Attention Models

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- Neural Machine Translation
- Text Summation
- Question Answering

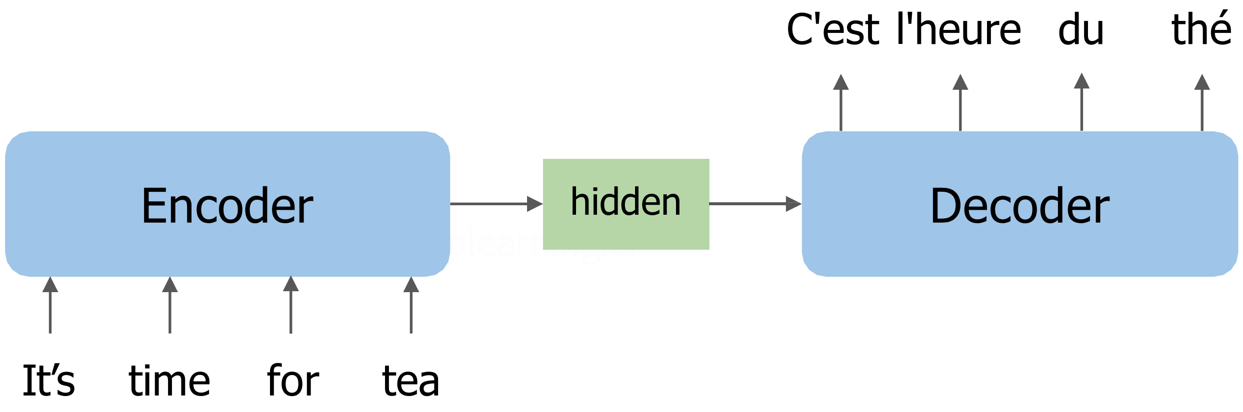
- Neural Machine Translation
  - Introduction to Neural Machine Translation
  - Seq2Seq model and its shortcomings
  - Solution for the information bottleneck

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

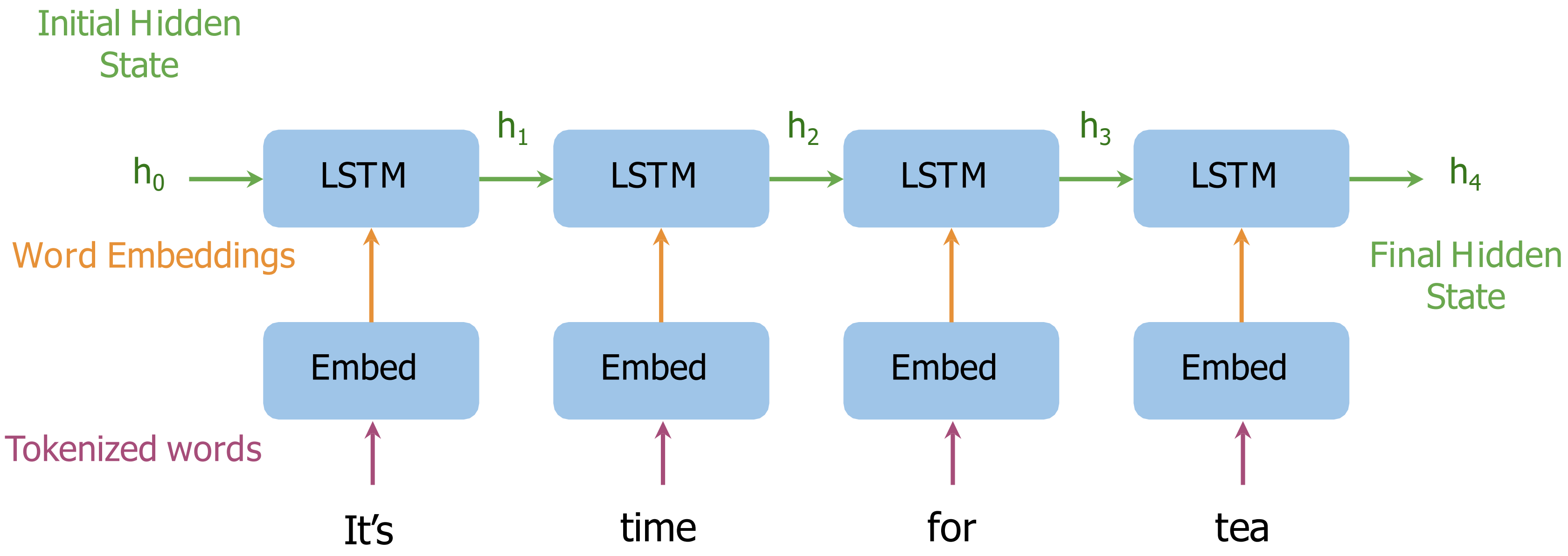
U F

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



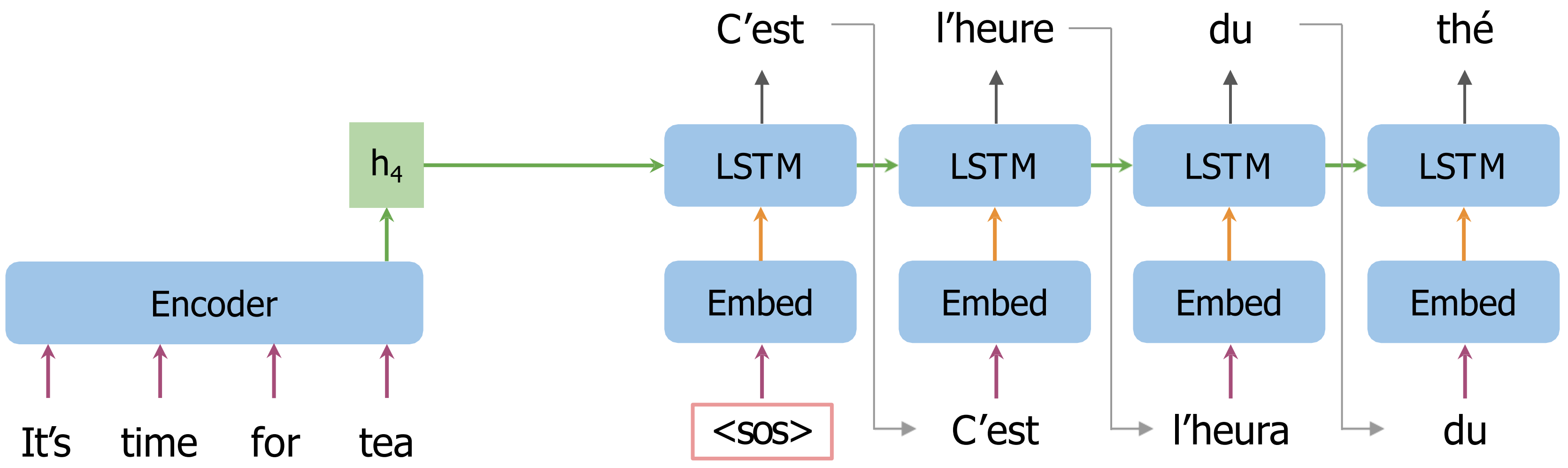
Seq2Seq encoder



Encodes the overall meaning of the sentence

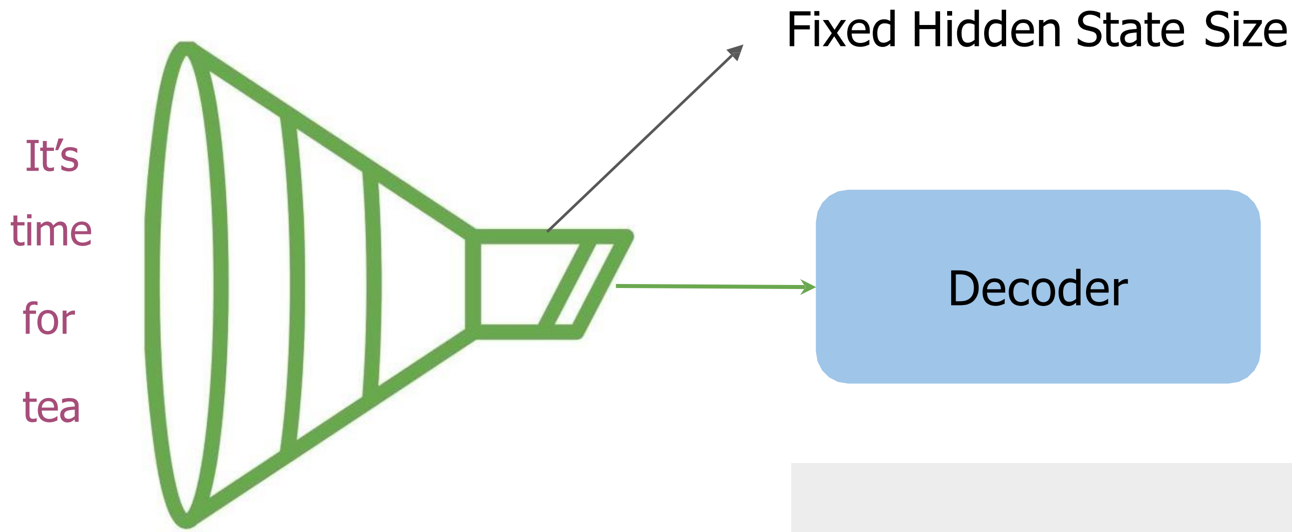
- typically consists of an embedding layer and an LSTM module with one or more layers
- transforms words tokenized first into a vector for input to the LSTM module
- the LSTM module receives inputs from the embedding layer, as well as the hidden states from the previous step

Seq2Seq decoder



- The decoder is constructed similarly with an embedding layer and an LSTM layer.
- the output word of a step as the input word for the next step.
- pass the LSTM hidden state to the next step.

The information bottleneck

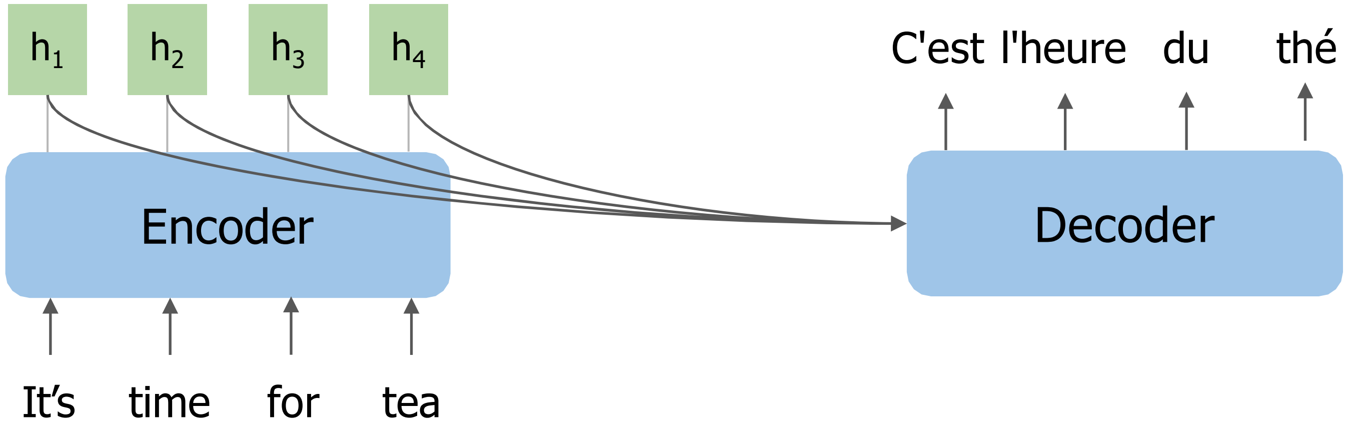


A fixed amount of informations goes from the encoder to the decoder

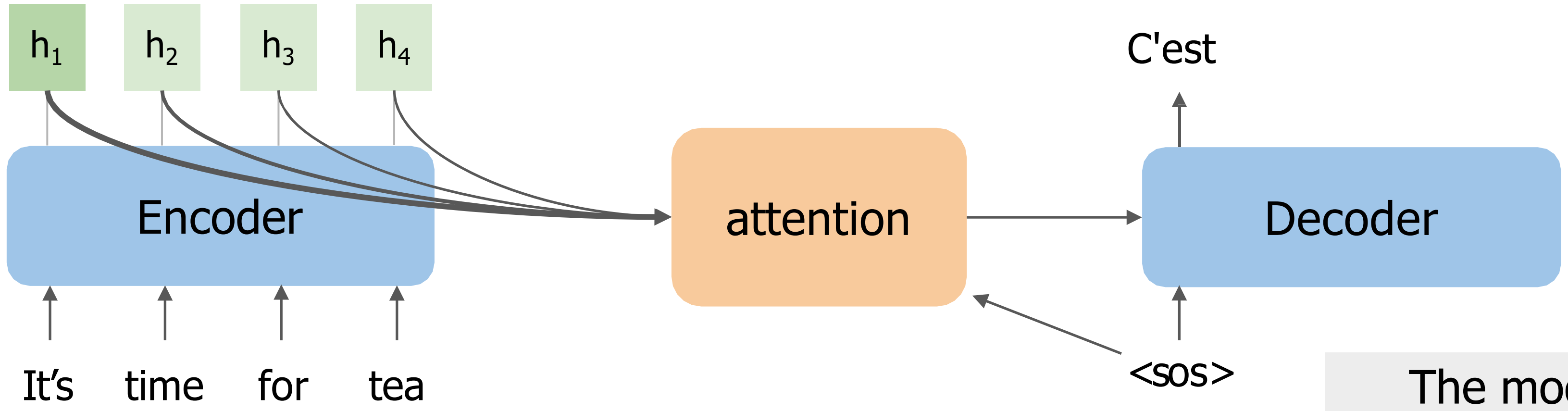
- Variable-length sentences + fixed-length memory

=>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

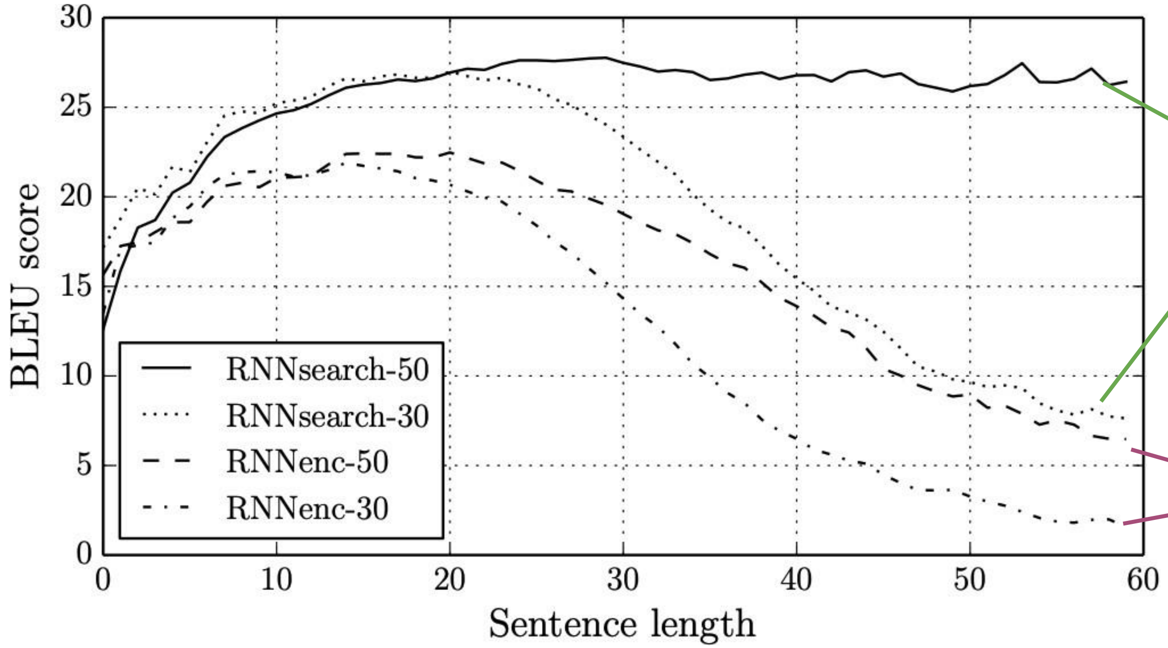
NEURAL MACHINE TRANSLATION
BY JOINTLY LEARNING TO ALIGN AND TRANSLATE

Dzmitry Bahdanau
Jacobs University Bremen, Germany

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

- Performance

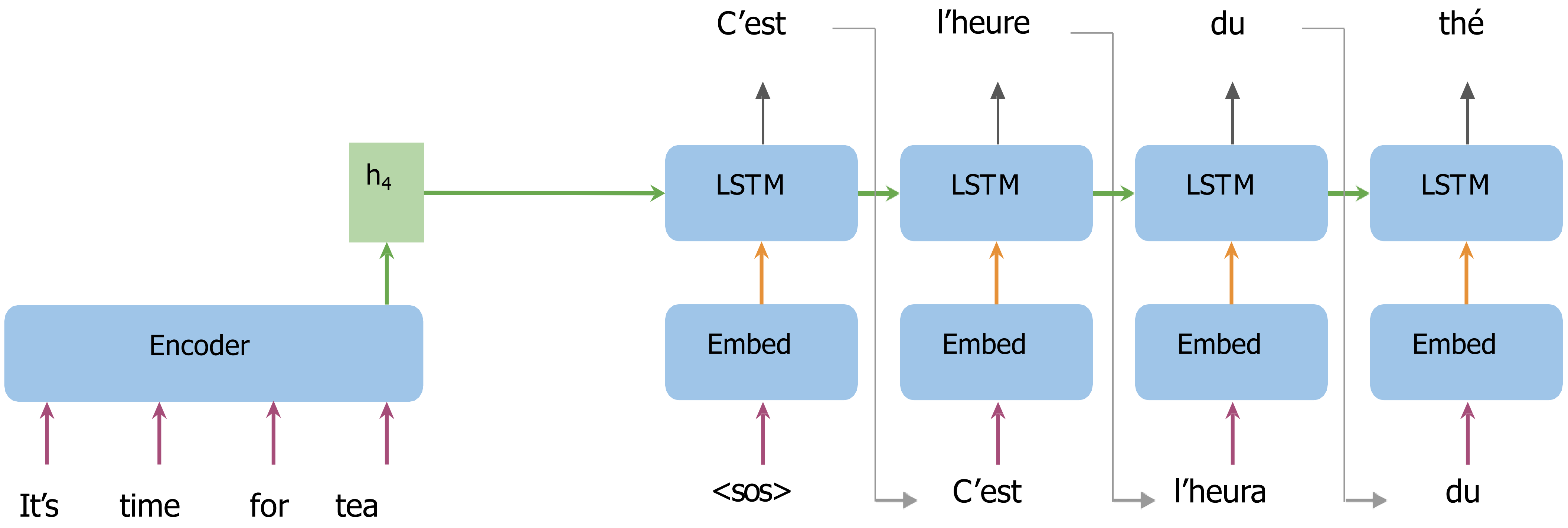
Greater BLEU is better



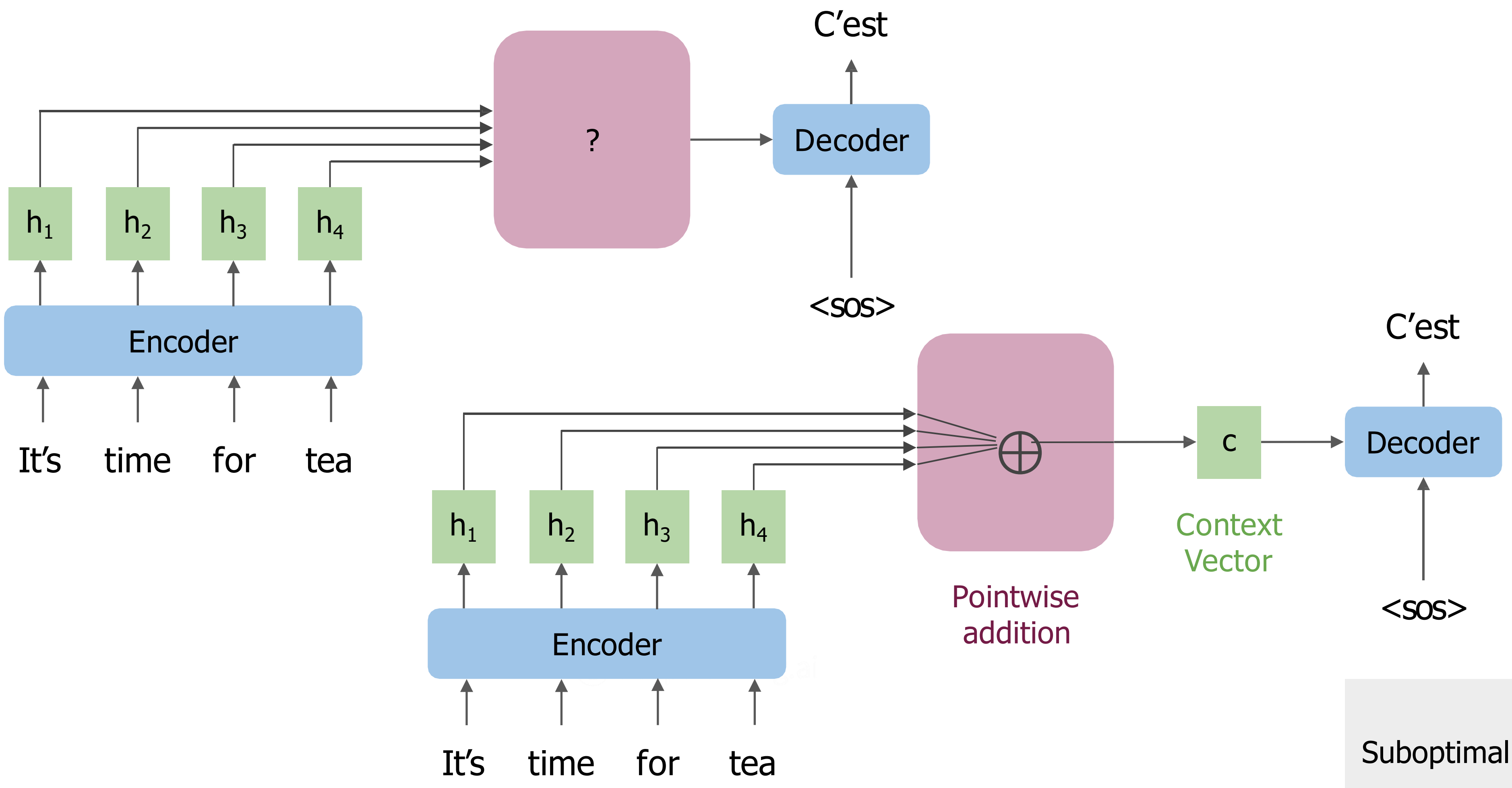
Seq2Seq with Attention

Traditional Seq2Seq
Models

Traditional seq2seq models

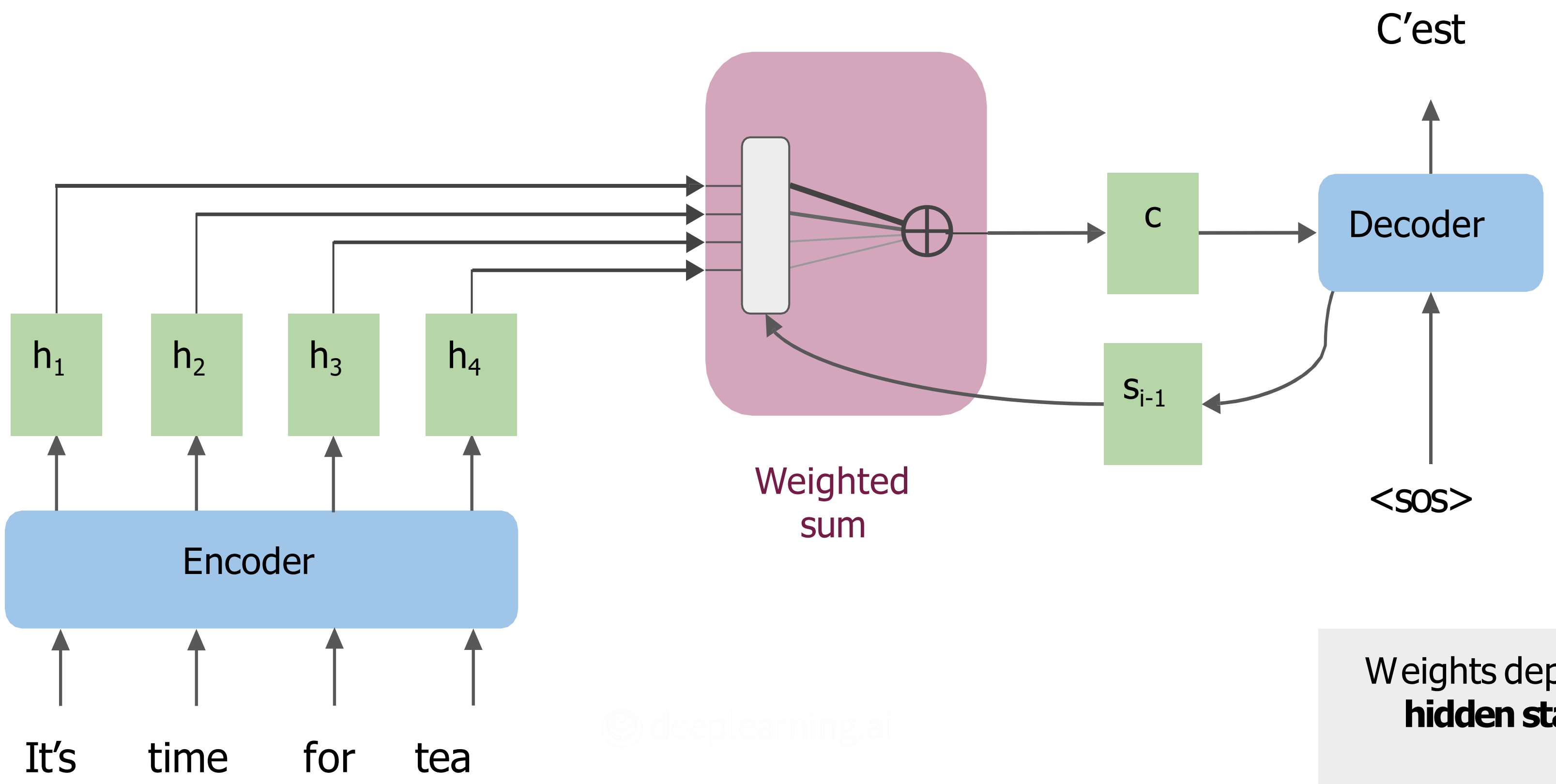


How to use all the hidden states?



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

Queries, Keys, Values and Attention

- Queries, Keys, Values

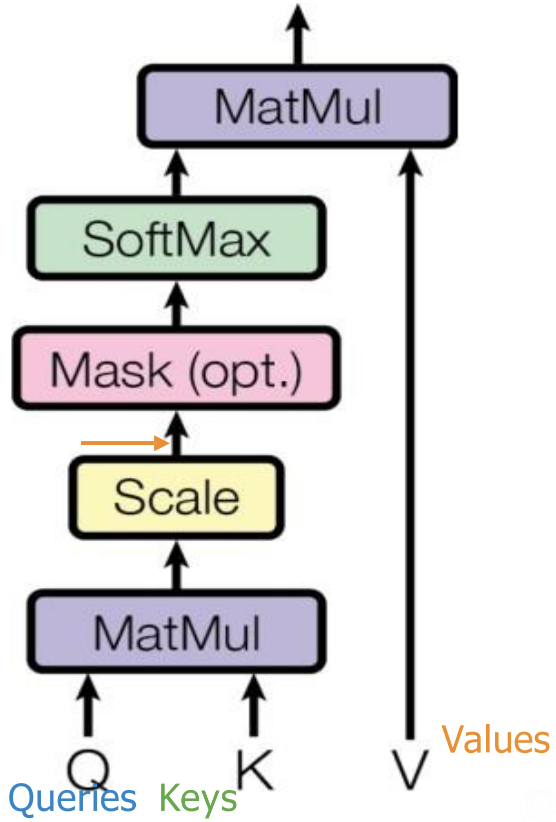
Query

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, …,]

Similarity is used in for weighted sum

Scaled dot-product attention



(Vaswani et al., 2017)

Similarity Between Q and K

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

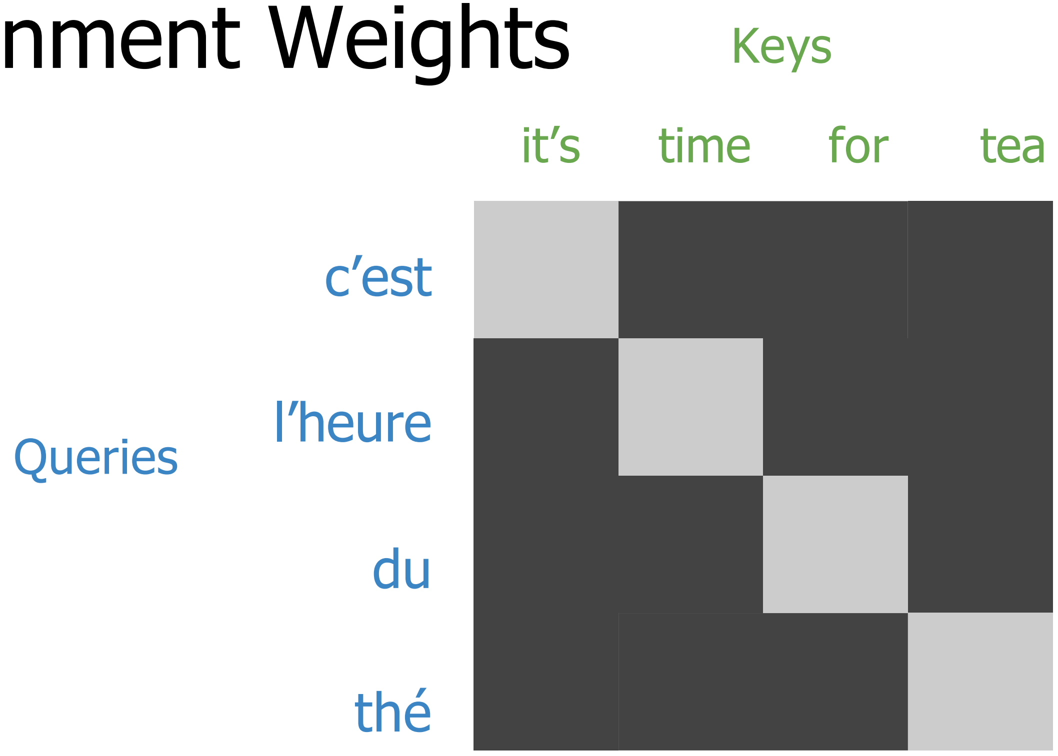
Weights for the weighted sum

Scale using the root of the key vector size

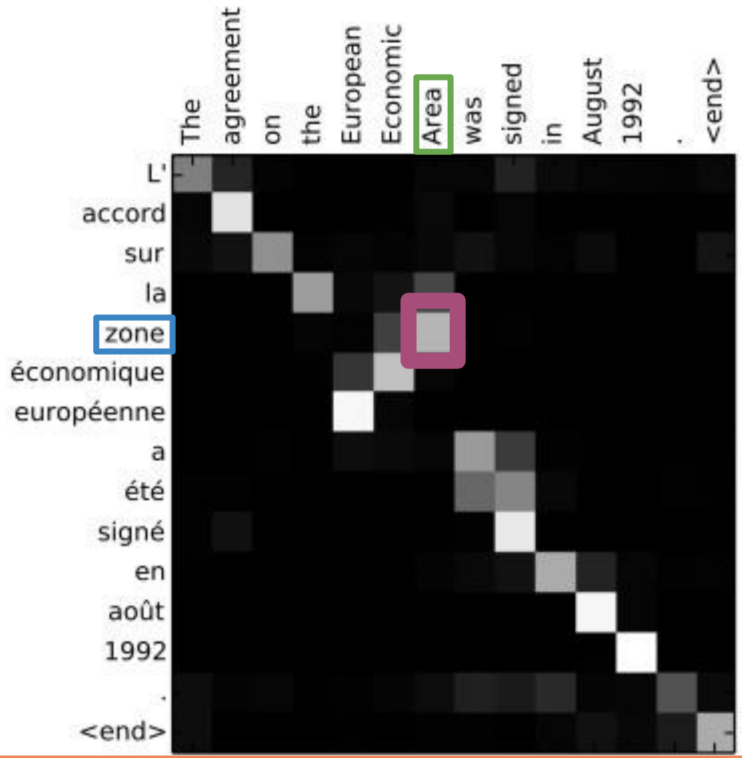
Weighted sum of values V

Just two matrix multiplications and a Softmax!

Alignment Weights



Similar words have large weights



- Flexible attention
- Works for languages with different grammar structures!

Summary

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- 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

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

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- 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

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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]

Padding

<EOS>

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 0]

Padding

<EOS>

Teacher Forcing

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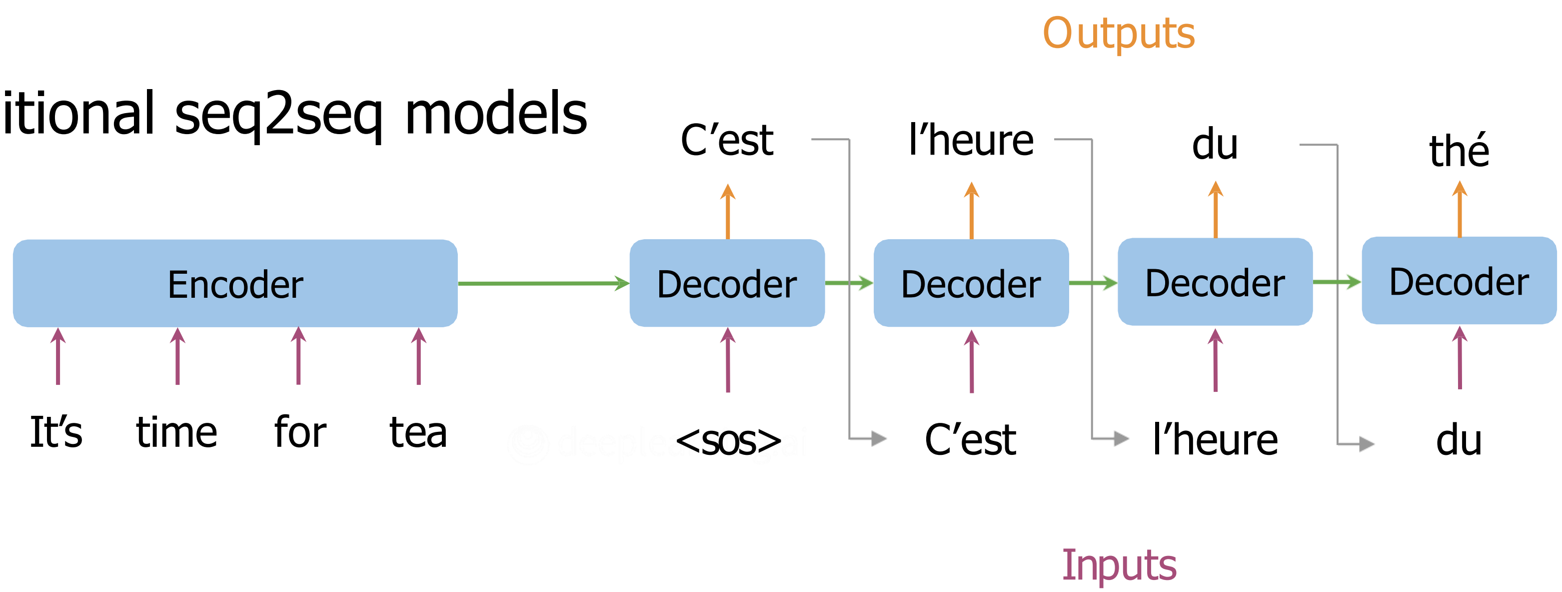
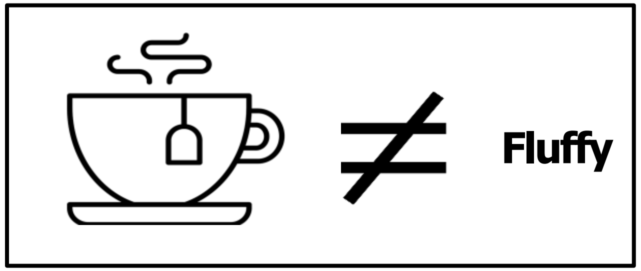
- Training for NMT
- Teacher forcing

- Traditional seq2seq models



Training seq2seq models



Targets C’est l’heura du thé

Yes! No... Even worse lol, no

Output ✓C’est ✗un ✗chat ✗duveteux

Decoder Decoder Decoder Decoder

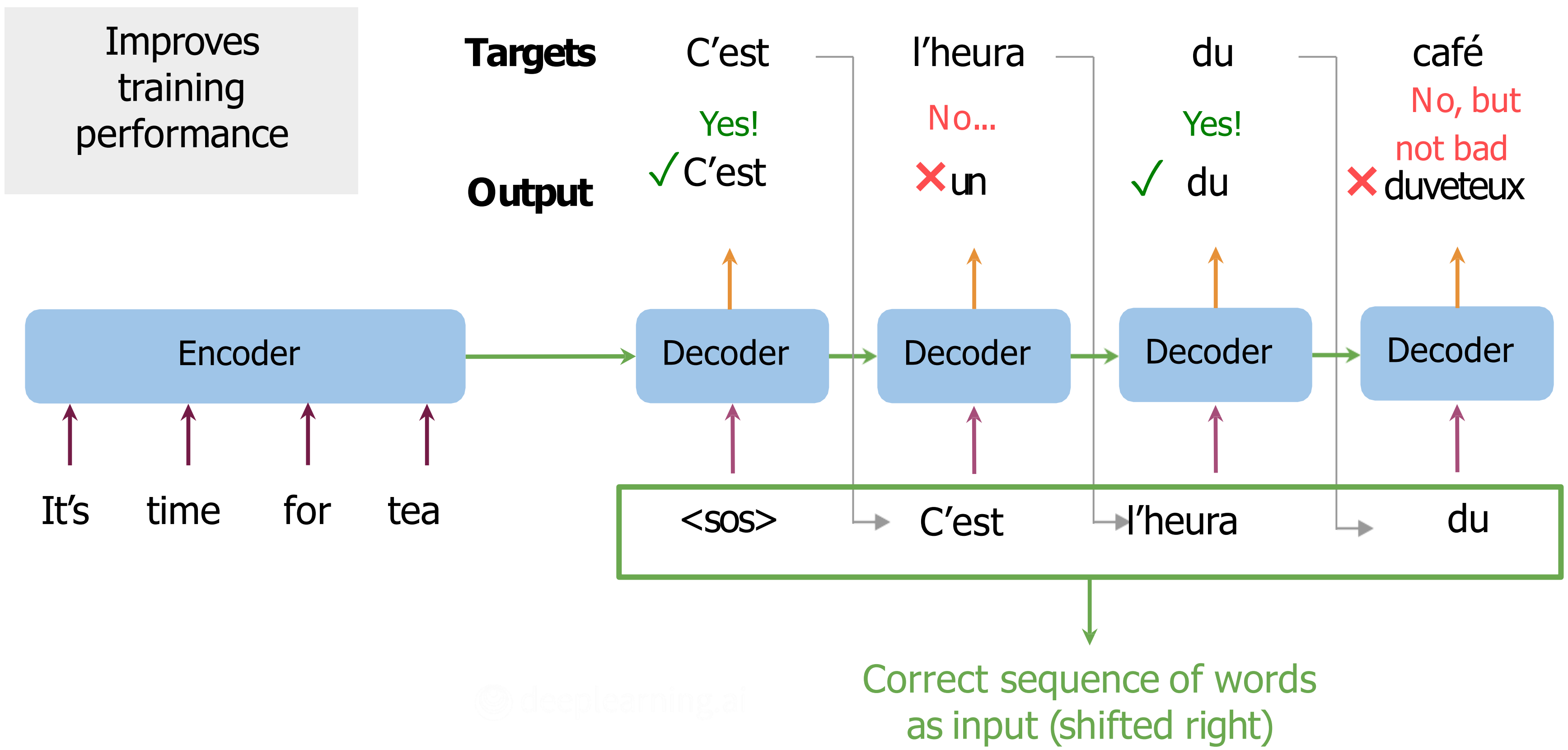
Encoder

It’s time for tea

<sos> C’est ✗un ✗chat

Errors from early steps propagate

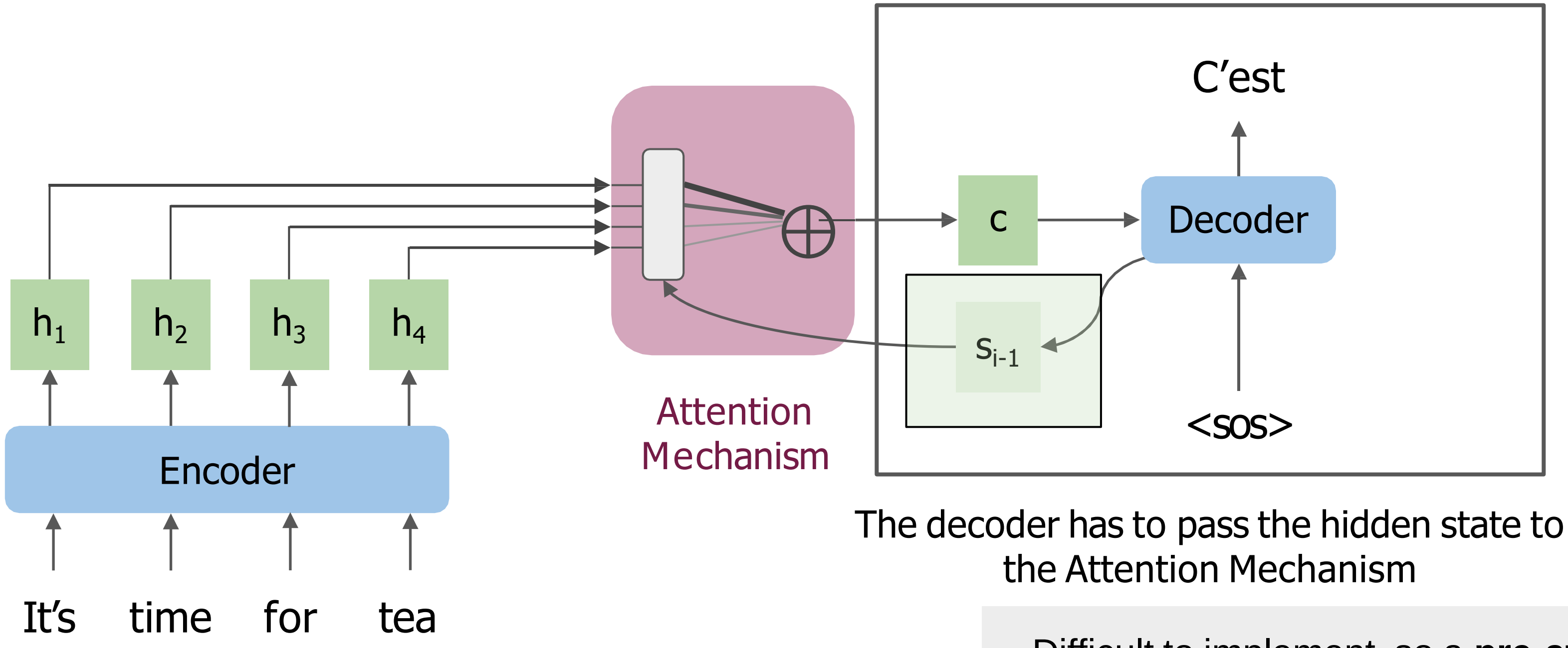
Teacher Forcing



Neural Machine Translation Model with Attention

- How everything fits together
- NMT model in detail

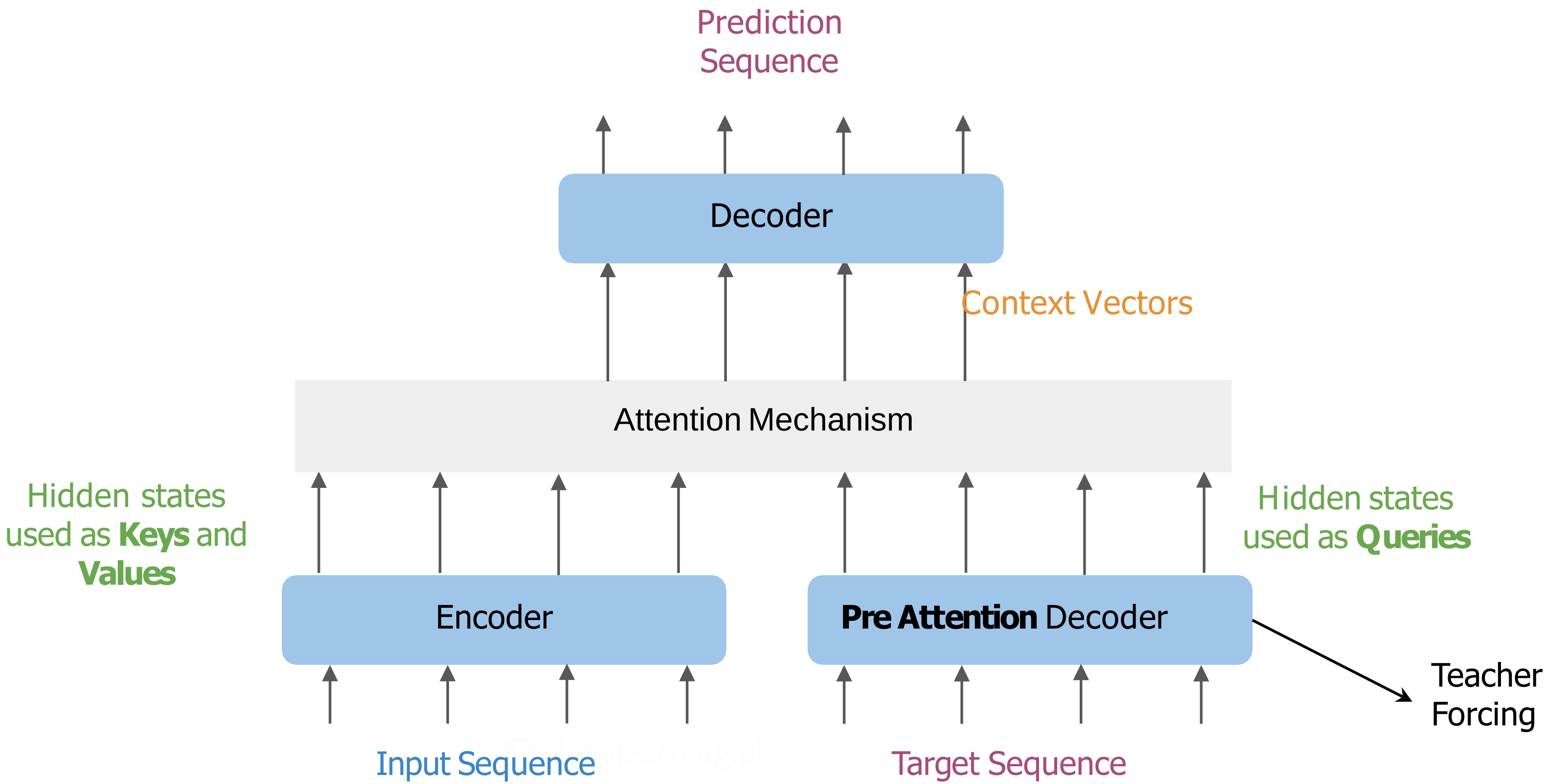
- NMT Model



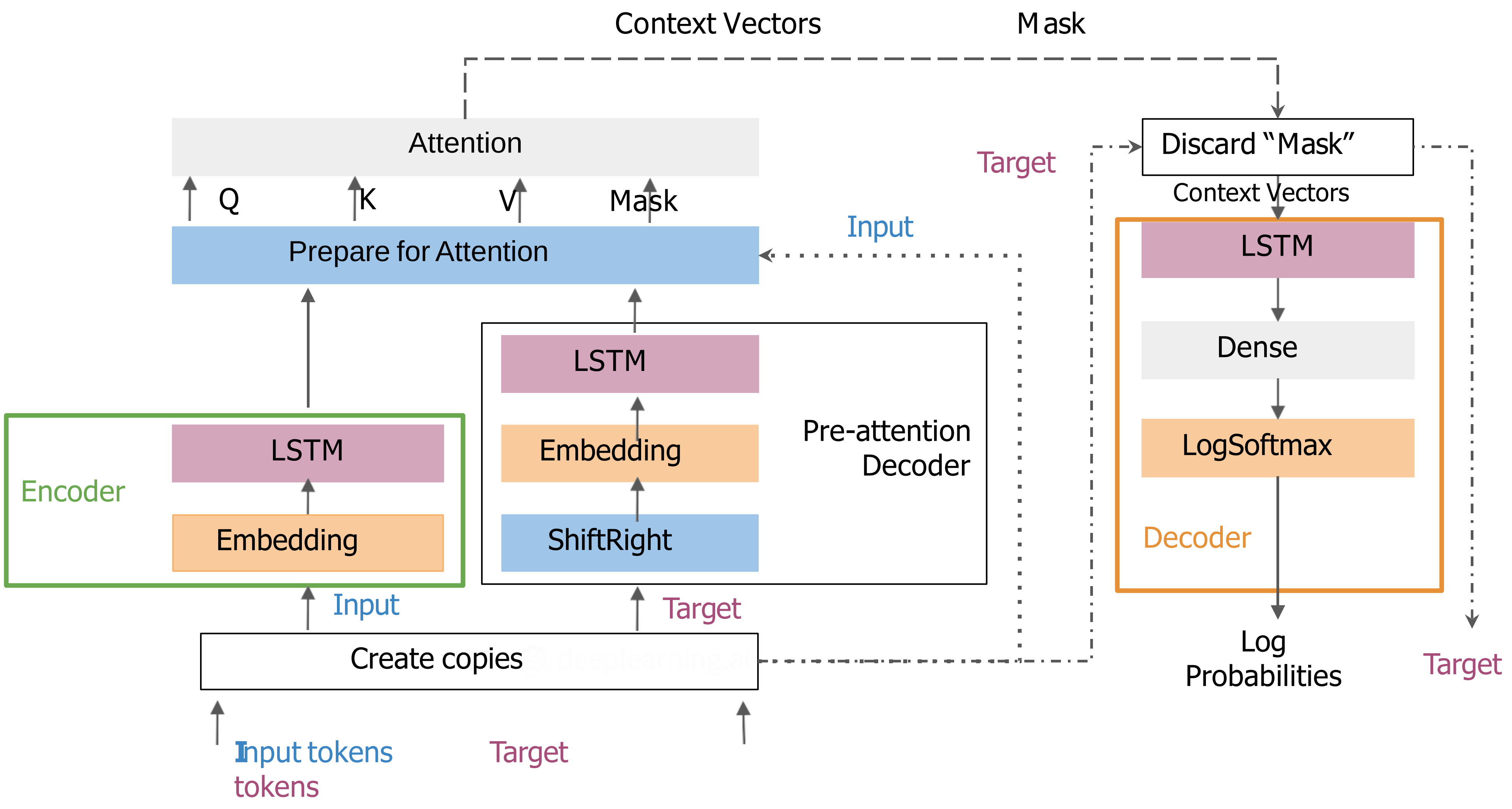
The decoder has to pass the hidden state to the Attention Mechanism

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

Neural Machine Translation Model

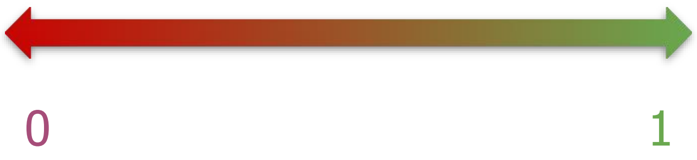


Neural Machine Translation Model



BLEU Score

- **Bi**Lingual **E**valuation **U**nderstudy
- Compares candidate translations to reference (human) translations The closer to **1**, the better



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

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

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

Better than the previous implementation version!

ROUGE

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

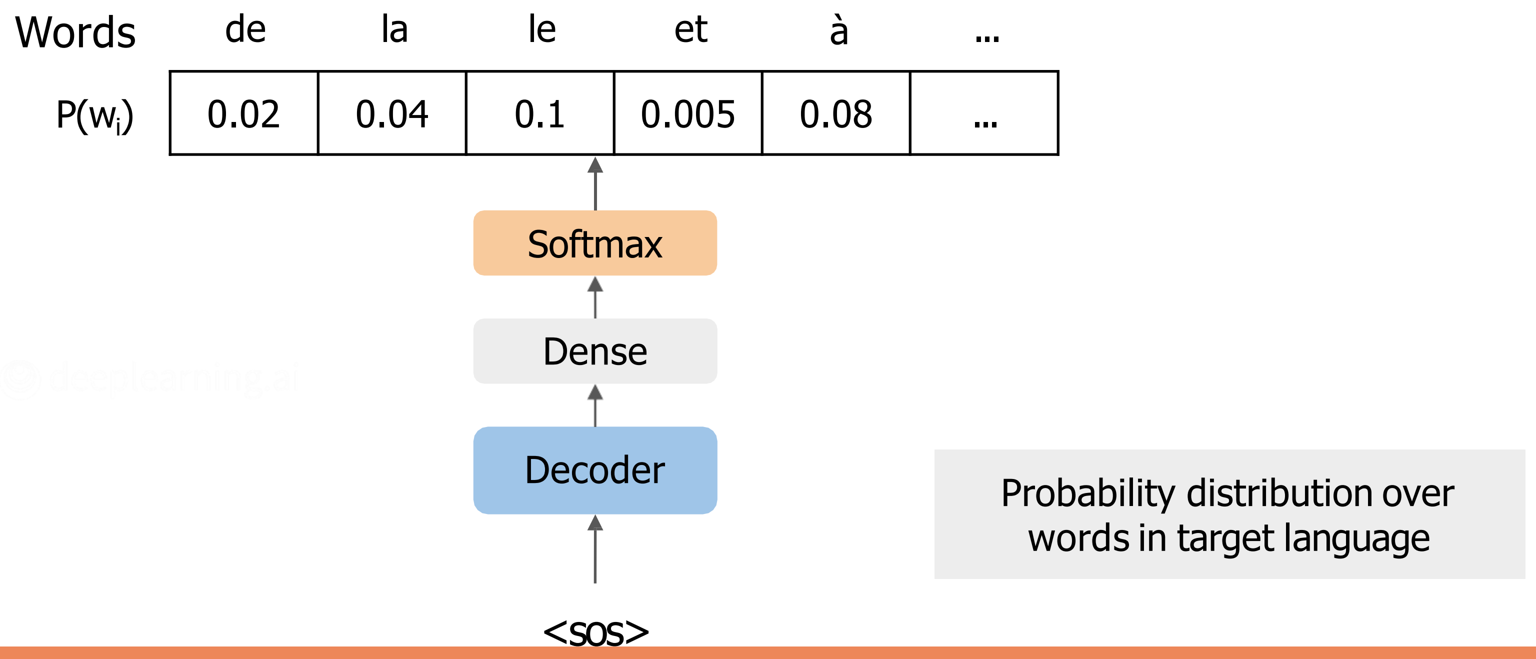
$$F1 = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \longrightarrow F1 = 2 \times \frac{\text{BLEU} \times \text{ROUGE-N}}{\text{BLEU} + \text{ROUGE-N}}$$

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

Sampling and Decoding

- Random sampling
- Temperature in sampling
- Greedy decoding

- Seq2Seq model



Greedy decoding

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- 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

Beam search

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

Solution

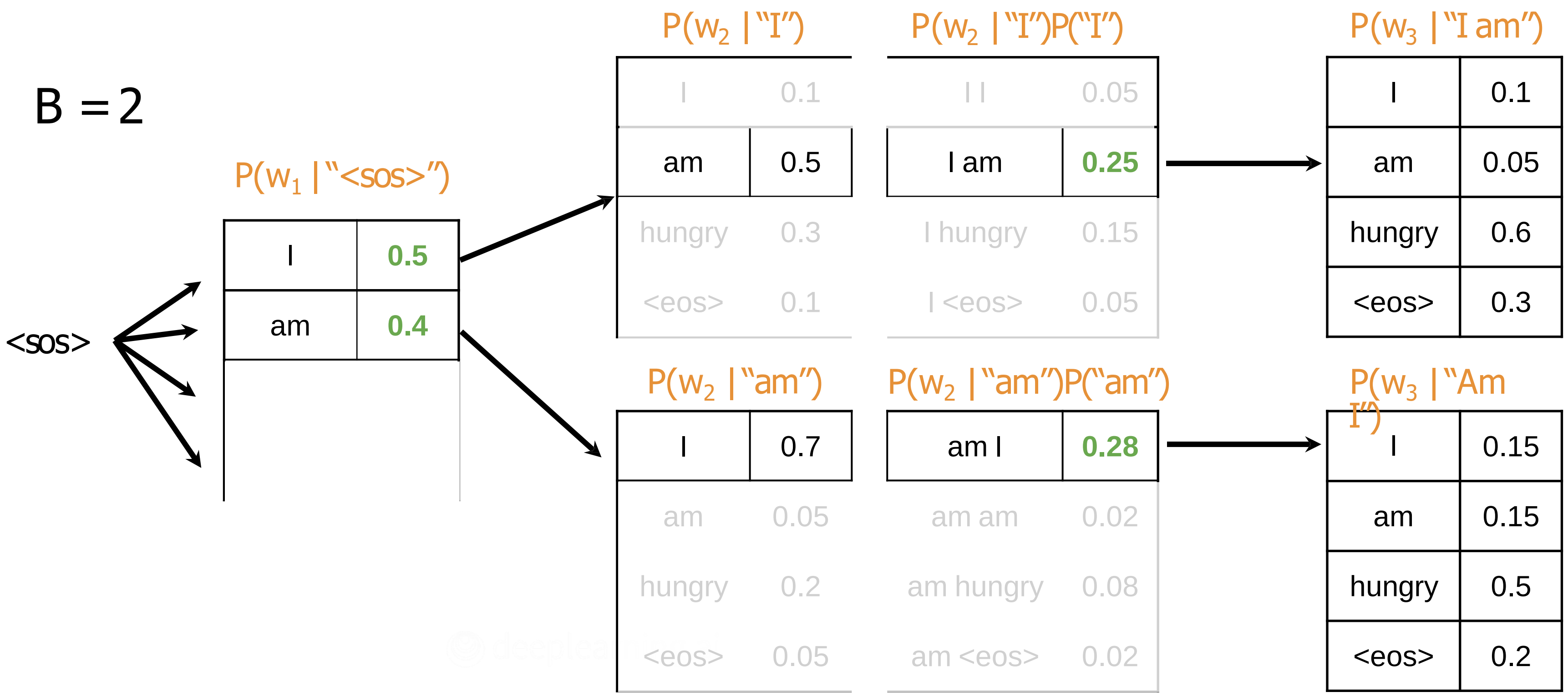
Calculate probability of multiple possible sequences

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>

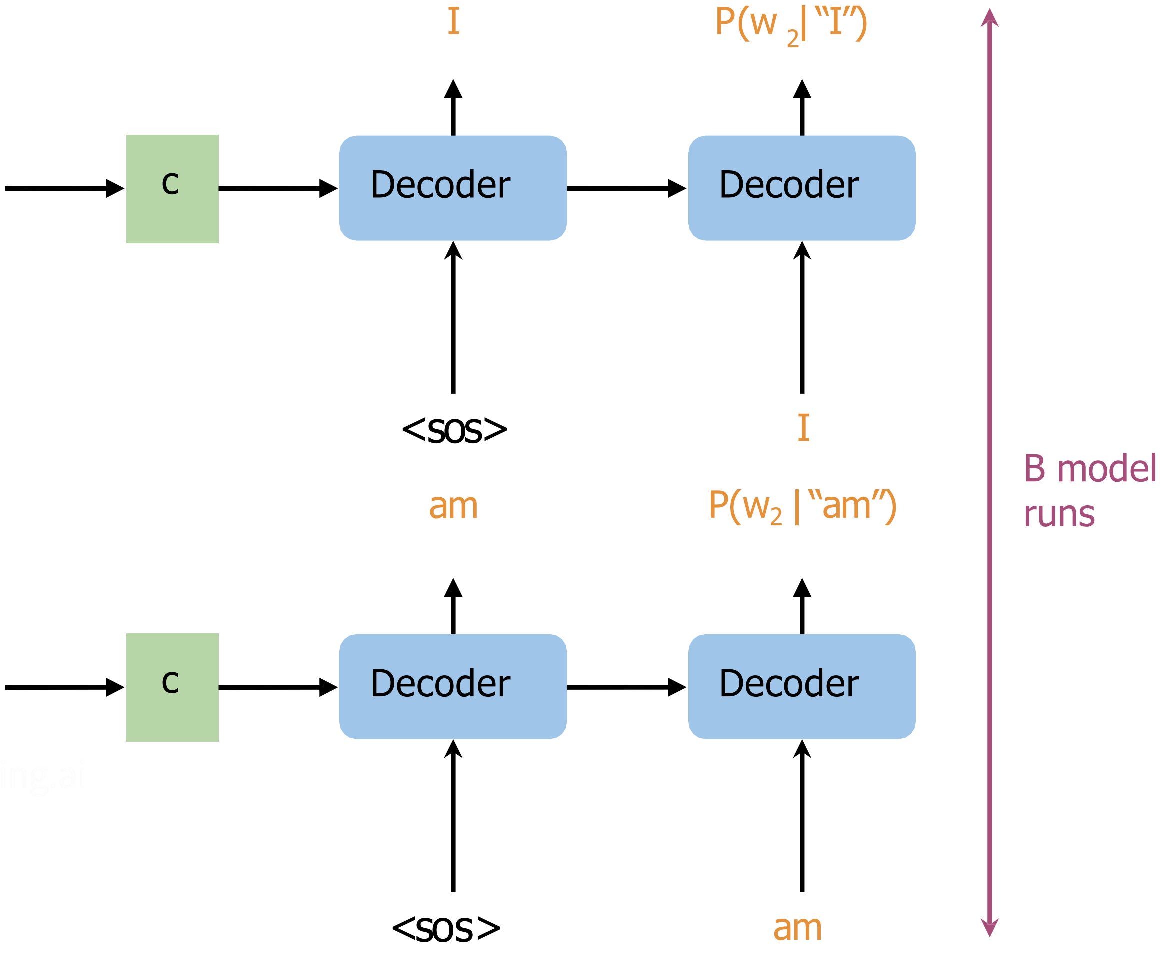
Beam search with **B=1** is **greedy decoding**.

Beam search example



Beam search decoding

Select B most probable words



Problems with beam search

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

Computationally expensive and consumes a lot of memory

- 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)

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

Find the candidate translation that maximizes

Compare with every other candidate

ROUGE score between pair of candidates

- Example: MBR Sampling

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

Compute average ROUGE

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

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

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

Repeat for every candidate

Select the candidate with the highest average