$	$\boxed{\text{am}}$	$\boxed{\text{I}}$	
Reference 1	Younes	said			hungry
Reference 2	He	said			hungry

Count: $\frac{1+1}{4} = 0.5$

Better than the previous implementation version!

BLEU score is great, but...

Consider the following:

- BLEU doesn't consider semantic meaning
- BLEU doesn't consider sentence structure:

"Ate I was hungry because!"

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ROUGE-N Score

ROUGE

Recall-Oriented Understudy for Gisting Evaluation

Compares candidates with reference (human) translations

Multiple versions for this metric

ROUGE-N

Candidate	I	I	am	I	
Reference 1	Younes	said	I	am	hungry
Reference 2	He	said	I	am	hungry

How many words from the reference appear in the candidate translations?

ROUGE-N

Candidate	I	I	am	I	
Reference 1	Younes	said	I	am	hungry
Reference 2	He	said	I	am	hungry

Count 1: $\frac{1+1}{5} = 0.4$

Count 2: $\frac{1+1}{5} = 0.4$

ROUGE-N, BLEU and F1 score

Candidate	I	I	am	I	
Reference 1	Younes	said	I	am	hungry
Reference 2	He	said	I	am	hungry

$$F1 = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \longrightarrow F1 = 2 \times \frac{\text{BLEU} \times \text{ROUGE-N}}{\text{BLEU} + \text{ROUGE-N}}$$

$$\boxed{F1 = 2 \times \frac{0.5 \times 0.4}{0.5 + 0.4} = \frac{4}{9} \approx 0.44}$$

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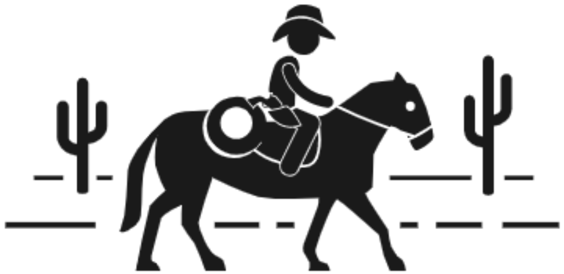
Sampling and Decoding

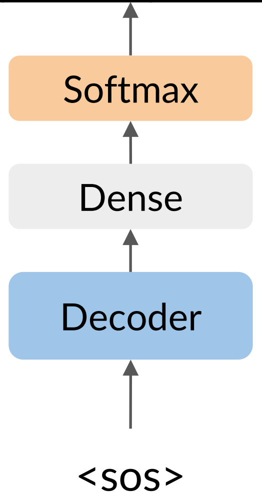
Outline

- Random sampling
- Temperature in sampling
- Greedy decoding



Seq2Seq model

Words	de	la	le	et	à	...
$P(w_i)$	0.02	0.04	0.1	0.005	0.08	...



Probability distribution over words in target language

Greedy decoding

Selects the most probable word at each step

But the best word at each step may not be the best for longer sequences...

Can be fine for shorter sequences, but limited by inability to look further down the sequence

J'ai faim.

I am hungry.

I am, am, am, am...

Random sampling

am	full	hungry	I	the
0.05	0.3	0.15	0.25	0.25

Often a little too random for accurate translation!

Solution: Assign more weight to more probable words, and less weight to less probable words.

Temperature

Can control for more or less randomness in predictions

Lower temperature setting : More confident, conservative network

Higher temperature setting : More excited, random network

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Beam Search

Beam search decoding

Most probable translation **is not** the one with the most probable word at each step

Solution

Calculate probability of multiple possible sequences

Beam search

Beam search decoding

Probability of multiple possible sequences at each step

Beam width B determines number of sequences you keep

Until all B most probable sequences end with <EOS>

Beam search with **B=1** is **greedy decoding**.

Beam search example

B = 2

<sos>

$P(w_1 \mid \text{“<sos>”})$

I	**0.5**
am	**0.4**
hungry	0.1
<eos>	0.0

Beam search example

B = 2

<sos>

$P(w_1 \mid \text{“<sos>”})$

I	**0.5**
am	**0.4**

$P(w_2 \mid \text{“I”})$

I	0.1
am	0.5
hungry	0.3
<eos>	0.1

$P(w_2 \mid \text{“I”})P(\text{“I”})$

I I	0.05
I am	**0.25**
I hungry	0.15
I <eos>	0.05

$P(w_2 \mid \text{“am”})$

I	0.7
am	0.05
hungry	0.2
<eos>	0.05

$P(w_2 \mid \text{“am”})P(\text{“am”})$

am I	**0.28**
am am	0.02
am hungry	0.08
am <eos>	0.02

Beam search example

B = 2

<sos>

P(w_1 | “<sos>”)

I	**0.5**
am	**0.4**

P(w_2 | “I”)

I	0.1
am	0.5
hungry	0.3
<eos>	0.1

P(w_2 | “I”)P(“I”)

I I	0.05
I am	**0.25**
I hungry	0.15
I <eos>	0.05

P(w_3 | “I am”)

I	0.1
am	0.05
hungry	0.6
<eos>	0.3

P(w_2 | “am”)

I	0.7
am	0.05
hungry	0.2
<eos>	0.05

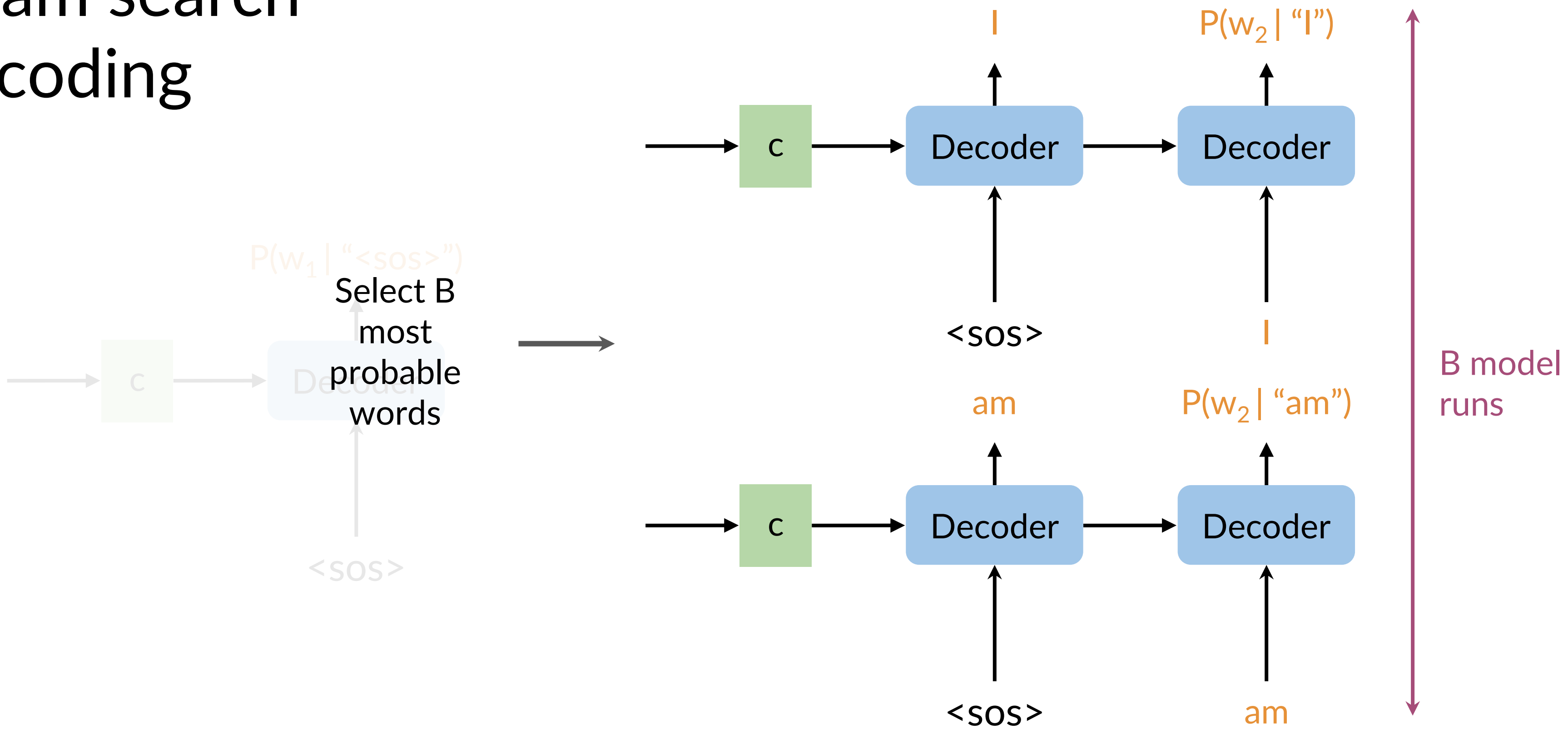
P(w_2 | “am”)P(“am”)

am I	**0.28**
am am	0.02
am hungry	0.08
am <eos>	0.02

P(w_3 | “Am I”)

I	0.15
am	0.15
hungry	0.5
<eos>	0.2

Beam search decoding



Problems with beam search

Penalizes long sequences, so you should normalize by the sentence length

Computationally expensive and consumes a lot of memory

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Minimum Bayes Risk

Minimum Bayes Risk (MBR)

- Generate several candidate translations
- Assign a similarity to every pair using a similarity score (such as ROUGE!)
- Select the sample with the highest average similarity

Minimum Bayes Risk (MBR)

$$\boxed{\arg\max_{E}} \frac{1}{n} \boxed{\sum_{E'}} \boxed{\mathrm{ROUGE}(E, E')}$$

Find the candidate translation that maximizes

Compare with every other candidate

ROUGE score between pair of candidates

Example: MBR Sampling

$\mathrm{ROUGE}(C_1, C_2)$

$\mathrm{ROUGE}(C_1, C_3)$

$\mathrm{ROUGE}(C_1, C_4)$

Compute average ROUGE

$$R_1 = \frac{1}{3} \sum_{i \neq 1} \mathrm{ROUGE}(C_1, C_i)$$

Repeat for every candidate

Select the candidate with the highest average

R_1 R_2 R_3 R_4

Summary

- Compare several candidate translations
- Choose candidate with highest average similarity
- Better performance than random sampling and greedy decoding