

Machine translation

Based on lecture by Ekaterina Artemova



- Encoder-decoder model
- Attention mechanism
- Machine translation quality metrics



Encoder-decoder model



Machine translation

English ▾



Hebrew ▾

hello world



שלום עולם



Community verified



Machine translation

- Popular and demanded task



Machine translation

- Popular and demanded task
- One of the first technologies in text preprocessing
- Georgetown–IBM experiment (1954)



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- Starting from 2016, neural machine translation (NMT) – industrial standard



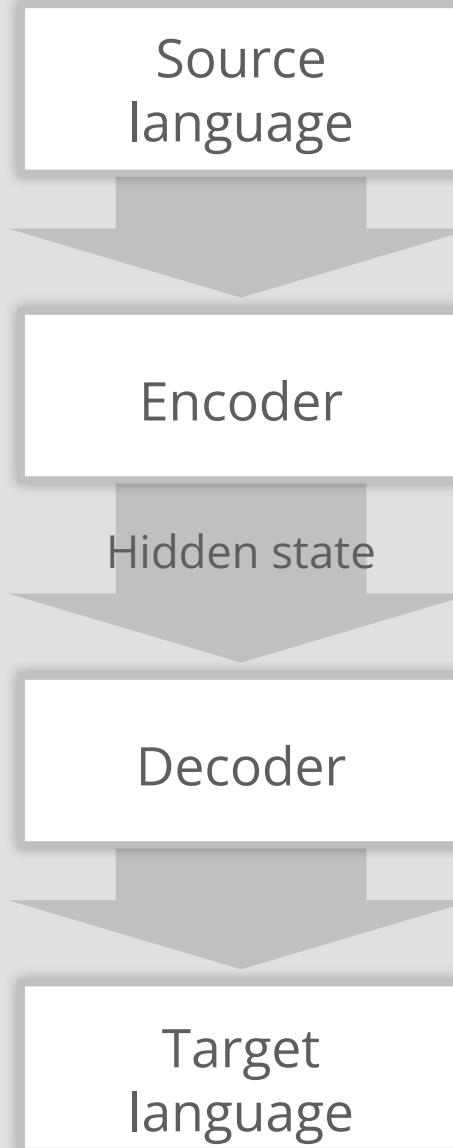
Machine translation

- Popular and demanded task
- One of the first technologies in text preprocessing
- Georgetown–IBM experiment (1954)
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- Starting from 2016, neural machine translation (NMT) – industrial standard
- As for now, MT works good for simple or formal texts, MT for fiction is still a problem



Encoder-decoder model

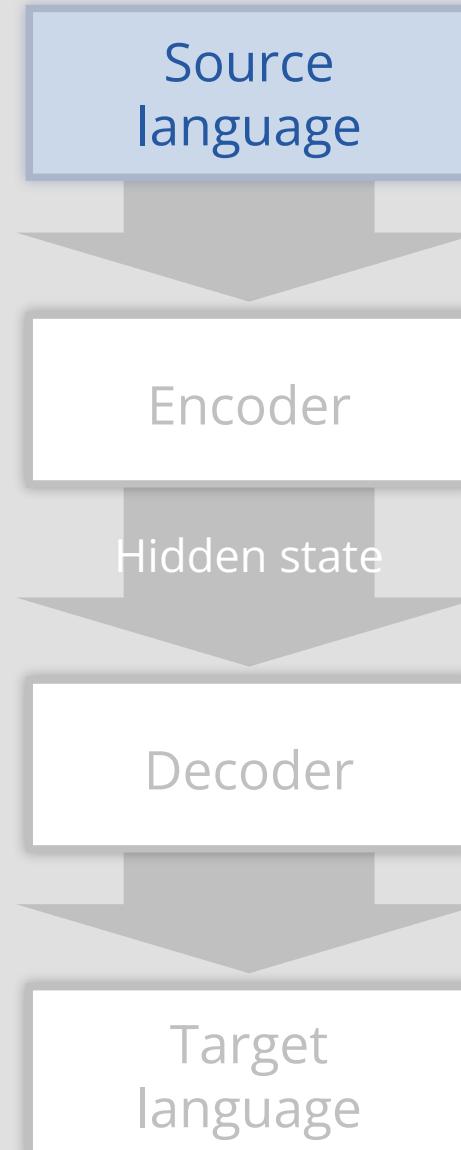
- Problem: translate text from one language to another



Problem formulation

- Given a sentence in source language:

$$\mathbf{x}_{source} = (x_1, \dots, x_n), x_i \in V_{source}$$



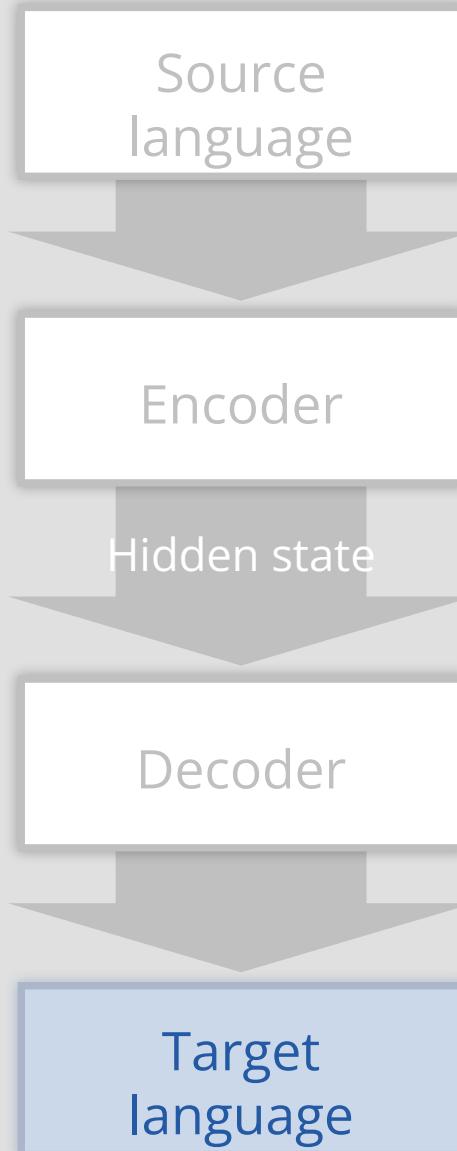
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- and the sentence in the target language:

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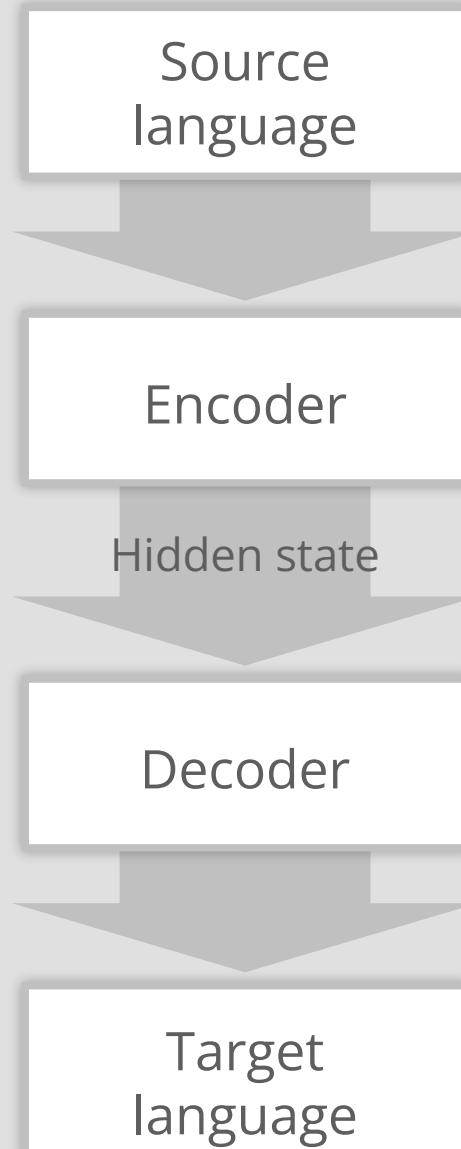
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- A parallel corpus **C** of pairs (\mathbf{x}, \mathbf{y})



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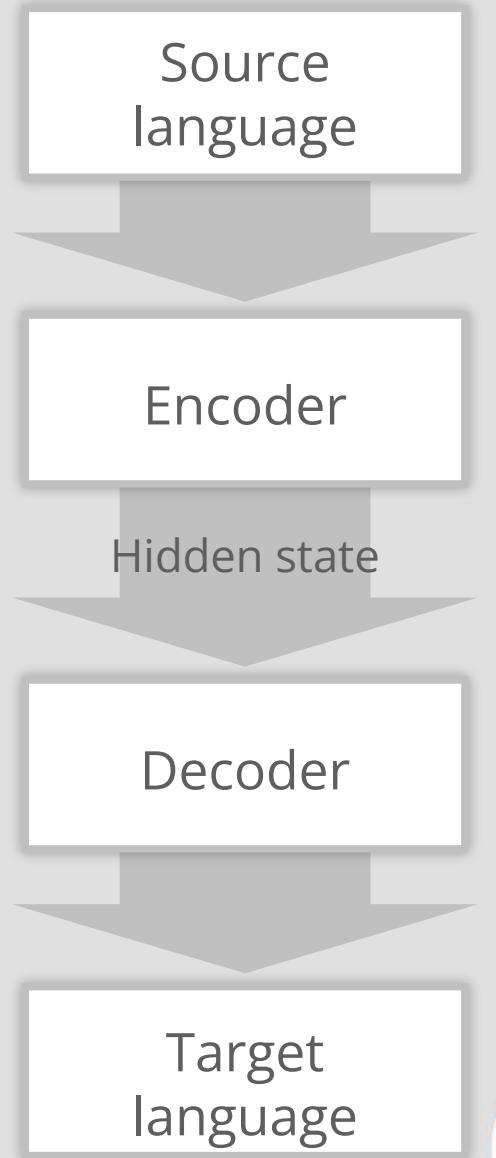
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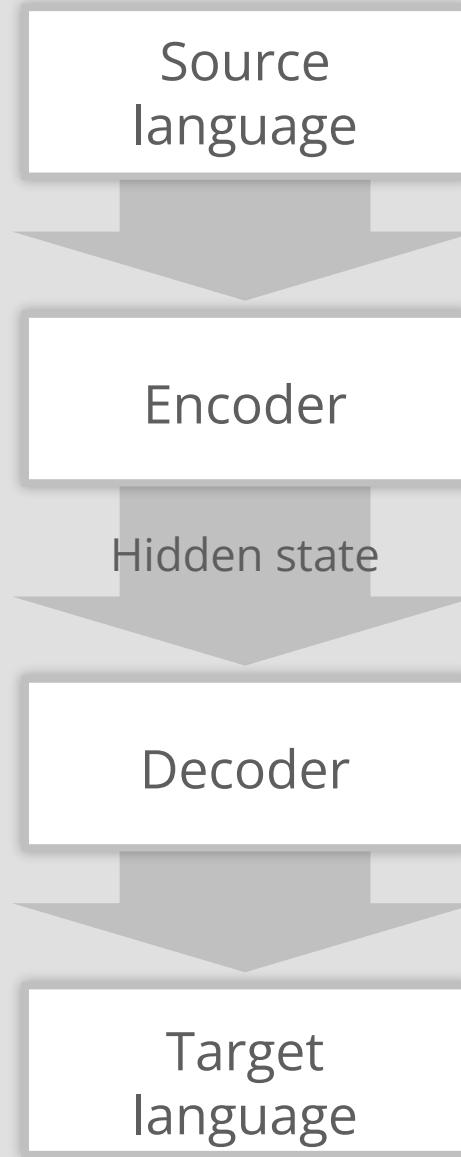
- A parallel corpus **C** of pairs (\mathbf{x}, \mathbf{y})
- Maximize the likelihood $p(\mathbf{y} | \mathbf{x})$
- Loss function $\mathcal{L}_\theta = \sum_{\mathbf{x}, \mathbf{y} \in C} \log p(\mathbf{y} | \mathbf{x}; \theta)$



Problem formulation

- Probability of target sentence provided source sentence:

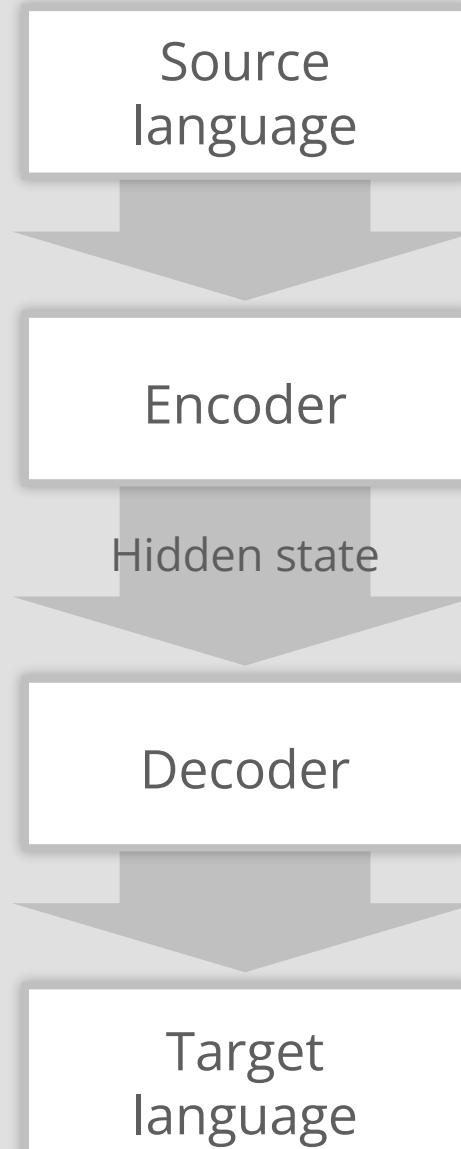
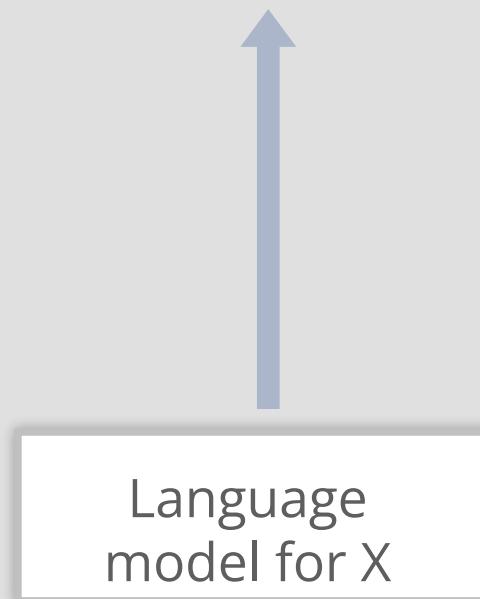
$$p(\mathbf{y}|\mathbf{x}; \theta) = \prod_{j=1}^m p(y_j|y_{<j}, \mathbf{x}; \theta)$$



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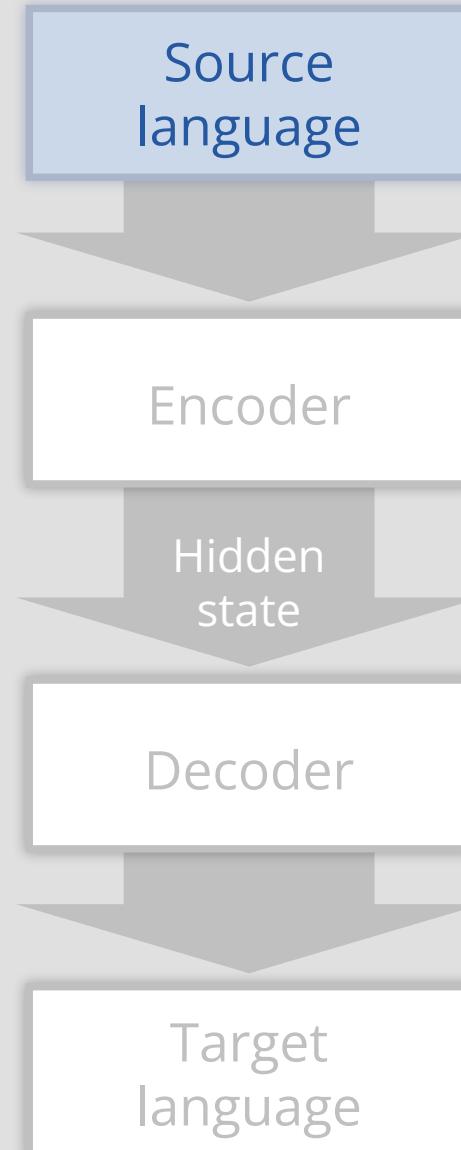
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Neural machine translation

- Input embeddings:

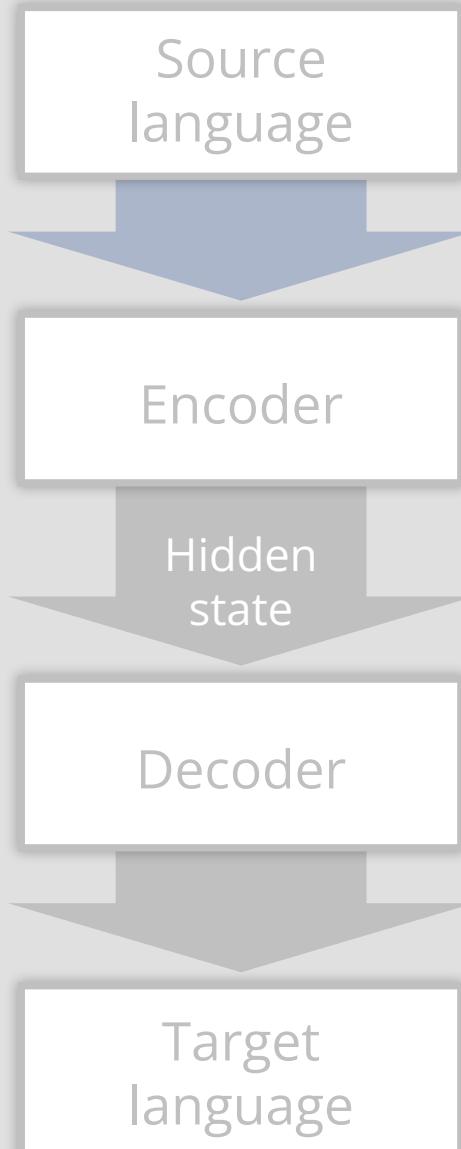
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Neural machine translation

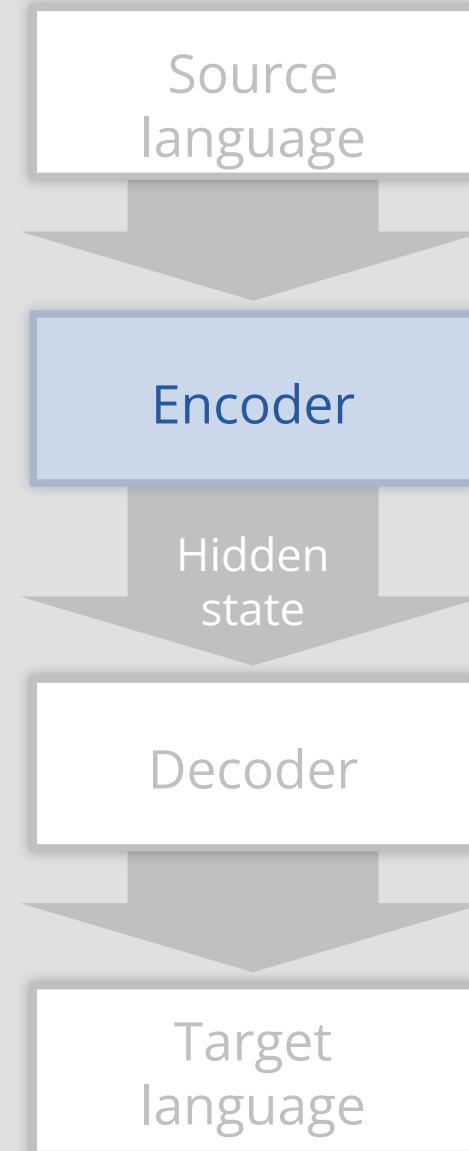
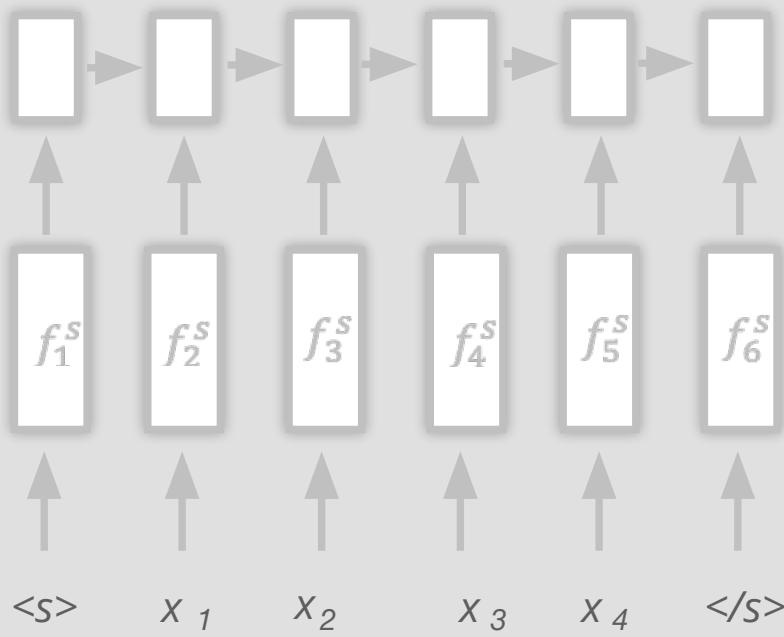
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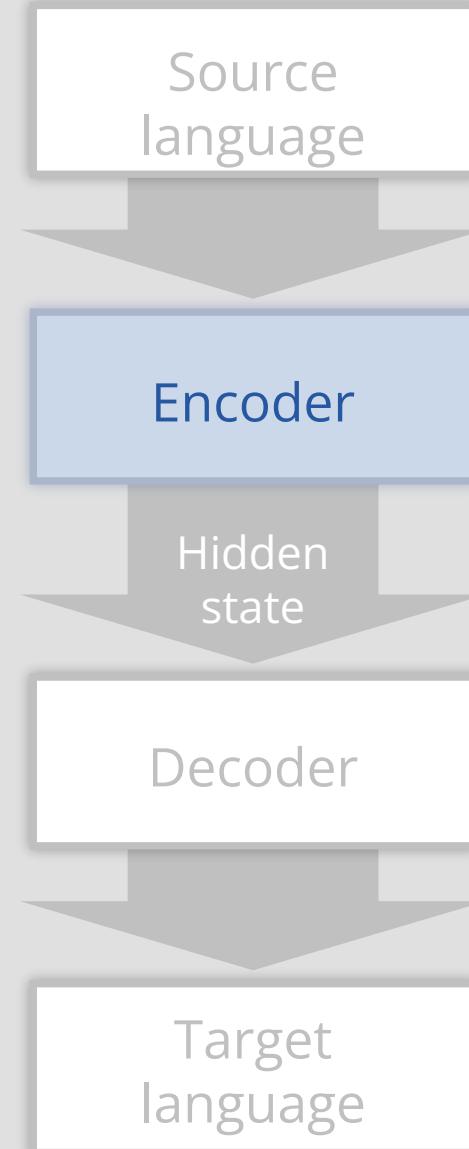
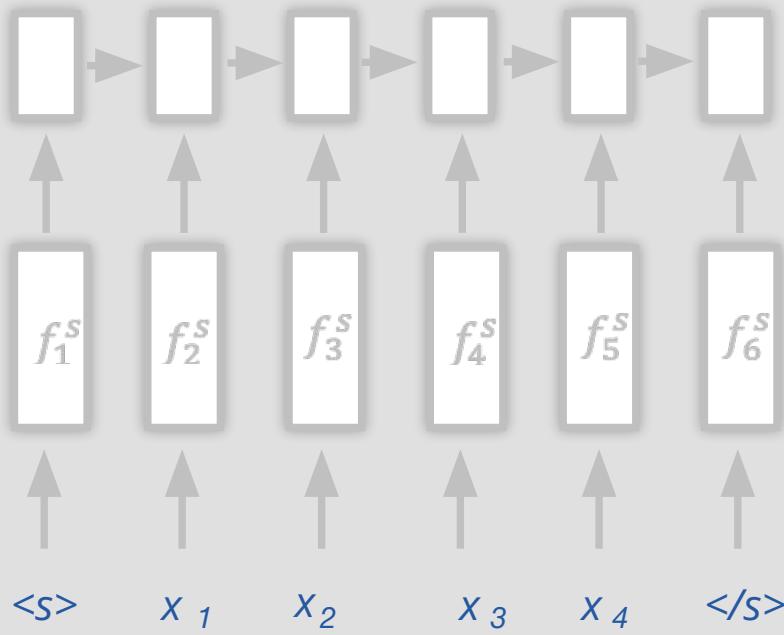
Neural machine translation

- Encoder architecture



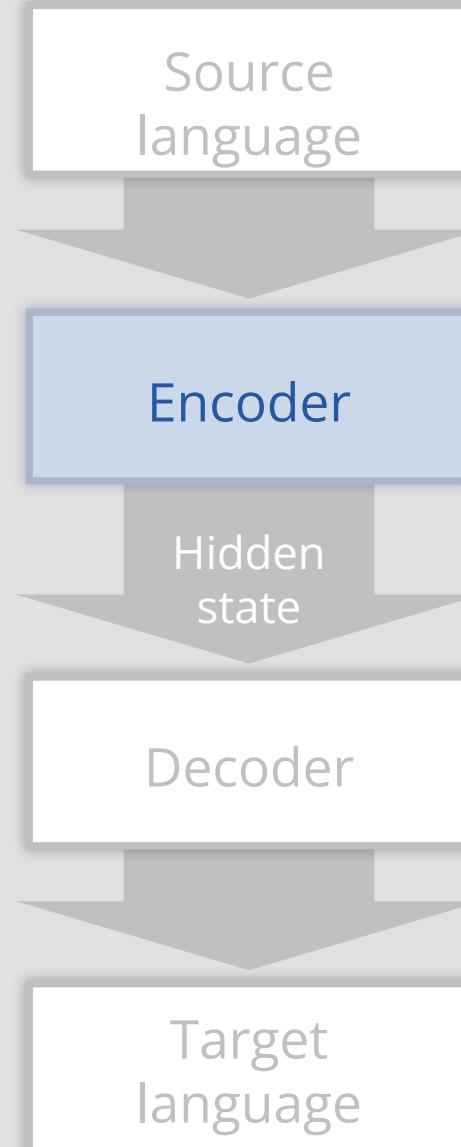
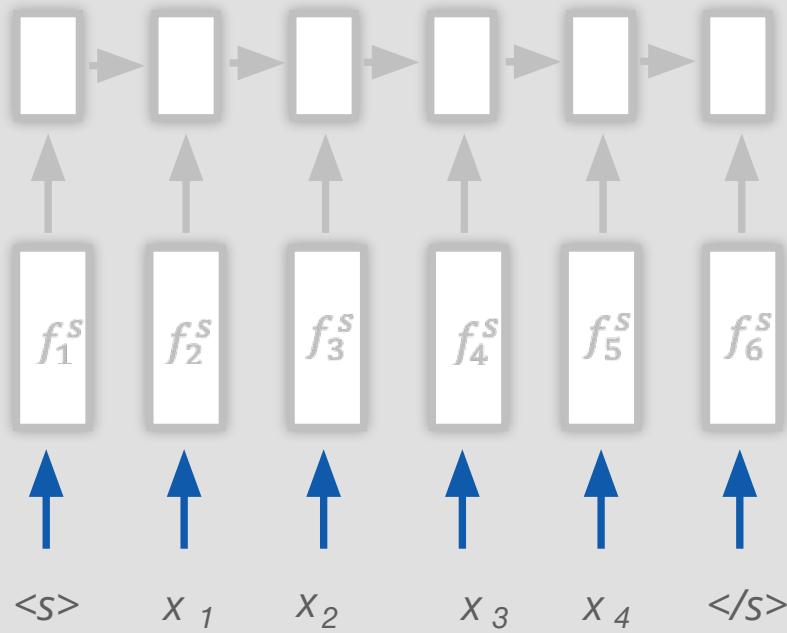
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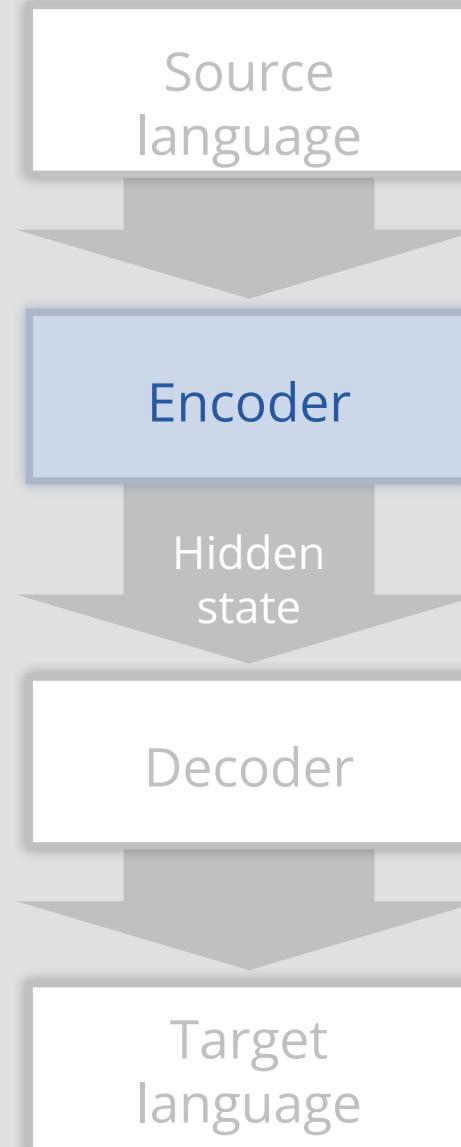
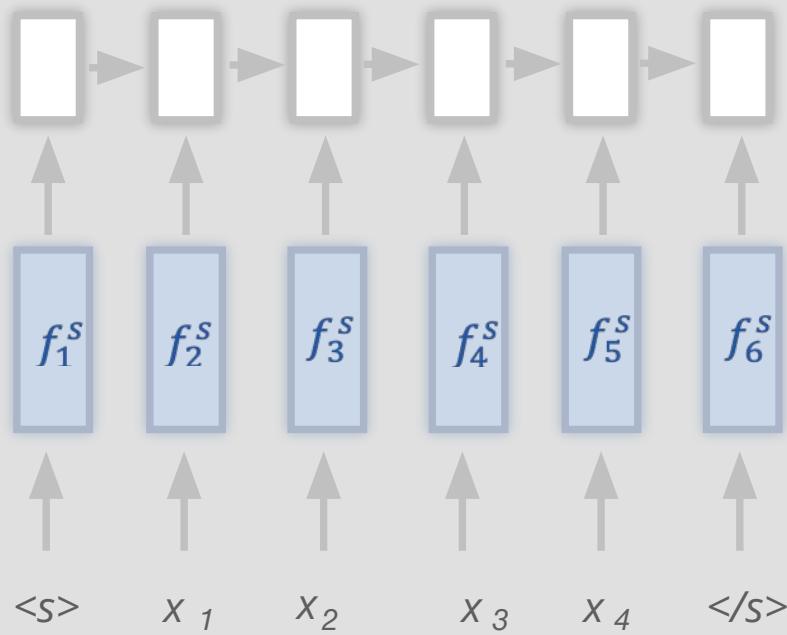
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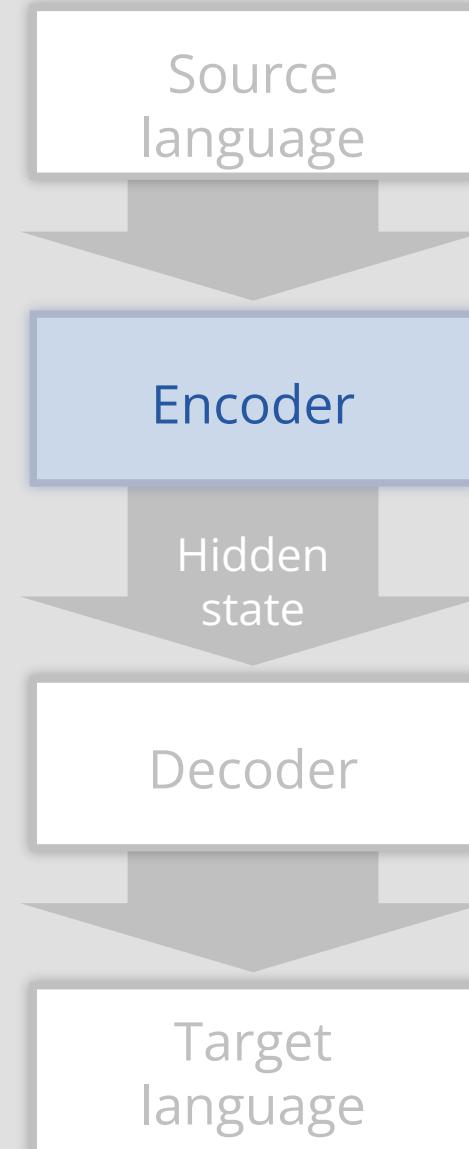
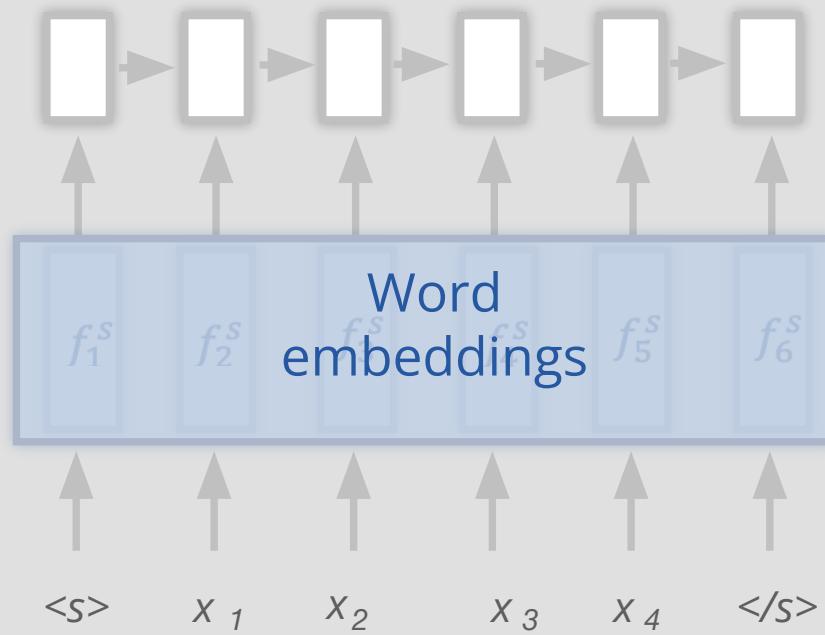
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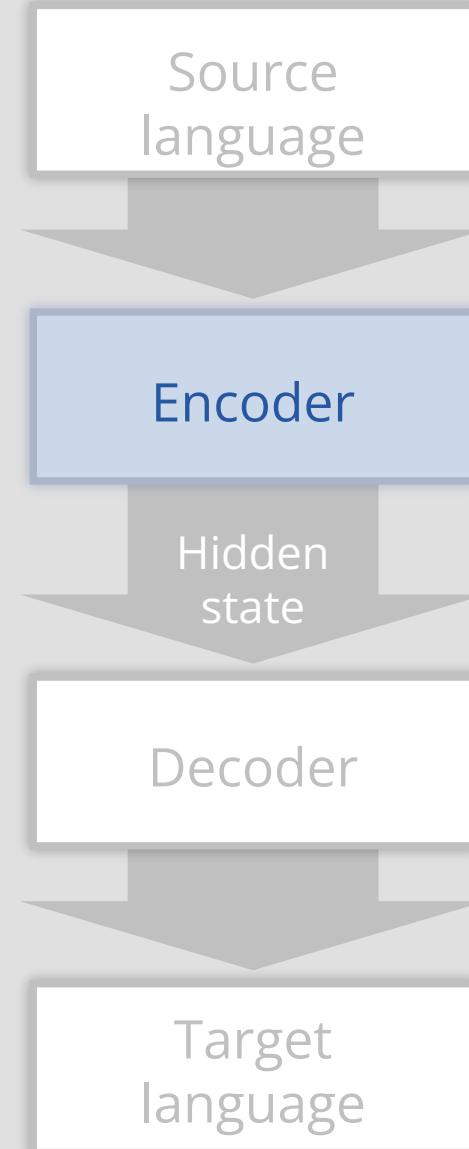
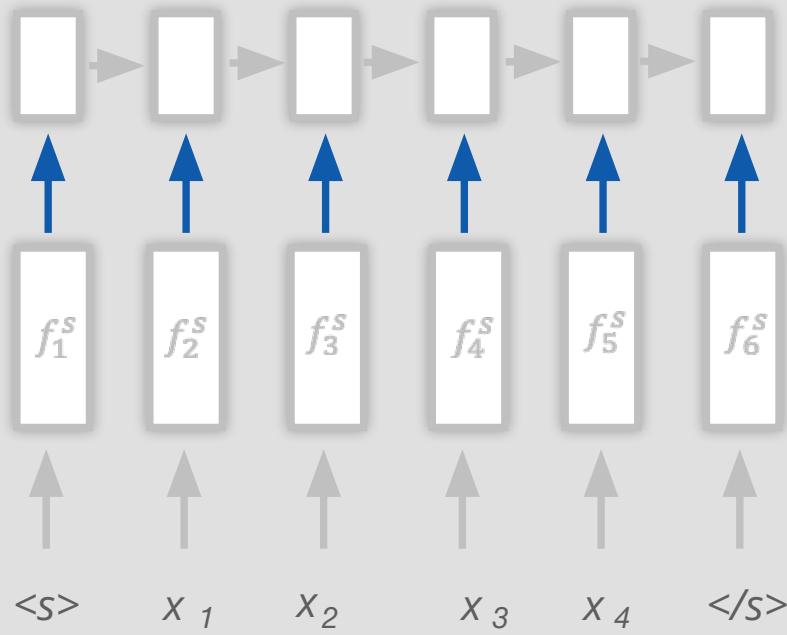
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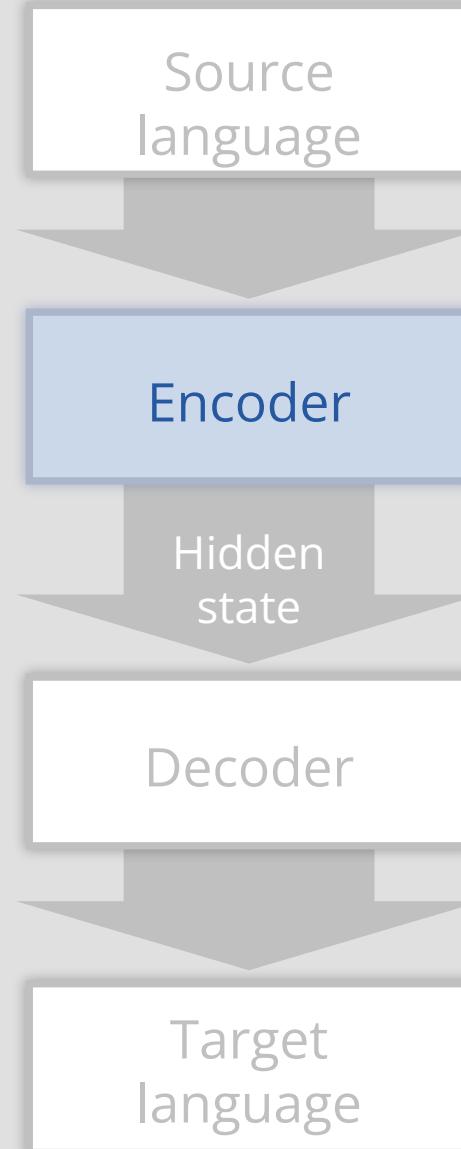
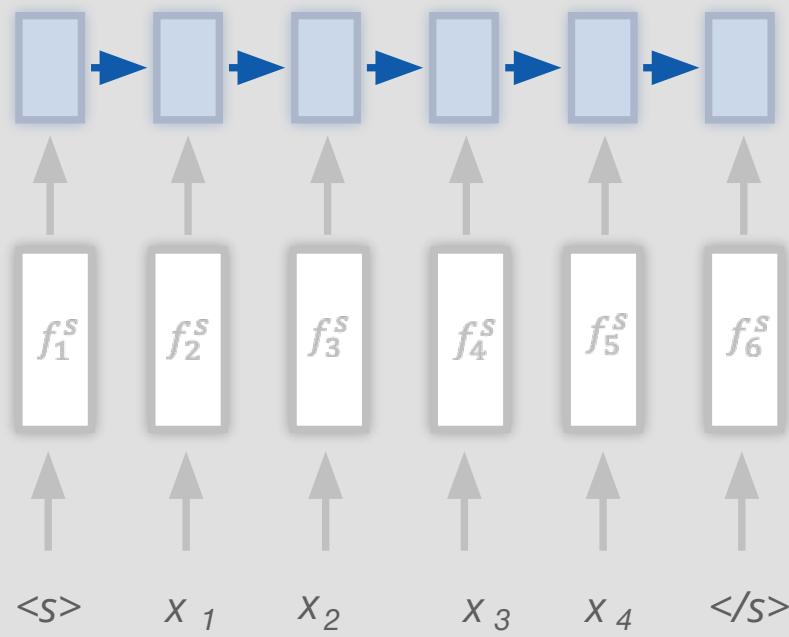
Neural machine translation

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Neural machine translation

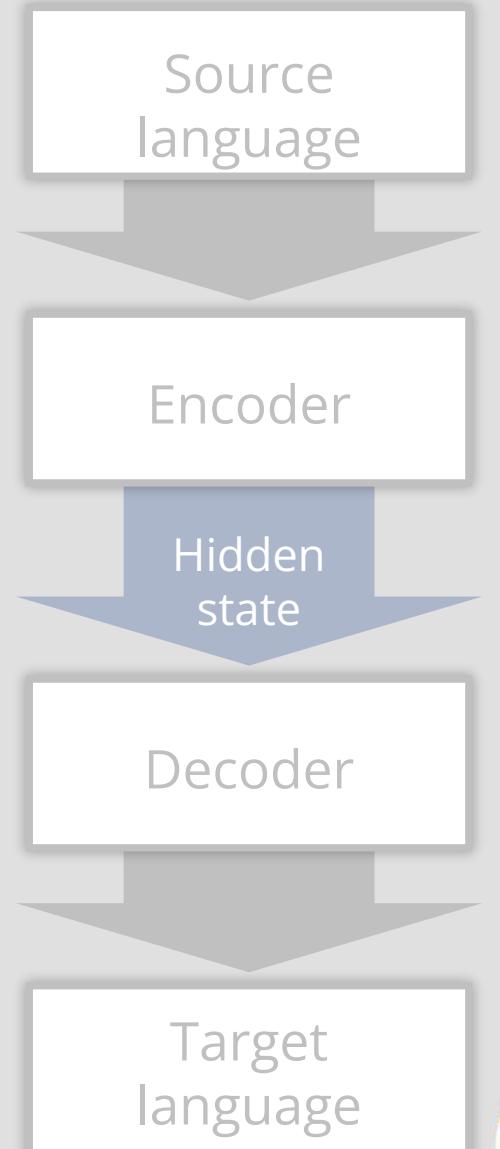
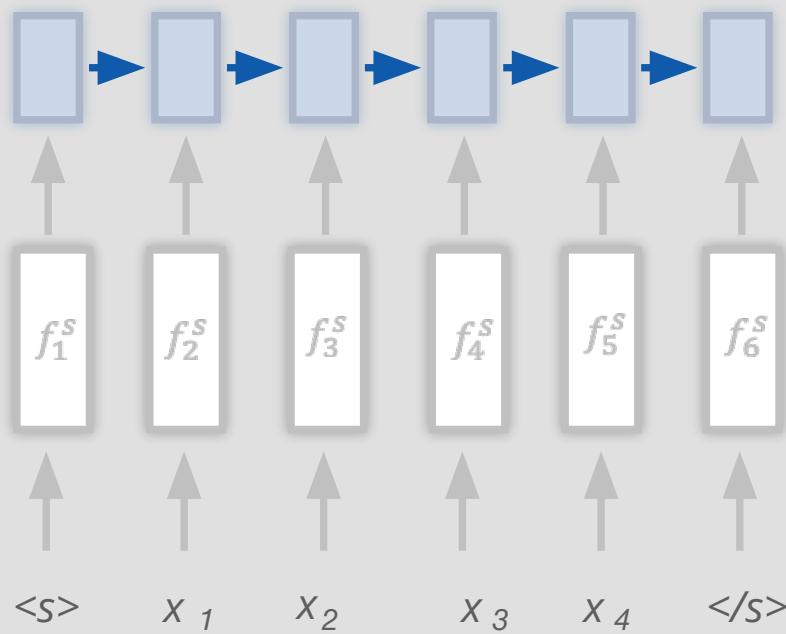
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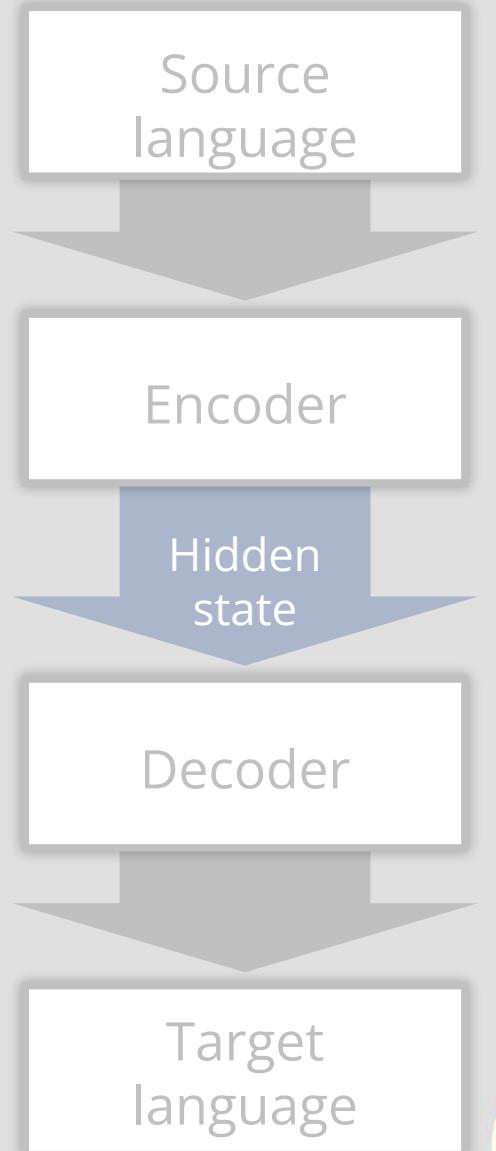
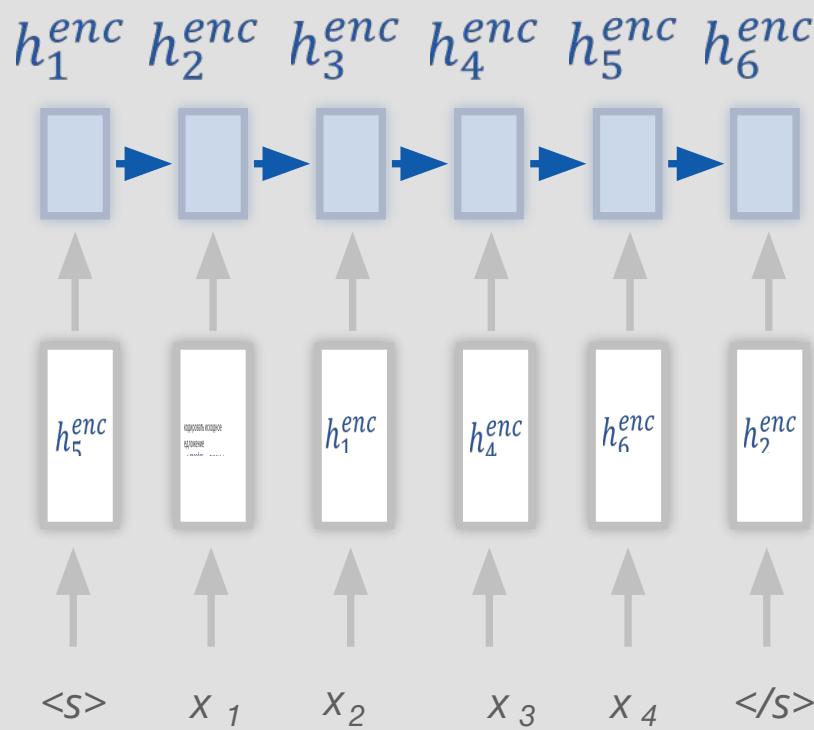
$$h^{encoder} = RNN(\mathbf{x})$$



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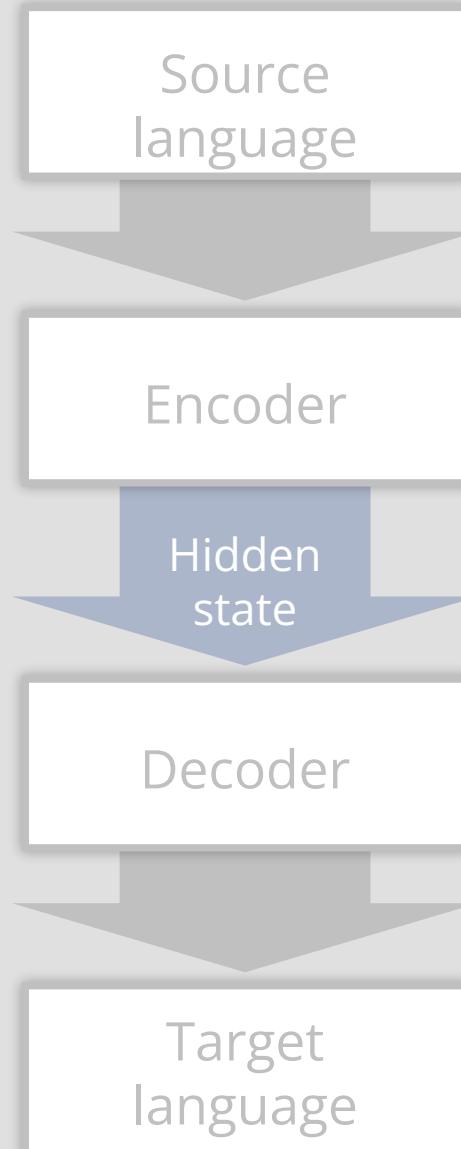
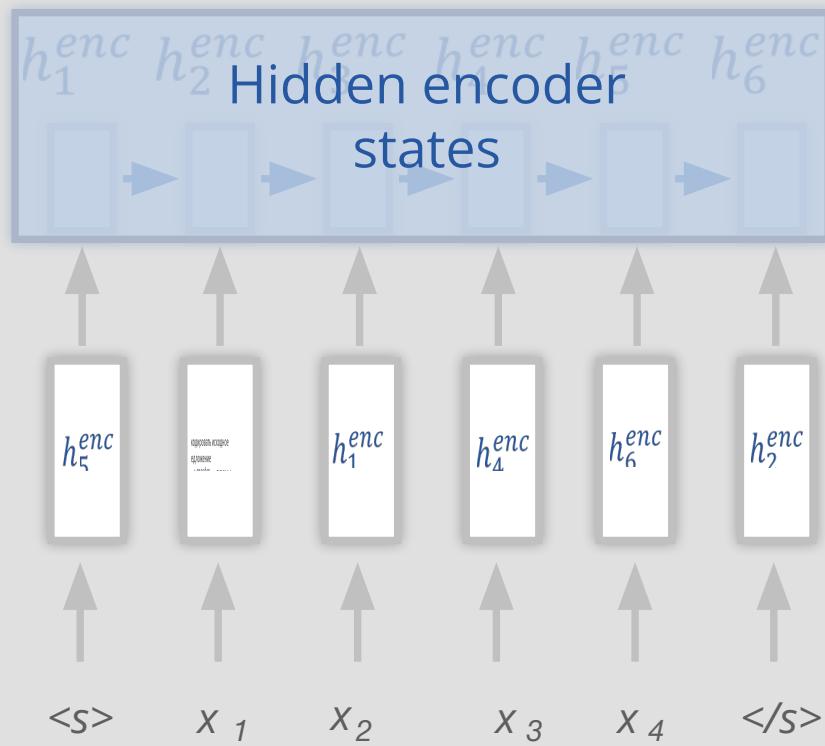
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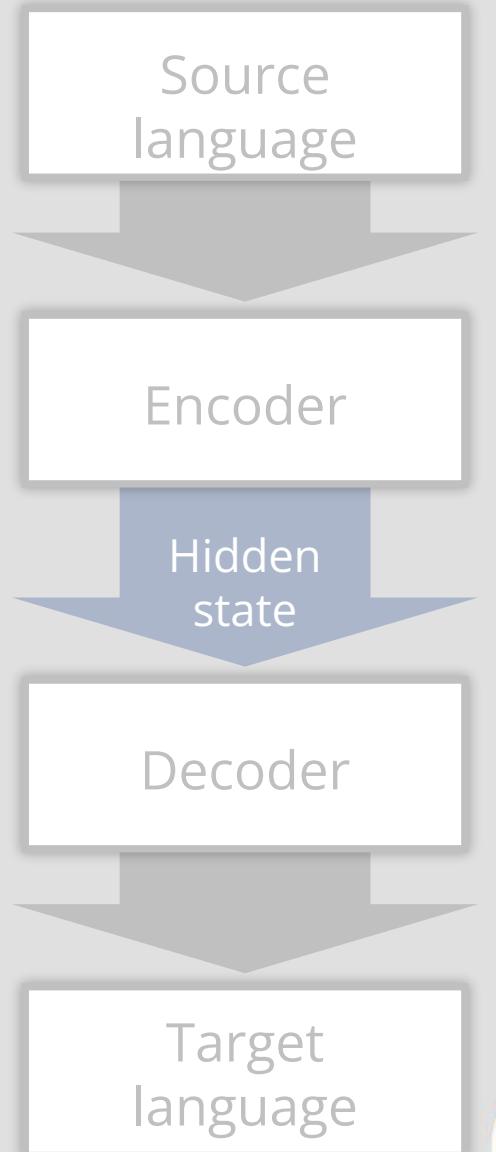
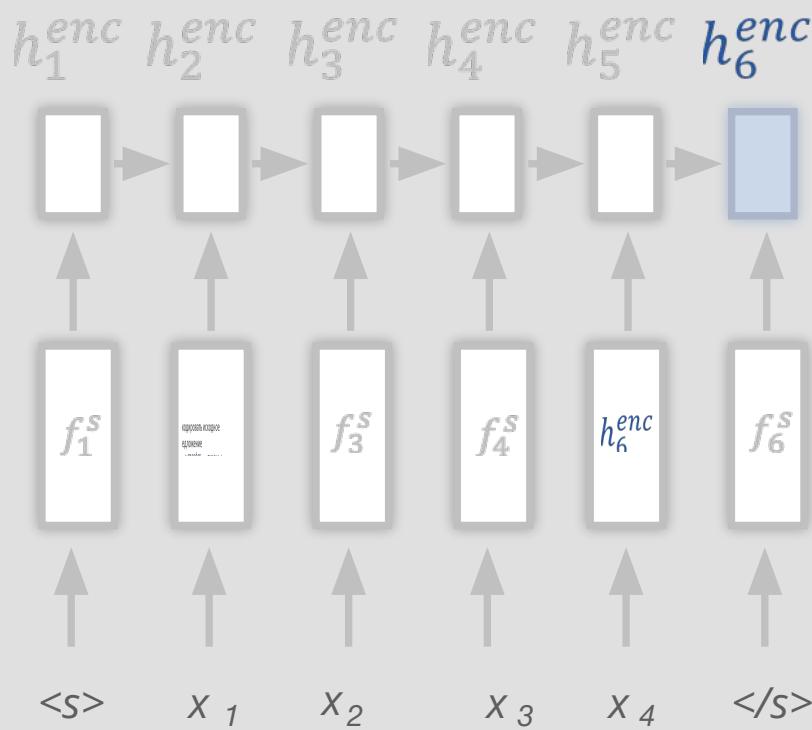
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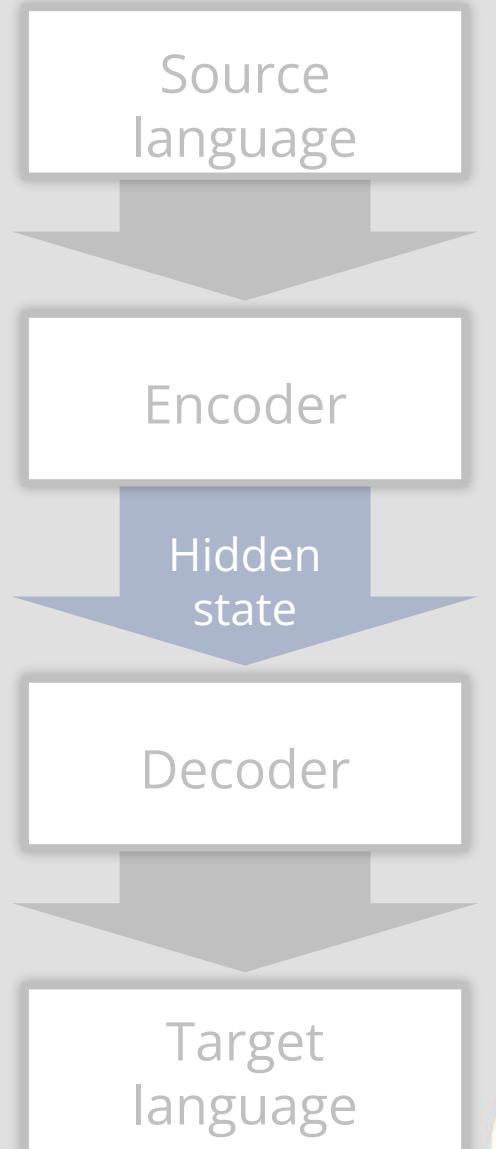
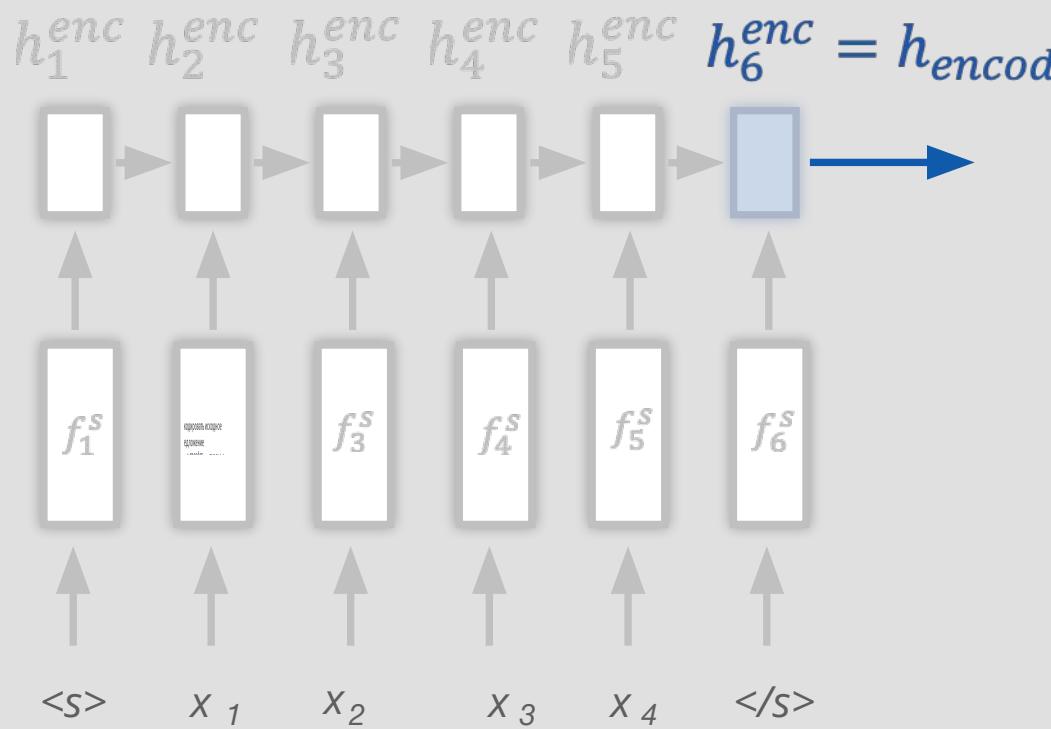
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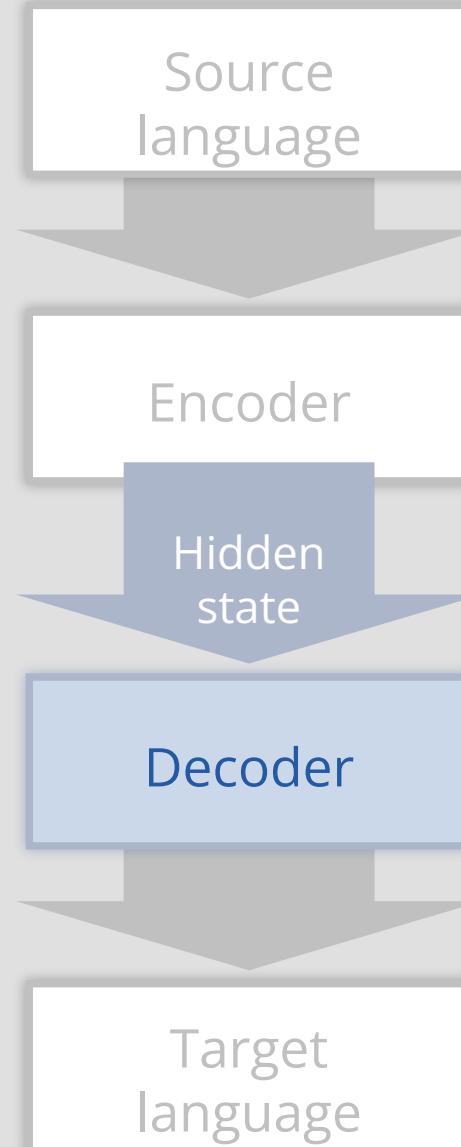
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Decoder architecture

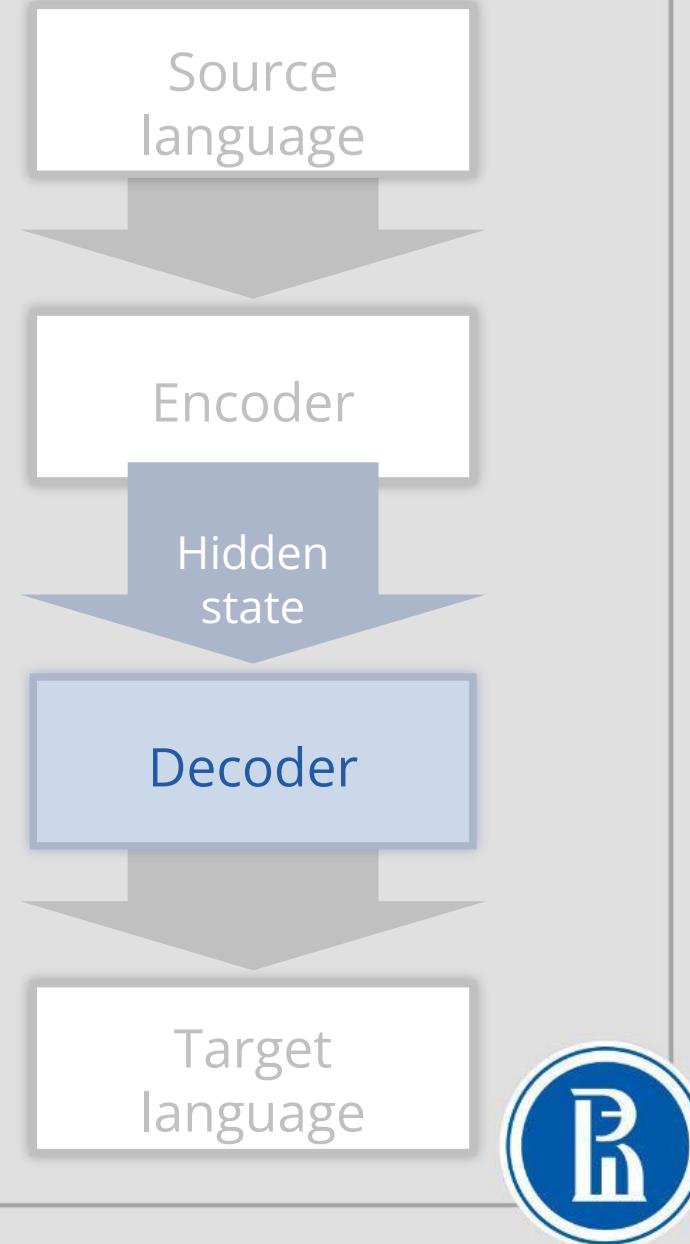
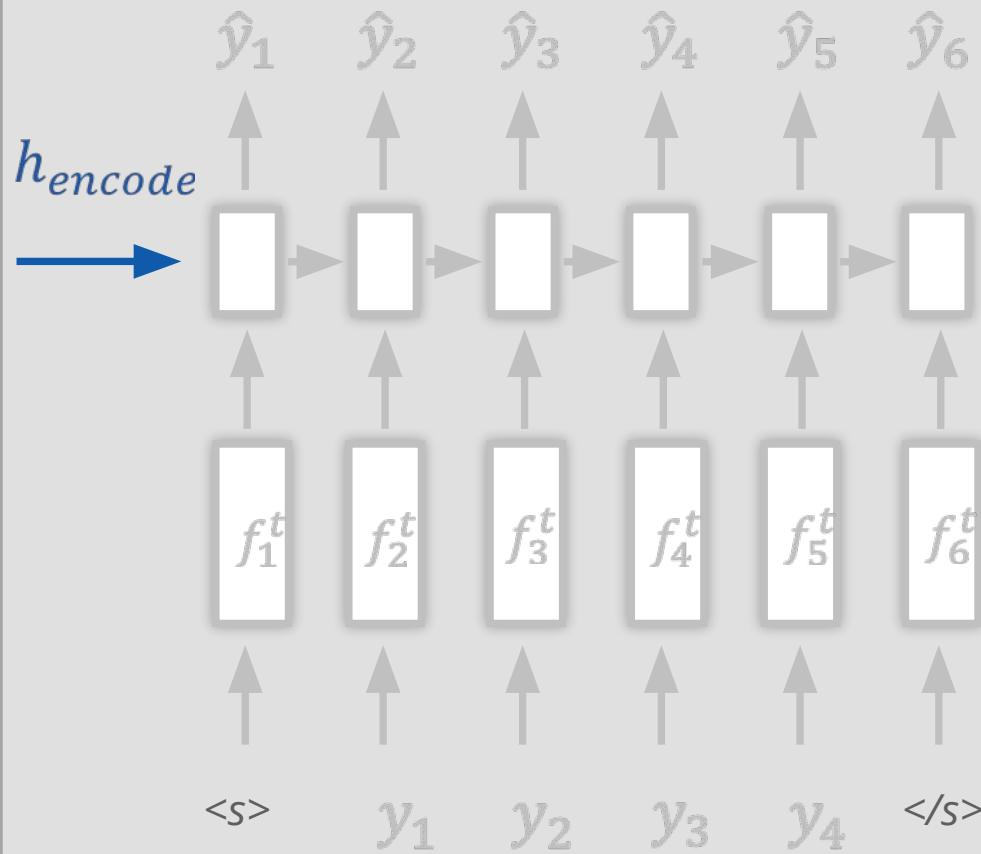
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h_{encode}



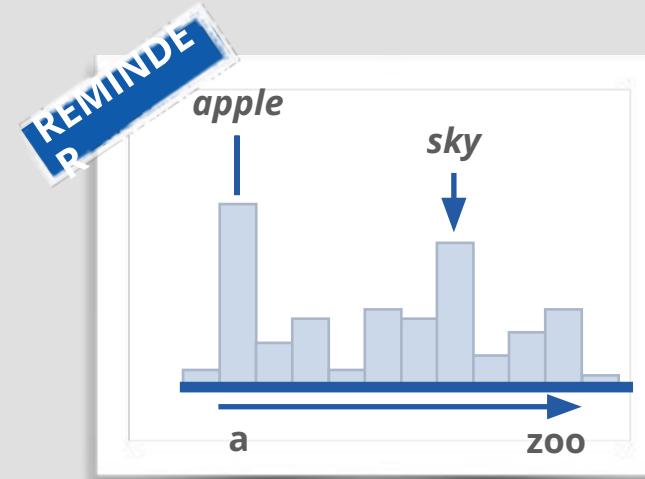
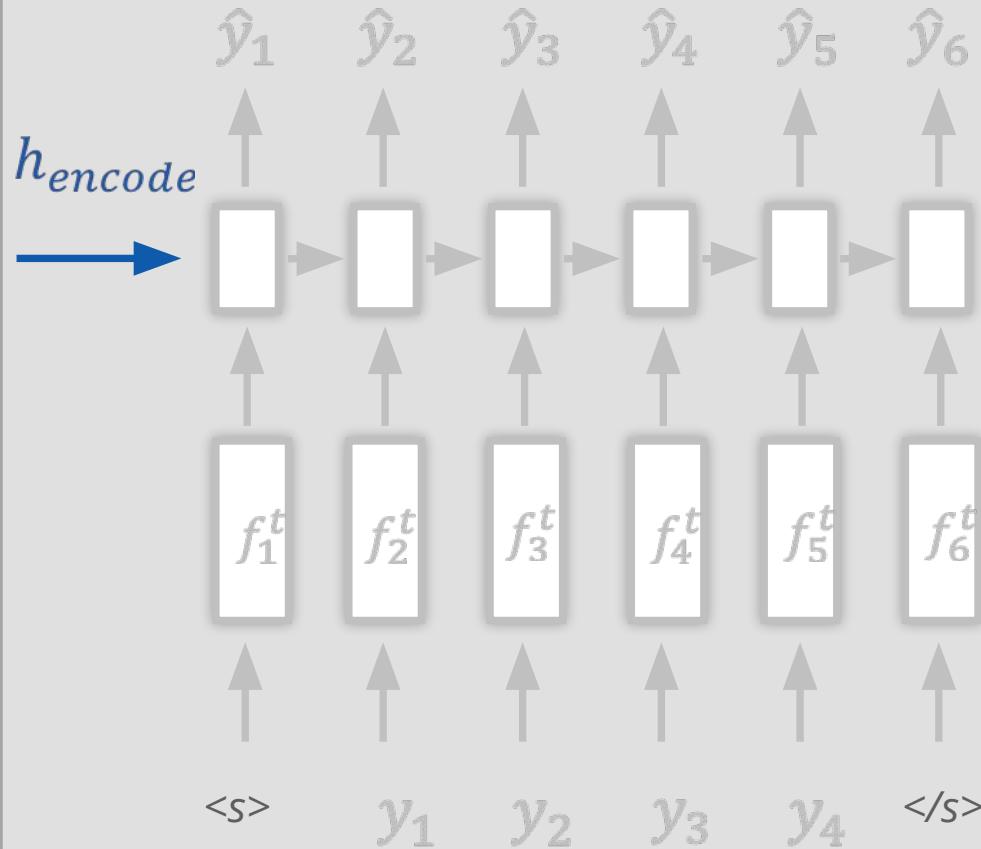
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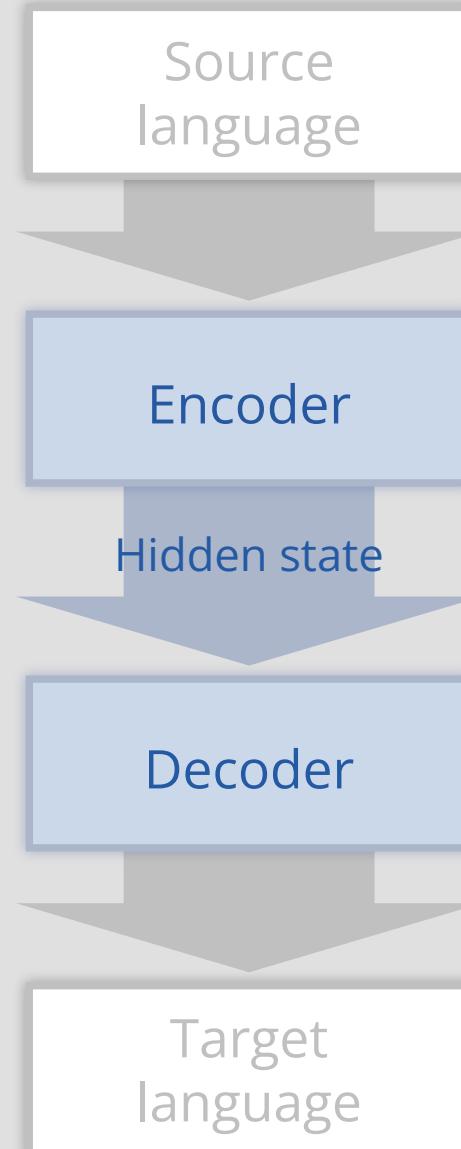
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Training process

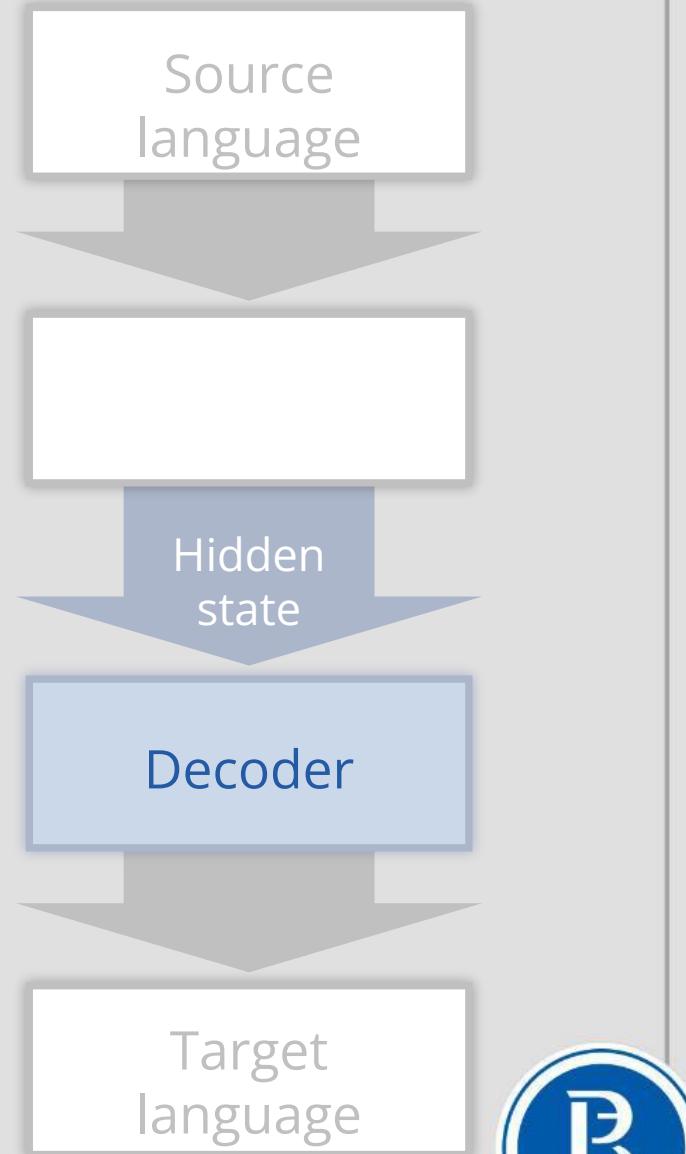
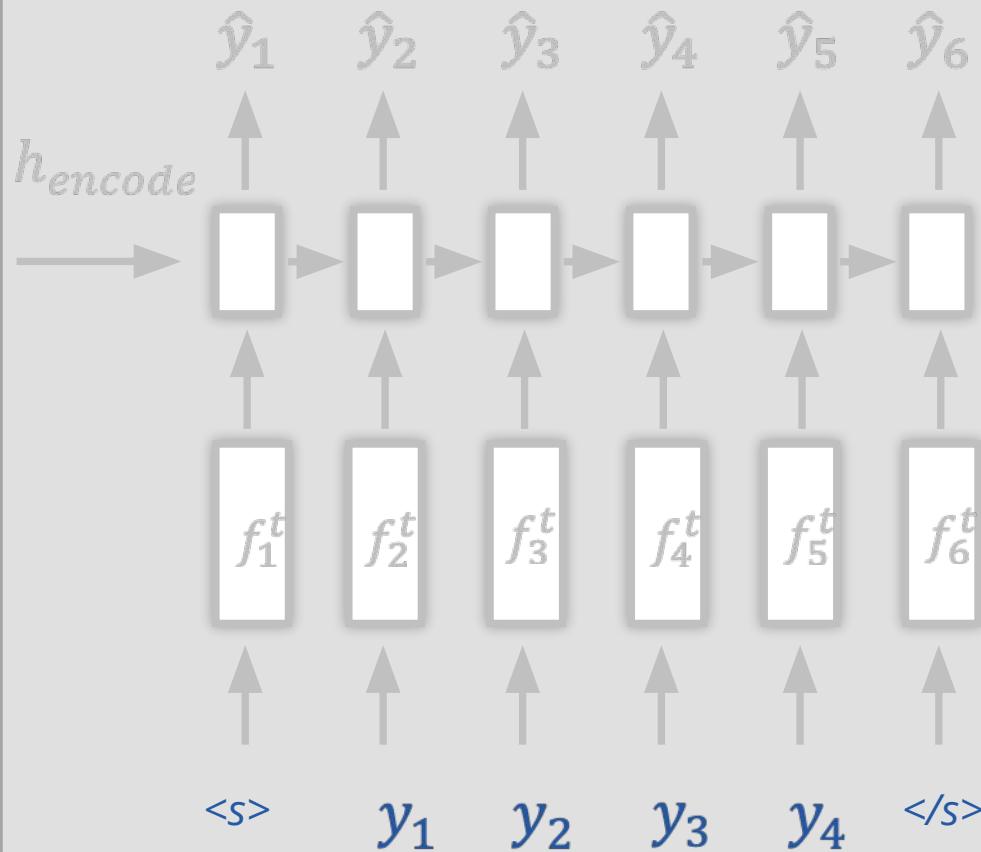
- Loss function

$$L(\mathbf{y}, \hat{\mathbf{y}}) = \sum_{j=1}^{V_{target}} y_j \log \hat{y}_j$$



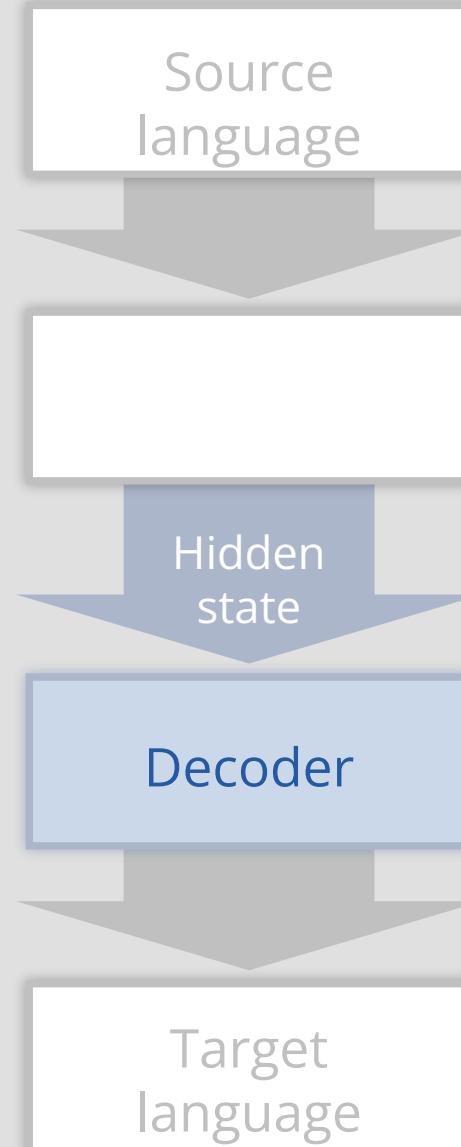
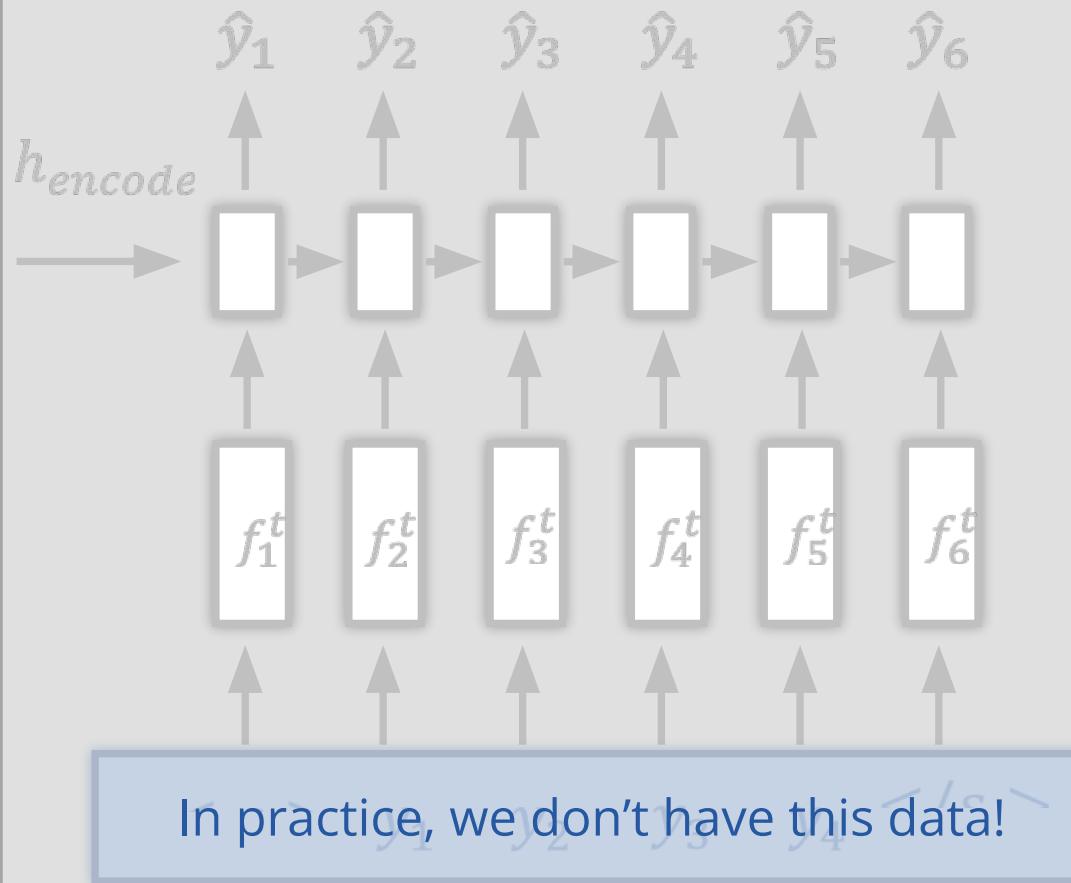
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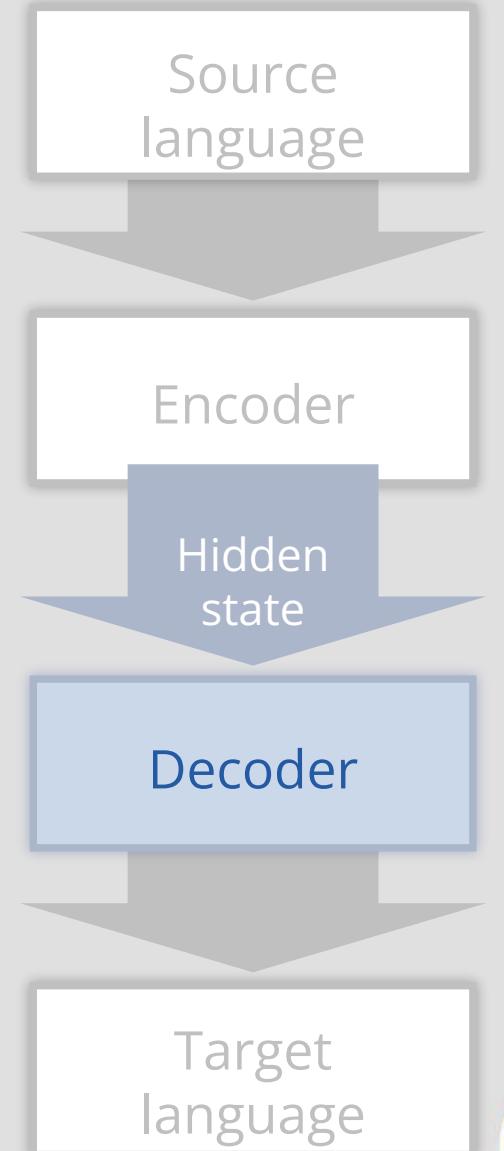
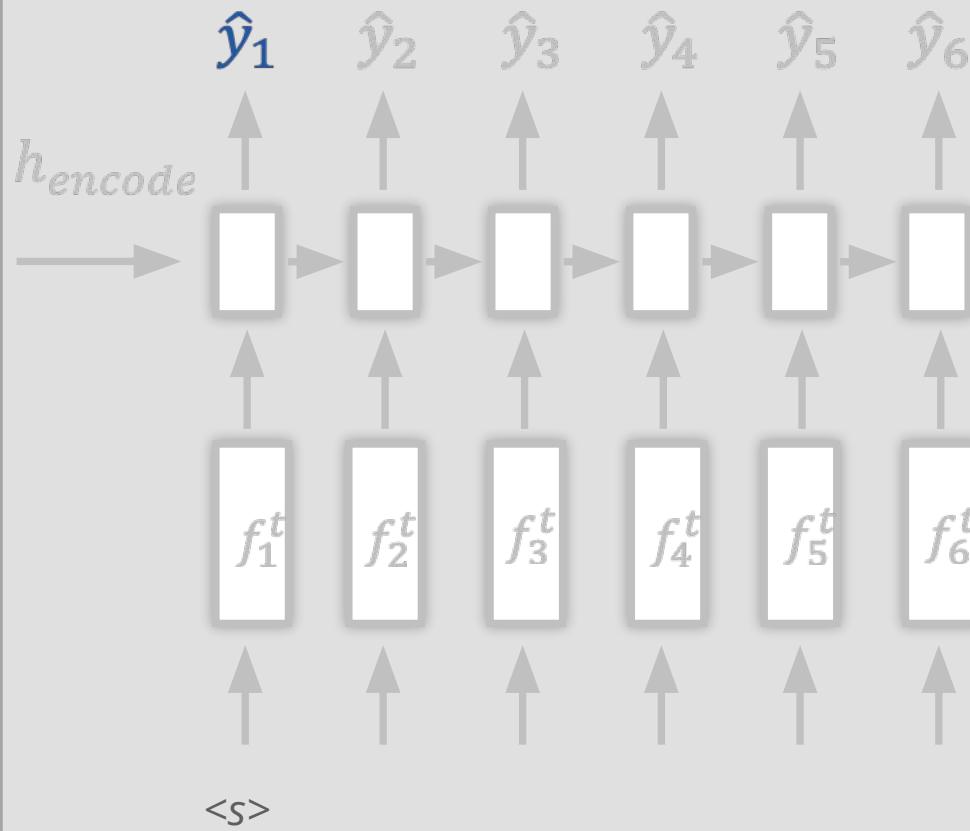
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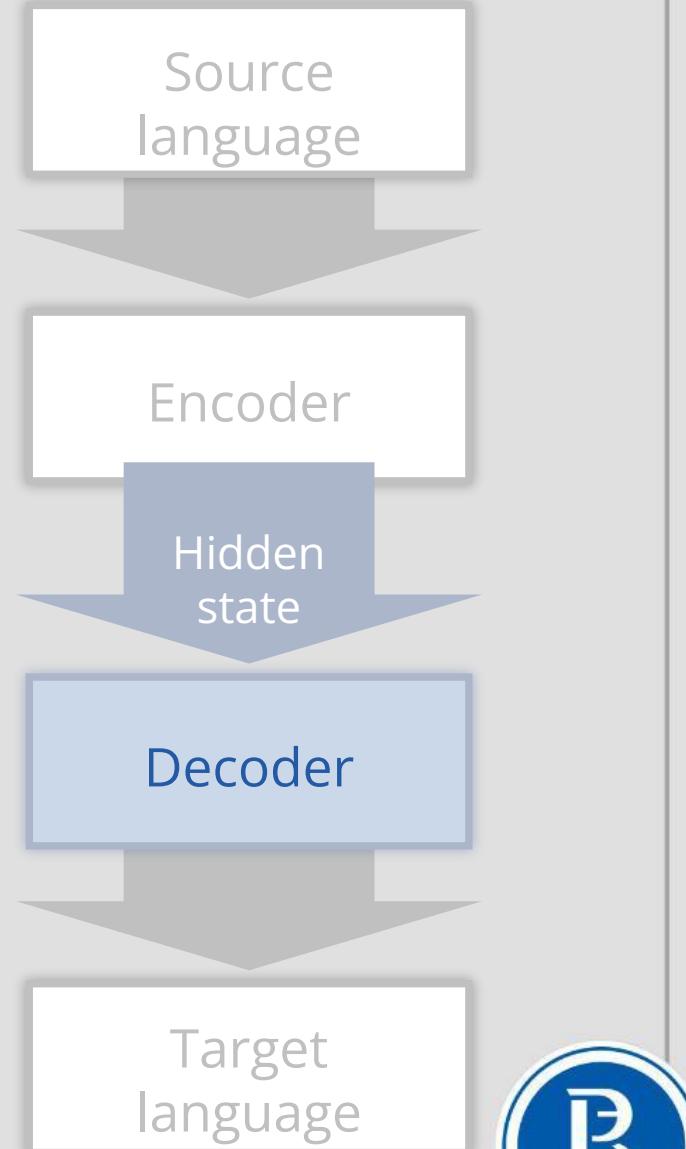
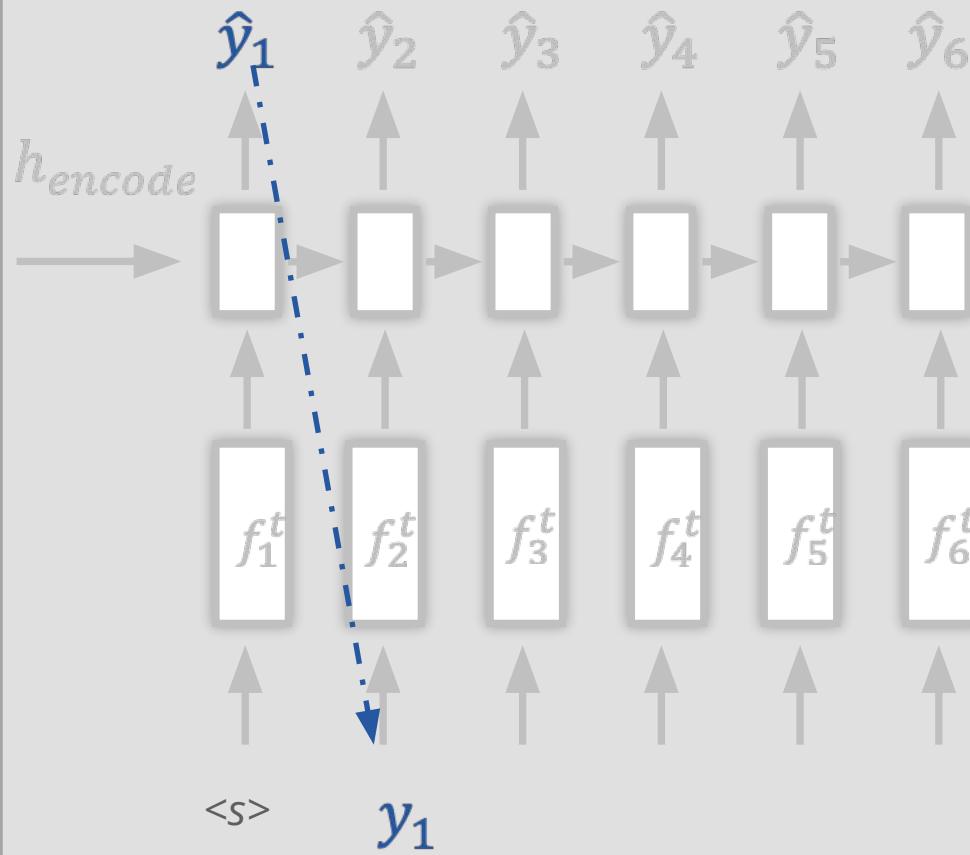
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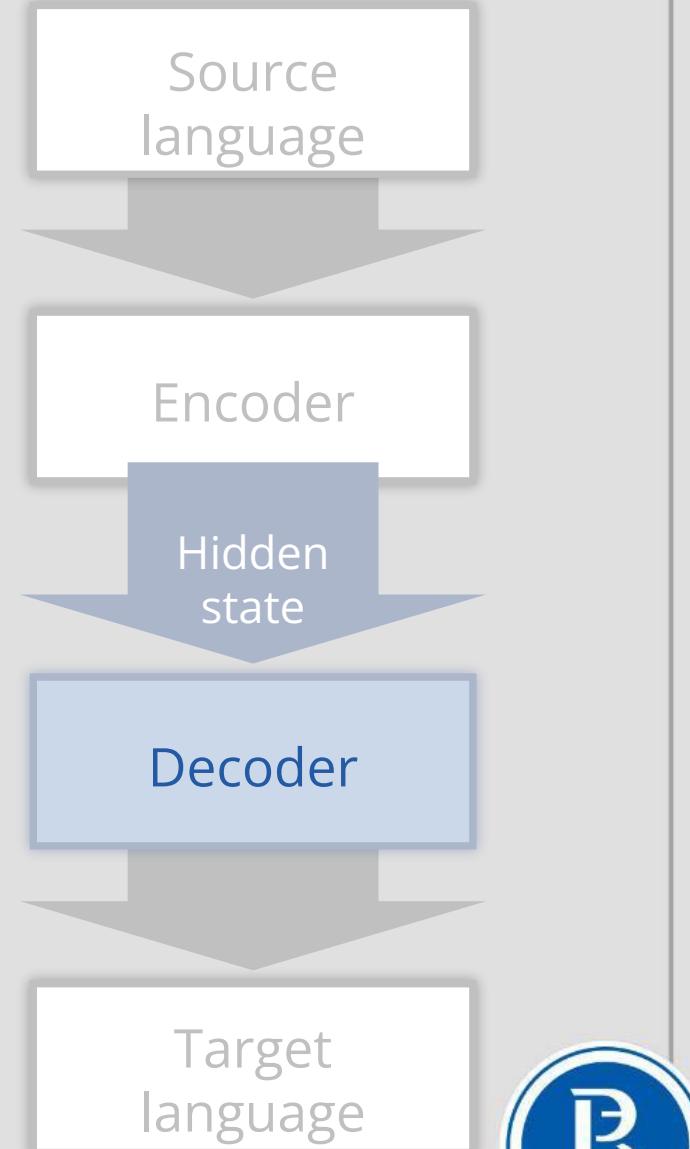
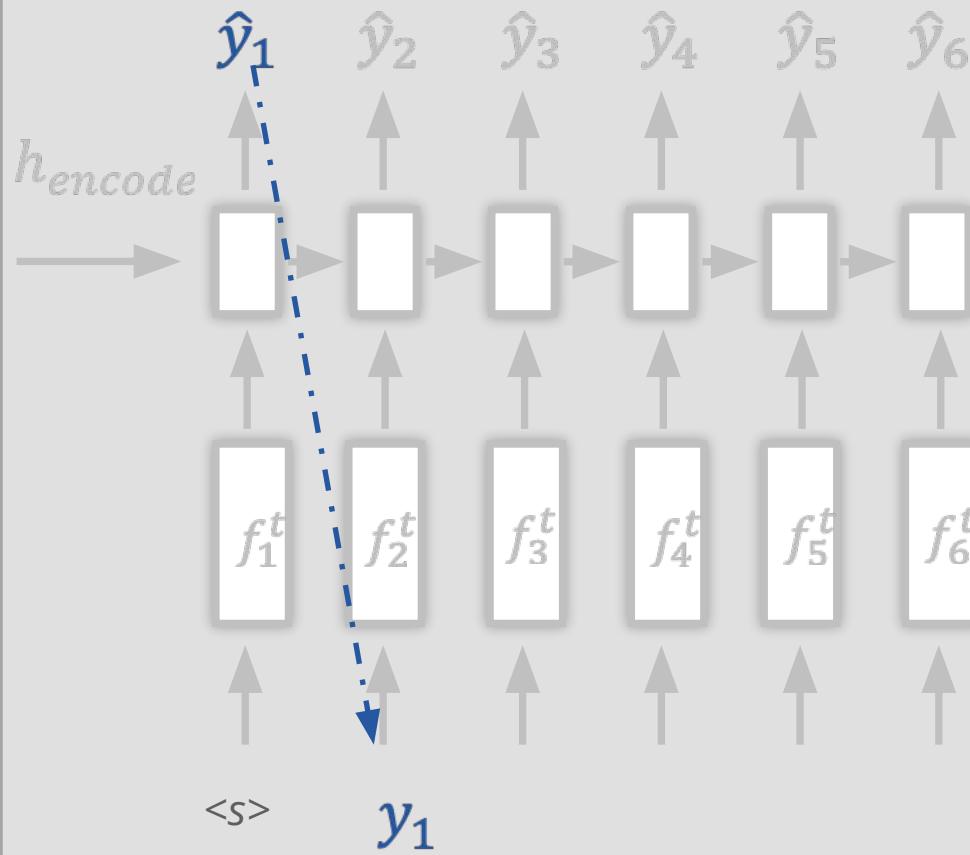
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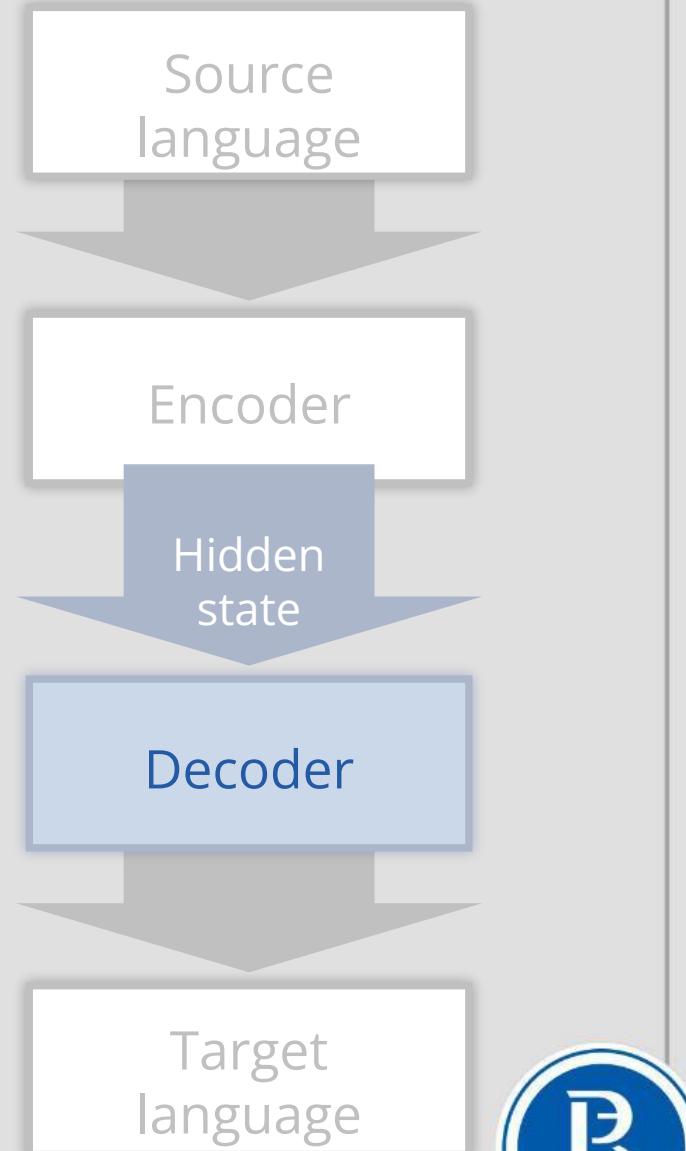
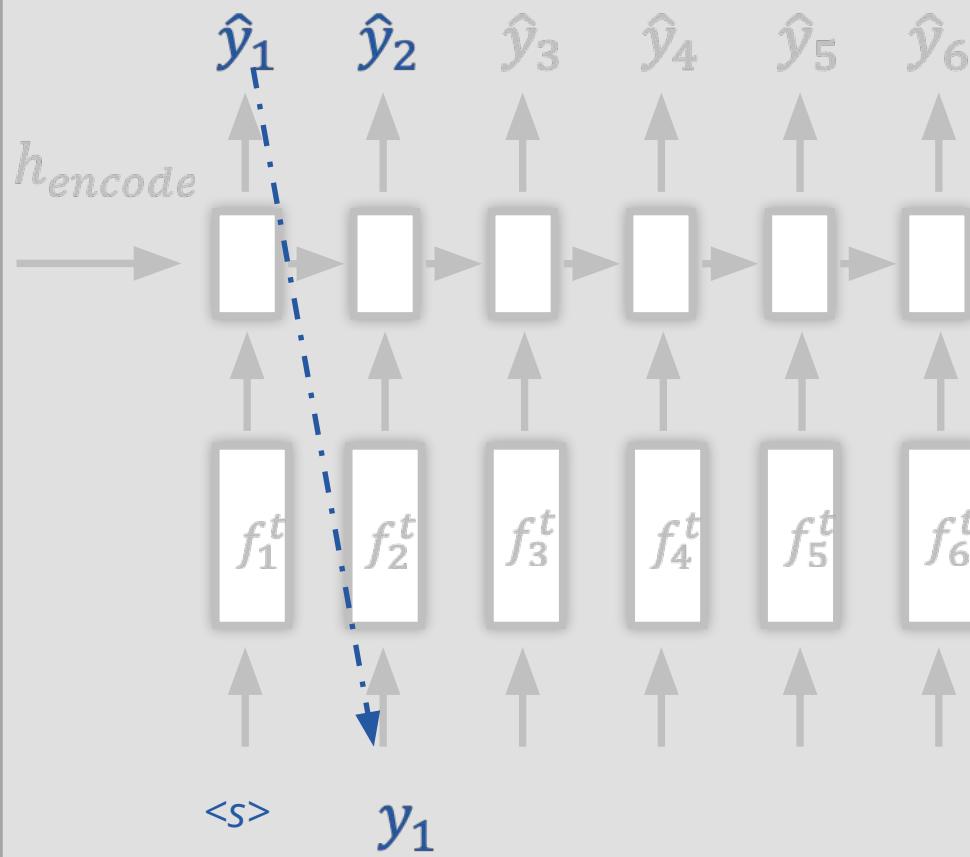
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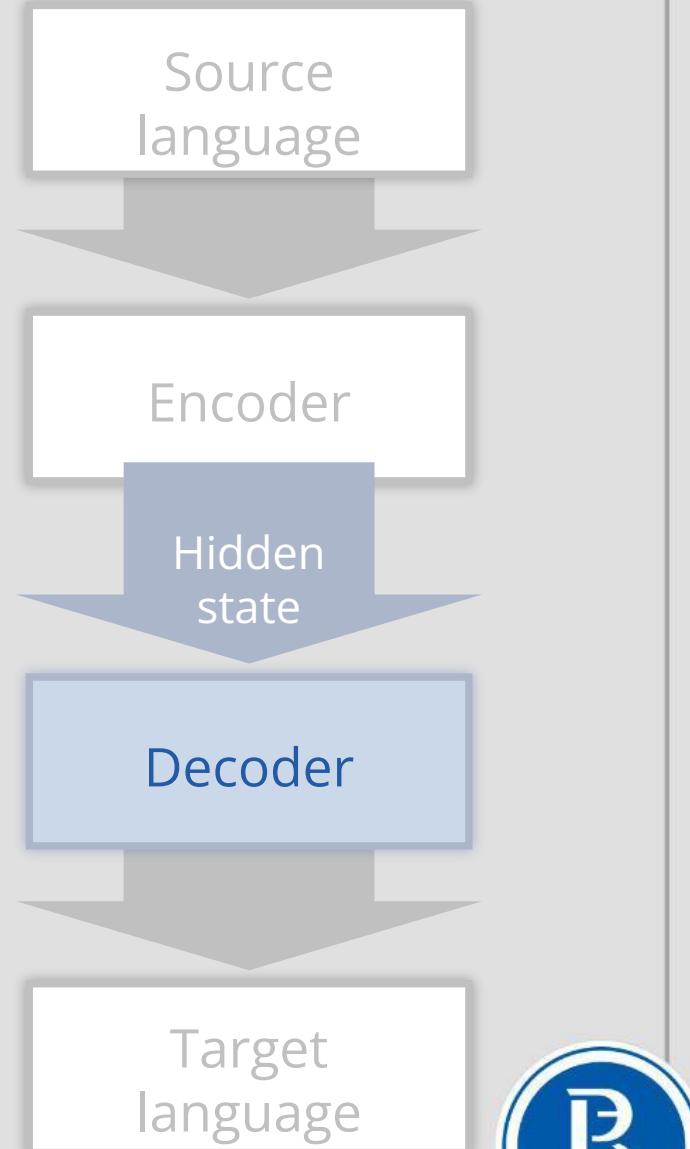
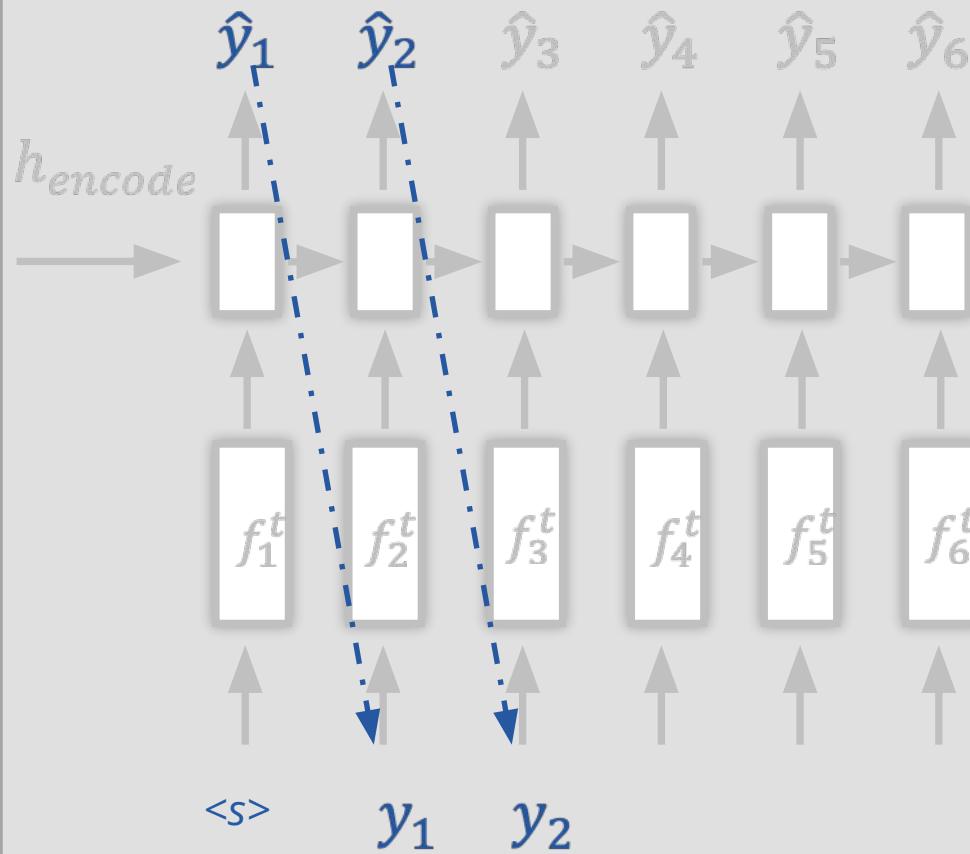
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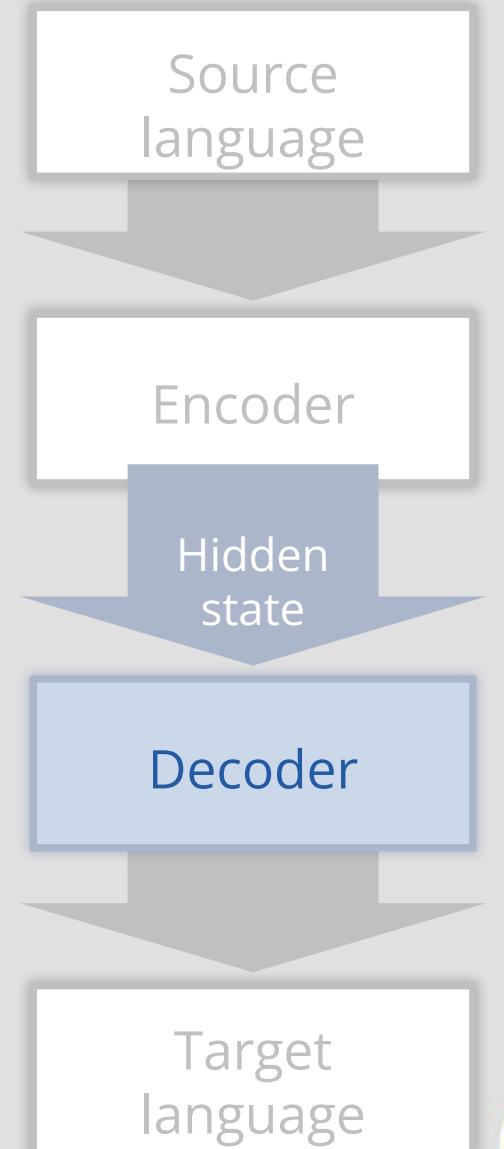
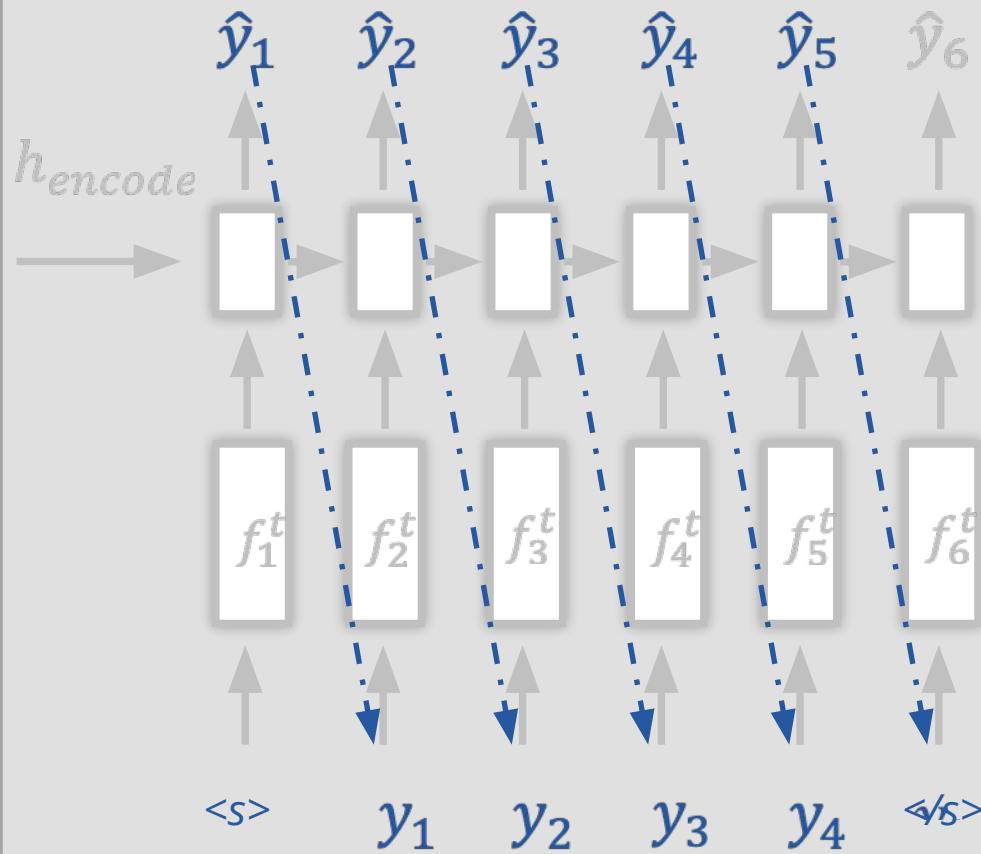
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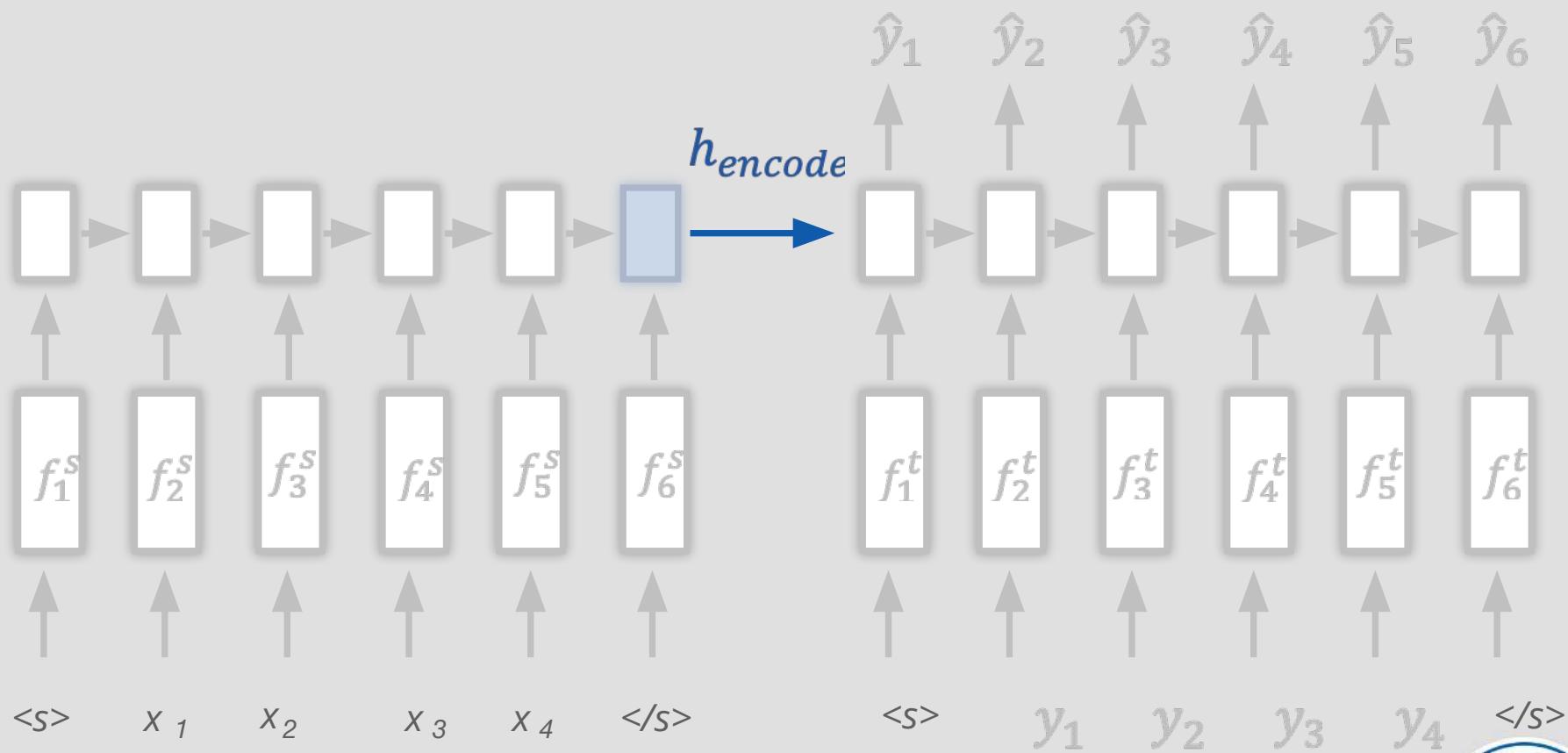


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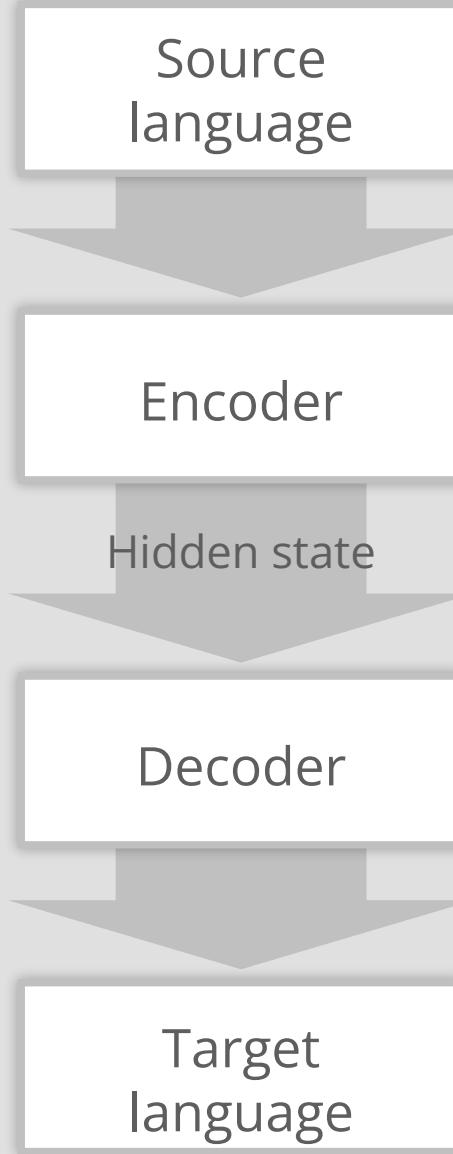


Neural machine translation



Encoder-decoder architecture

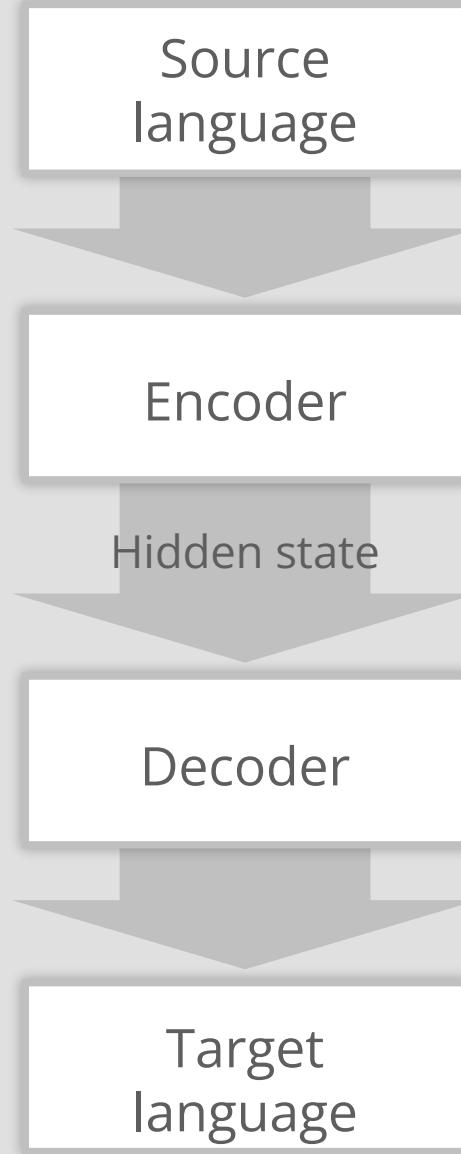
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Encoder-decoder architecture

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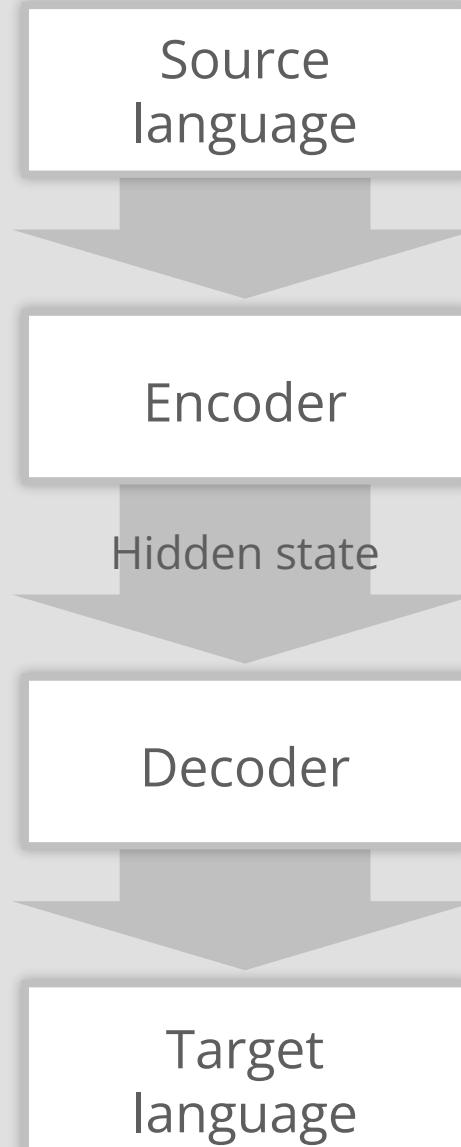
- Encoder encodes input word sequence



Encoder-decoder architecture

Consists of two parts:

- Encoder encodes input word sequence
- Decoder generates the output words sequence

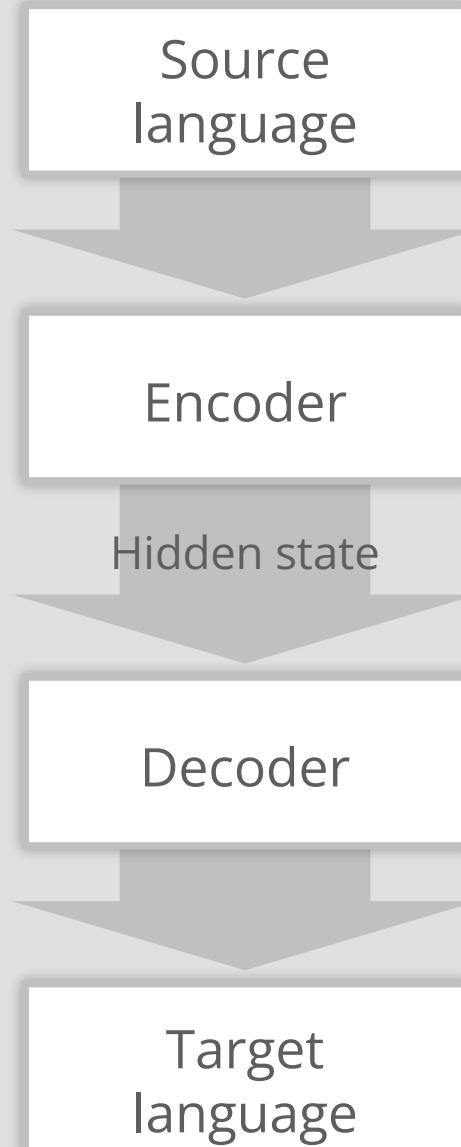


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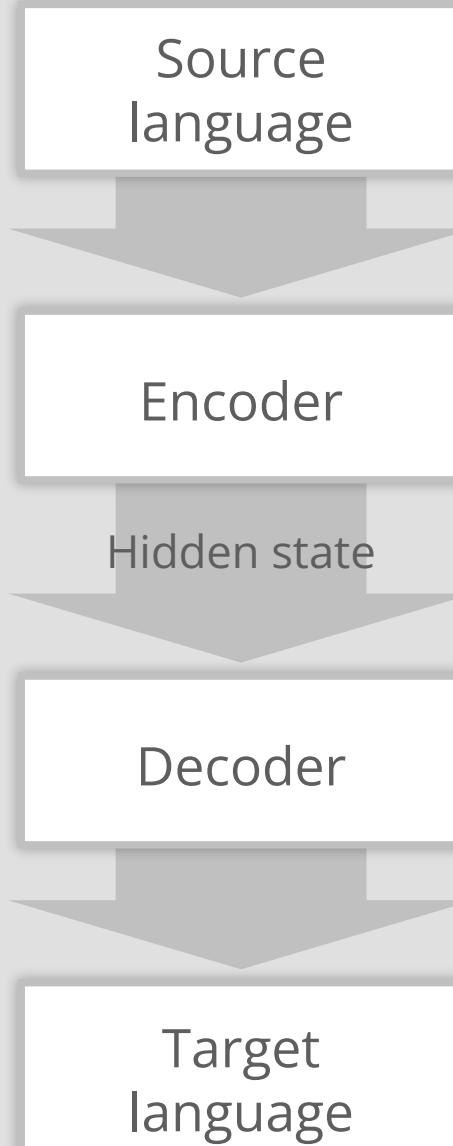
- Encoder encodes input word sequence
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Decoder is a language model!



Encoder-decoder architecture

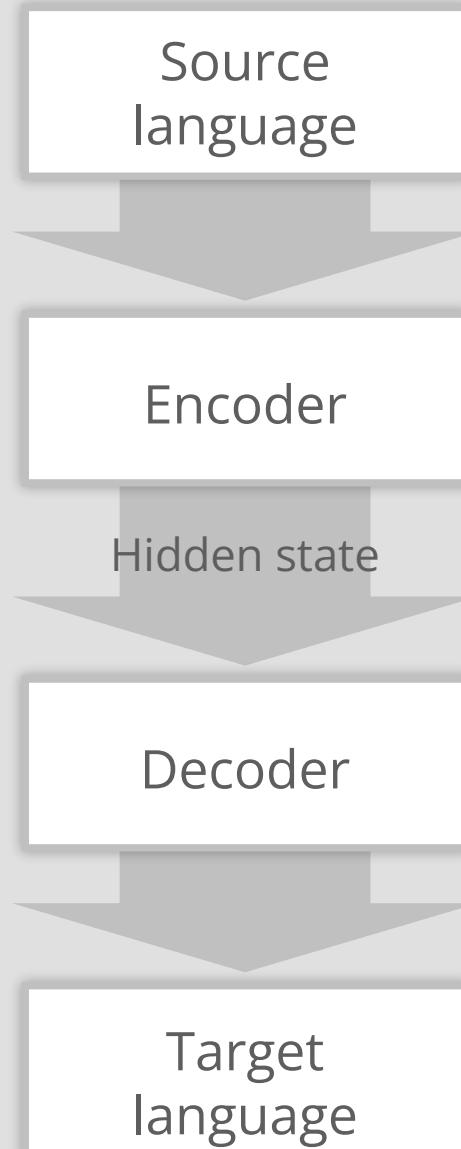
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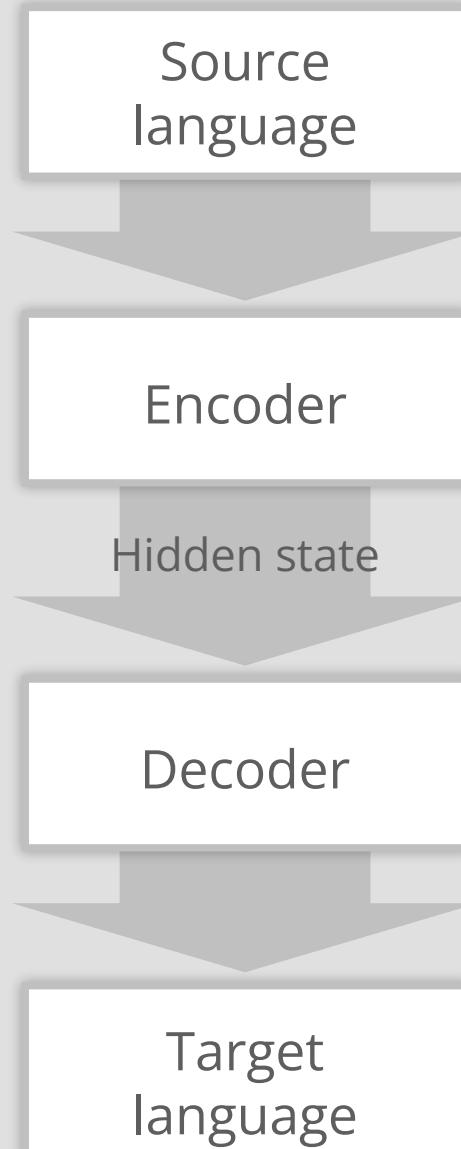
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Encoder-decoder architecture

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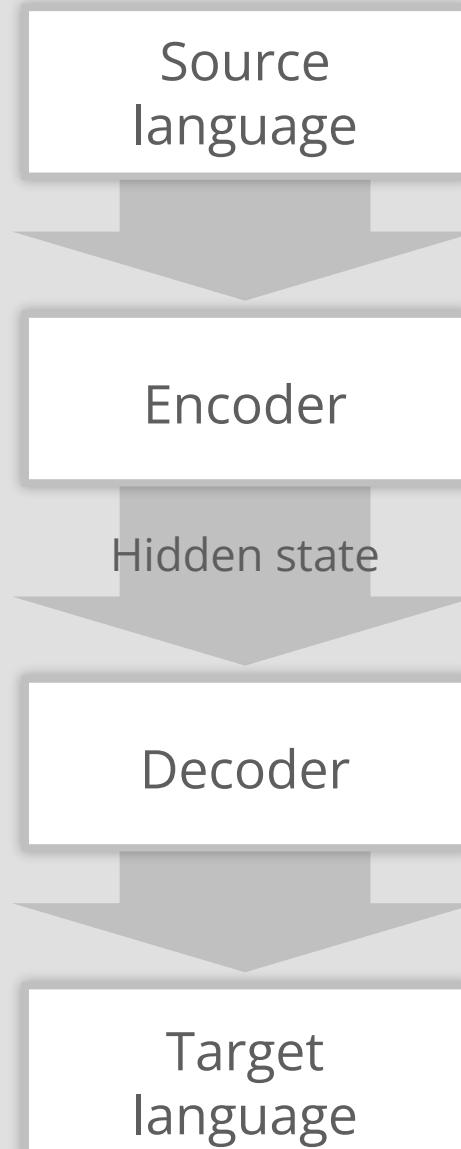
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Encoder-decoder architecture

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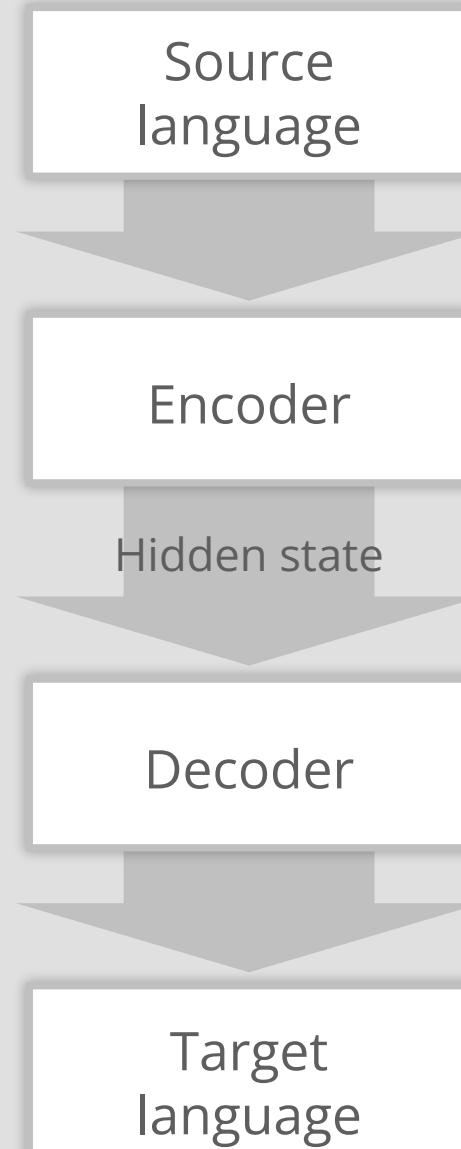
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Encoder-decoder architecture

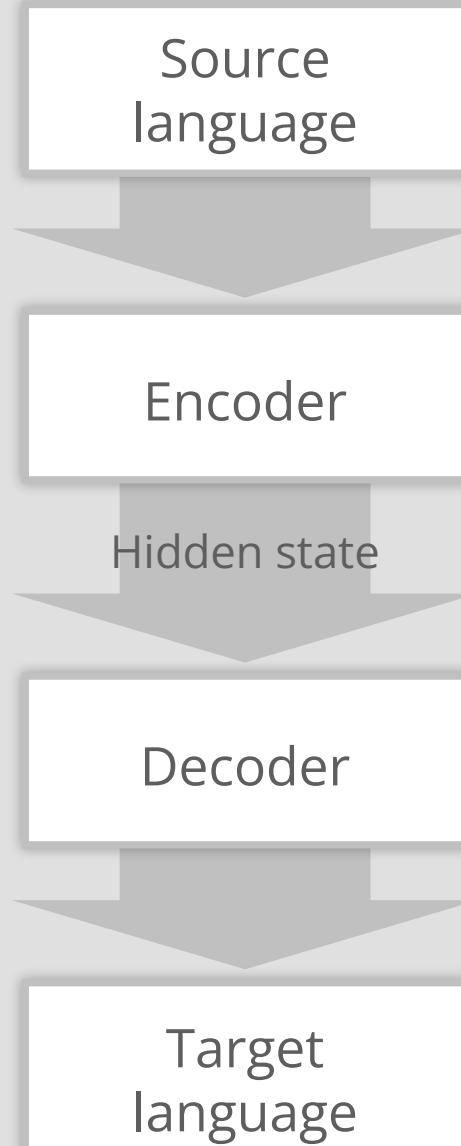
Encoder-decoder architectures can be used in various tasks:

- question answering
- Image capturing
- Speech recognition
- Code switching



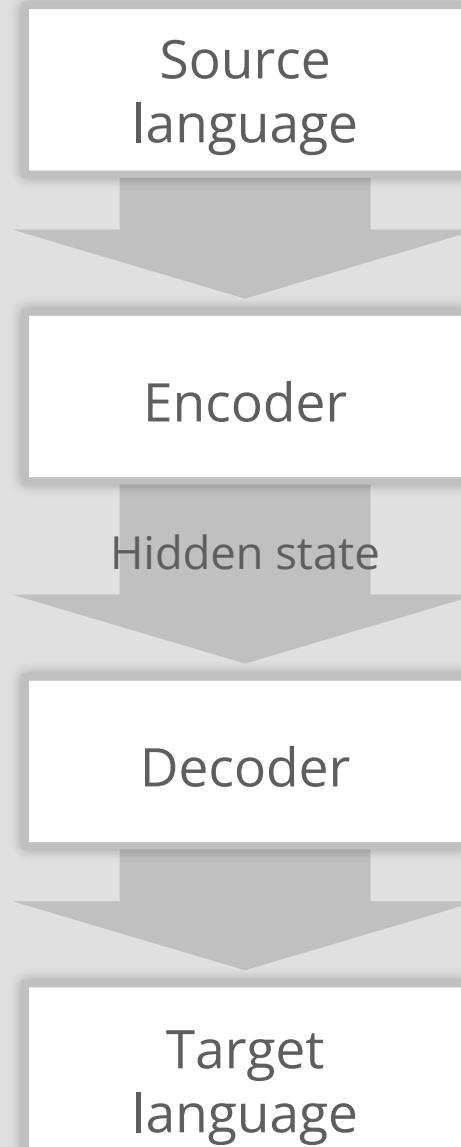
Encoder-decoder architecture

- Problem: only the last decoder state is used



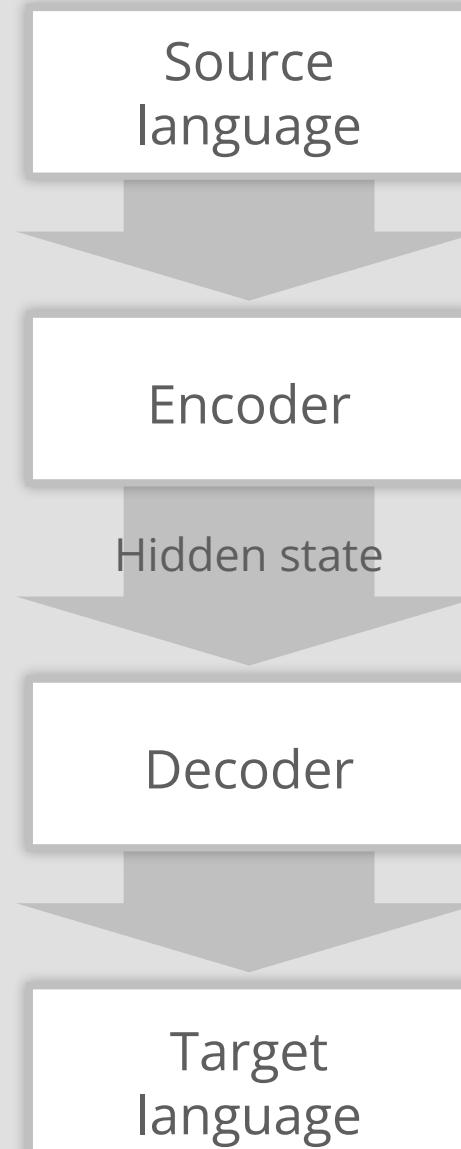
Encoder-decoder architecture

- Problem: only the last decoder state is used
- Last words have more impact than the first ones



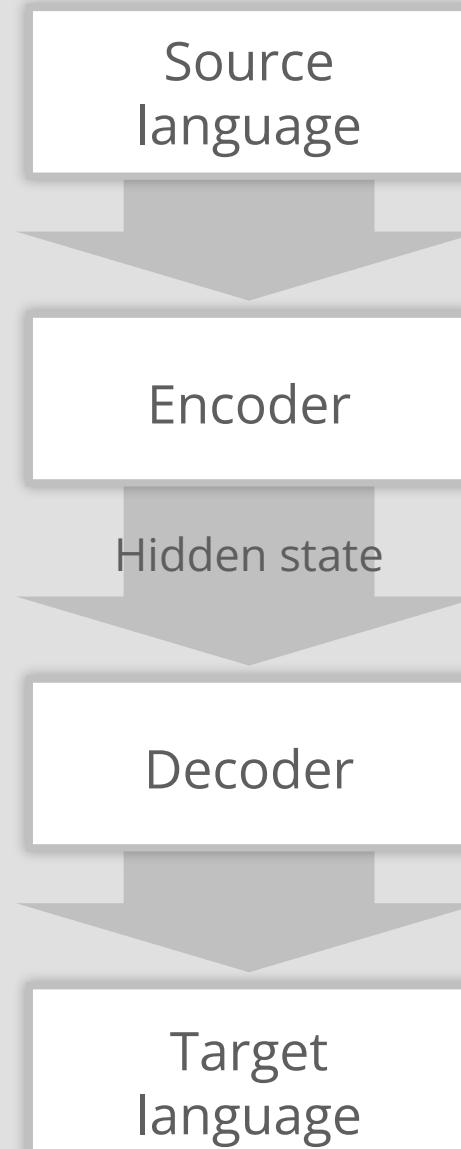
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Encoder-decoder architecture

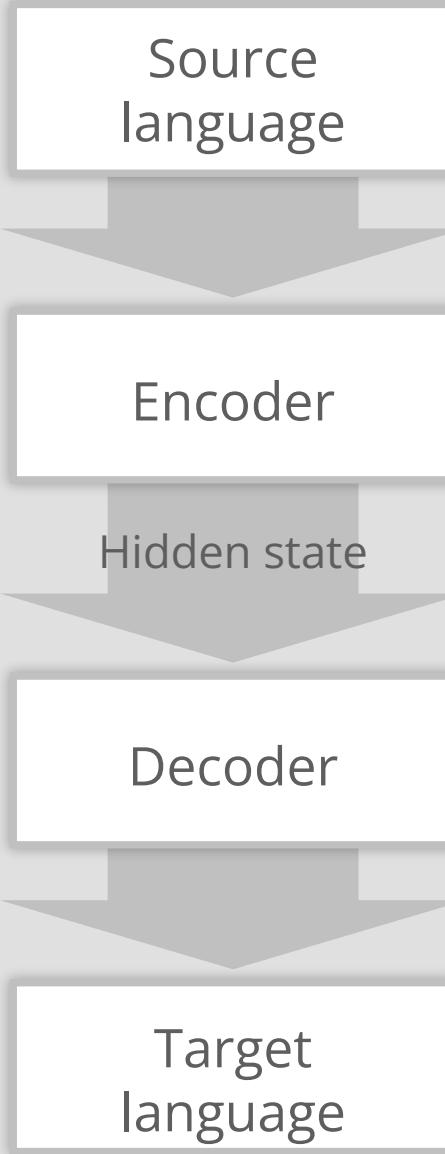
- Problem: only the last decoder state is used
- Last words have more impact than the first ones
- Short sentences are processed better
- The architecture can be improved by adding attention mechanism



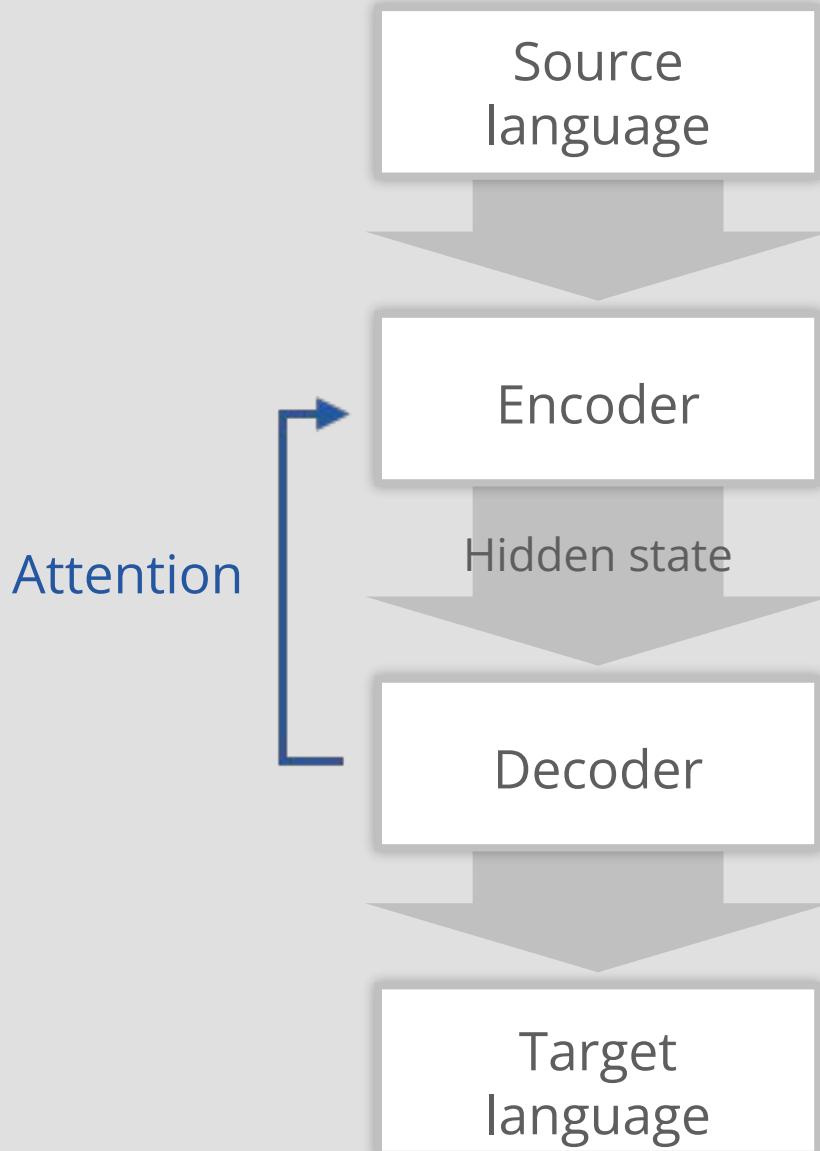
Attention mechanism



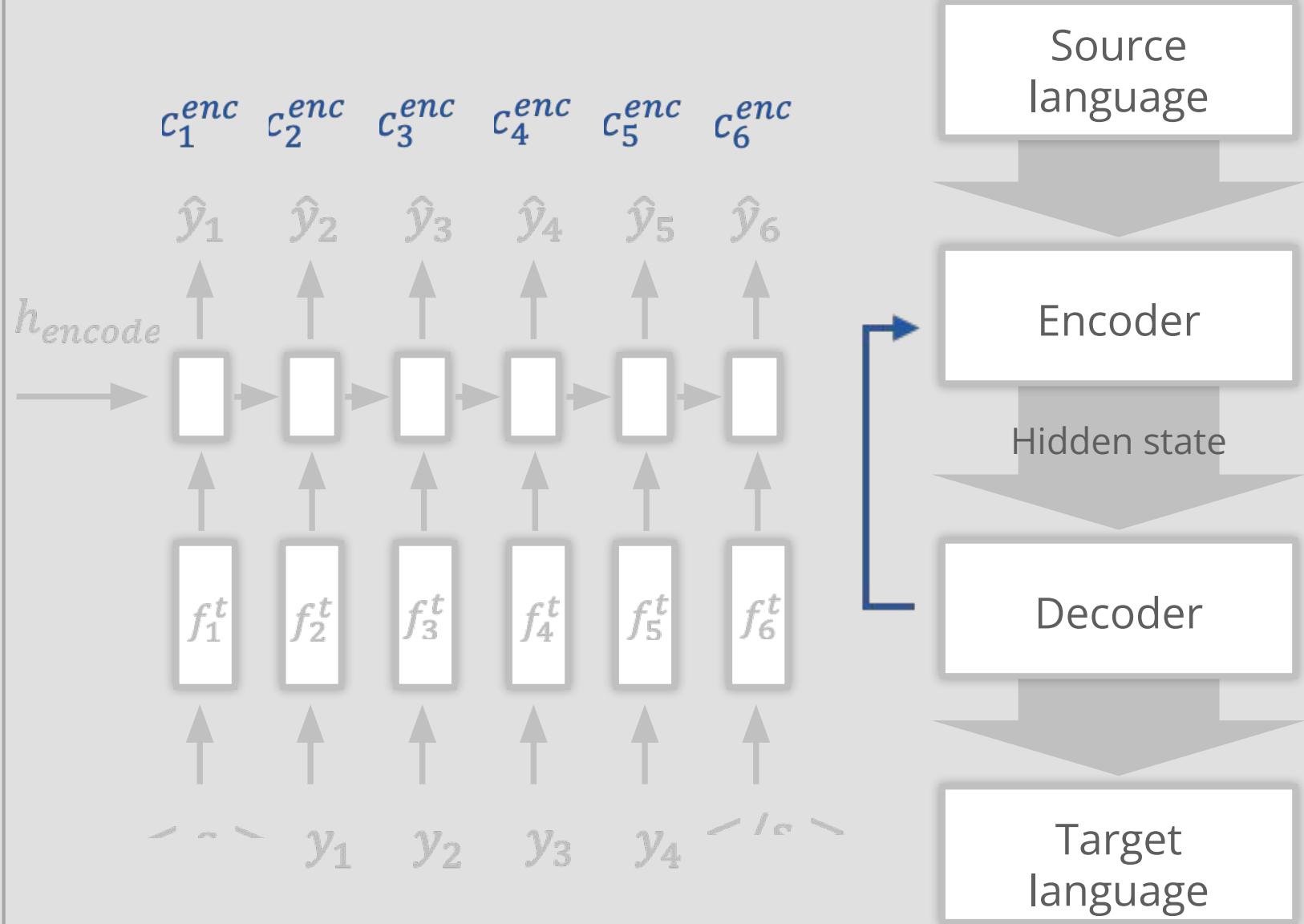
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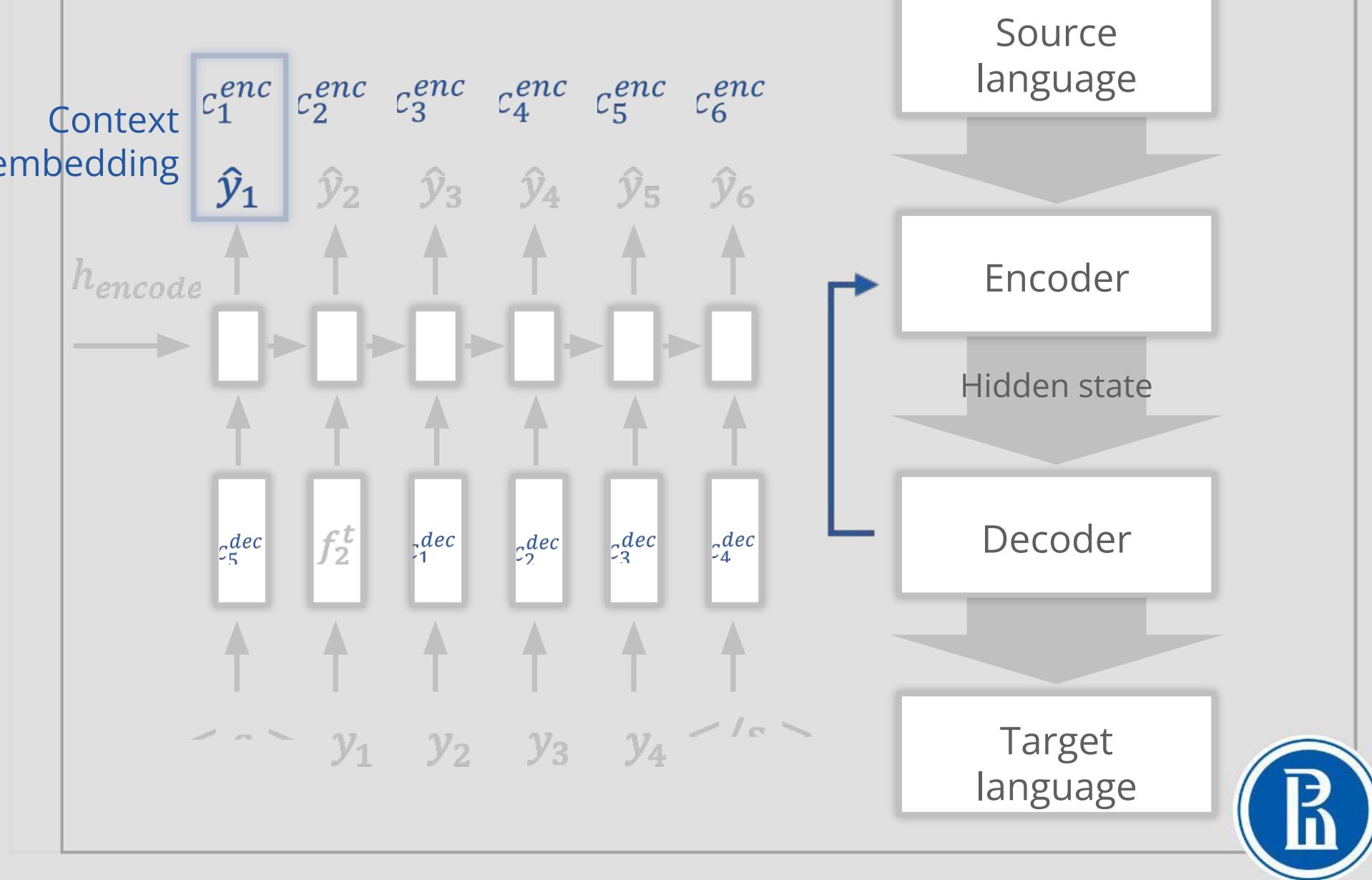
Attention mechanism



Attention mechanism



Attention mechanism



Attention mechanism

- Weights:

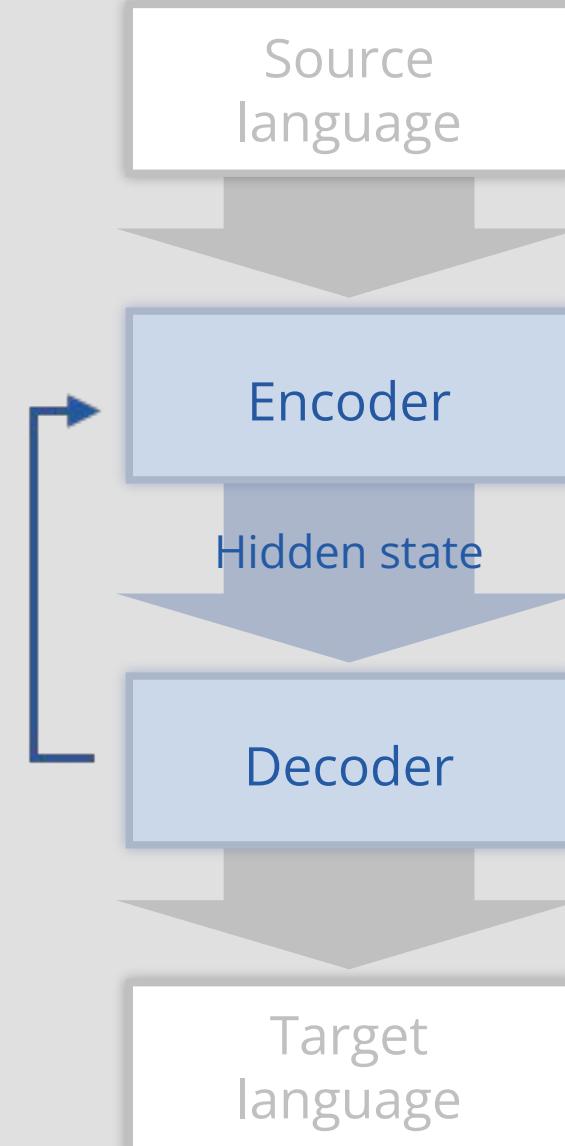
$$a_{ij} = \text{sim}(h_i^{enc}, h_j^{dec})$$

- Normalization:

$$\alpha_{ij} = \frac{e^{a_{ij}}}{\sum_k e^{a_{kj}}}$$

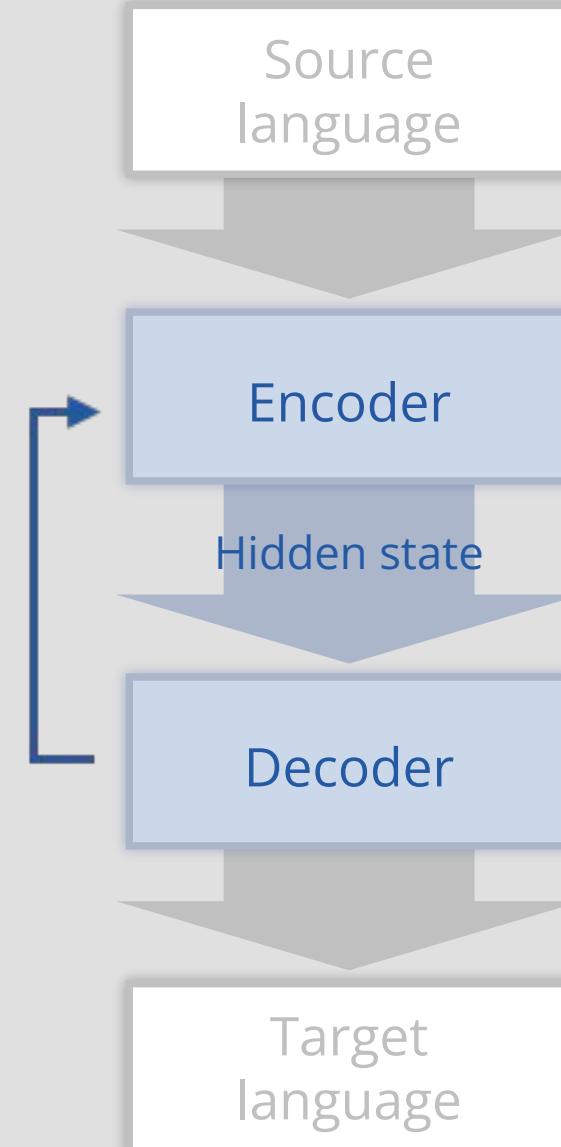
- Context embedding:

$$c_j = \sum_i \alpha_{ij} h_i^{enc}$$



Attention mechanism

- dot-product: $sim(h, s) = h^T s$

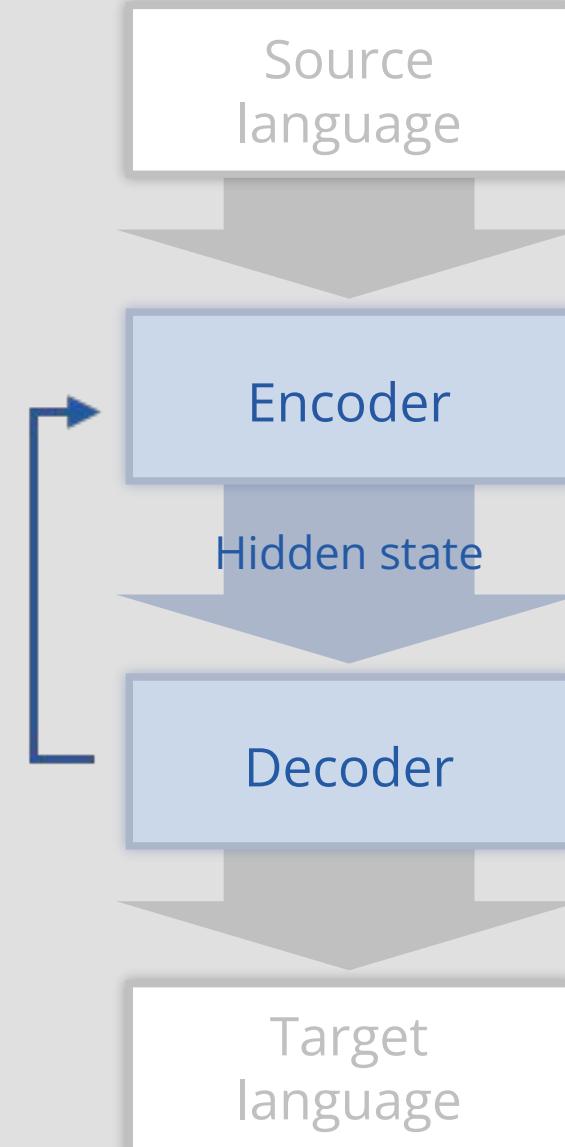


Attention mechanism

- dot-product: $sim(h, s) = h^\top s$

- Additive:

$$sim(h, s) = w^\top \tanh(W_h h + W_s s)$$



Attention mechanism

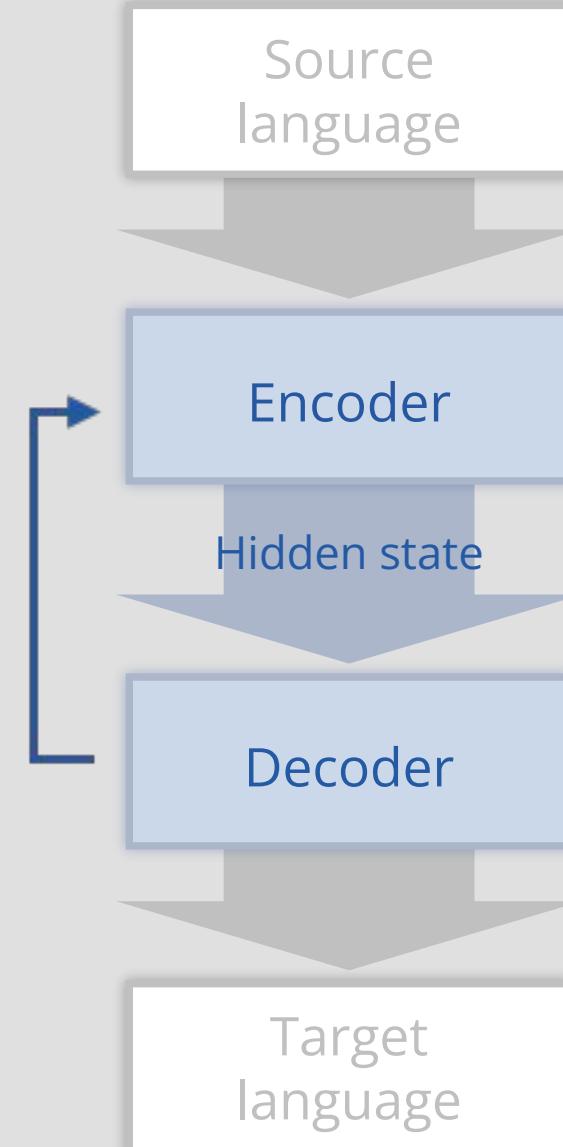
- dot-product: $sim(h, s) = h^T s$

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- Multiplicative:

$$sim(h, s) = h^T W s$$



Attention mechanism

- dot-product: $sim(h, s) = h^T s$

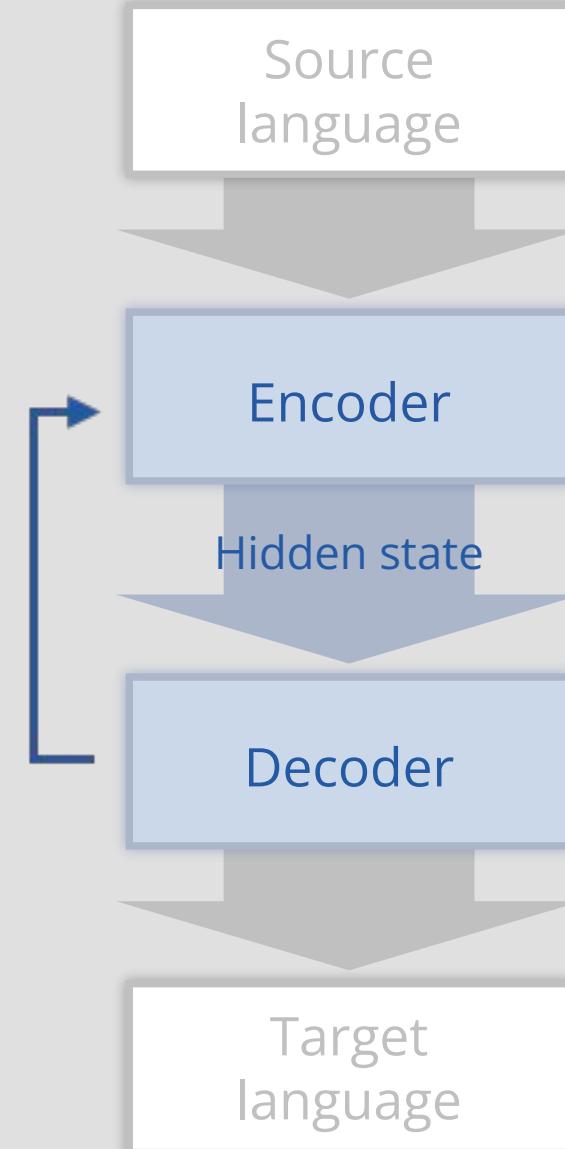
- Additive:

$$sim(h, s) = w^T \tanh(W_h h + W_s s)$$

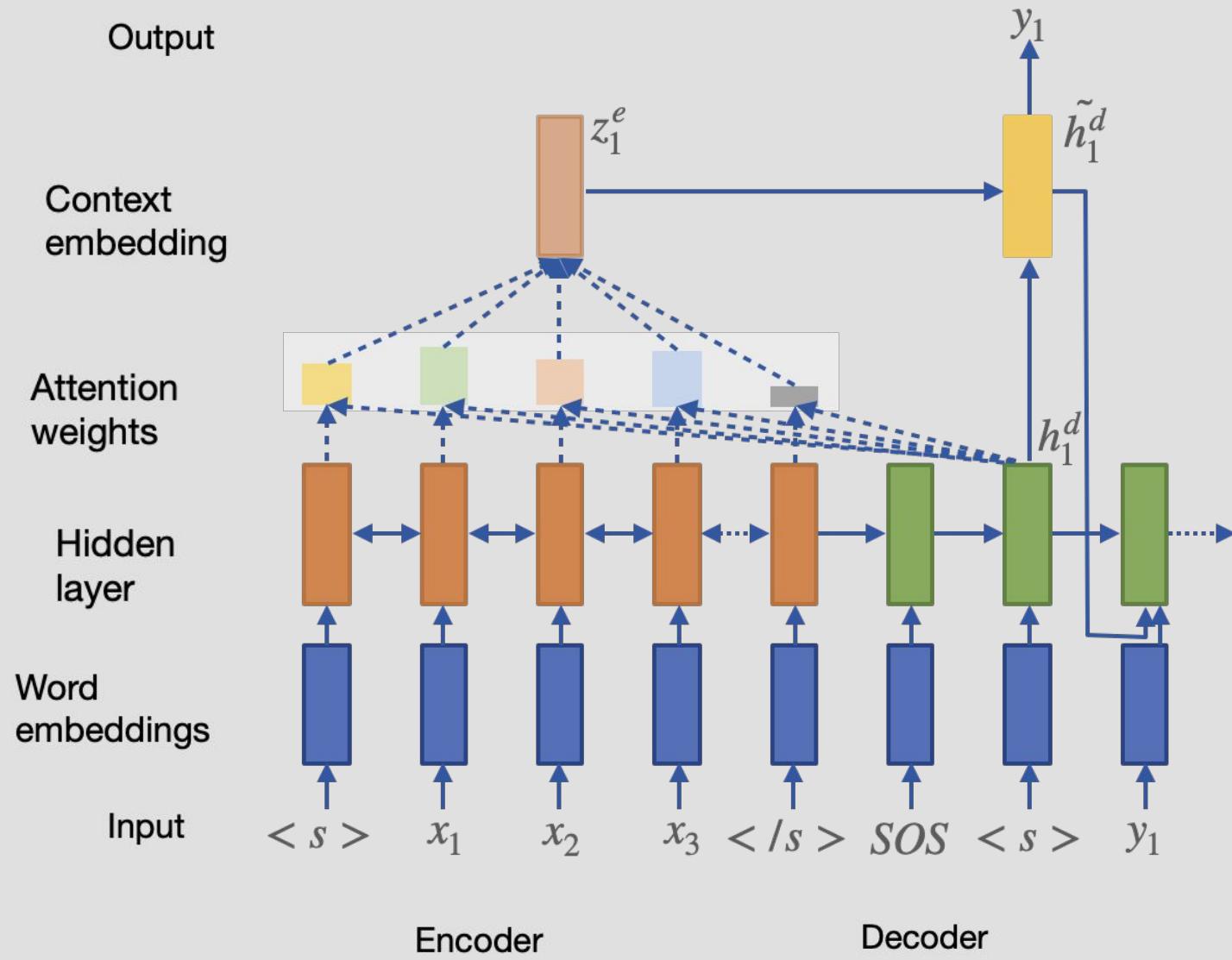
- Multiplicative:

$$sim(h, s) = h^T W s$$

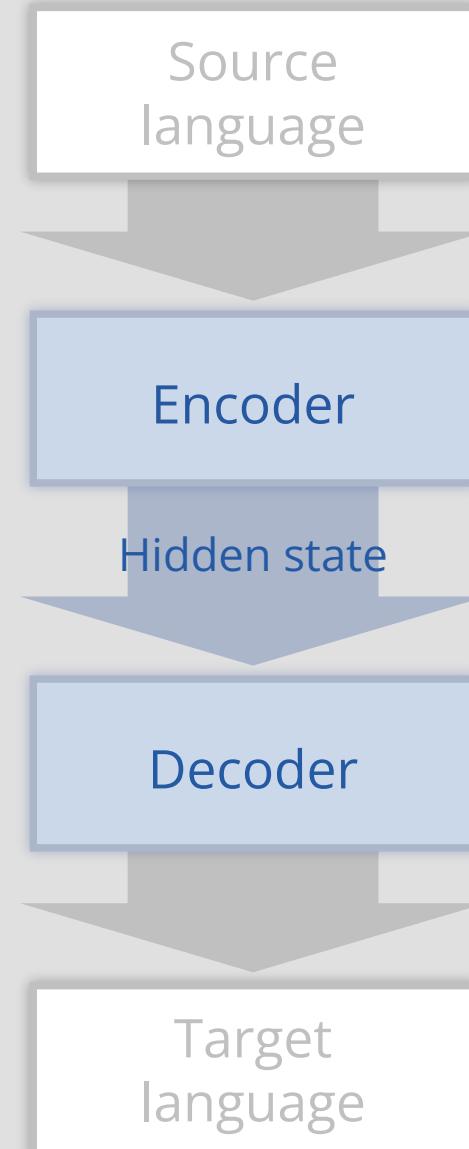
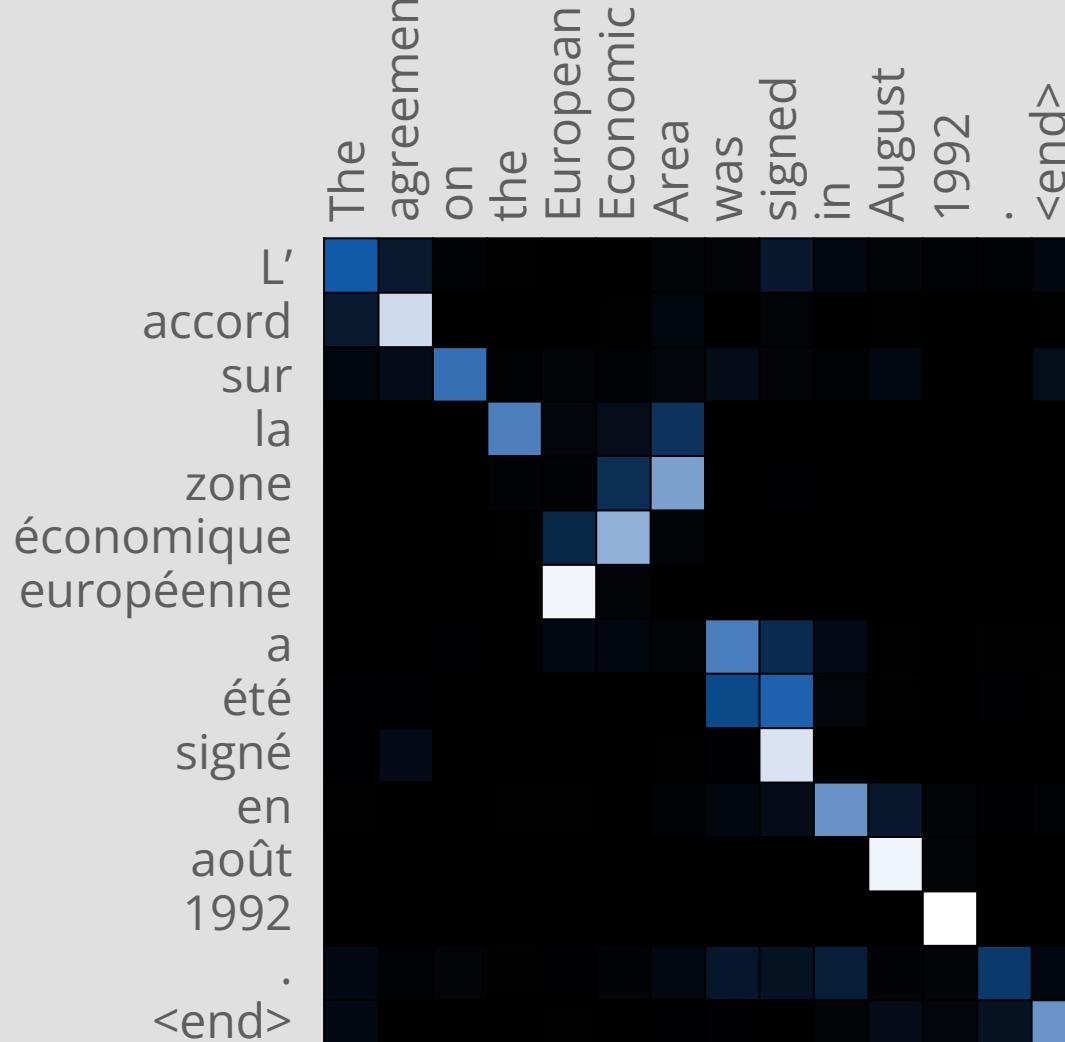
Weights are trained.



Attention mechanism



Attention maps



Machine translation quality metrics



Expert review

- We will show the sentence in the source language and the translation to the experts and ask them to rate the translation on a scale, for example, from 0 to 5



Expert review

- We will show the sentence in the source language and the translation to the experts and ask them to rate the translation on a scale, for example, from 0 to 5

Advantages

- exact

Disadvantages

- expensive
- slow



Comparison with the gold standard

- Machine translation model is trained on a parallel corpus: sentence on a source language and several options of translations
- Split data into train and test



Comparison with the gold standard

- Machine translation model is trained on a parallel corpus: sentence on a source language and several options of translations
- Split data into train and test
- Estimate MT quality on a test data



Comparison with the gold standard

- Machine translation model is trained on a parallel corpus: sentence on a source language and several options of translations
- Split data into train and test
- Estimate MT quality on a test data

Advantages

- quick
(if corpus is given)

Disadvantages

- corpuses can become obsolete



Back translation

- Apply MT to translate sentence from source tp target language



Back translation

- Apply MT to translate sentence from source to target language



Russian ▾ ↔ German ▾

Никогда и ничего не просите!
Никогда и ничего, и в особенности у тех, кто сильнее вас. Сами предложат и сами все дадут!

Nikogda i nichego ne prosite!
Nikogda i nichego, i v osobennosti u tekh, kto sil'neye vas. Sami predlozhat i sami vse dadut!

Fragen Sie niemals nach etwas! Niemals etwas, besonders nicht diejenigen, die stärker sind als du. Sie werden es selbst anbieten und alles geben!

Speaker icon | Copy icon

A screenshot of the Google Translate mobile application. It shows a Russian sentence being translated into German. The source text is "Никогда и ничего не просите! Никогда и ничего, и в особенности у тех, кто сильнее вас. Сами предложат и сами все дадут!". The machine-generated translation below it is "Nikogda i nichego ne prosite! Nikogda i nichego, i v osobennosti u tekh, kto sil'neye vas. Sami predlozhat i sami vse dadut!". To the right of the text, there is a German translation: "Fragen Sie niemals nach etwas! Niemals etwas, besonders nicht diejenigen, die stärker sind als du. Sie werden es selbst anbieten und alles geben!". At the bottom of the screen are icons for a speaker and a copy function.

translate.google.co
m



Back translation

- Apply MT to translate sentence from source to target language
- ... and back

The screenshot shows a Google Translate interface. At the top, there are flags for Germany (black, red, and gold) and Russia (white, blue, and red), separated by a large grey arrow pointing from left to right. Below the flags, the language selection is set to German on the left and Russian on the right. A double-headed arrow icon is positioned between the language dropdowns. The German input text is:

Fragen Sie
niemals nach
etwas! Niemals
etwas, besonders
nicht diejenigen,
die stärker sind
als du. Sie
werden es selbst
anbieten und

To the right of the input, there is a close button (an 'X') and a large block of Russian text:

Никогда не проси
ничего! Никогда
ничего, особенно
тем, кто сильнее
тебя, они сами это
предложат и все
отдадут!

Below this Russian text is its English back-translation:

Nikogda ne prosi nichego! Nikogda
nichego, osobenno tem, kto sil'neye
tebya, oni sami eto predlozhat i vse
otdadut!

At the bottom of the interface, there are three small icons: a speaker icon, a refresh/circular arrow icon, and a square icon.



Back translation

- Apply MT to translate sentence from source to target language
- ... and back
- Compare the original text and the resulting one after back translation

The screenshot shows the Google Translate interface with two Russian flags at the top. Below them is a double-headed arrow icon. The interface has "Russian" selected for both the source and target languages. In the center, there are two columns of text. The left column contains the original Russian text and its English machine-translated equivalent. The right column contains the English text and its Russian machine-translated equivalent. At the bottom right of the interface are a speaker icon and a copy/paste icon.

Russian	English	Russian
Никогда и ничего не просите! Никогда и ничего, и в особенностях тех, кто сильнее вас. Сами предложат и сами все дадут!	Nikogda i nichego ne prosite! Nikogda i nichego, i v osobennosti u tekh, kto sil'neye vas. Sami predlozhat i sami vse dadut!	Никогда не проси ничего! Никогда ничего, особенно тем, кто сильнее тебя, они сами это предложат и все отдадут!



BLEU (bilingual evaluation understudy)

- Compare sentences:

- *Never ask for help!*
- *Don't ask for help!*



BLEU (bilingual evaluation understudy)

- Compare sentences:
 - *Never ask for help!*
 - *Don't ask for help!*
- BLEU – algorithm for comparing an automatically translated sentence with the gold standard



BLEU (bilingual evaluation understudy)

- Input - machine translation and gold standard



BLEU (bilingual evaluation understudy)

- Input - machine translation and gold standard
- Count precision of word N-grams ($N = 1 \dots 4$) $pr_i, i \in \{1,4\}$



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$$score = \sqrt[4]{\prod_{i=1}^4 pr_i}$$



BLEU (bilingual evaluation understudy)

- Input - machine translation and gold standard
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$$score = \sqrt[4]{\prod_{i=1}^4 pr_i}$$

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BLEU (bilingual evaluation understudy)

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$$BLEU = bp \times score$$



BLEU (bilingual evaluation understudy)

Quote:



Remember that the most dangerous prison is the one in your head.



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Quote:



Remember that the most dangerous prison is the one in your head.

Gold standard:



Помни, что самая опасная тюрьма – в твоей голове.



BLEU (bilingual evaluation understudy)

Quote:



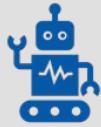
Remember that the most dangerous prison is the one in your head.

Gold standard:



Помни, что самая опасная тюрьма – в твоей голове.

MT1:



Помните, что самая опасная тюрьма находится в вашей голове.

MT2:



Помни, что самая опасная тюрьма – это тюрьма в твоей голове.



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MT2:

Помни, что самая опасная тюрьма – это тюрьма в твоей голове.

	MT1	MT2
Precision, n=1		
Precision, n=2		
Precision, n=3		
Precision, n=4		
Brevity penalty		
BLEU		



BLEU (bilingual evaluation understudy)



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MT2:

Помни, что самая опасная тюрьма – это тюрьма в твоей голове.

	MT1	MT2
Precision, n=1	5/9	
Precision, n=2	3/8	
Precision, n=3	2/7	
Precision, n=4	1/6	
Brevity penalty		
BLEU		



BLEU (bilingual evaluation understudy)



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	MT1	MT2
Precision, n=1	5/9	
Precision, n=2	3/8	
Precision, n=3	2/7	
Precision, n=4	1/6	
Brevity penalty	1	
BLEU		



BLEU (bilingual evaluation understudy)



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	MT1	MT2
Precision, n=1	5/9	
Precision, n=2	3/8	
Precision, n=3	2/7	
Precision, n=4	1/6	
Brevity penalty	1	
BLEU	0.330 3	

BLEU (bilingual evaluation understudy)



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MT2:

Помни, что самая опасная тюрьма – это тюрьма в твоей голове.

	MT1	MT2
Precision, n=1	5/9	7/10
Precision, n=2	3/8	5/9
Precision, n=3	2/7	3/8
Precision, n=4	1/6	2/7
Brevity penalty	1	1
BLEU	0.330 3	0.6389



WER (word error rate)

- The minimum number of operations required for transforming MT result into gold standard
- Operations: replacement, deletion, adding words

$$WER = \frac{\# \text{deletion} + \# \text{adding words} + \# \text{replacement}}{\# \text{(gold standard)}}$$



WER (word error rate)

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WER (word error rate)



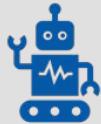
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MT1:

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MT2:

Помни, что самая опасная тюрьма – это тюрьма в твоей голове.

	MT1	MT2
# adding words		
# replacement		
# deletion		
WER		



WER (word error rate)



Quote:

Remember that the most dangerous prison is the one in your head.



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Помни, что самая опасная тюрьма – в твоей голове.



MT1:

~~Помните помни~~, что самая опасная тюрьма находится в вашей голове.



MT2:

Помни, что самая опасная тюрьма – это тюрьма в твоей голове.

	MT1	MT2
# adding words		
# замен	1	
# deletion		
WER		



WER (word error rate)



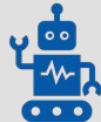
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MT2:

Помни, что самая опасная тюрьма – это тюрьма в твоей голове.

	MT1	MT2
# adding words		
# replacement	1	
# deletion		
WER		



WER (word error rate)



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MT2:

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	MT1	MT2
# adding words		
# replacement	1	
# deletion	1	
WER		



WER (word error rate)



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Помните помни, что самая опасная тюрьма находится в вашей твоей голове.



MT2:

Помни, что самая опасная тюрьма – это тюрьма в твоей голове.

	MT1	MT2
# adding words		
# replacement	2	
# deletion	1	
WER		



WER (word error rate)



Quote:

Remember that the most dangerous prison is the one in your head.



Gold standard:

Помни, что самая опасная тюрьма – в твоей голове.



MT1:

Помните помни, что самая опасная тюрьма находится в вашей твоей голове.



MT2:

Помни, что самая опасная тюрьма – это тюрьма в твоей голове.

	MT1	MT2
# adding words	0	
# replacement	2	
# deletion	1	
WER		



WER (word error rate)



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MT1:

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MT2:

Помни, что самая опасная тюрьма – это тюрьма в твоей голове.

	MT1	MT2
# adding words	0	
# replacement	2	
# deletion	1	
WER	0.33	



WER (word error rate)



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Помни, что самая опасная тюрьма – ~~это тюрьма~~ в твоей голове.

	MT1	MT2
# adding words	0	
# replacement	2	
# deletion	1	
WER	0.33	

WER (word error rate)



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MT2:

Помни, что самая опасная тюрьма – ~~это тюрьма~~ в твоей голове.

	MT1	MT2
# adding words	0	0
# replacement	2	0
# deletion	1	2
WER	0.33	0.2



WER and BLEU

Advantages

- Simple and quick
- Correlate with expert review

Disadvantages

- Operate with short fragments
- Can't estimate genre specifics
- The ratings are relative,
difficult to compare with each
other
- An important technical
problem: estimates are not
differentiable

