



# Natural Language Processing: Seq2seq and Attention

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Machine Learning and Data-Intensive Systems

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- **Sequence to Sequence (seq2seq)**
- Attention
- Practical tips

# Machine translation requires training parameters to provide results

## Human Translation

$$y^* = \arg \max_y p(y|x)$$

The “probability” is intuitive and is given by a human translator’s expertise

## Machine Translation

model parameters

$$y' = \arg \max_y p(y|x, \theta)$$

Questions we need to answer

- **modeling**

How does the model for  $p(y|x, \theta)$  look like?

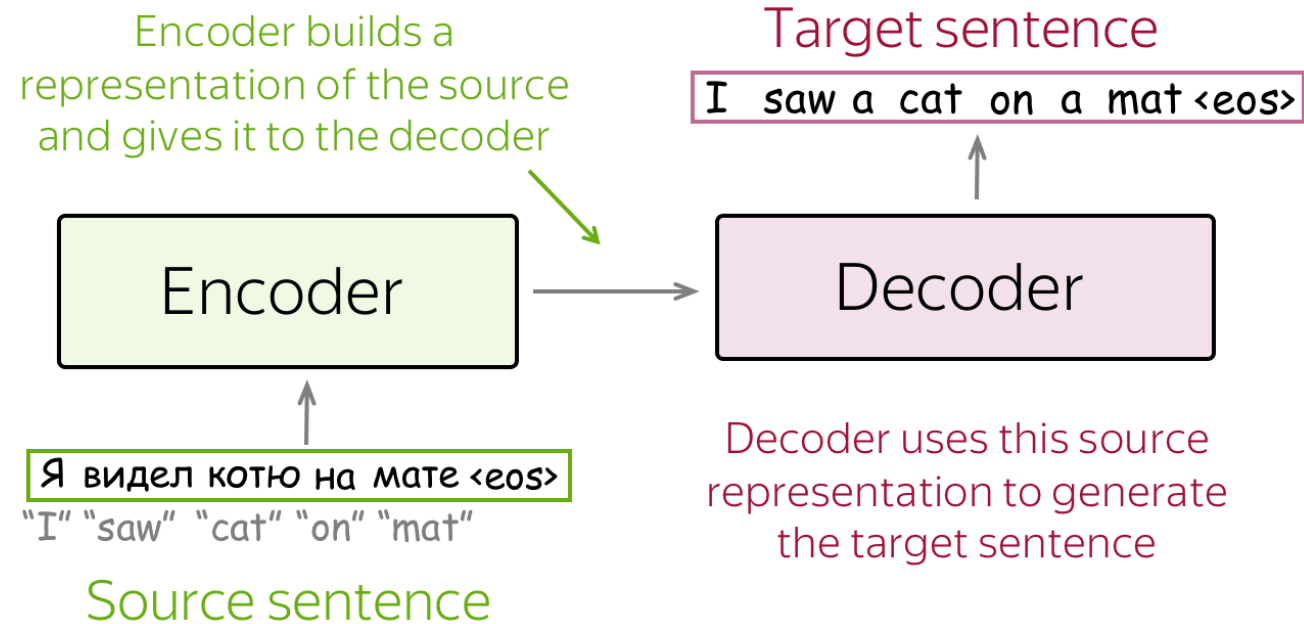
- **learning**

How to find  $\theta$ ?

- **search**


How to find the argmax?

## Encoder-decoder architecture maps data semantics

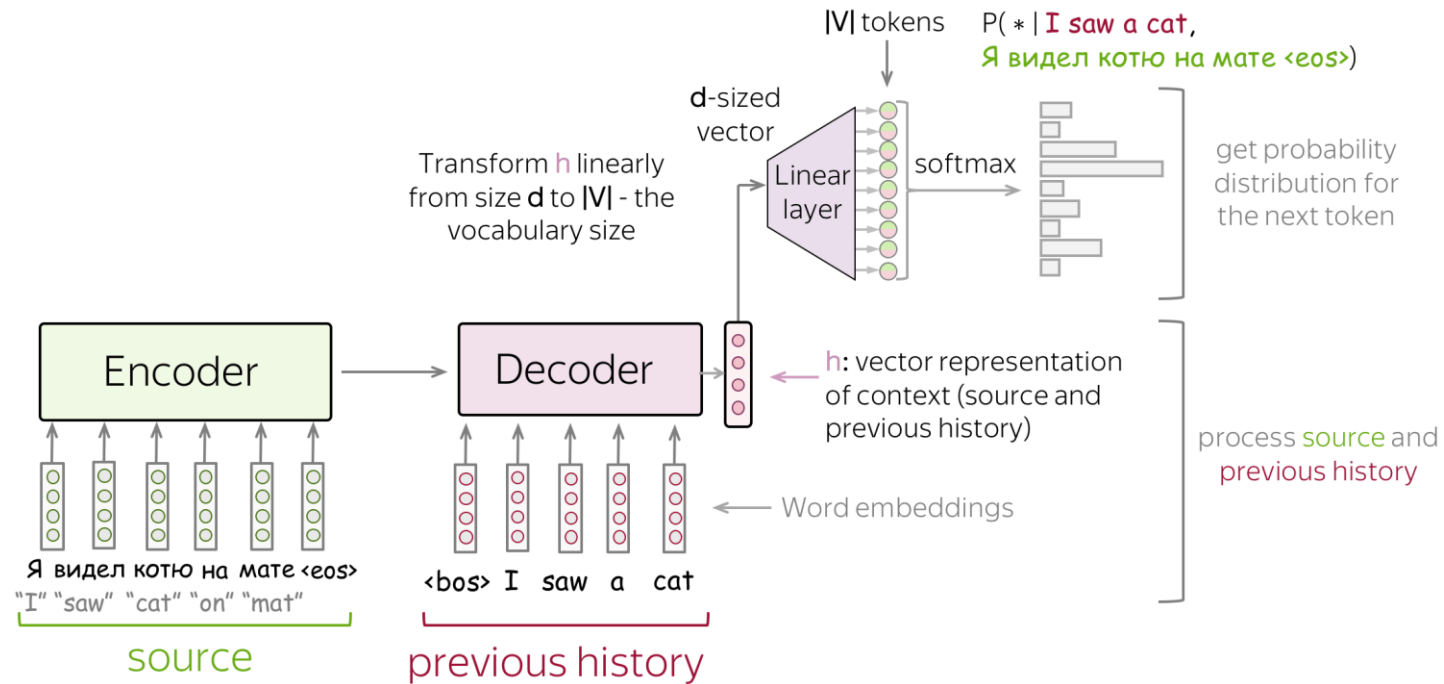


## Encoder encapsulates a condition for a decoder Language Model

Language Models: 
$$P(y_1, y_2, \dots, y_n) = \prod_{t=1}^n p(y_t | y_{<t})$$

Conditional  
Language Models: 
$$P(y_1, y_2, \dots, y_n, | \textcolor{green}{x}) = \prod_{t=1}^n p(y_t | y_{<t}, \textcolor{green}{x})$$
  
  
condition on source  $x$

# A helicopter view on the Encoder-Decoder architecture



# Model Loss is a well-known Cross-Entropy

Source sequence:

Я видел котю на мате <eos>  
"I" "saw" "cat" "on" "mat"

Target sequence:

I saw a cat on a mat <eos>

← one training example

← one step for this example

previous tokens we want the model to predict this

Model prediction:  $p(* | \text{I saw a, Я ... <eos>})$

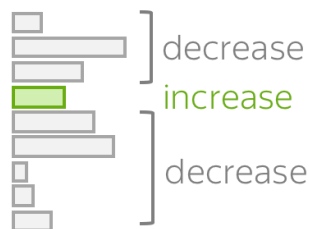


Target

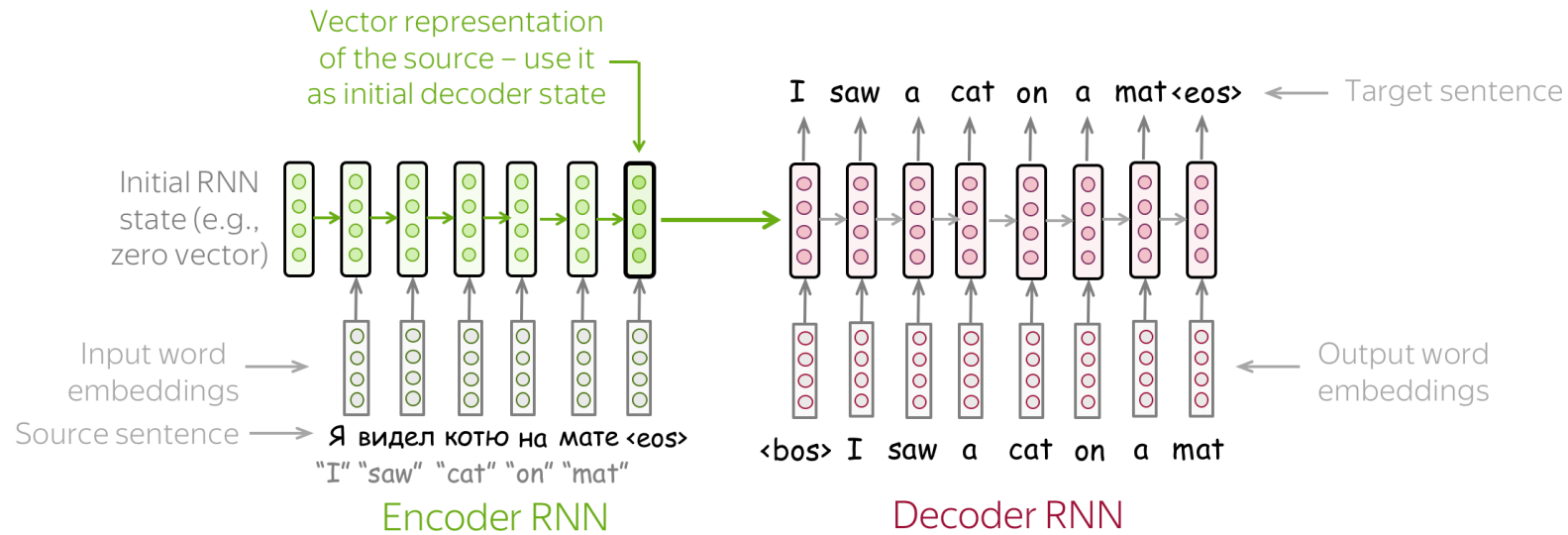
0  
0  
0  
0  
1  
0  
0  
0  
0  
0  
0

cat

Loss =  $-\log(p(\text{cat})) \rightarrow \min$

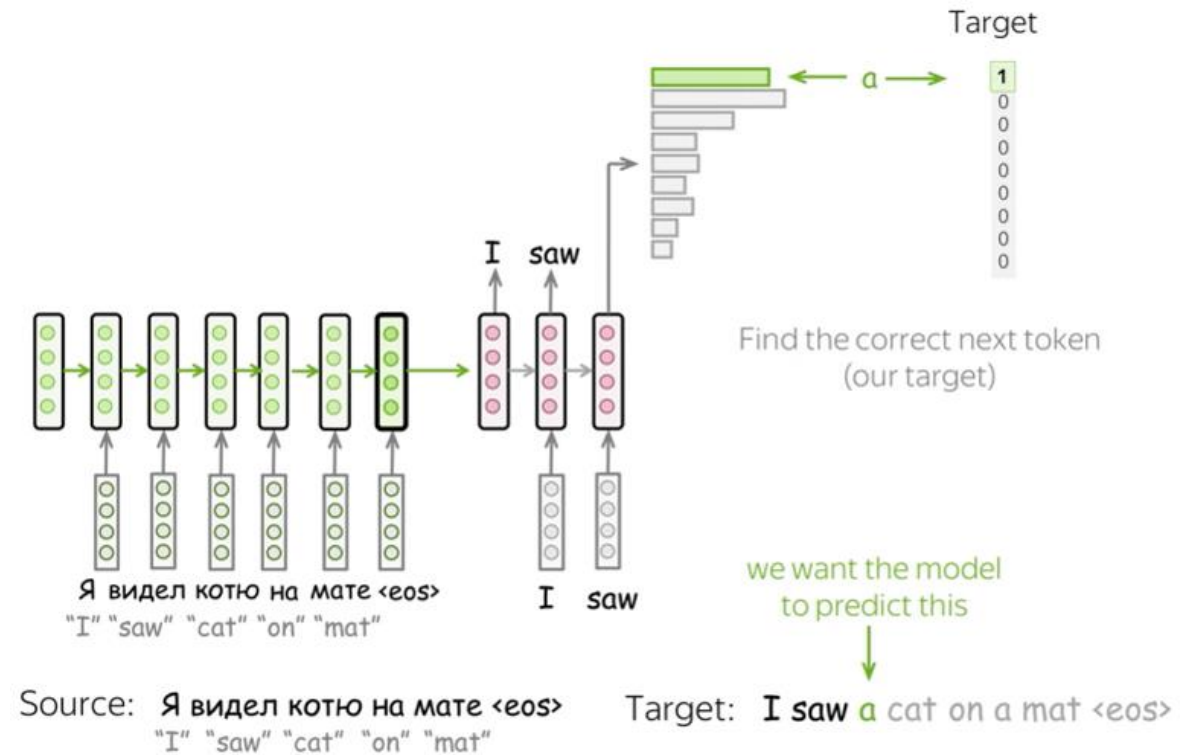


# A simple RNN is a valid Encoder-Decoder model

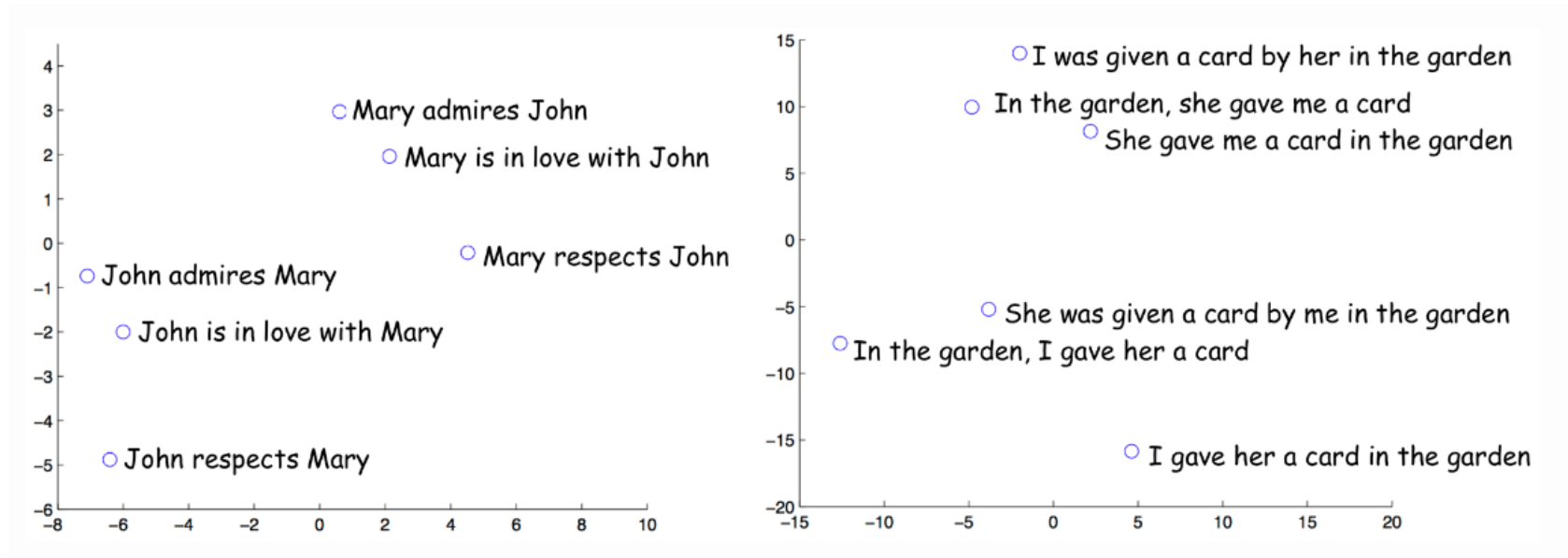




# A simple RNN is a valid Encoder-Decoder model



# Semantic space of text embeddings

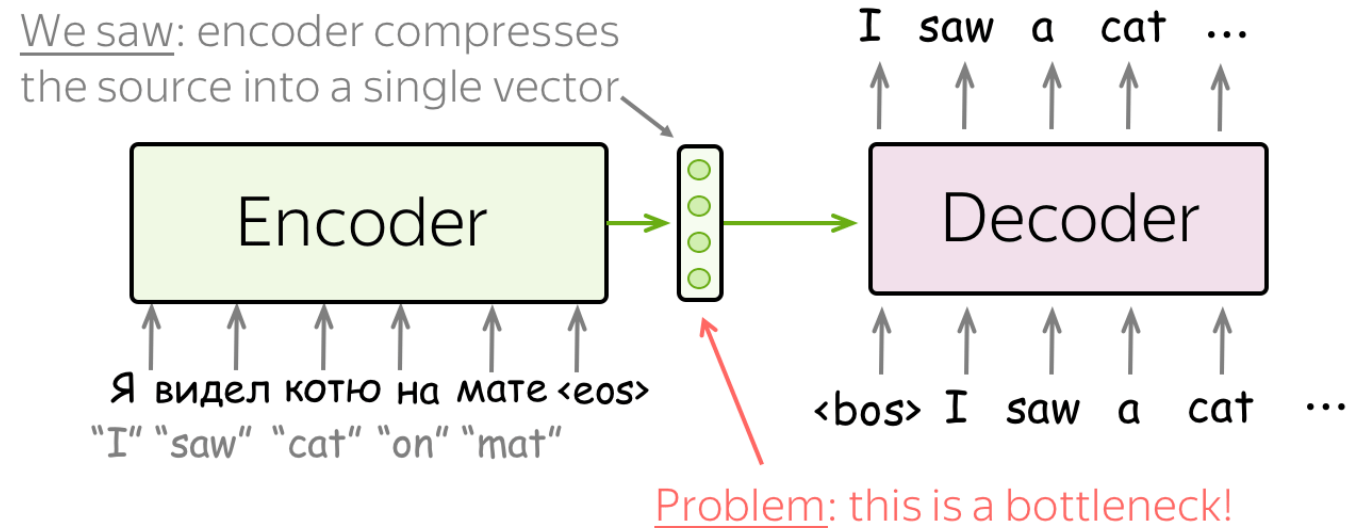




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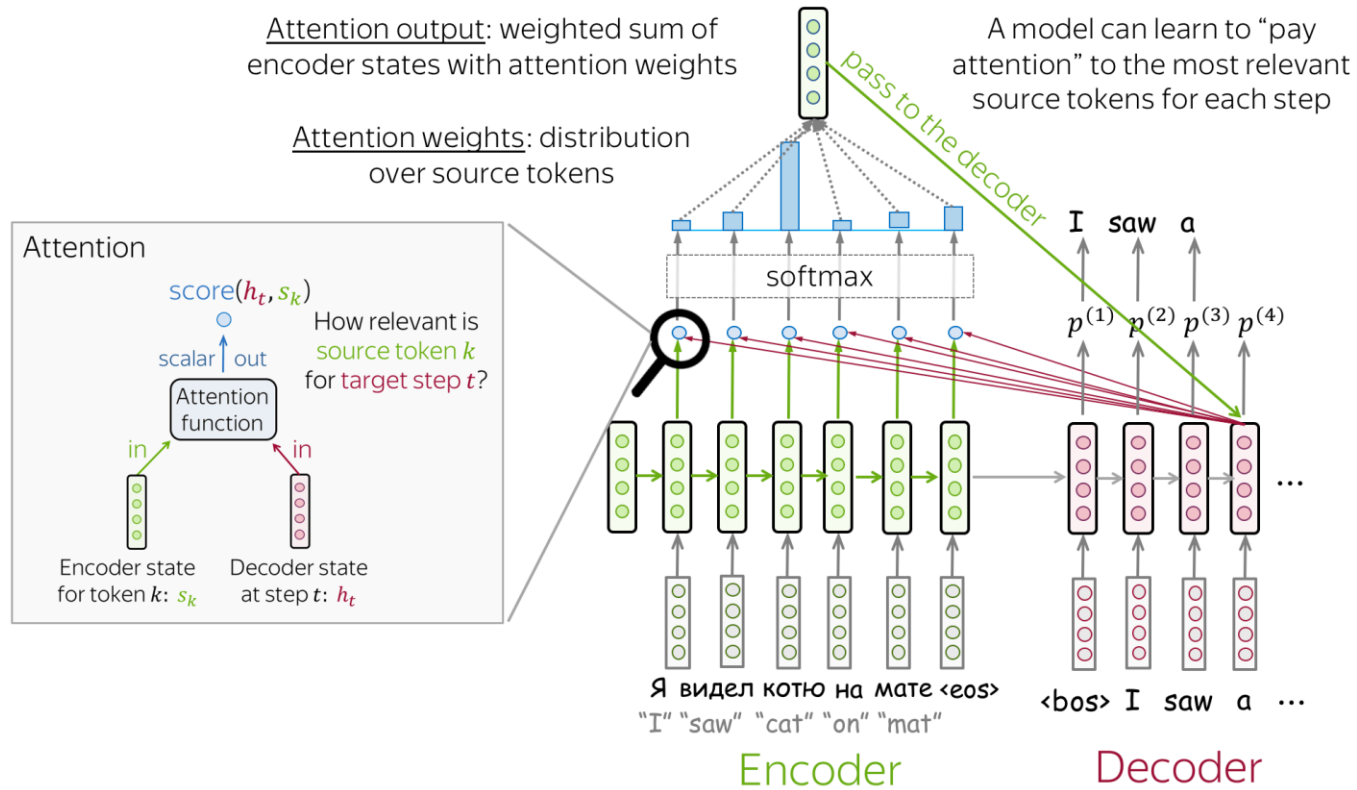
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## The final hidden state is a bottleneck

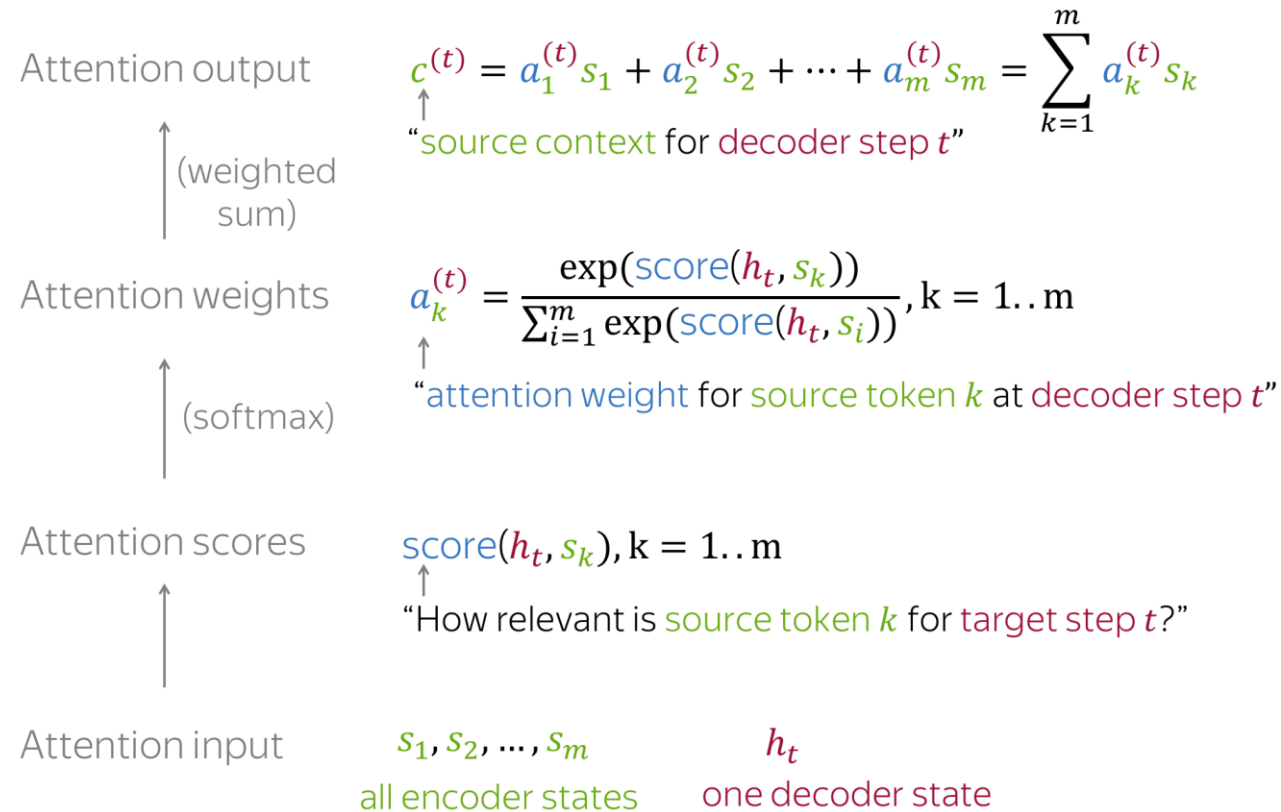


# A simple Attention overview

$$\begin{bmatrix} - & h_1 & - \\ & e & \\ - & h_2 & - \\ & e & \\ & \vdots & \\ - & h_t & - \end{bmatrix} \begin{matrix} d \\ h_t \end{matrix}$$

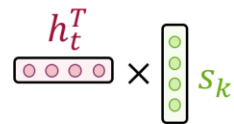


# Encoder hidden states are weighed according to their attention score



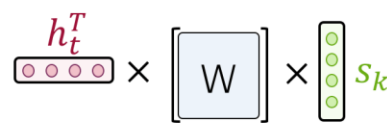
# Encoder hidden states are weighed according to their attention score

Dot-product



$$\text{score}(h_t, s_k) = h_t^T s_k$$

Bilinear



$$\text{score}(h_t, s_k) = h_t^T W s_k$$

Multi-Layer Perceptron



$$\text{score}(h_t, s_k) = w_2^T \cdot \tanh(W_1 [h_t, s_k])$$



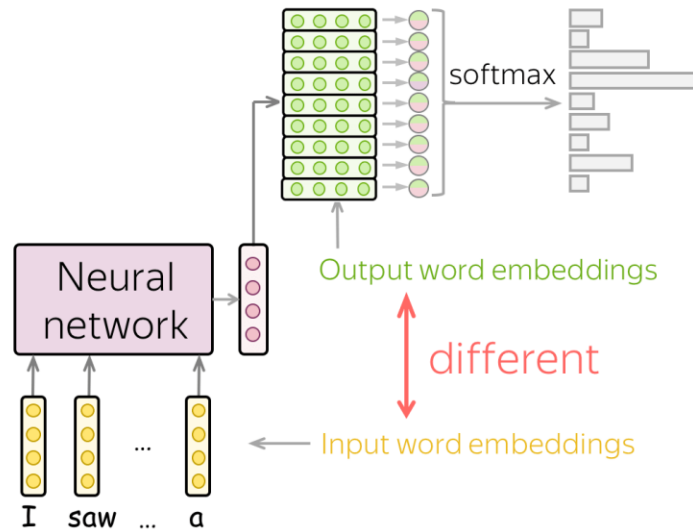
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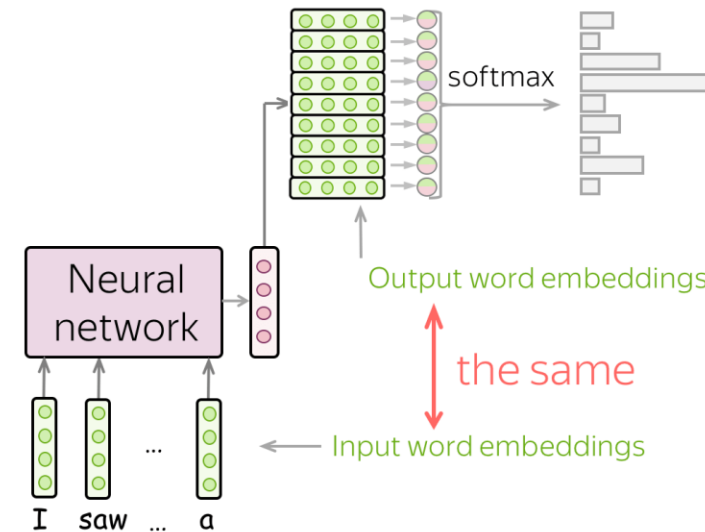


Weight tying is a way to significantly reduce the amount of parameters

### Default (no weight tying)



### Weight tying



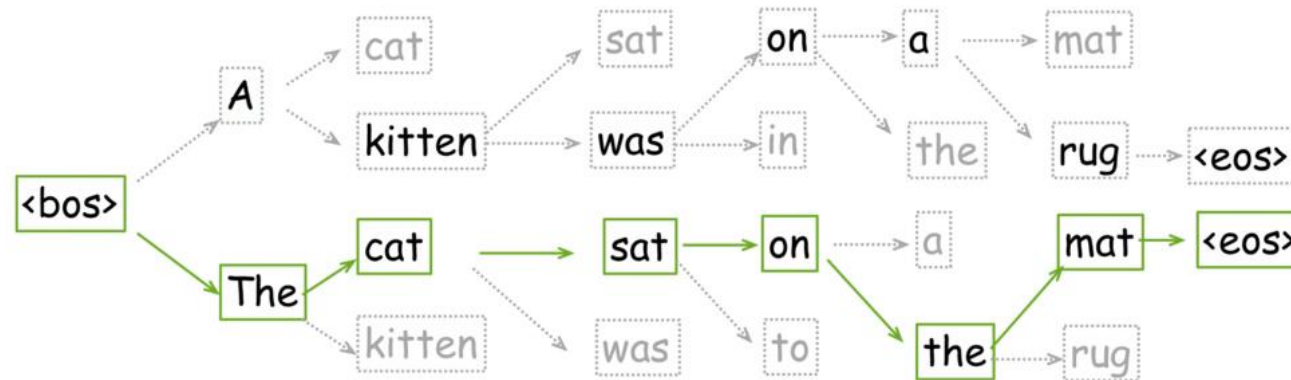
## Finding the next token is not that trivial

$$y' = \arg \max_y p(y|x) = \arg \max_y \prod_{t=1}^n p(y_t|y_{<t}, x) \quad \text{How to find the argmax?}$$

Greedy Decoding: At each step, pick the most probable token

$$\arg \max_y \prod_{t=1}^n p(y_t | y_{<t}, x) \neq \prod_{t=1}^n \arg \max_{y_t} p(y_t | y_{<t}, x)$$

## A beam search illustration



Pick the hypothesis with the highest probability



Temperature: the higher, the more chaotic the choice becomes

$$w_{next} \sim \frac{P(w_{next}|X)^{1/\tau}}{\sum_{\hat{w}} P(\hat{w}|X)^{1/\tau}}$$

