Seq2seq and Attention

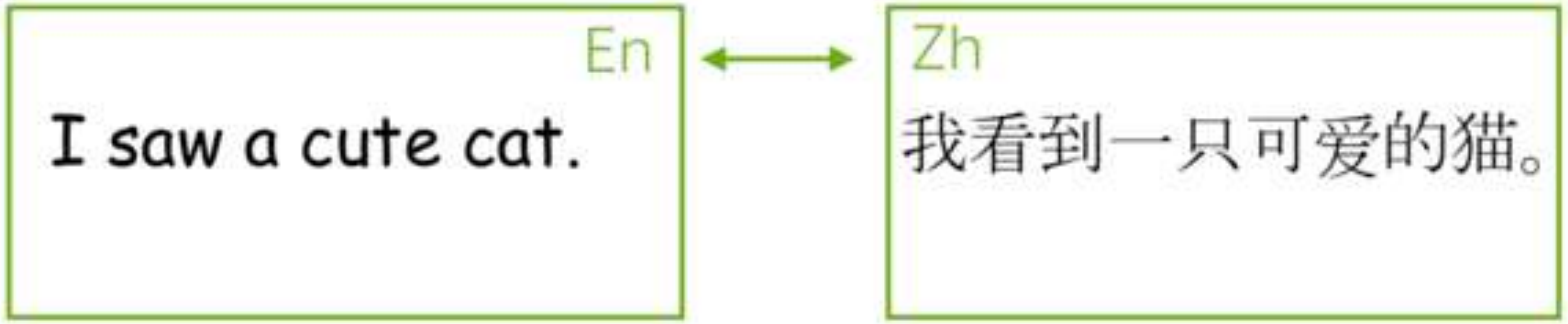
Lena Voita

Lecture-blog and lots of additional materials are here:
https://lena-voita.github.io/nlp_course/seq2seq_and_attention.html

Sequence to Sequence Task

- Translation between natural languages

- More generally, translation between any sequences



What is going to happen:

- Seq2seq Basics
- Attention
- Transformer
- Subword Segmentation: BPE
-  Analysis and Interpretability

What is going to happen:

- Seq2seq Basics
  - Machine Translation Task
  - Encoder-Decoder Framework
  - Conditional LMs
  - The Simplest RNN Model
  - Training
  - Inference
- Attention
- Transformer
- Subword Segmentation: BPE
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<u>Human Translation</u>

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

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- modeling

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

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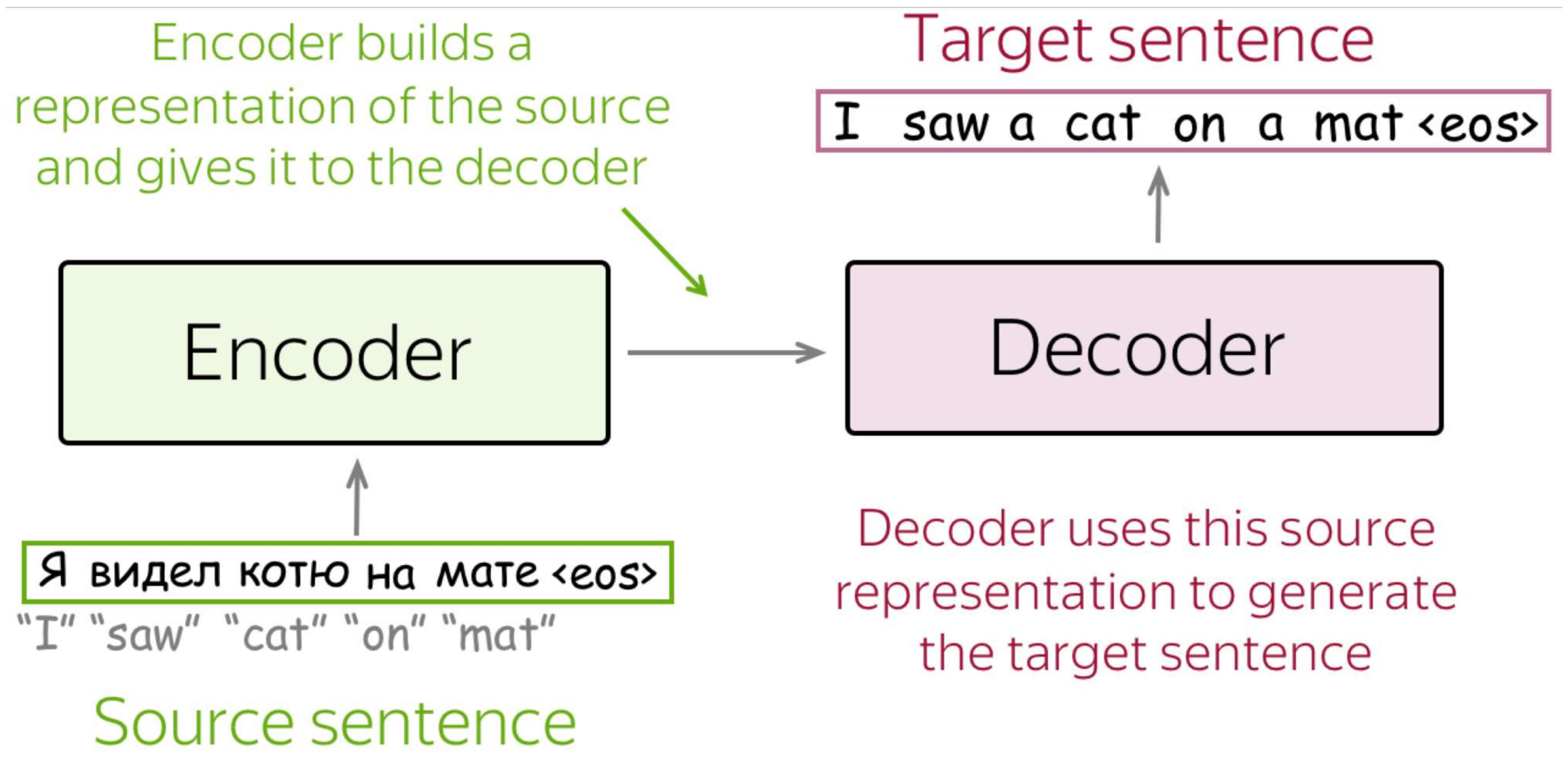
Encoder-Decoder Framework

The standard modeling paradigm:

- Encoder – reads the source sentence and produces its representation



Encoder-Decoder Framework

The standard modeling paradigm:

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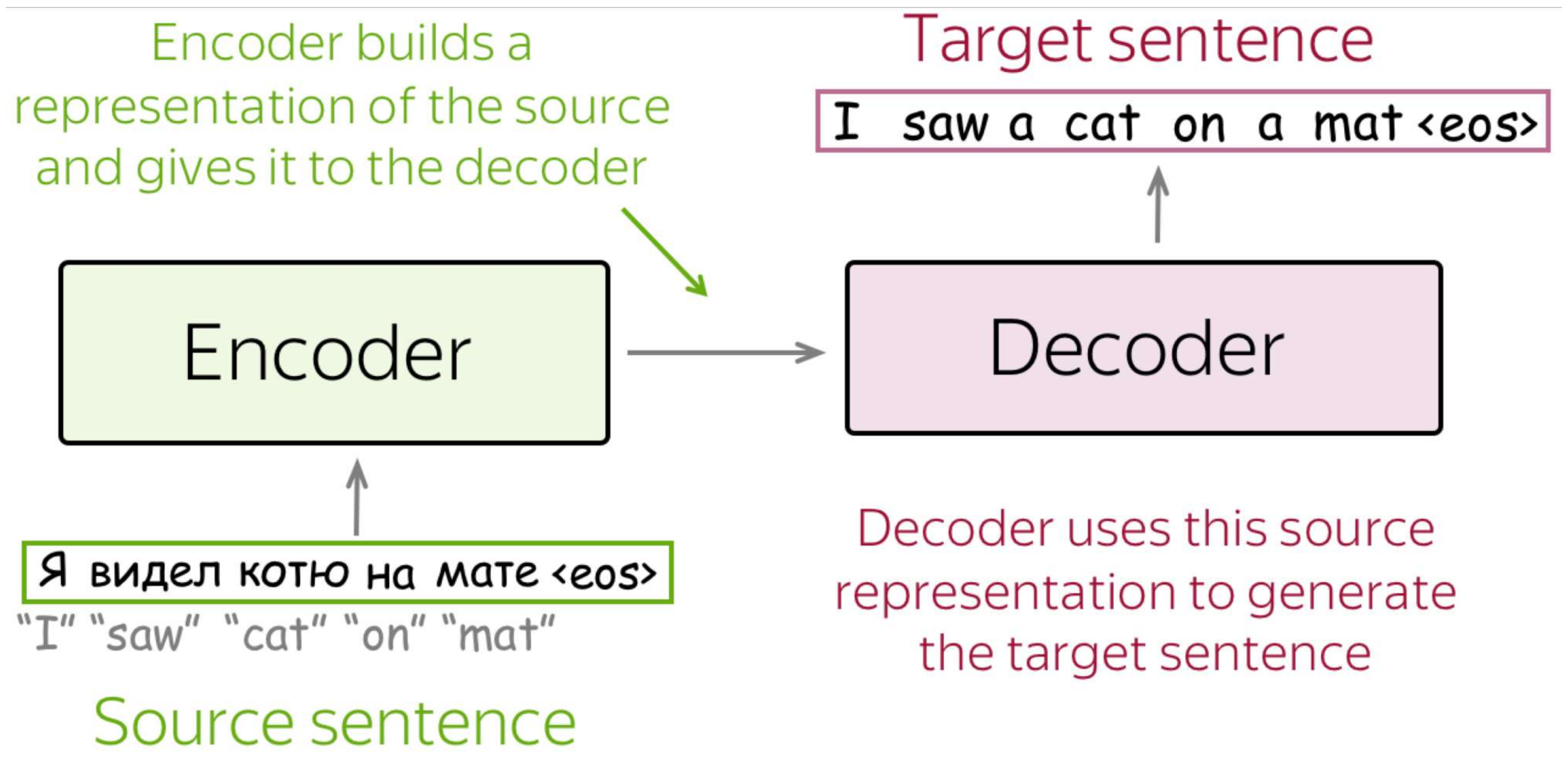
- Decoder - uses source representation from the encoder to generate the target sequence.



Conditional Language Models

Language Models: $P\left(y_{1,}y_2, \ldots, y_n\right) = \prod_{t=1}^{n} p(y_t | y_{<t})$
(left-to-right)

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condition on source x

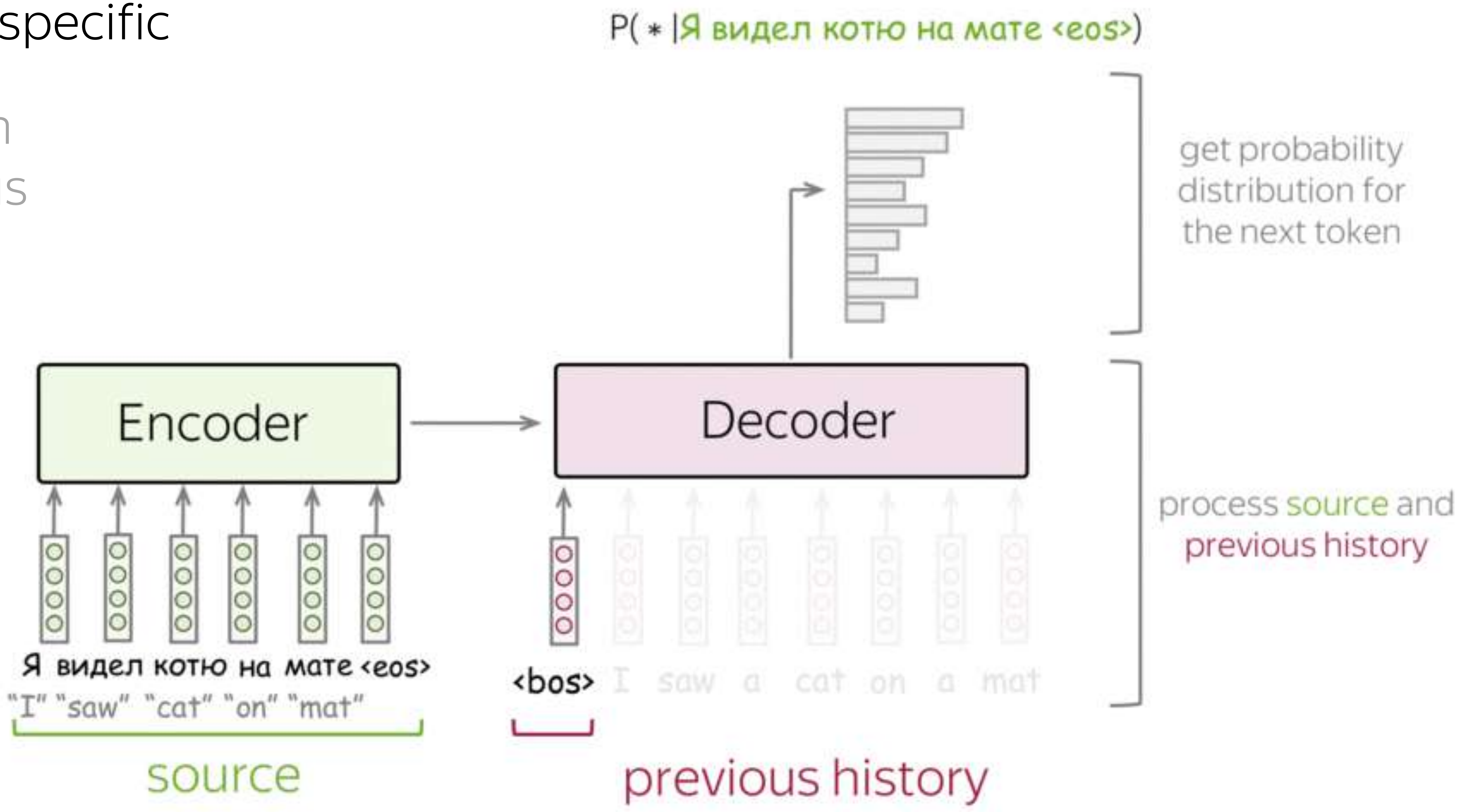
General View

- process context – model-specific

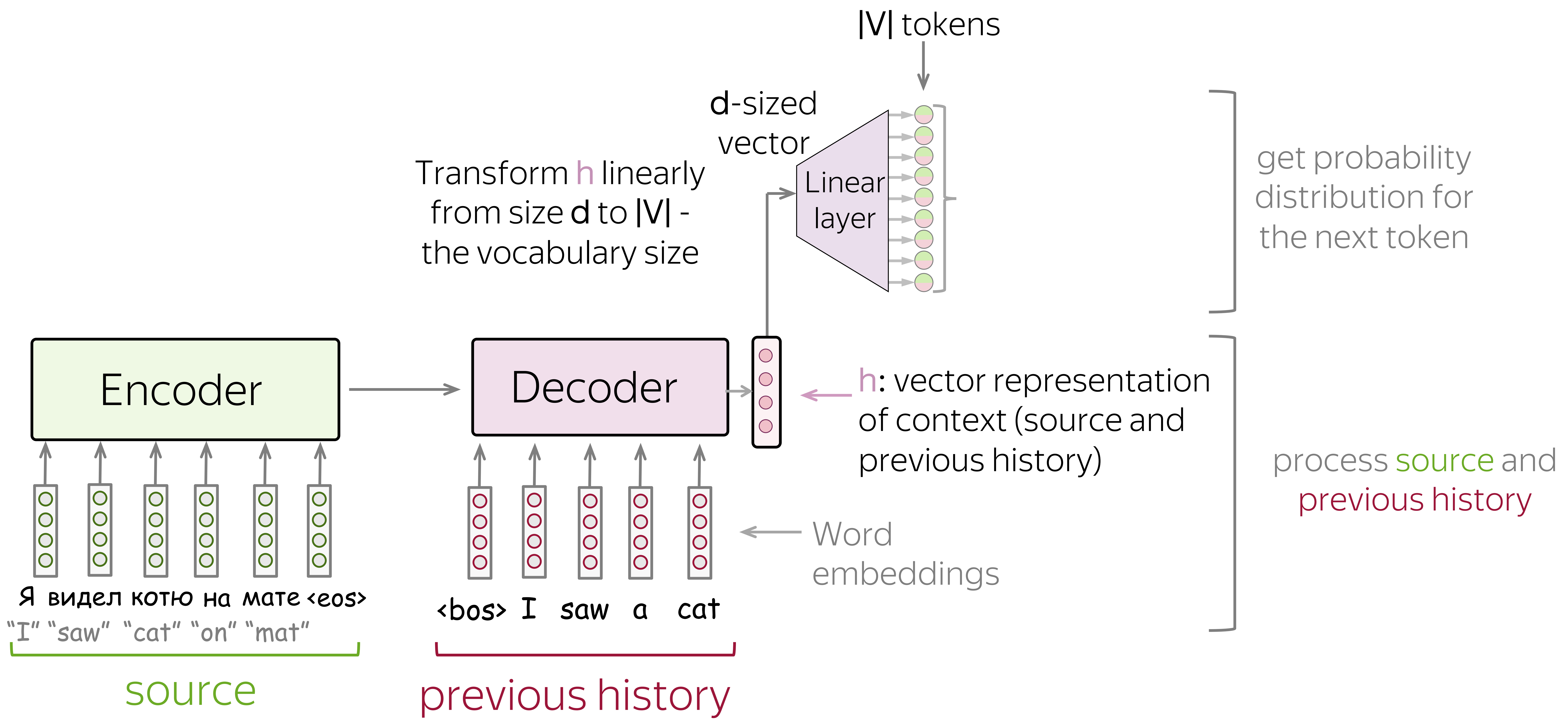
  Get vector representation of the source and previous target tokens

- evaluate probabilities – model-agnostic

  Predict probability distribution for the next target token



High-Level Pipeline



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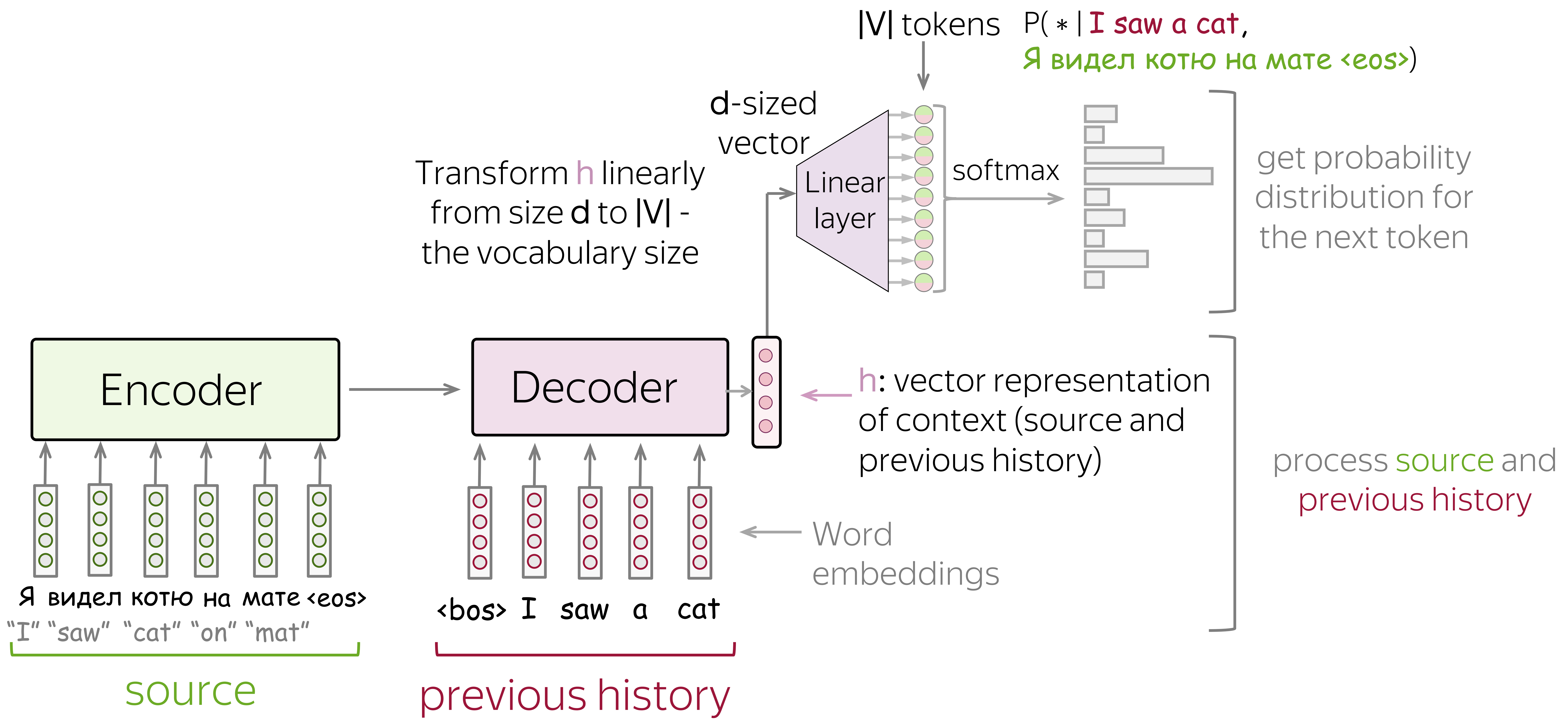
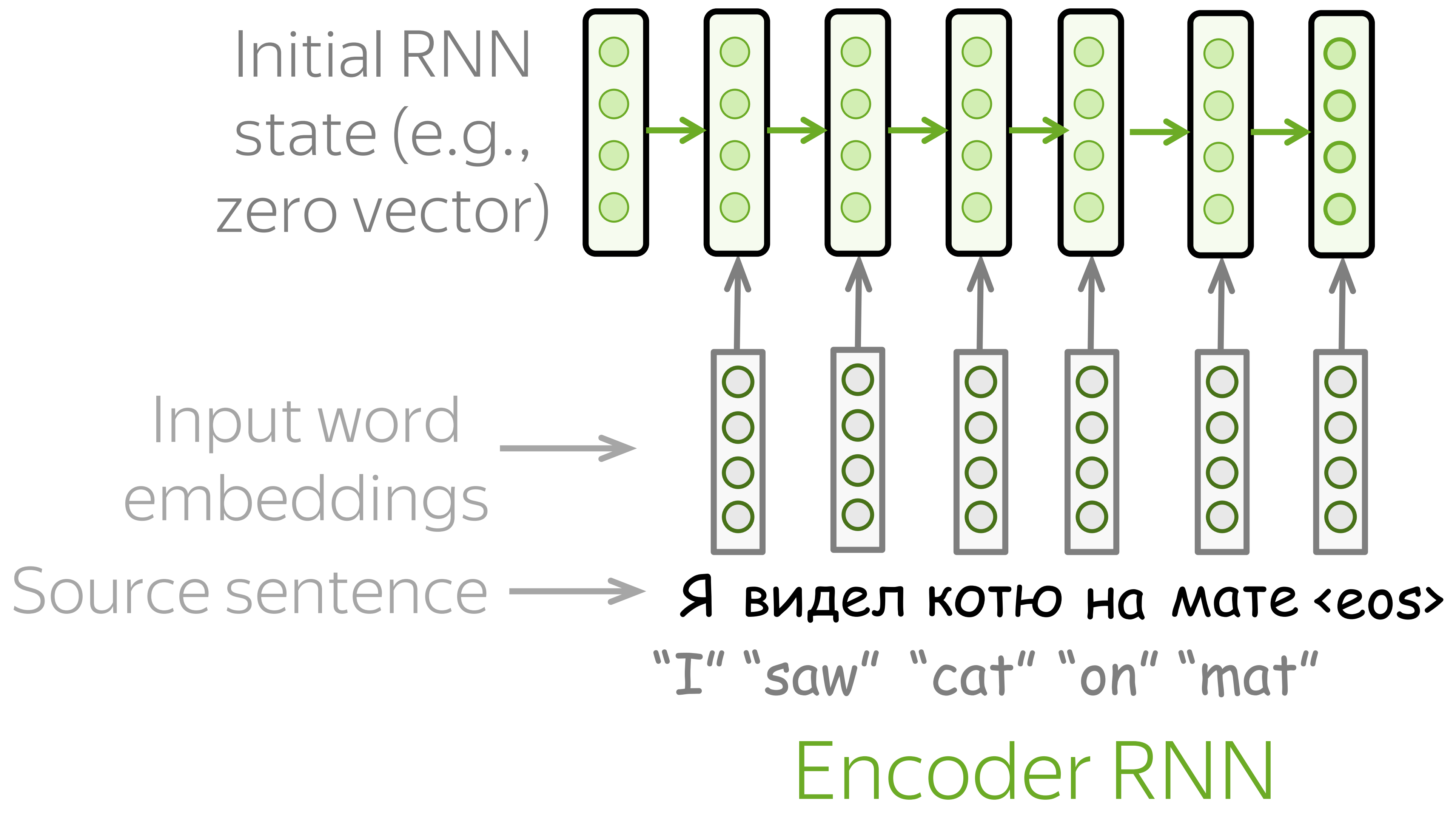


The Simplest Model: RNN Encoder and Decoder



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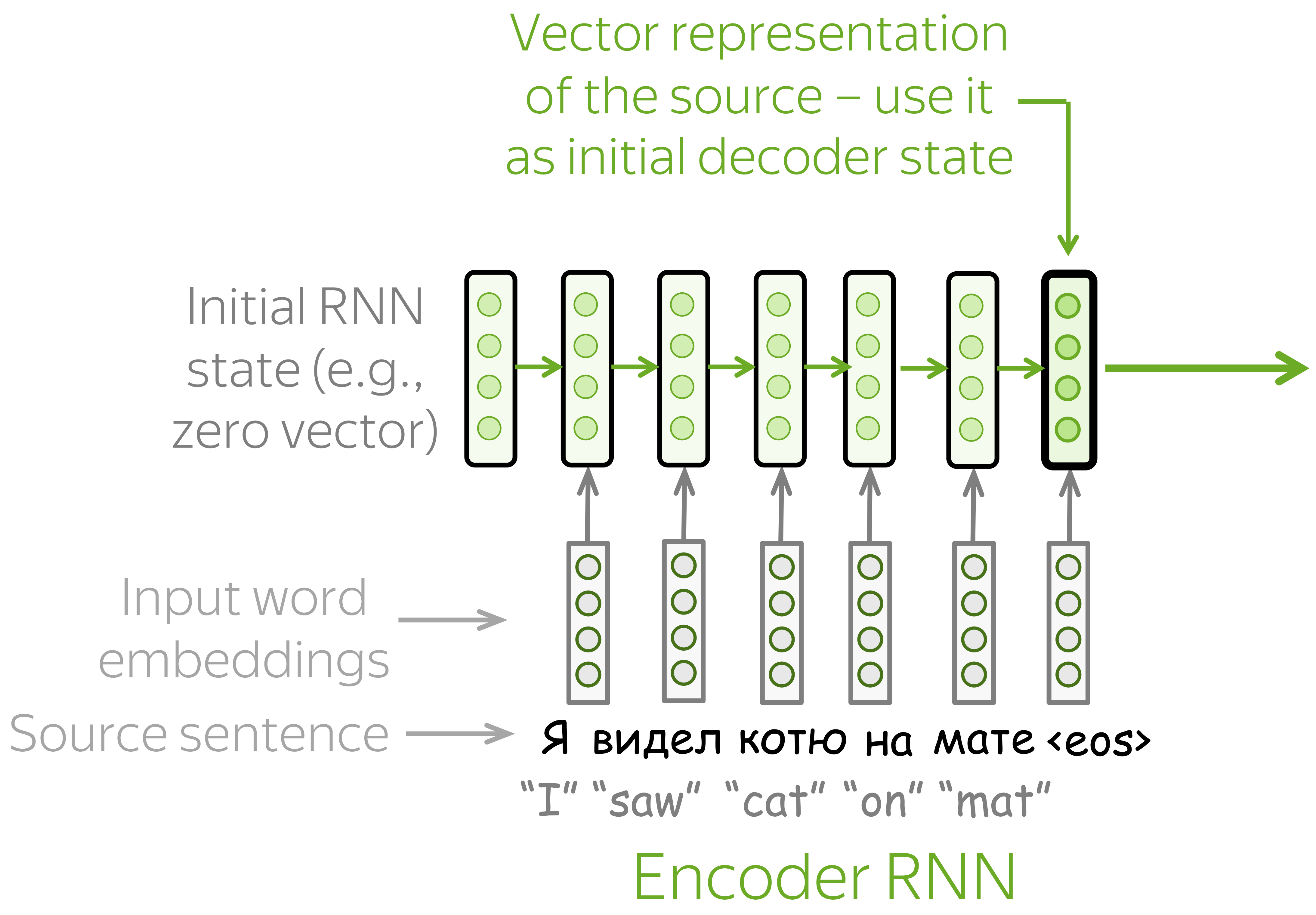

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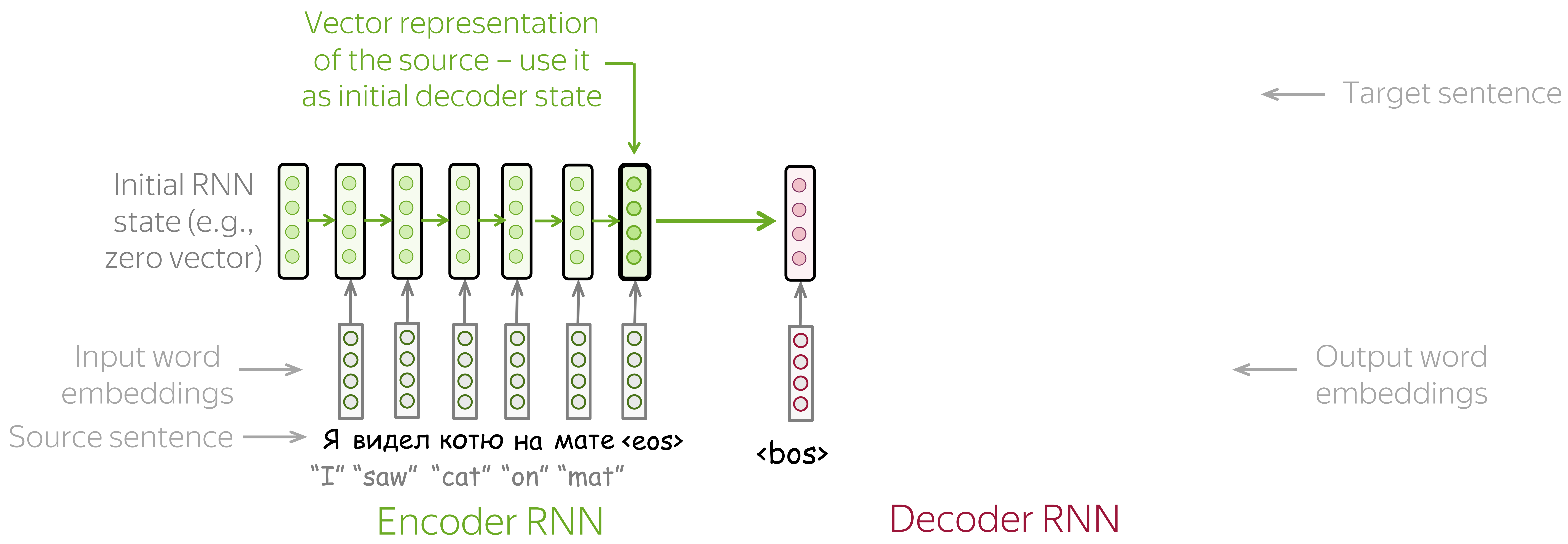

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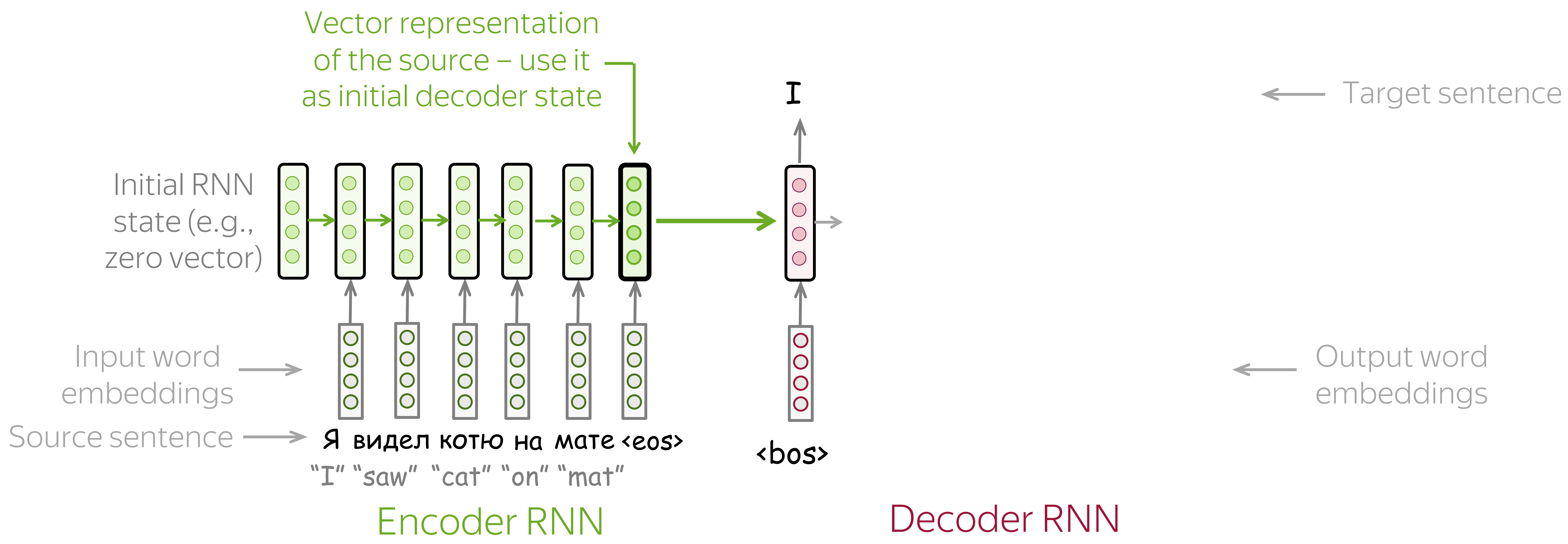

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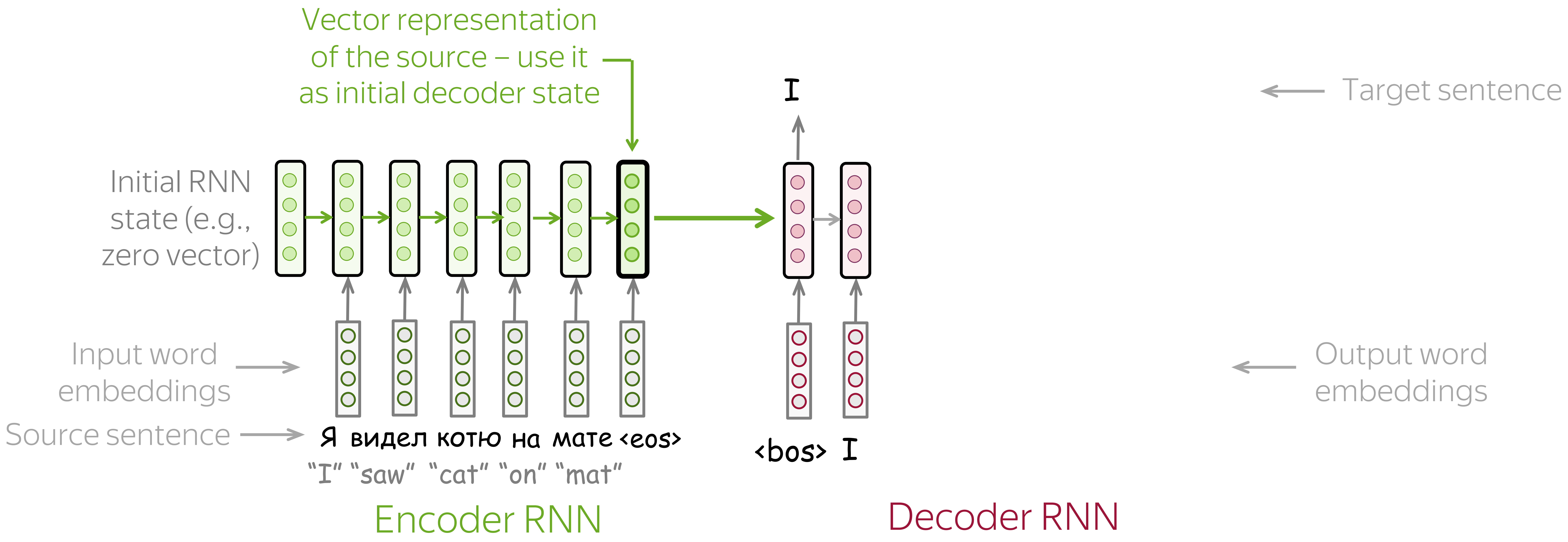

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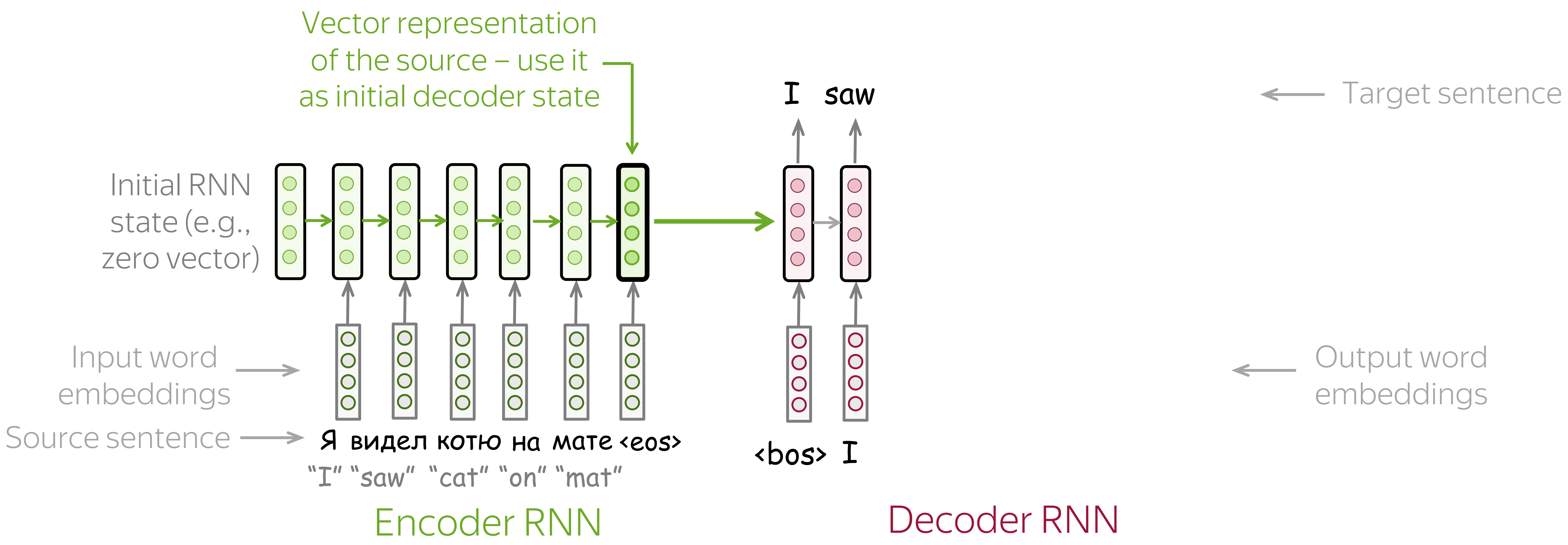

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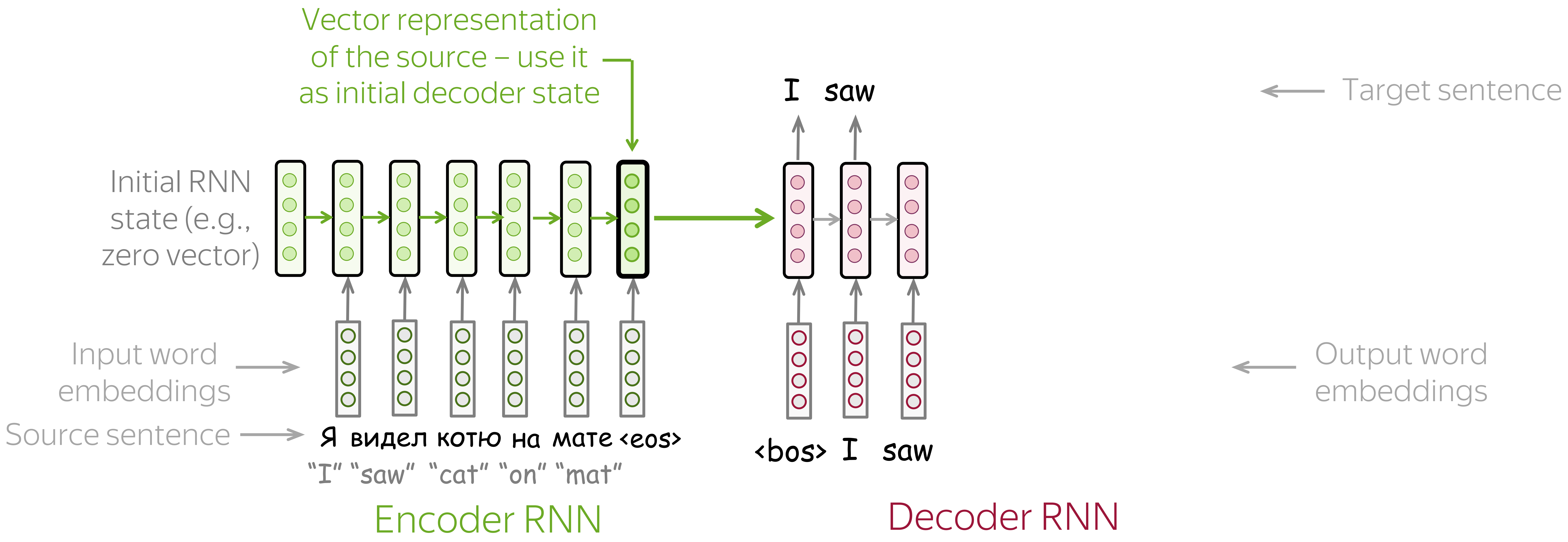

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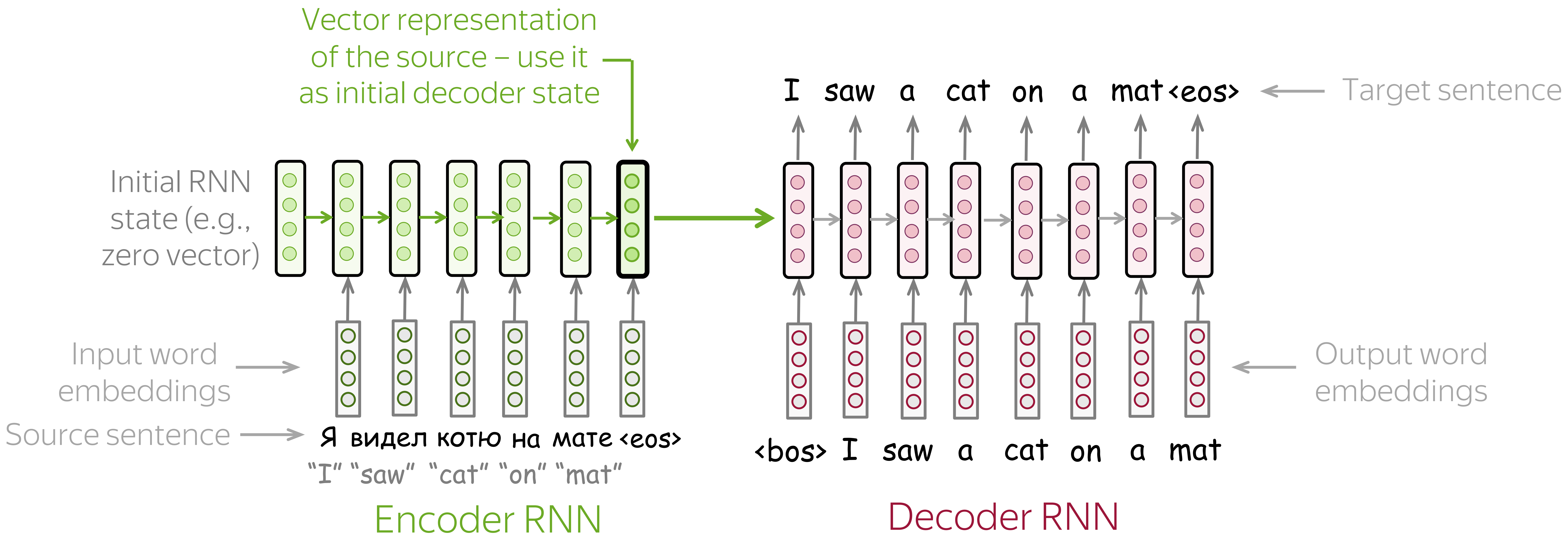
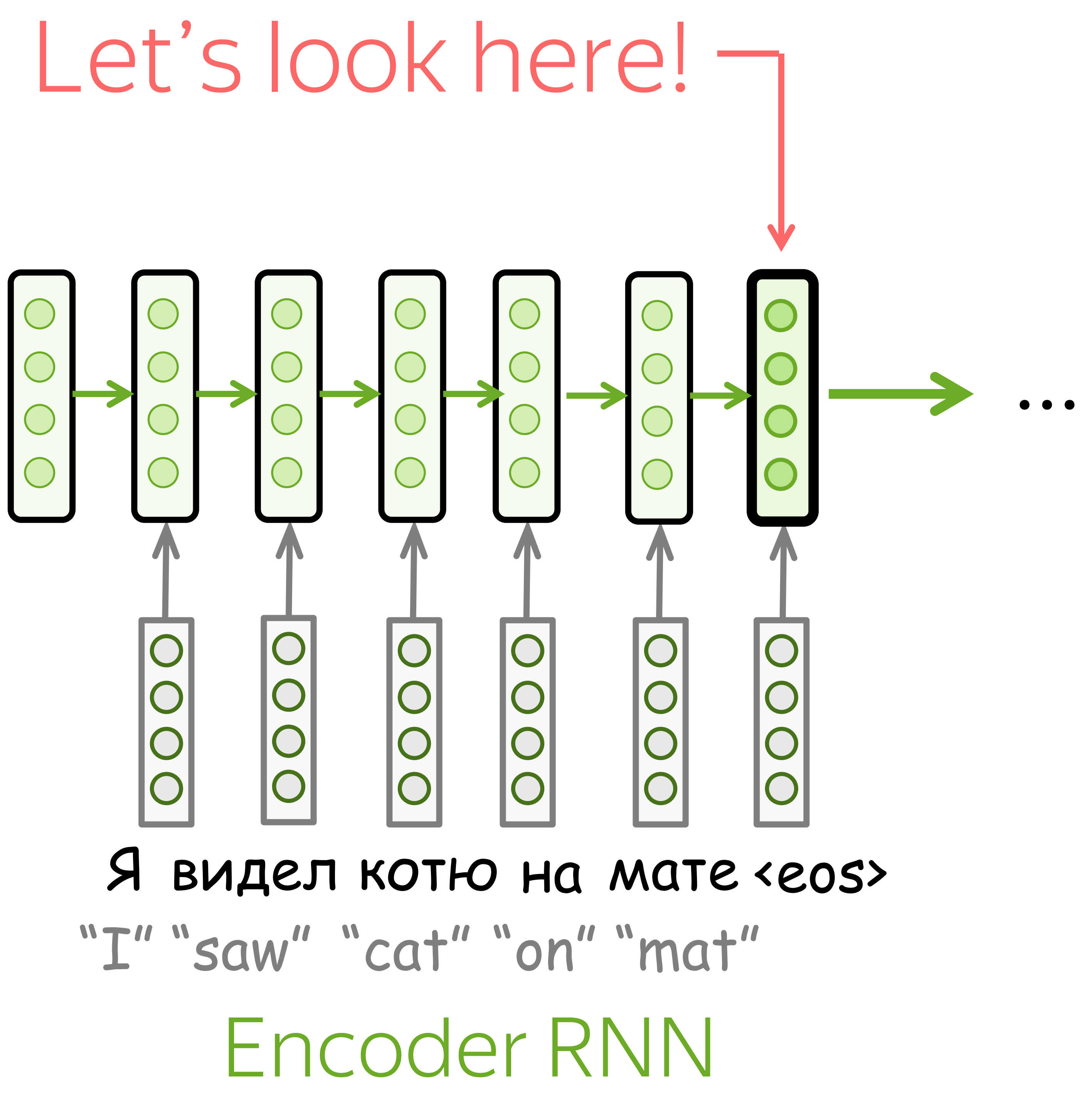
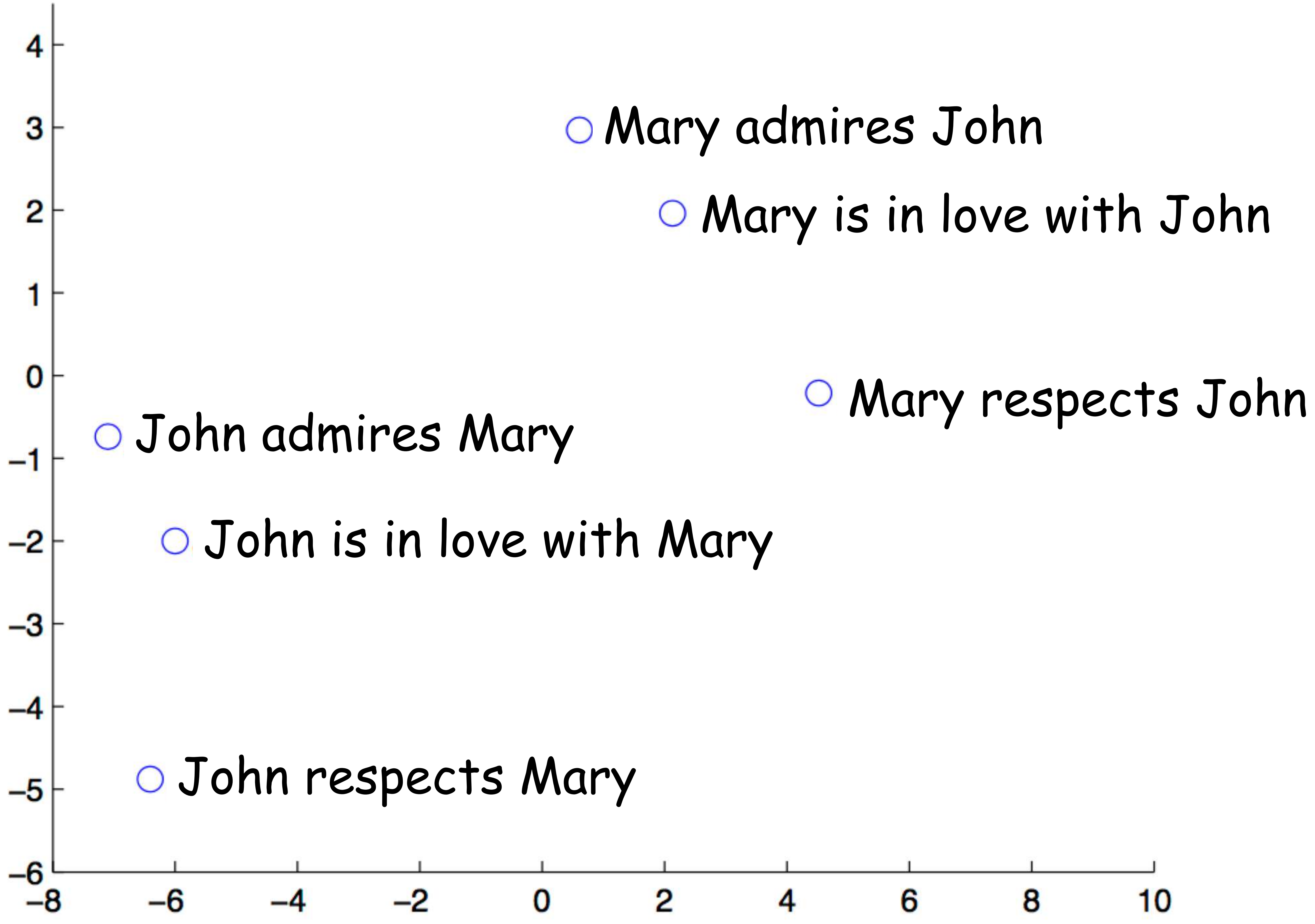


What does final encoder state represent?





The examples are from the paper Sequence to Sequence Learning with Neural Networks

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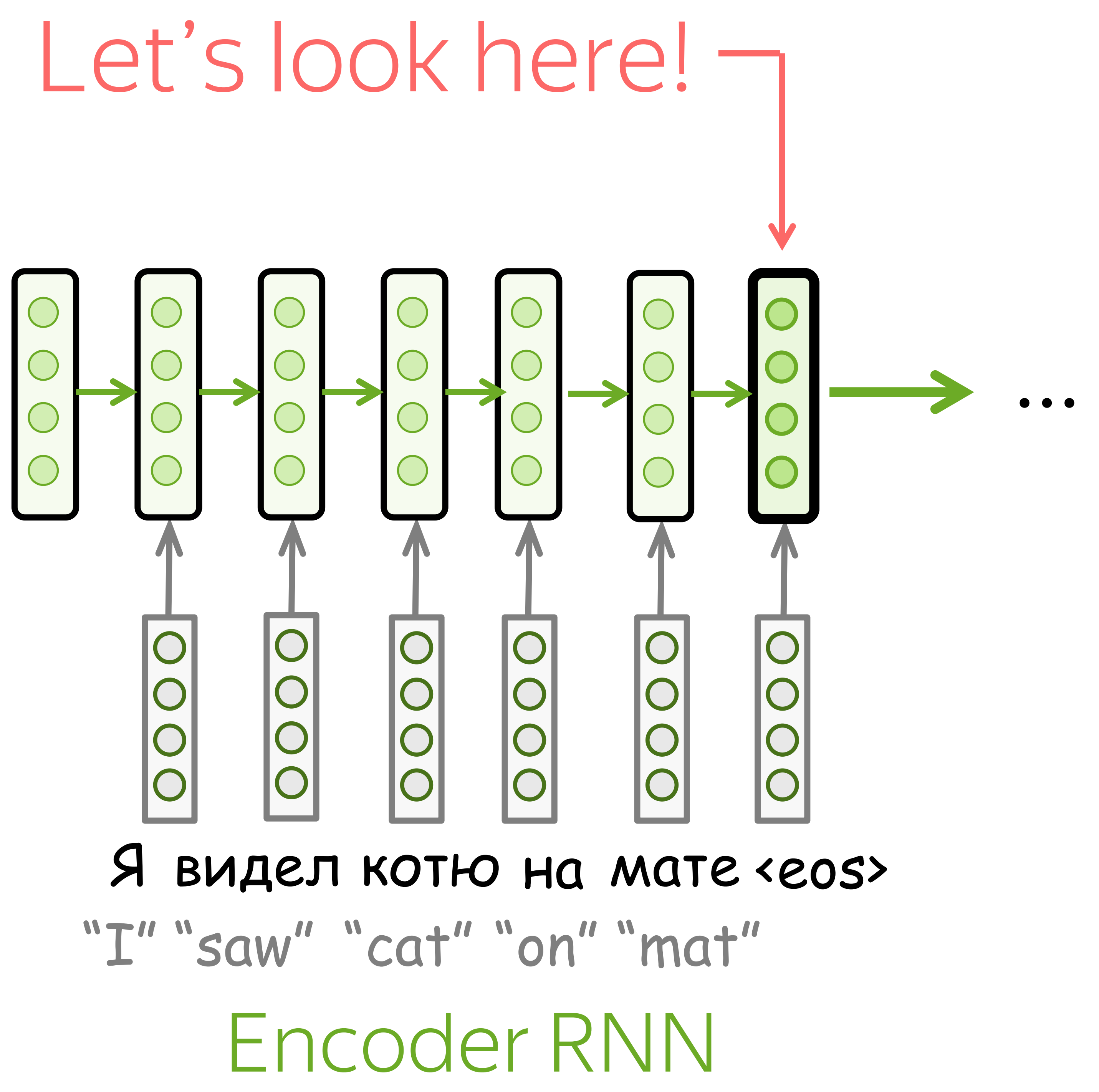

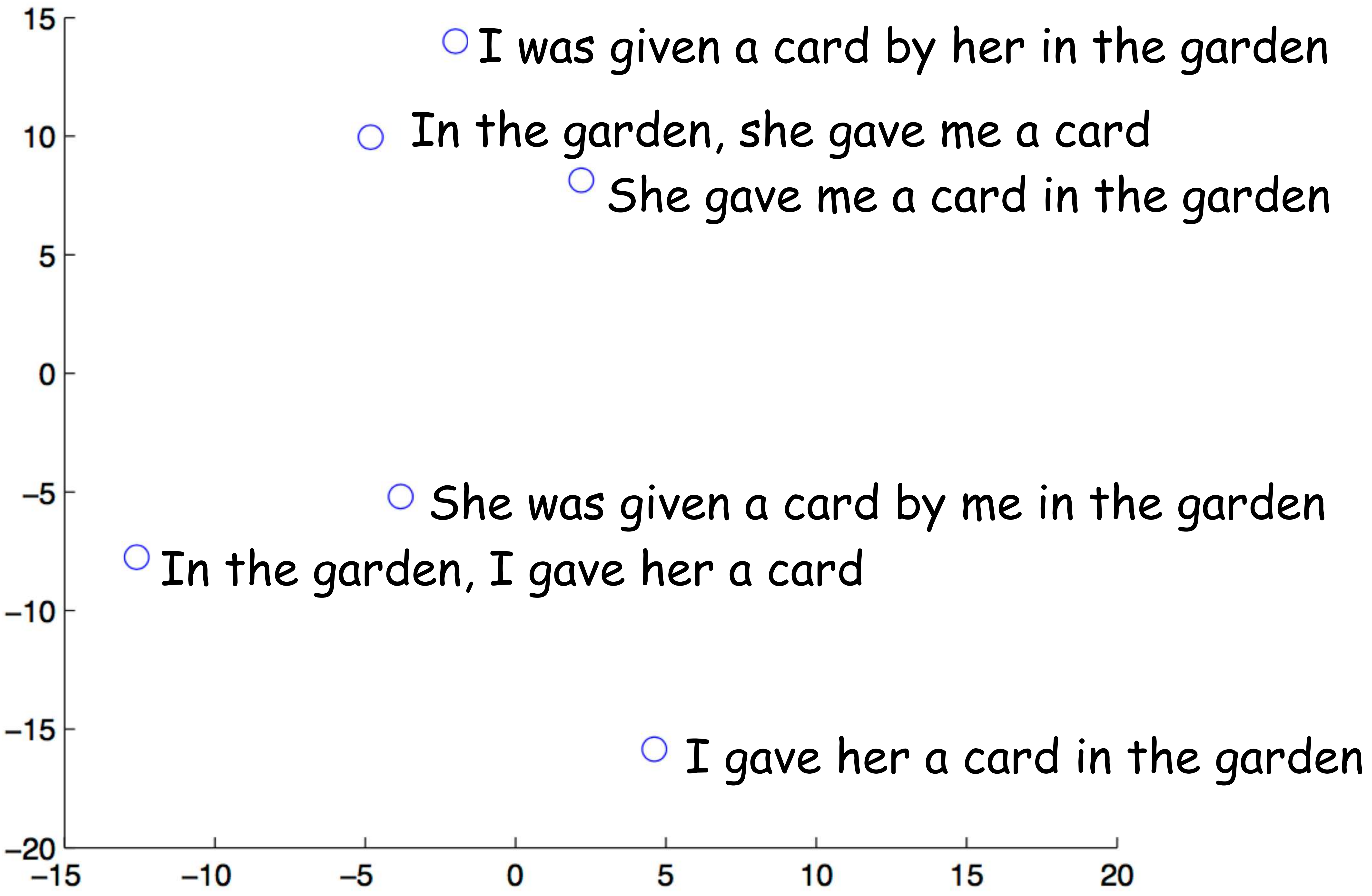

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Cross-Entropy – again!

Source sequence:

Я видел котю на мате <eos>

"I" "saw" "cat" "on" "mat"

Target sequence: ← one training example

I saw a cat on a mat <eos> ← one step for this example

previous tokens

we want the model to predict this

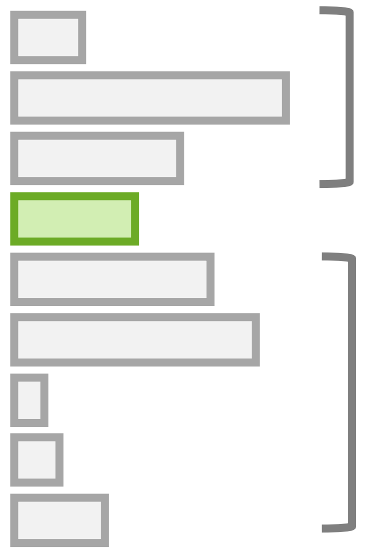
Model prediction: p(∗ |I saw a, Я … <eos>)

← cat →

Target

0
0
0
1
0
0
0
0
0

Loss = -log (p(cat)) → min



decrease

increase

decrease

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How To Generate a Translation?

$$y' = \arg\max_y p(y|x) = \arg\max_y \prod_{t=1}^{n} p(y_t|y_{<t}, x)$$

Greedy Decoding

$$y' = \arg\max_y p(y|x) = \arg\max_y \prod_{t=1}^{n} p(y_t|y_{<t}, x)$$

Straightforward:

- **greedy** - at each step, pick token with the highest probability

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Wait a minute...

Greedy Decoding

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Straightforward:

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

- this is bad!

Beam Search

- At each step, keep several best hypotheses

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<bos>

Start with the begin of sentence token or with an empty sequence

Beam Search

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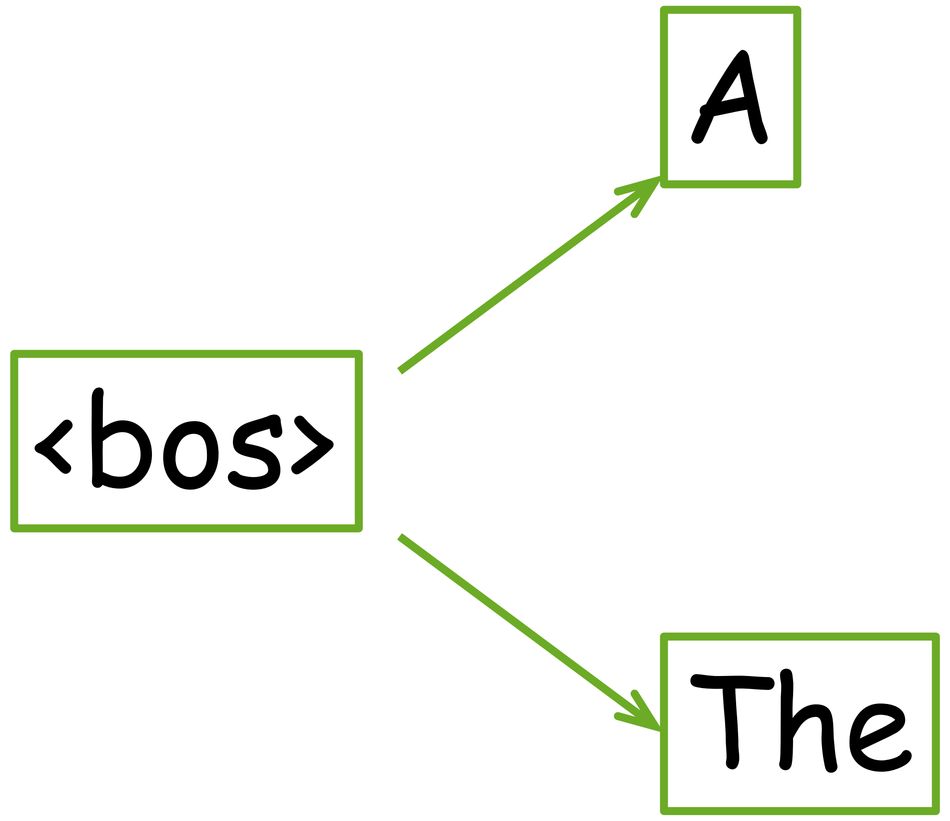

Generate: **`beam_size`** most probable tokens

Beam Search

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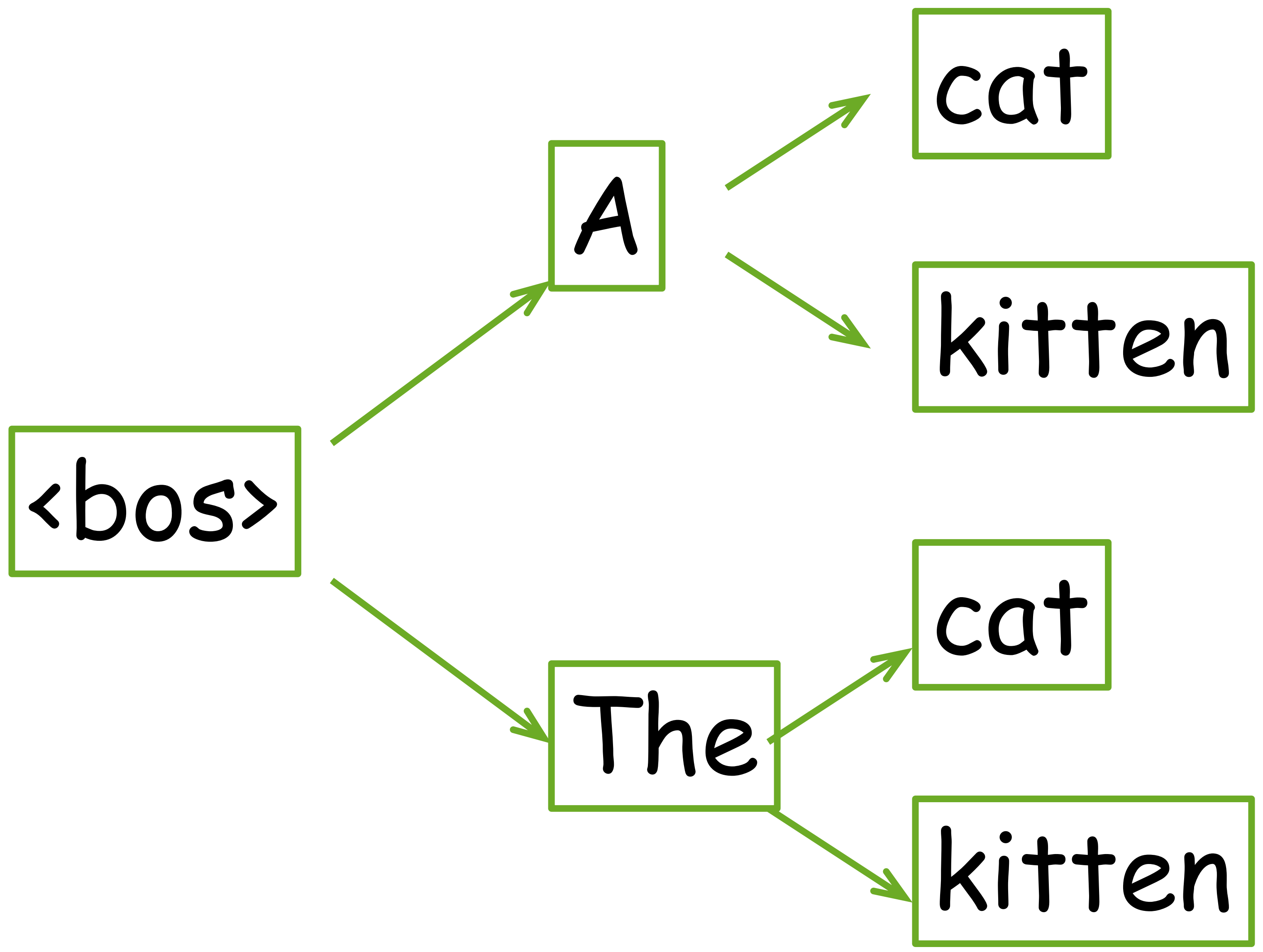

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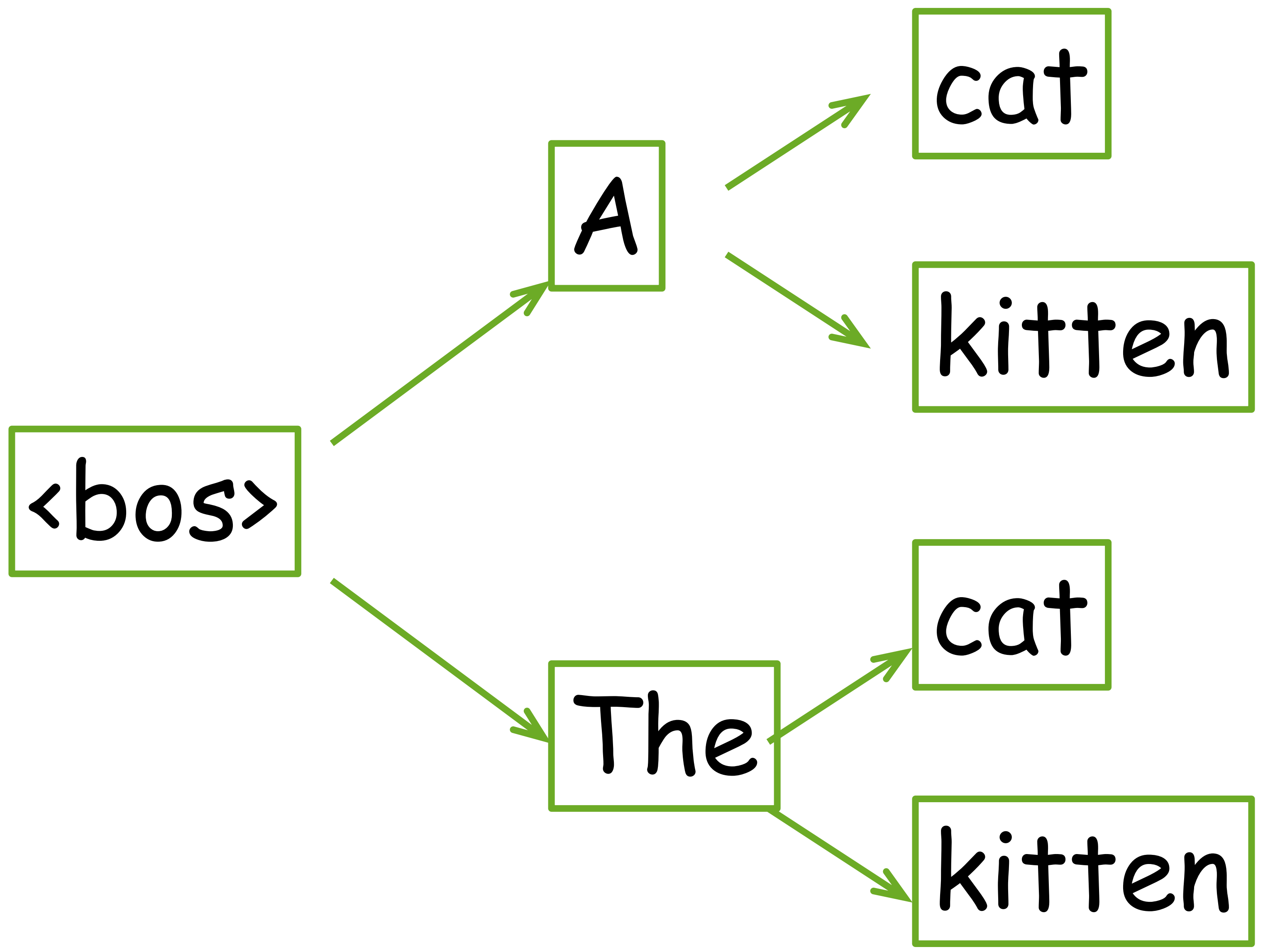

Look at probabilities: $\underbrace{P(\text{The cat}) > P(\text{A kitten})}_{\text{Top 2 hypos}} > P(\text{A cat}) > P(\text{The kitten})$

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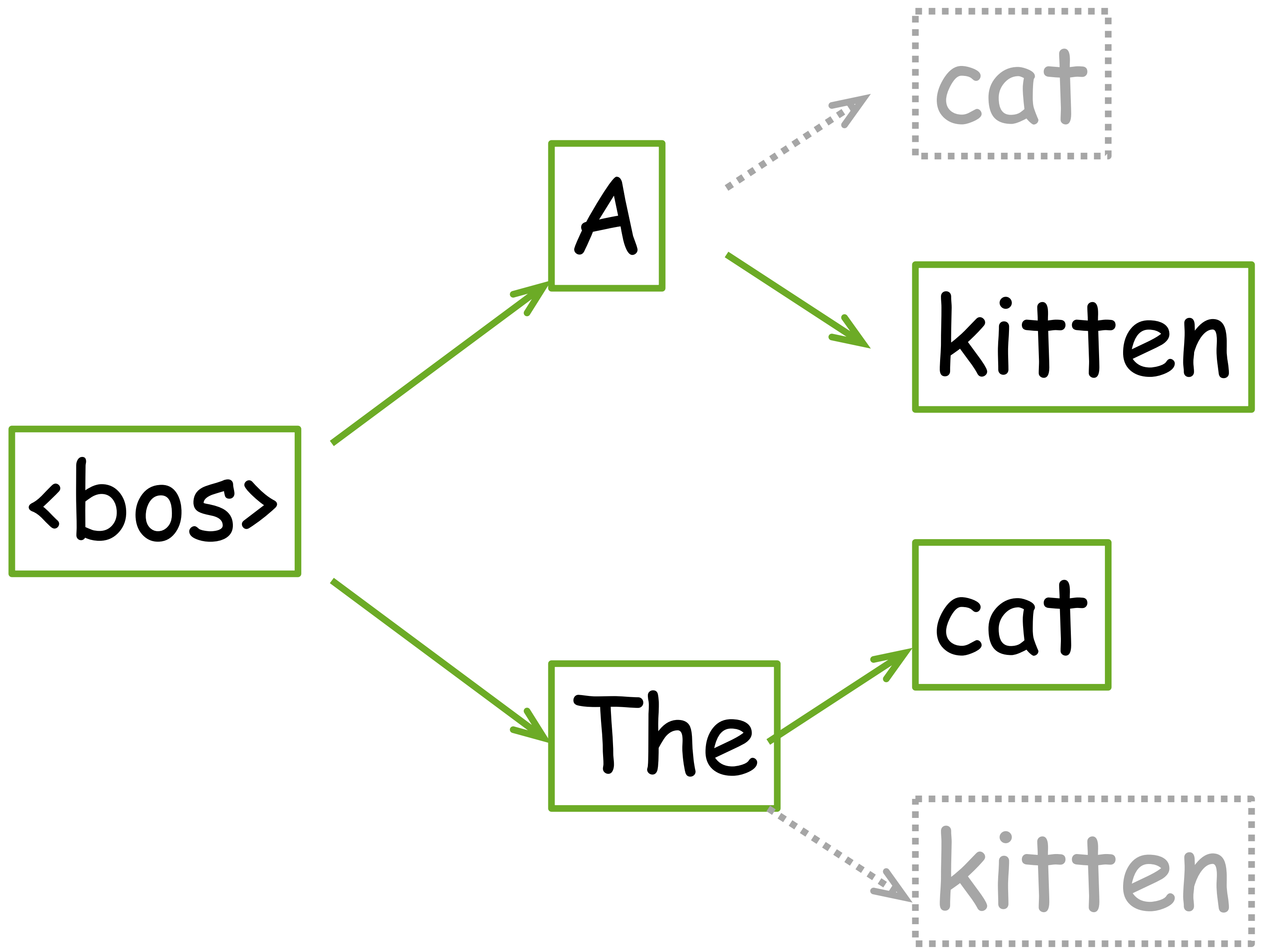

Pick top **`beam_size`** hypos, terminate the rest

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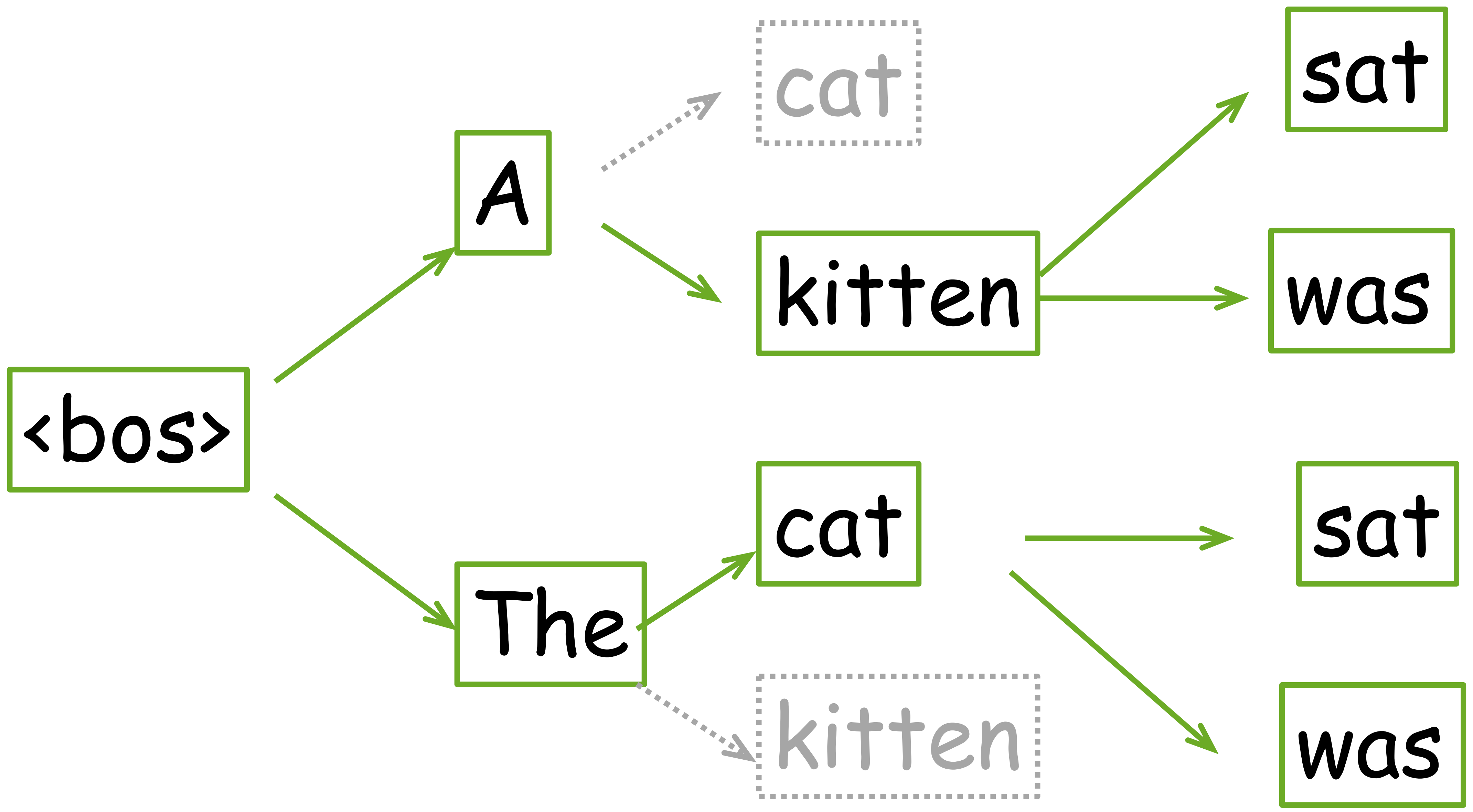

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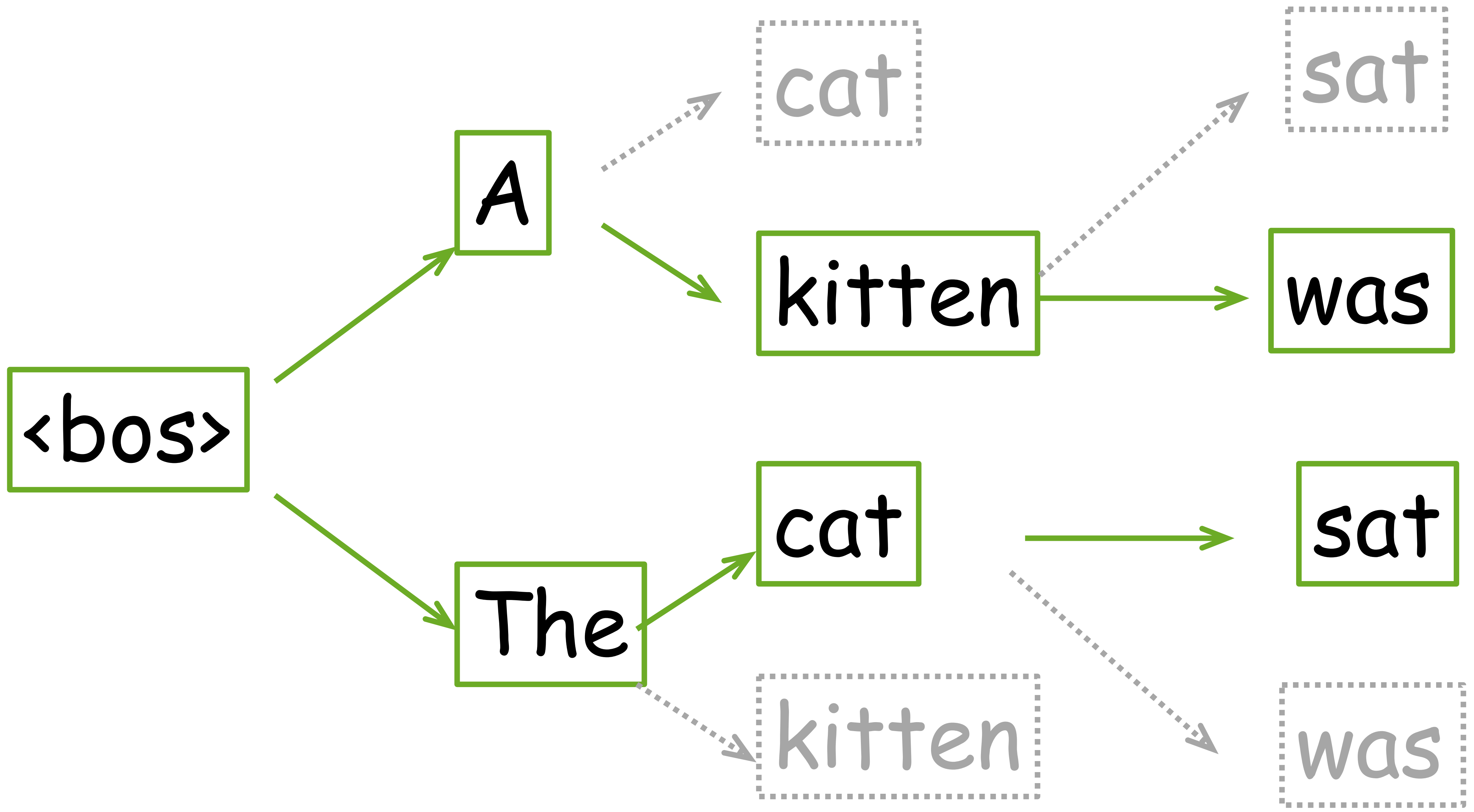

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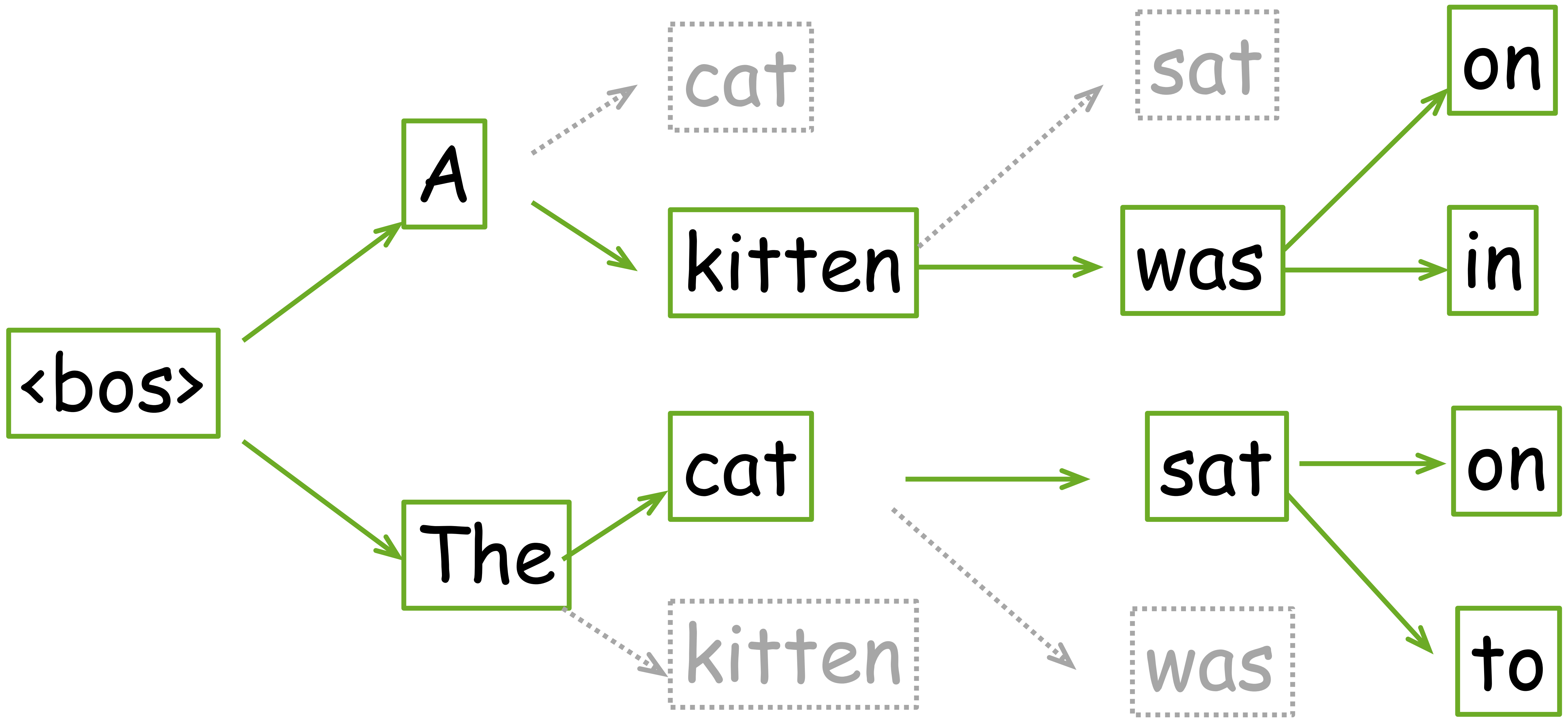

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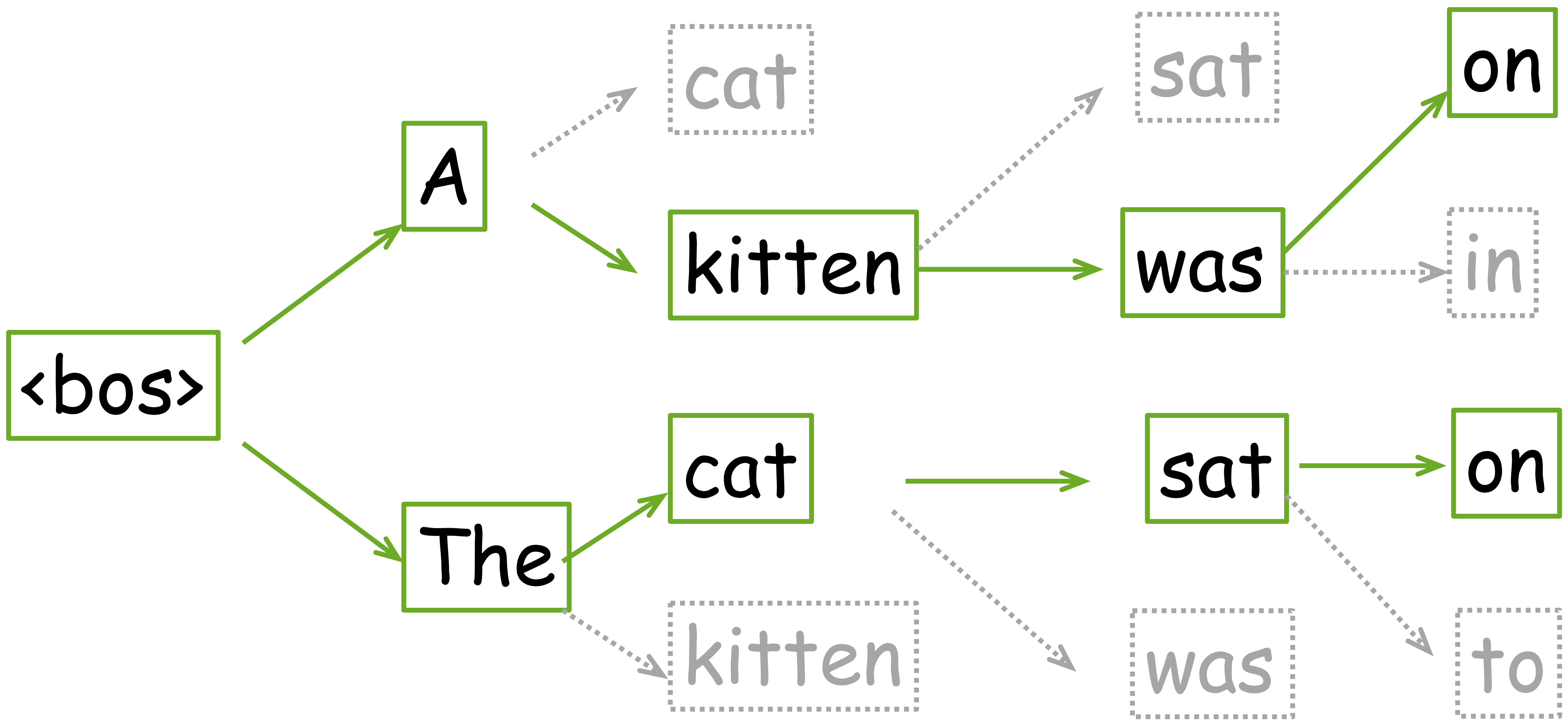

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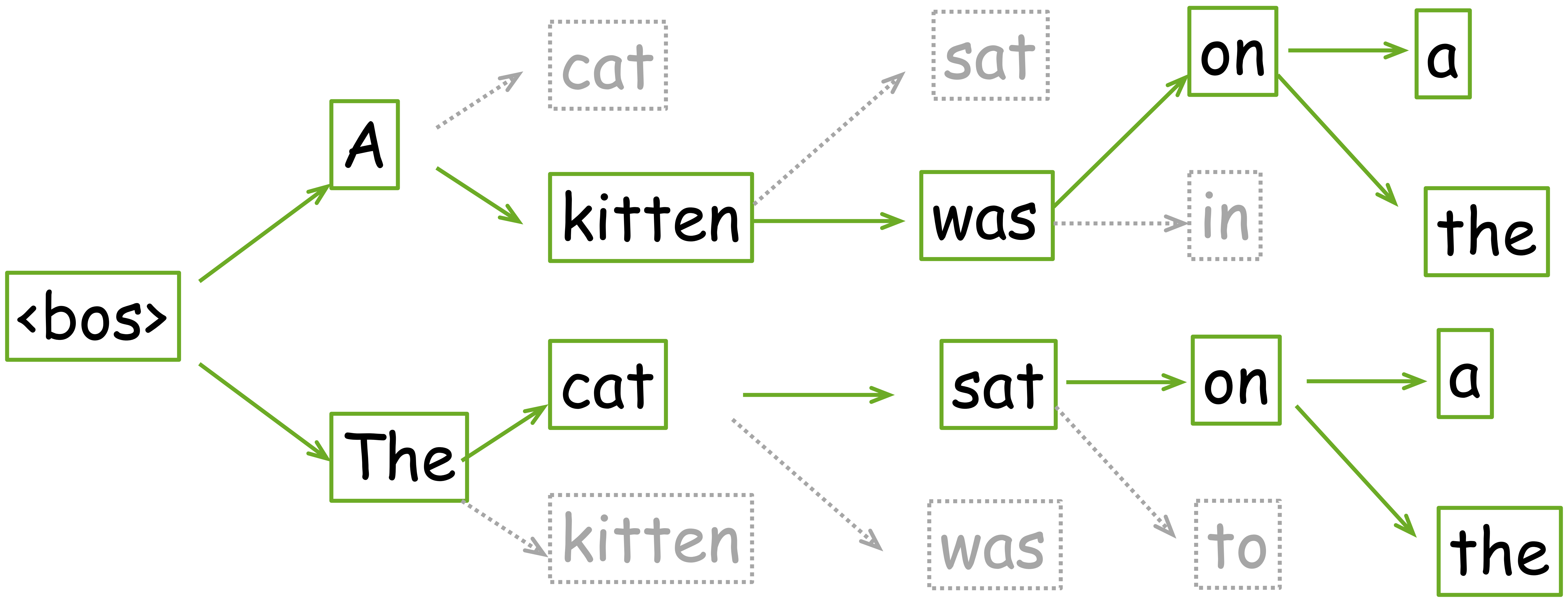

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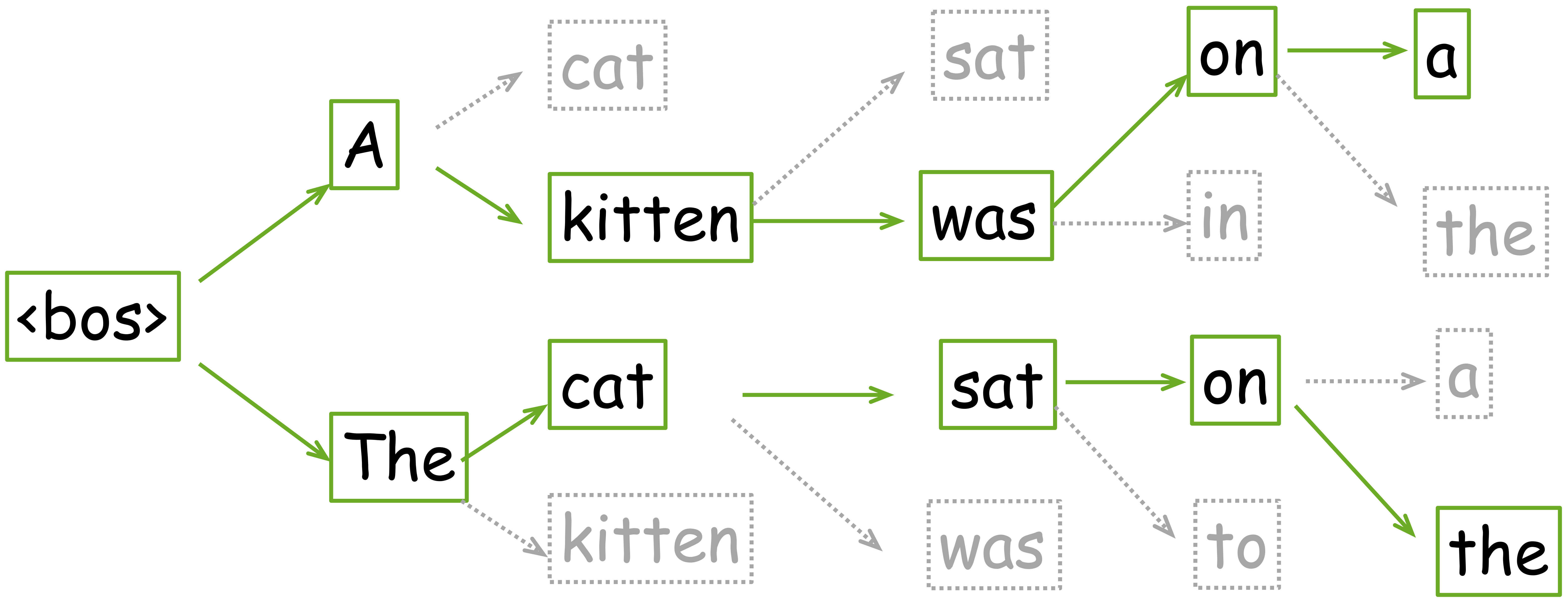

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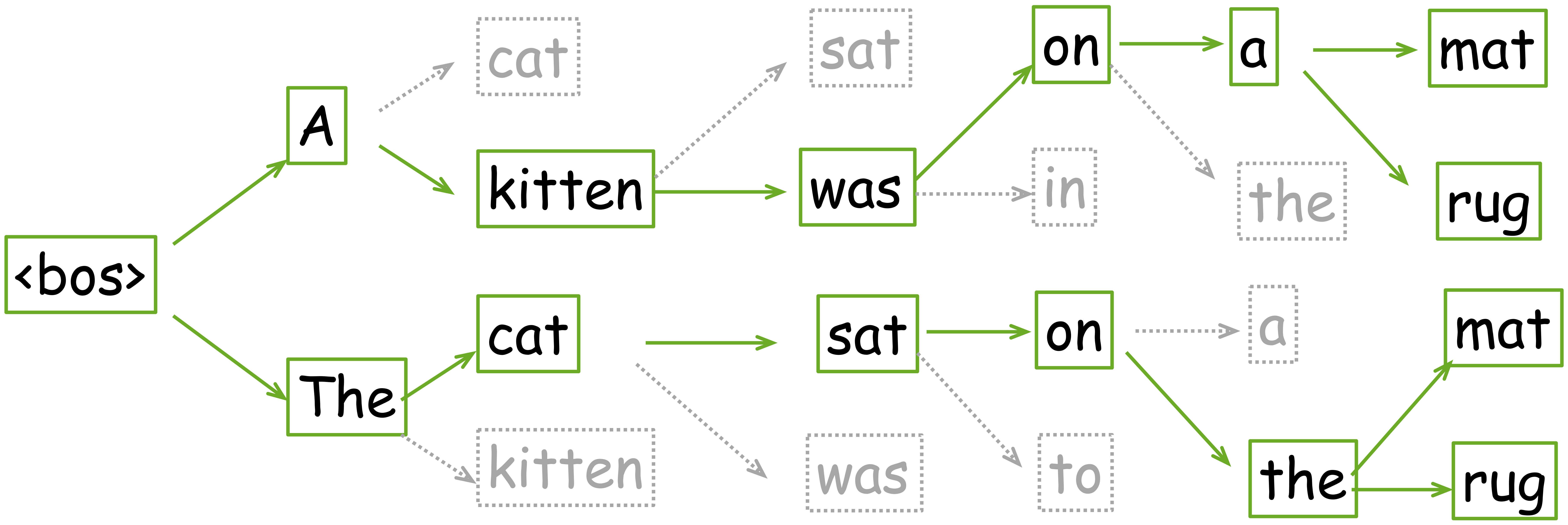

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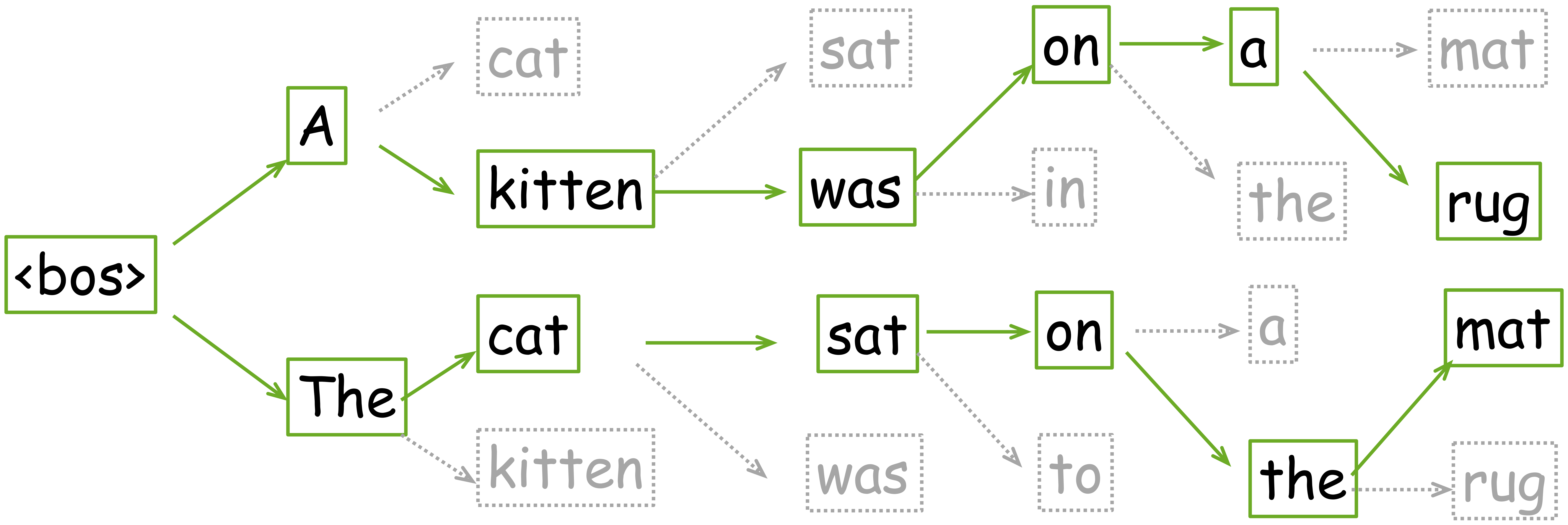

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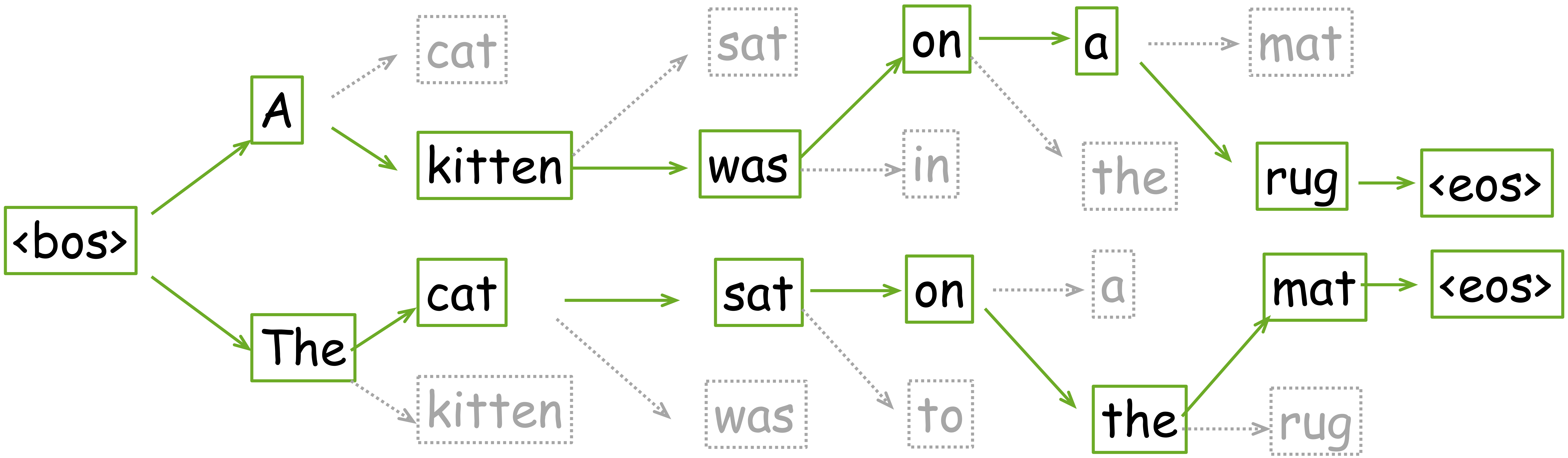

All hypotheses are complete - generation ended

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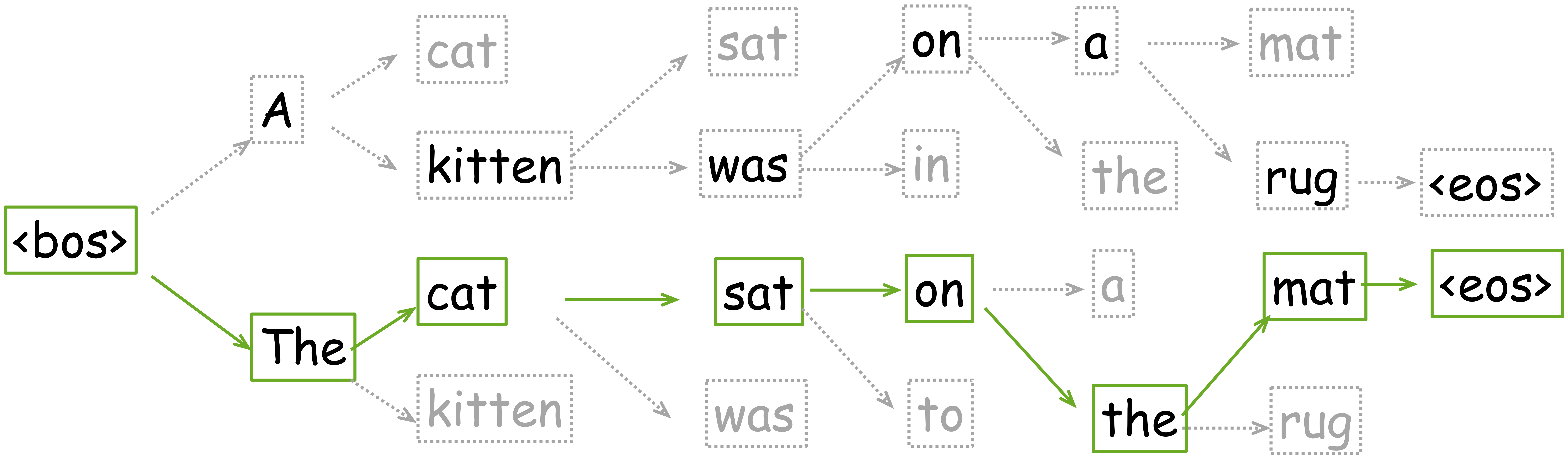

Pick the hypothesis with the highest probability

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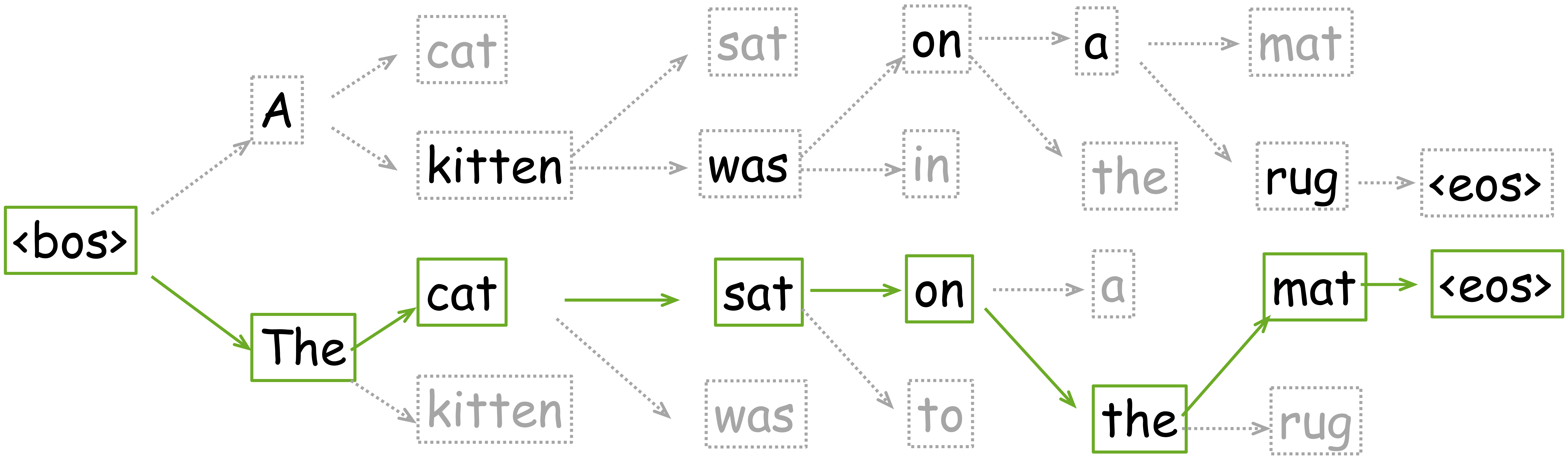

Result: **The cat sat on the mat**

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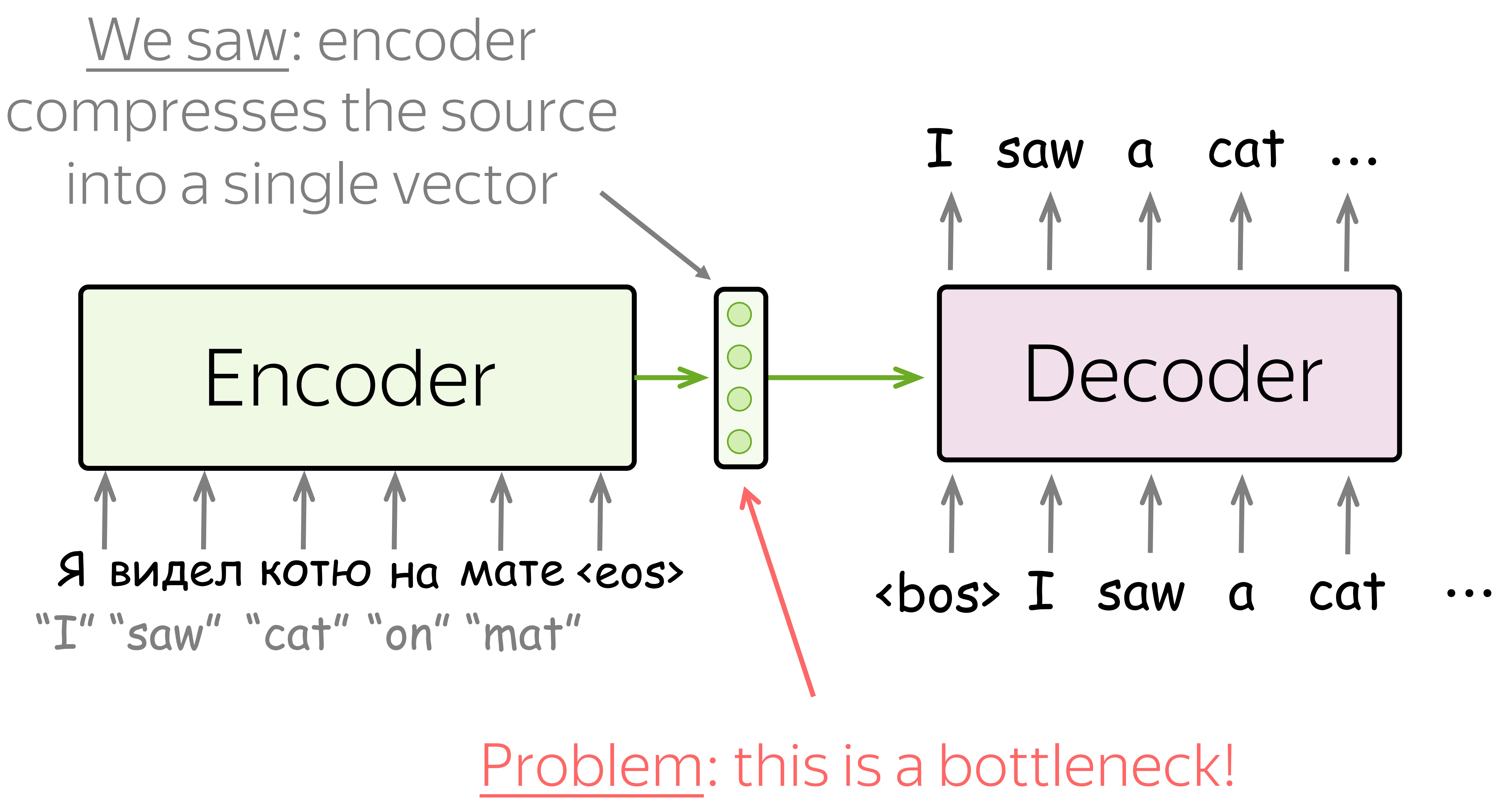
What is going to happen:

- Seq2seq Basics
- Attention
  - Why do we need it?
  - Attention: High-Level
  - Attention Score Functions
  - Models: Bahdanau vs Luong
- Transformer
- Subword Segmentation: BPE
- Analysis and Interpretability

The Problem of Fixed Encoder Representation

Fixed source representation is bad:

- for encoder, it is hard to compress a sentence
- for decoder, different information may be needed at different steps



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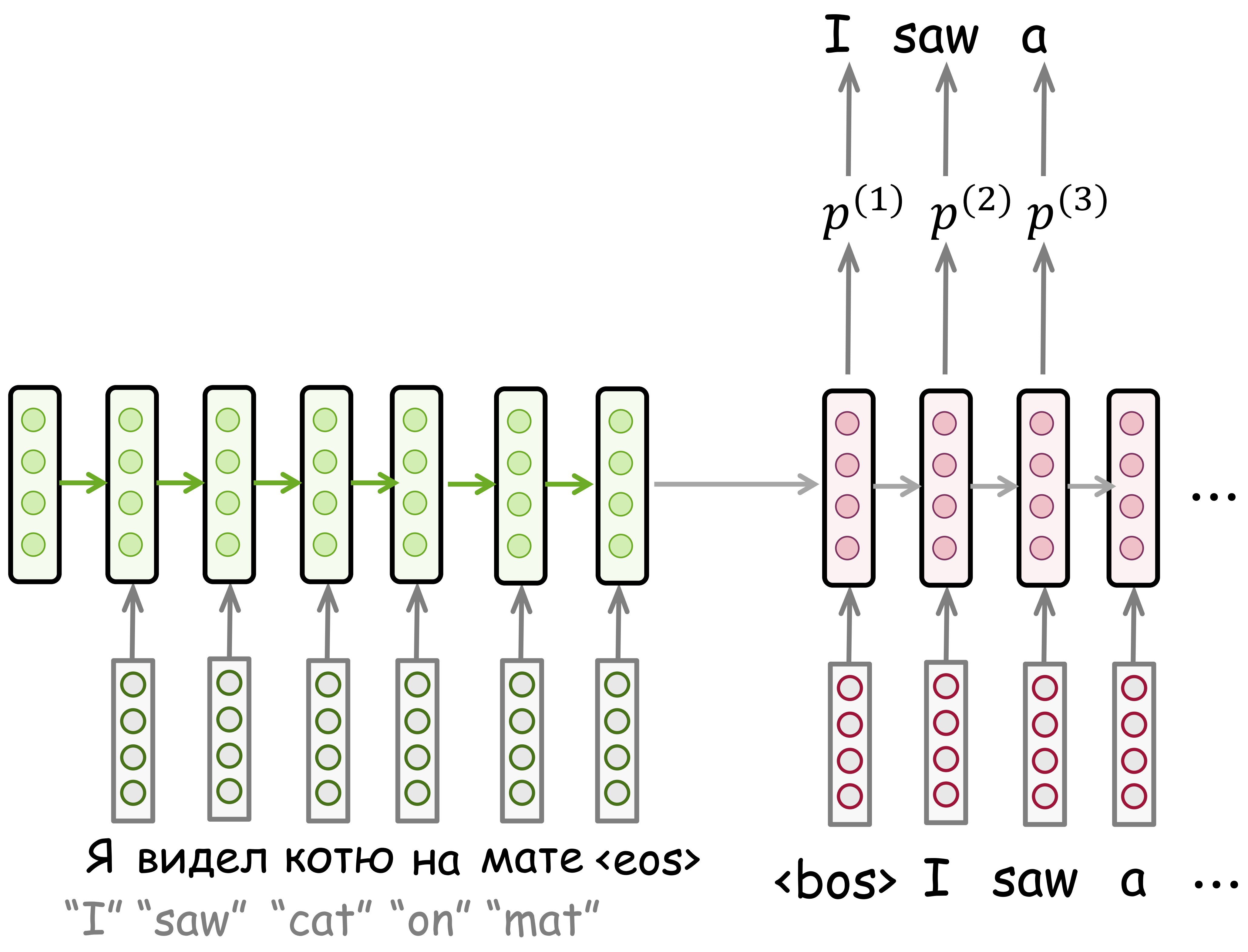
> Attention: At different steps, let a model "focus" on different parts of the input.



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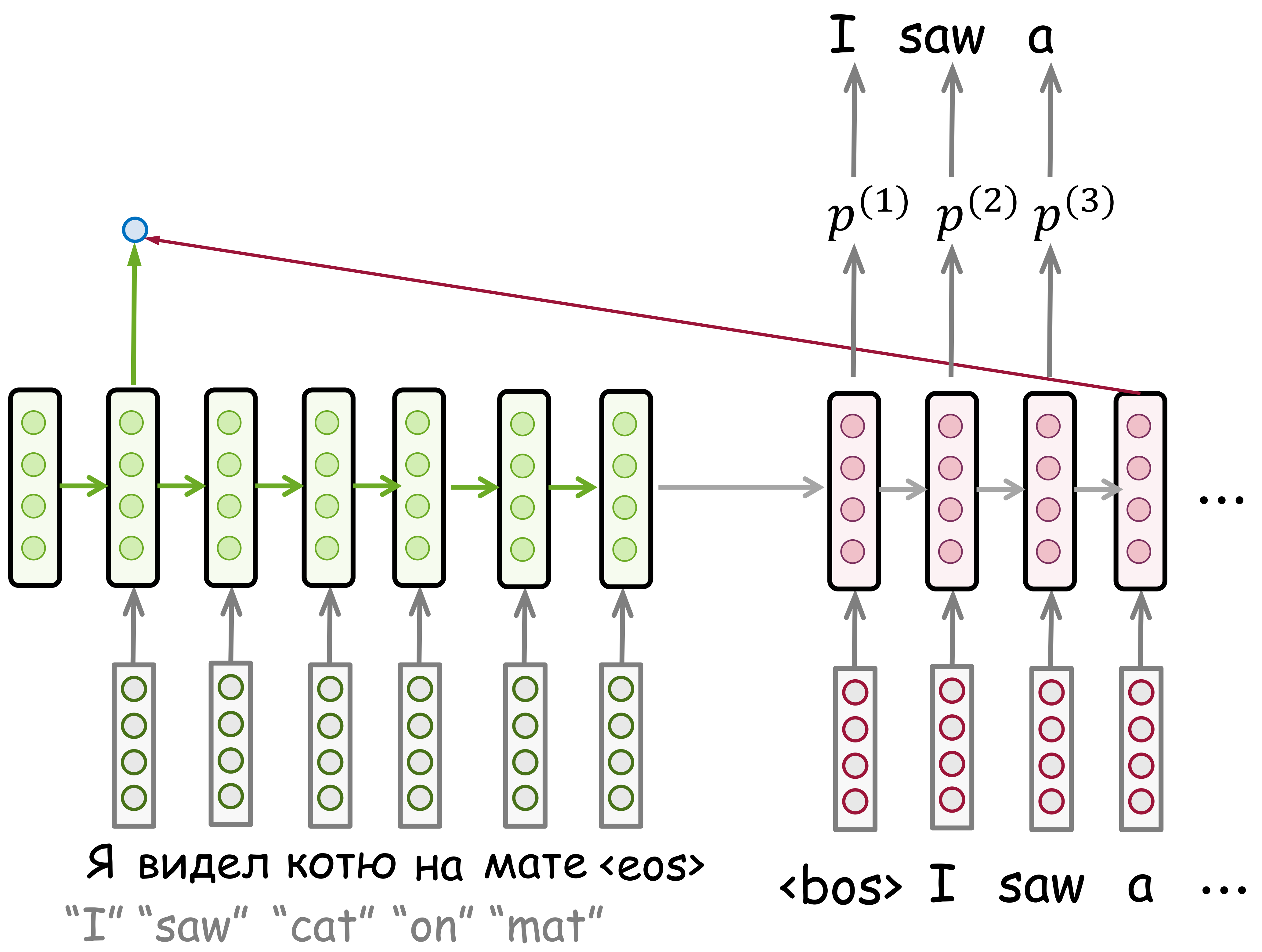

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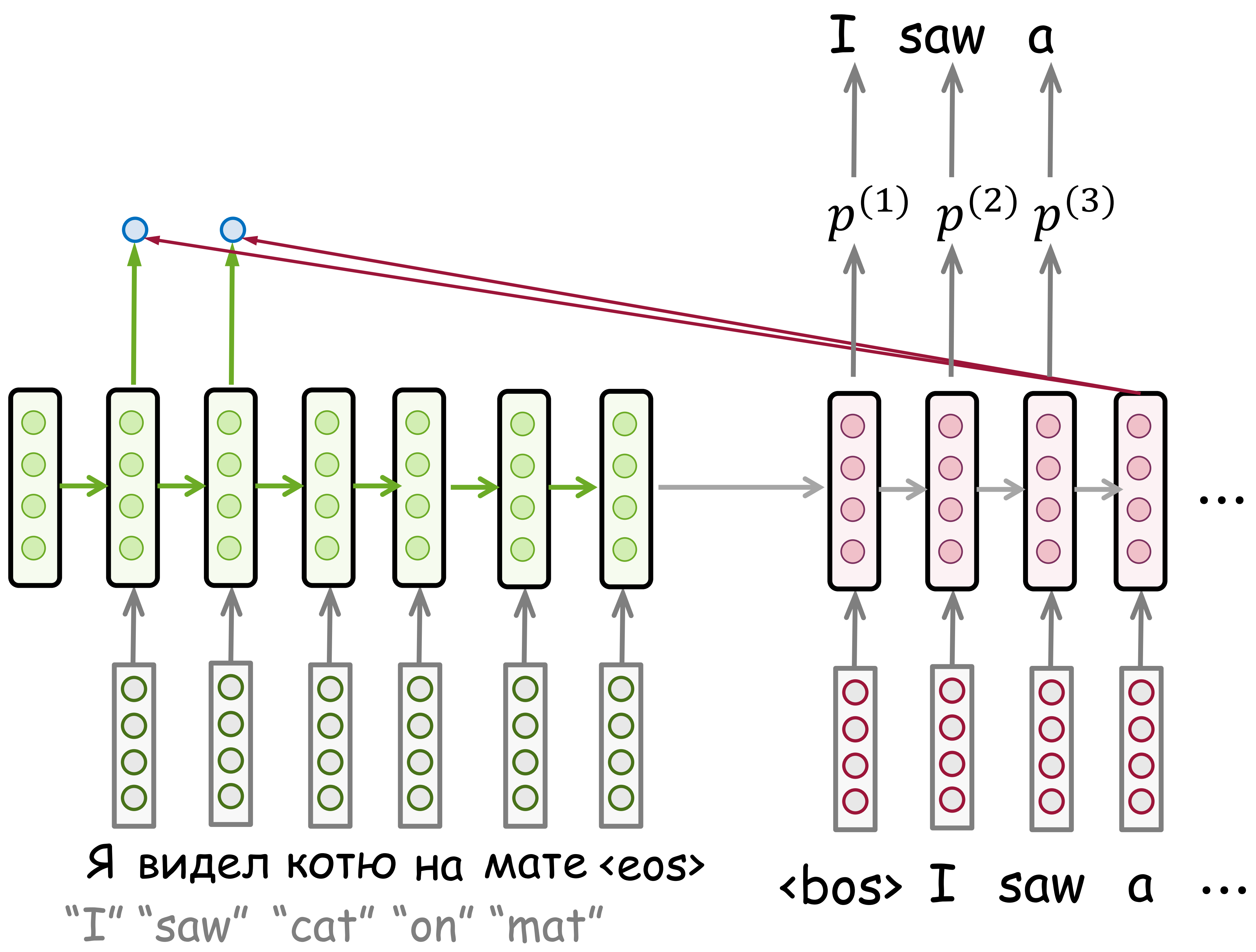

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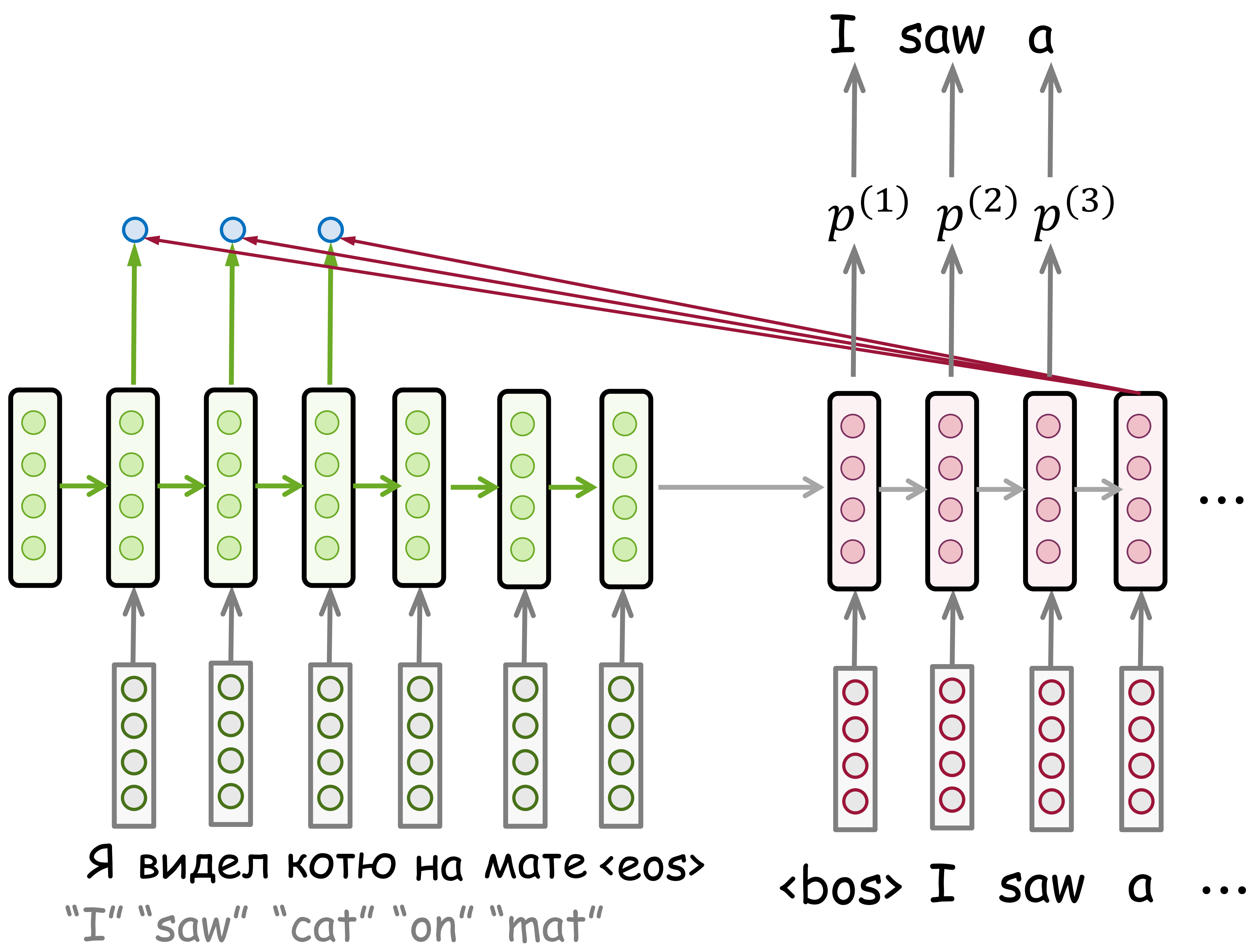

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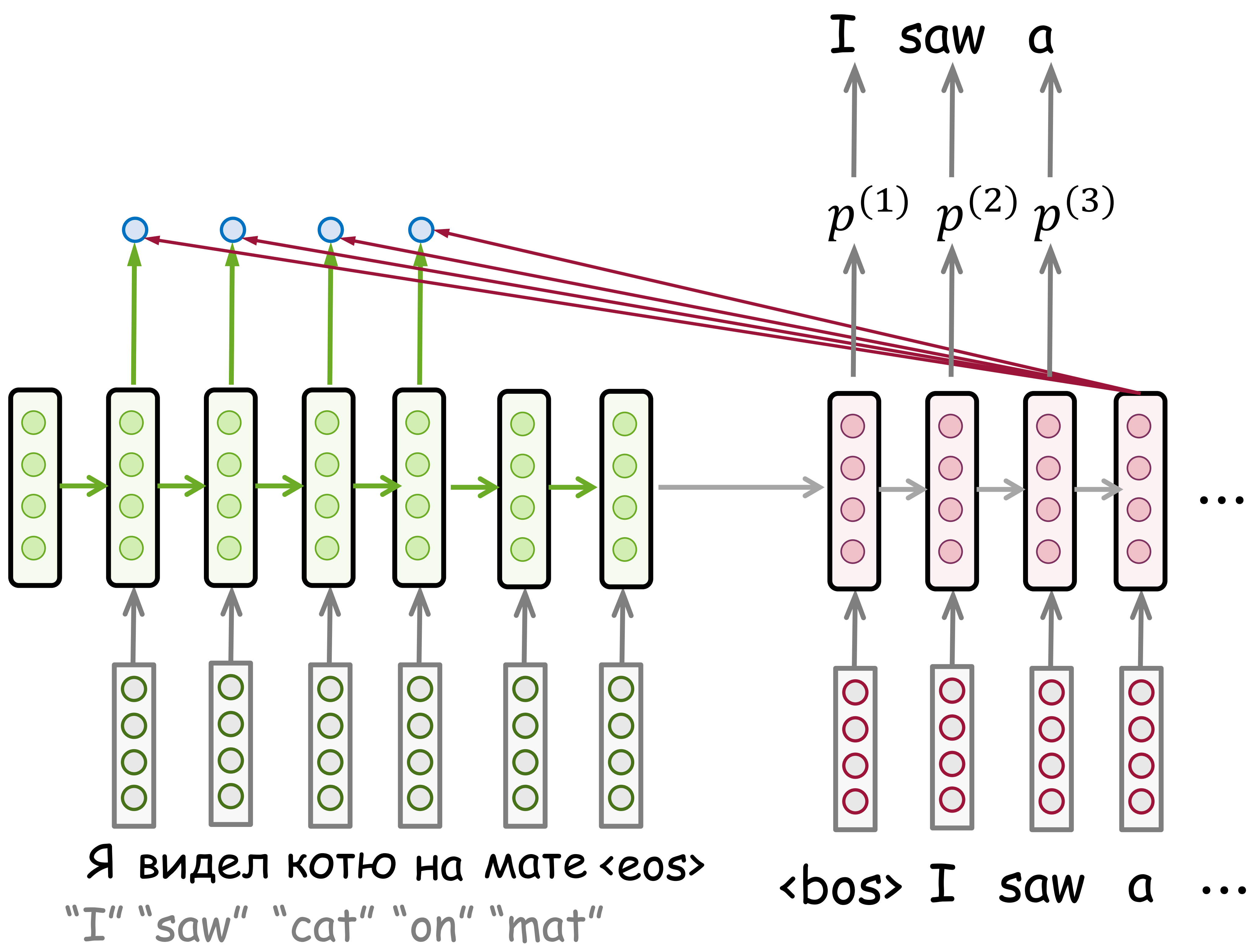

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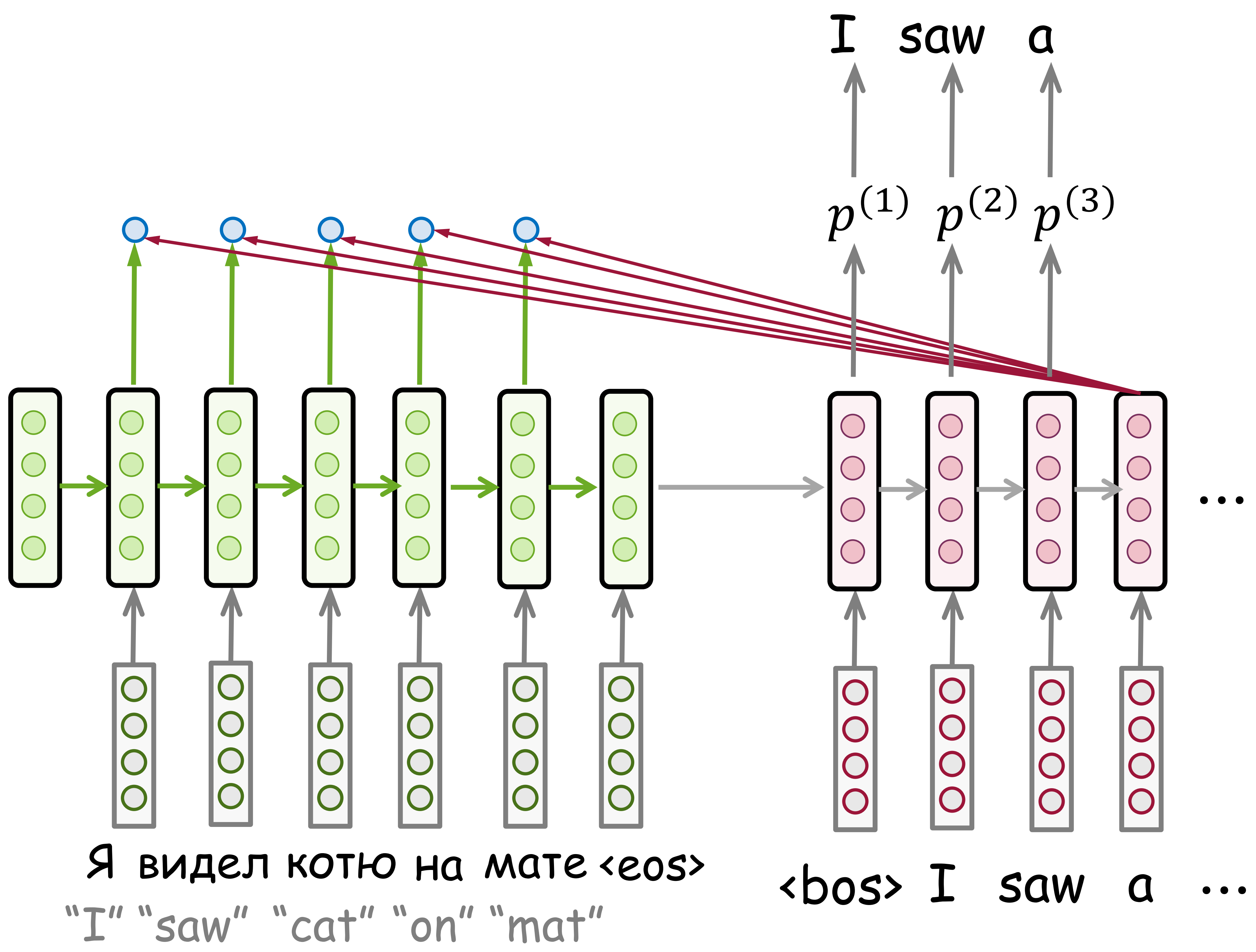

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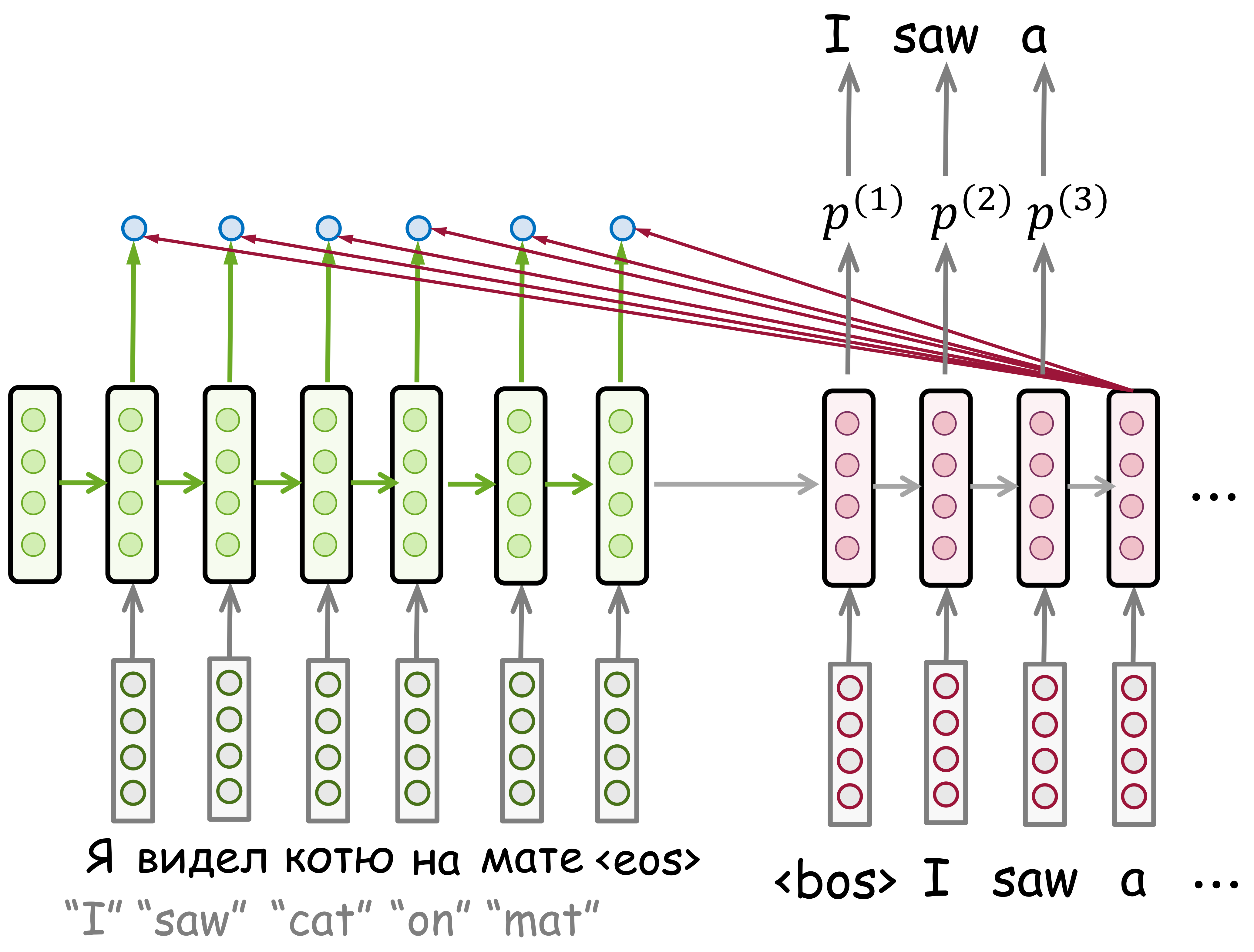

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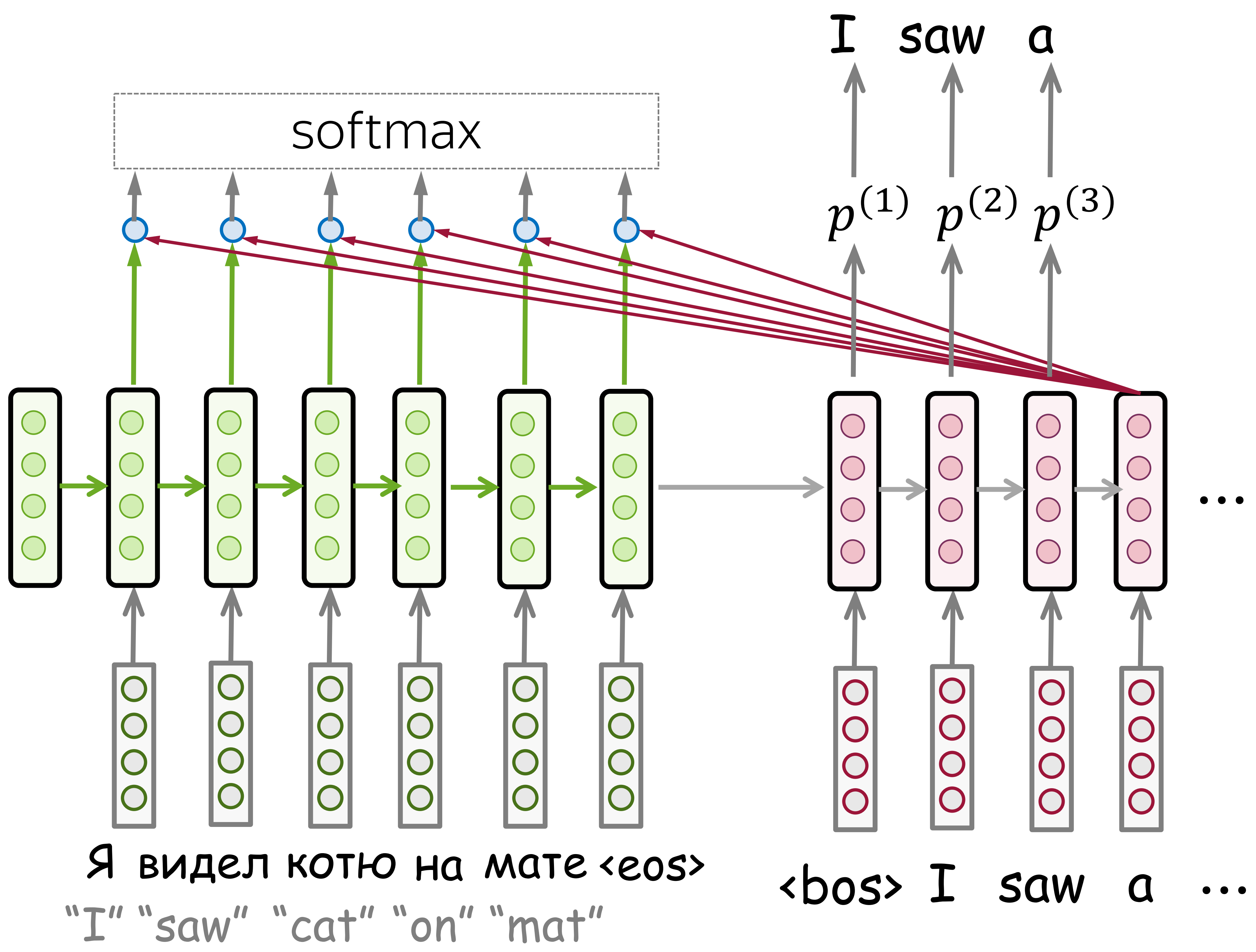

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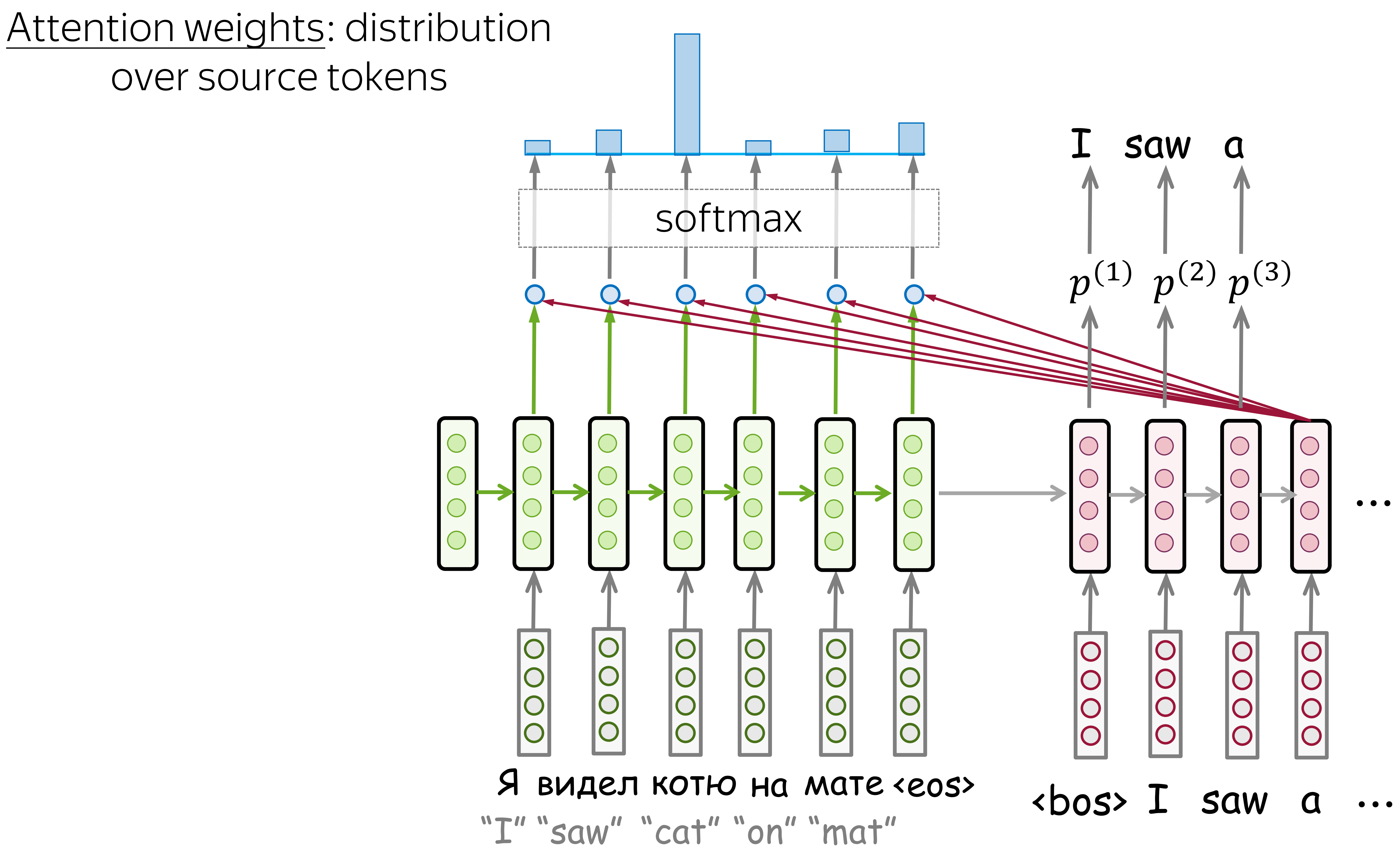

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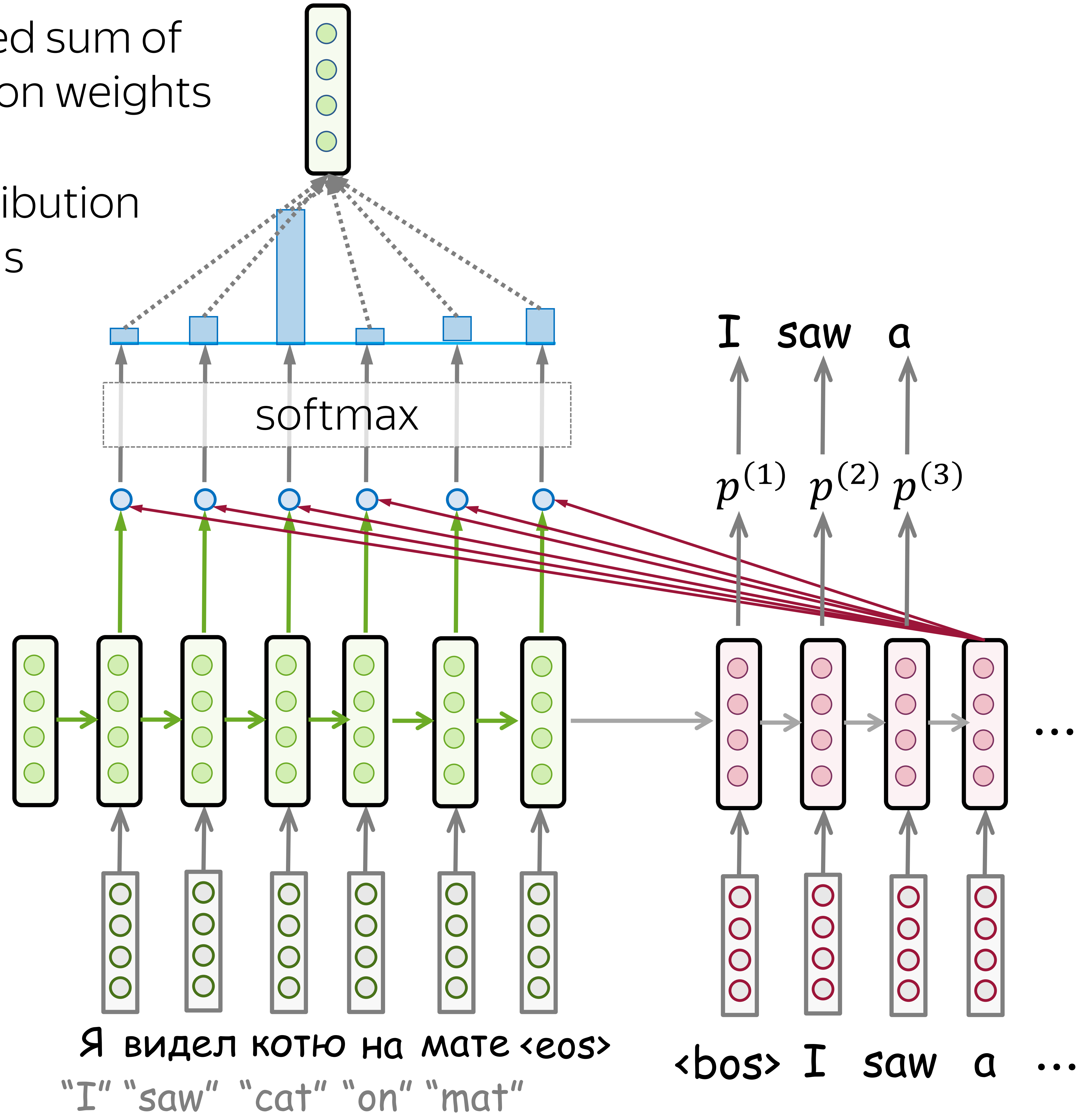
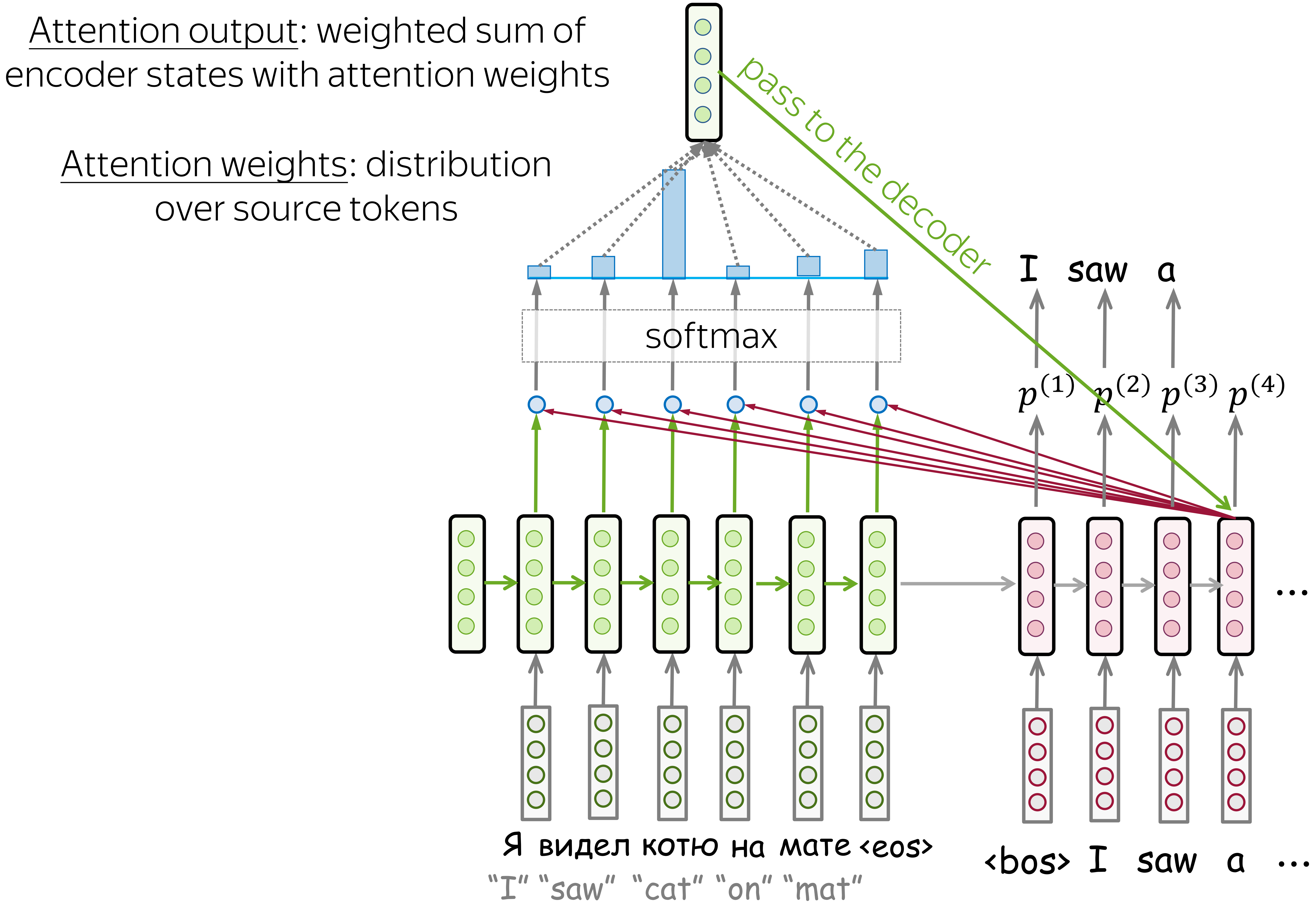
Attention output: weighted sum of encoder states with attention weights

Attention weights: distribution over source tokens



Attention: High-Level View

Attention: At different steps, let a model "focus" on different parts of the input.



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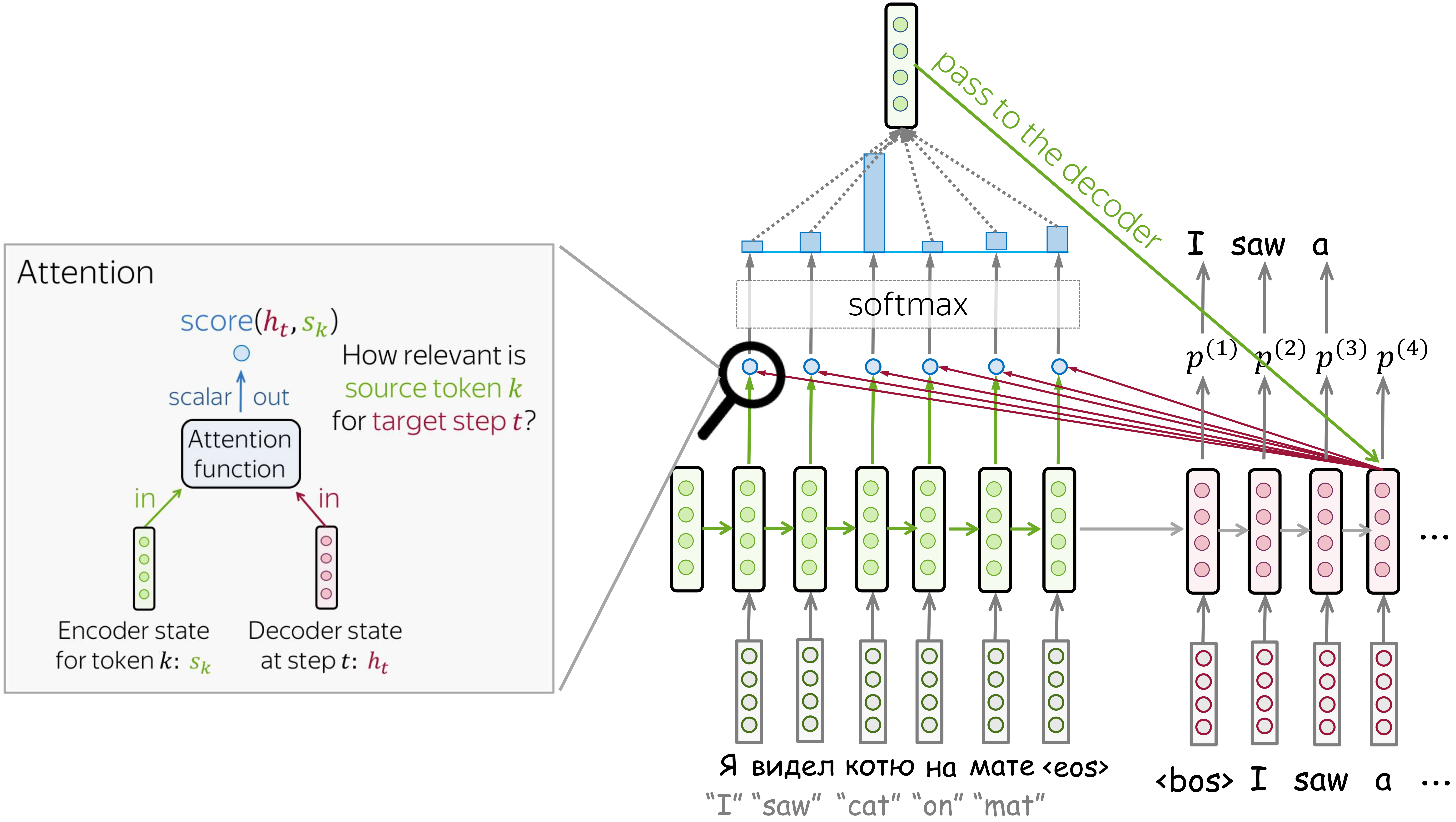

Computation Pipeline

Attention input $s_1, s_2, \ldots, s_m$ h_t

all encoder states one decoder state

Computation Pipeline

Attention scores $\text{score}(h_t, s_k), \mathrm{k} = 1..\mathrm{m}$

↑

Attention input $s_1, s_2, \dots, s_m$ h_t

all encoder states one decoder state

Computation Pipeline

Attention scores

$\text{score}(h_t, s_k), \mathrm{k} = 1..\mathrm{m}$

"How relevant is source token k for target step t?"

Attention input

$s_1, s_2, \ldots, s_m$

all encoder states

h_t

one decoder state

Computation Pipeline

Attention weights

$$a_k^{(t)} = \frac{\exp(\mathrm{score}(h_t, s_k))}{\sum_{i=1}^{m} \exp(\mathrm{score}(h_t, s_i))}, \mathrm{k} = 1..\mathrm{m}$$

(softmax)

Attention scores

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“attention weight for source token k at decoder step t”

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“How relevant is source token k for target step t?”

Attention input

$s_1, s_2, \ldots, s_m$

all encoder states

h_t

one decoder state

Computation Pipeline

Attention output

$$c^{(t)} = a_1^{(t)} s_1 + a_2^{(t)} s_2 + \cdots + a_m^{(t)} s_m = \sum_{k=1}^{m} a_k^{(t)} s_k$$

(weighted sum)

Attention weights

$$a_k^{(t)} = \frac{\exp(\text{score}(h_t, s_k))}{\sum_{i=1}^{m} \exp(\text{score}(h_t, s_i))}, \mathrm{k} = 1..\mathrm{m}$$

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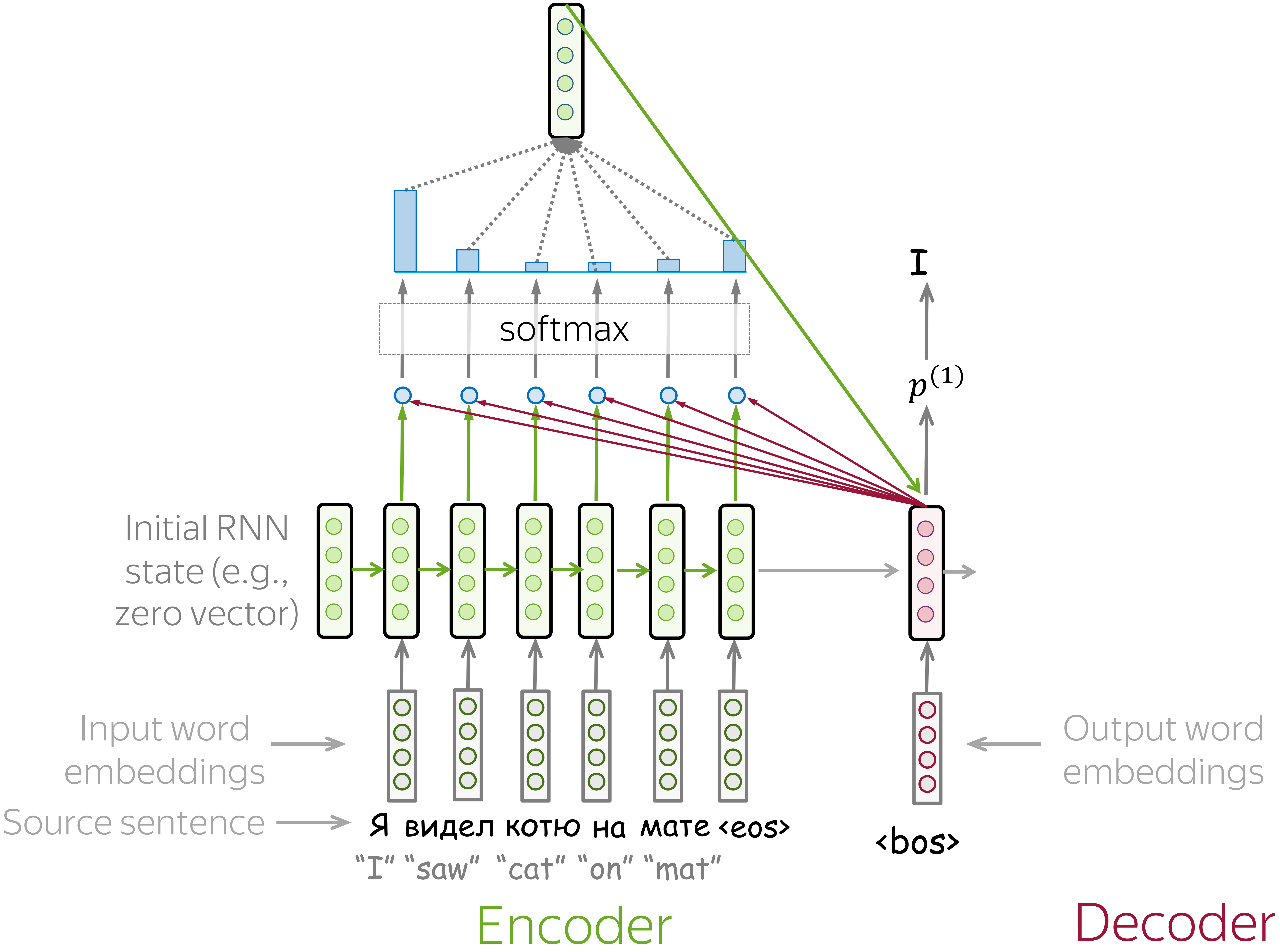
Model Learns to Pick Relevant Tokens



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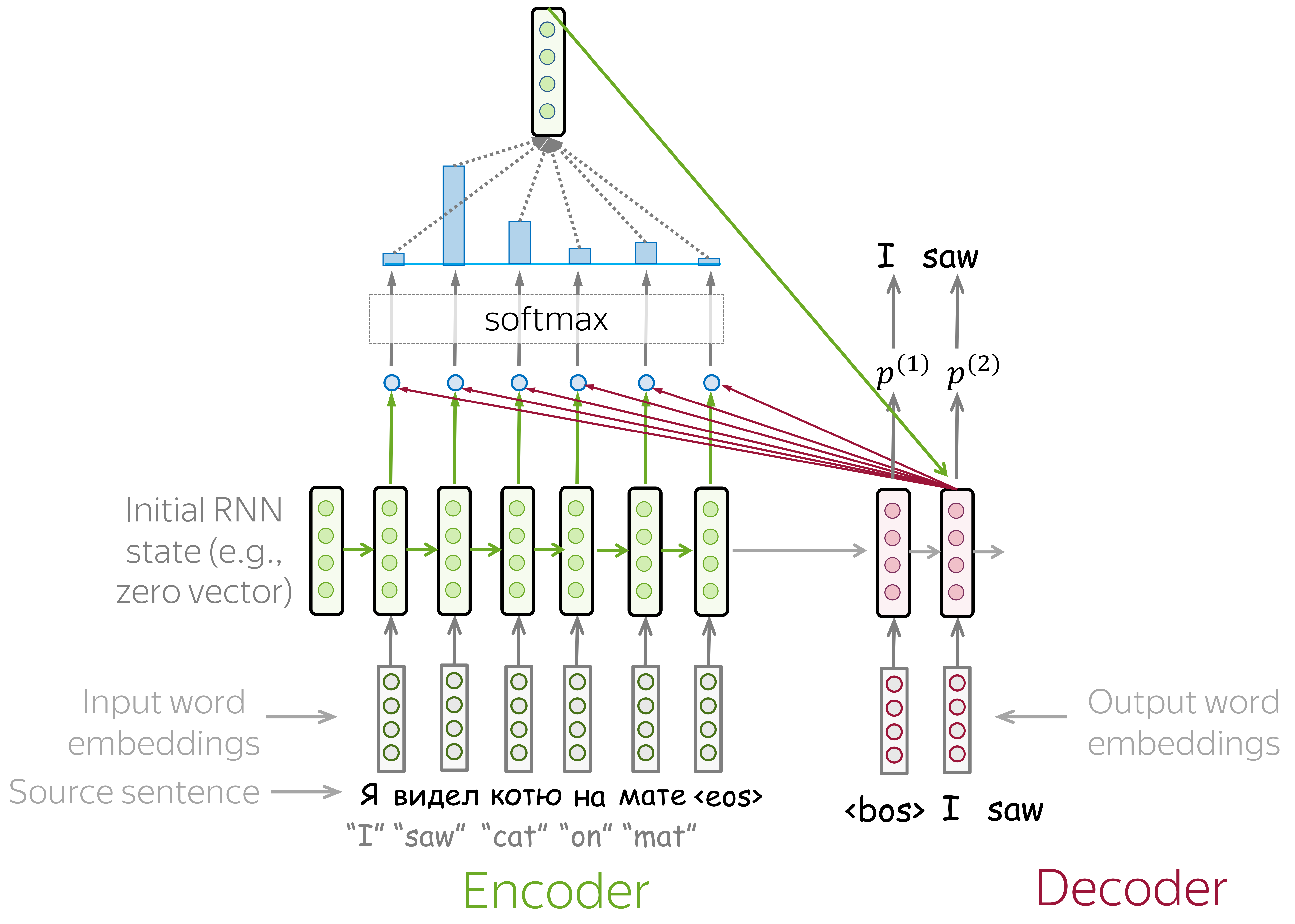

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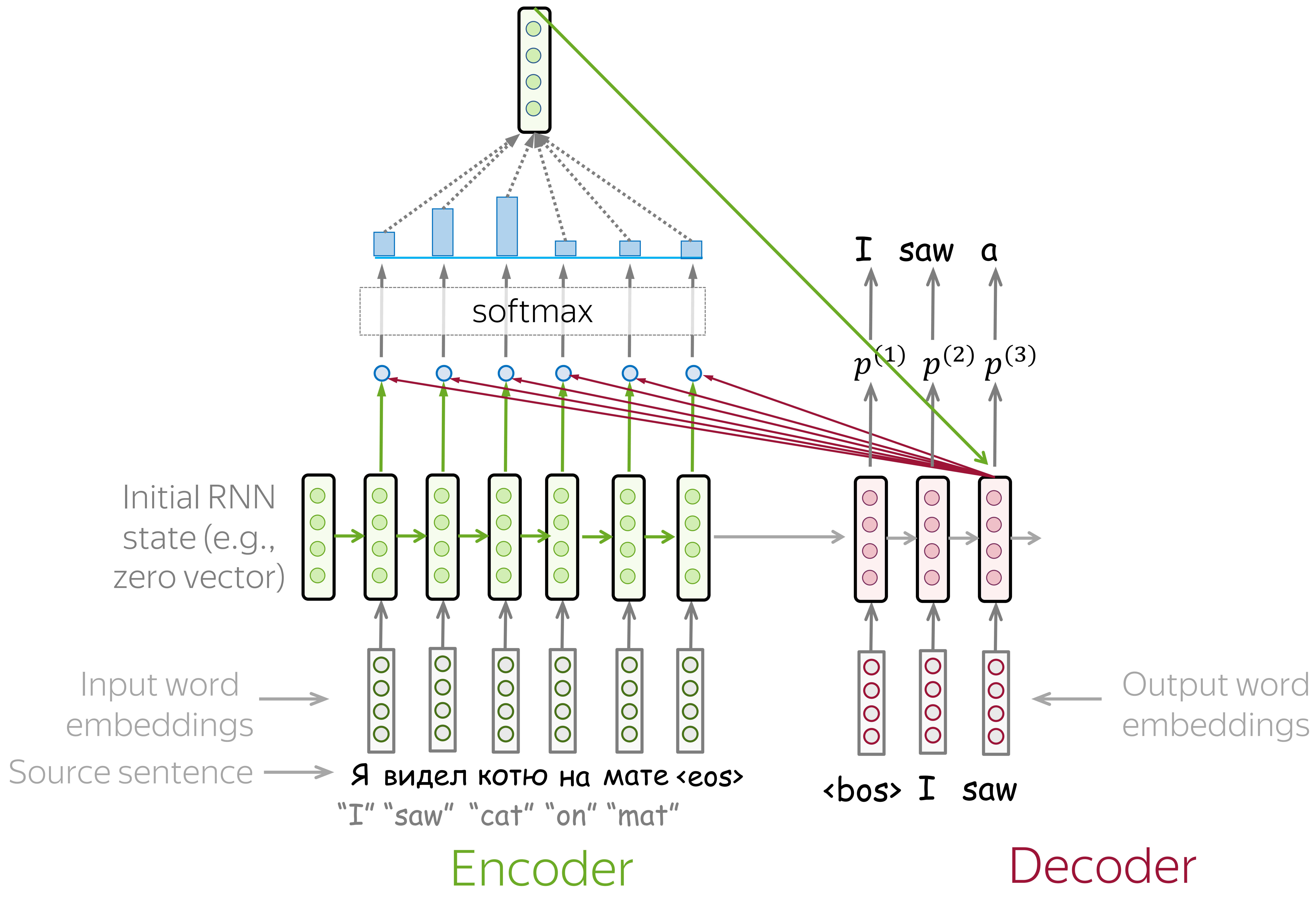

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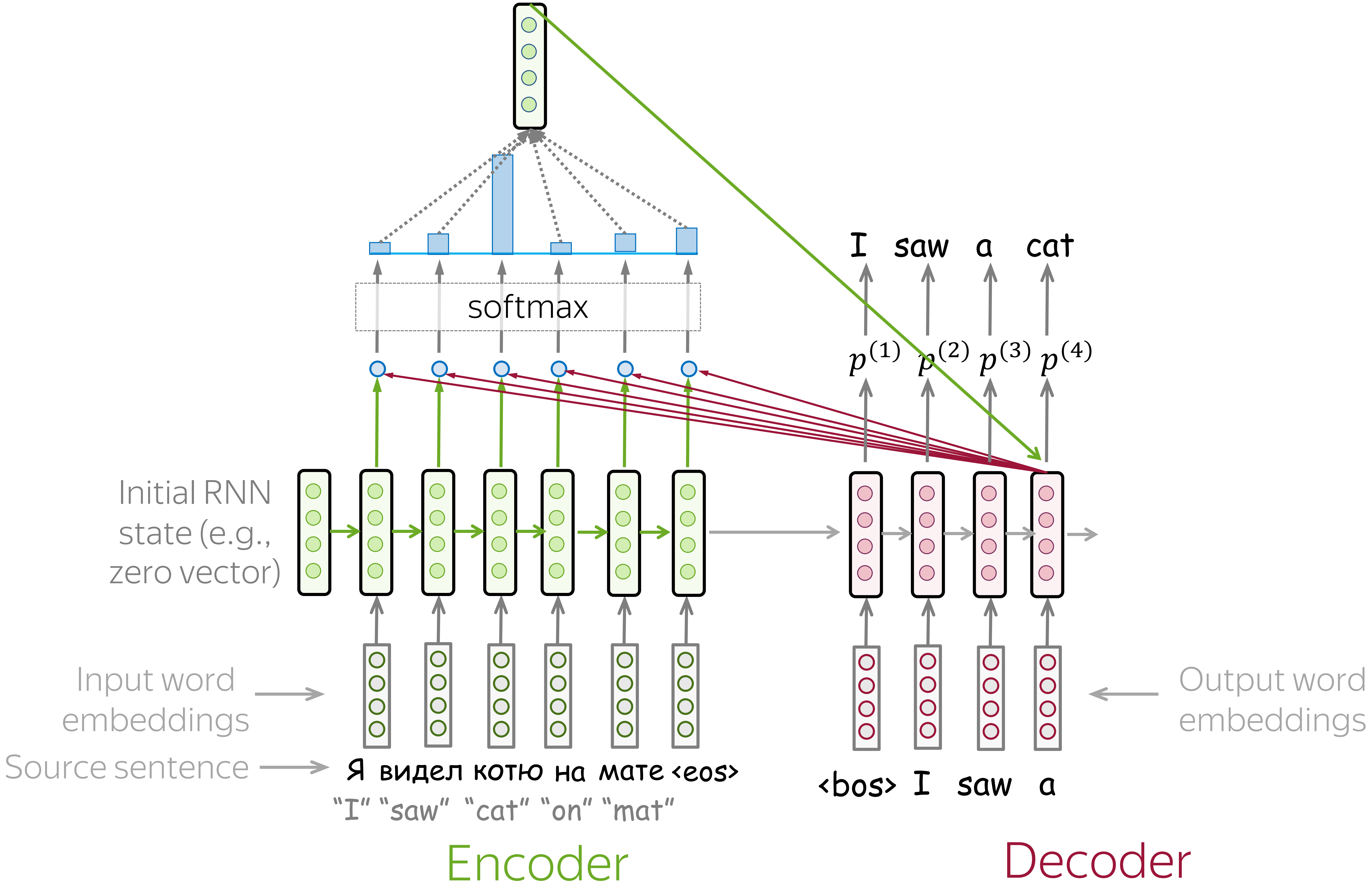

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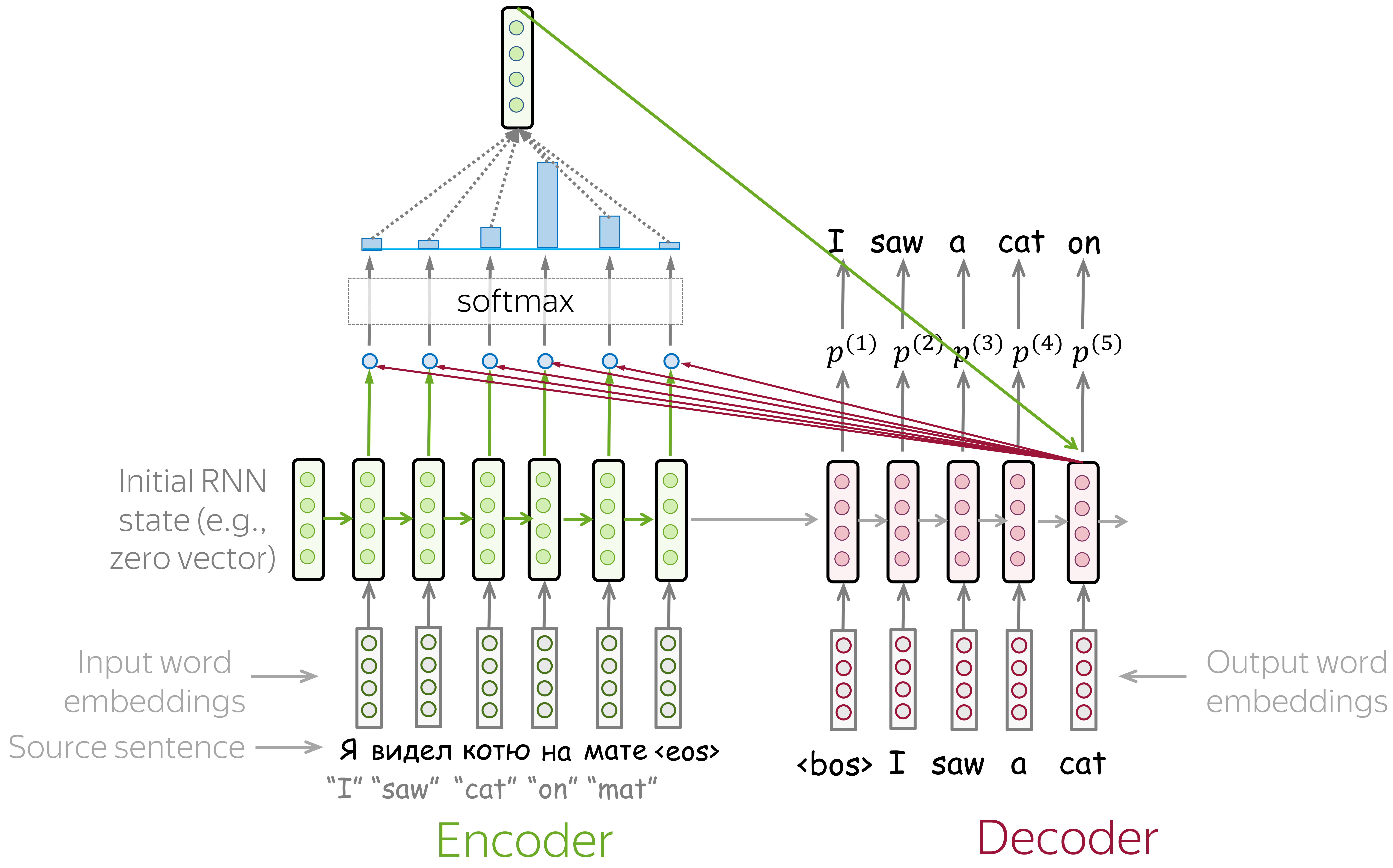

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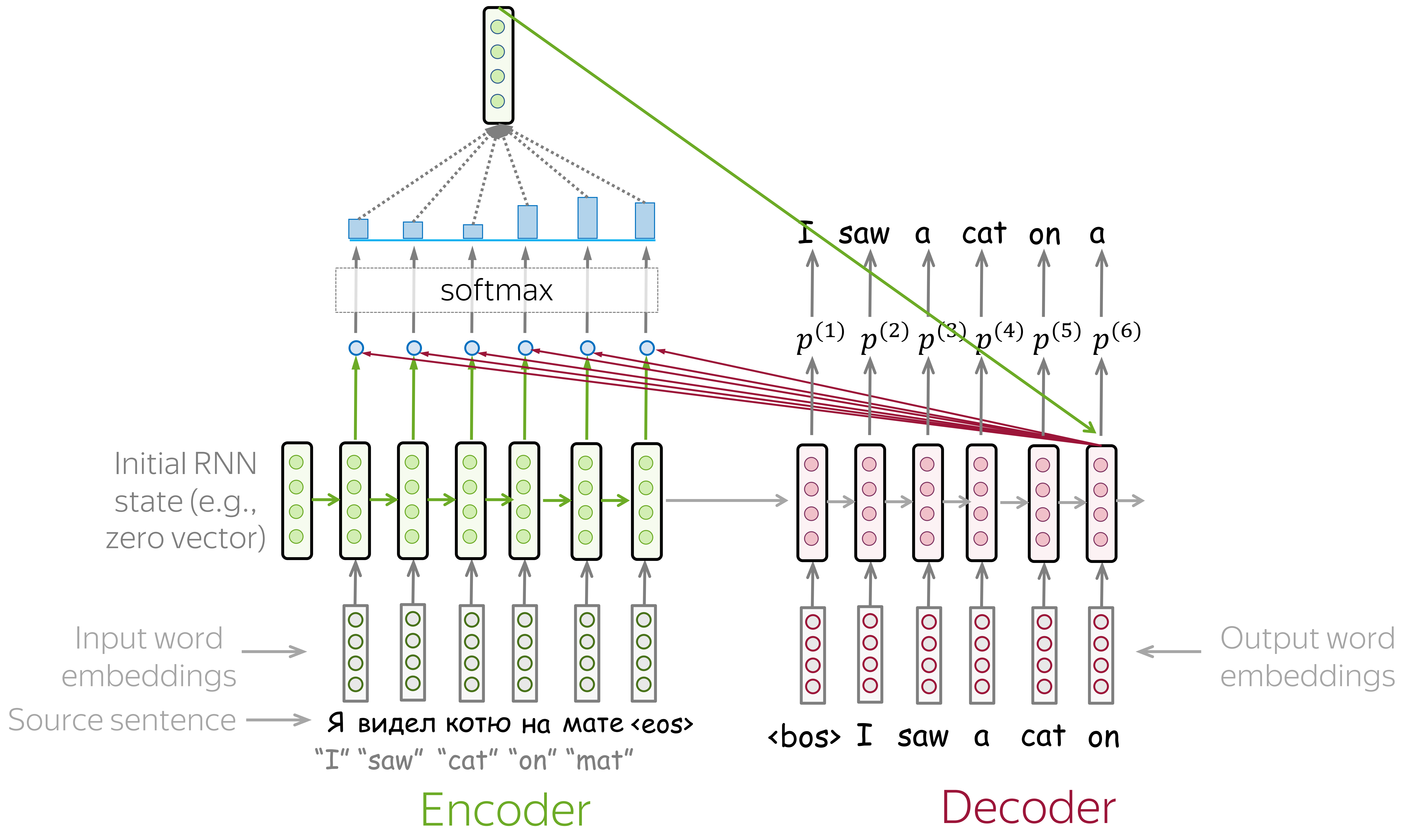

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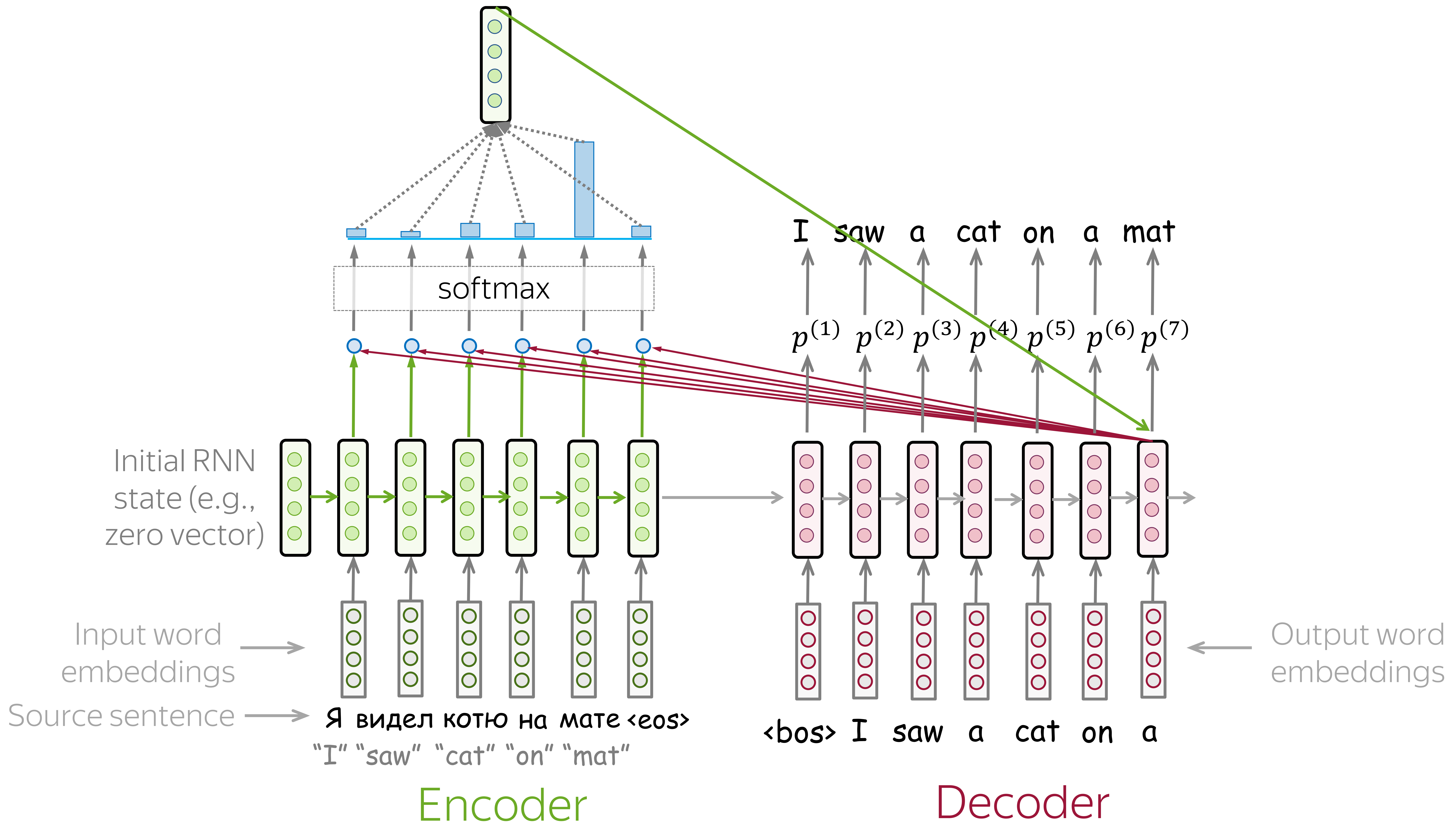

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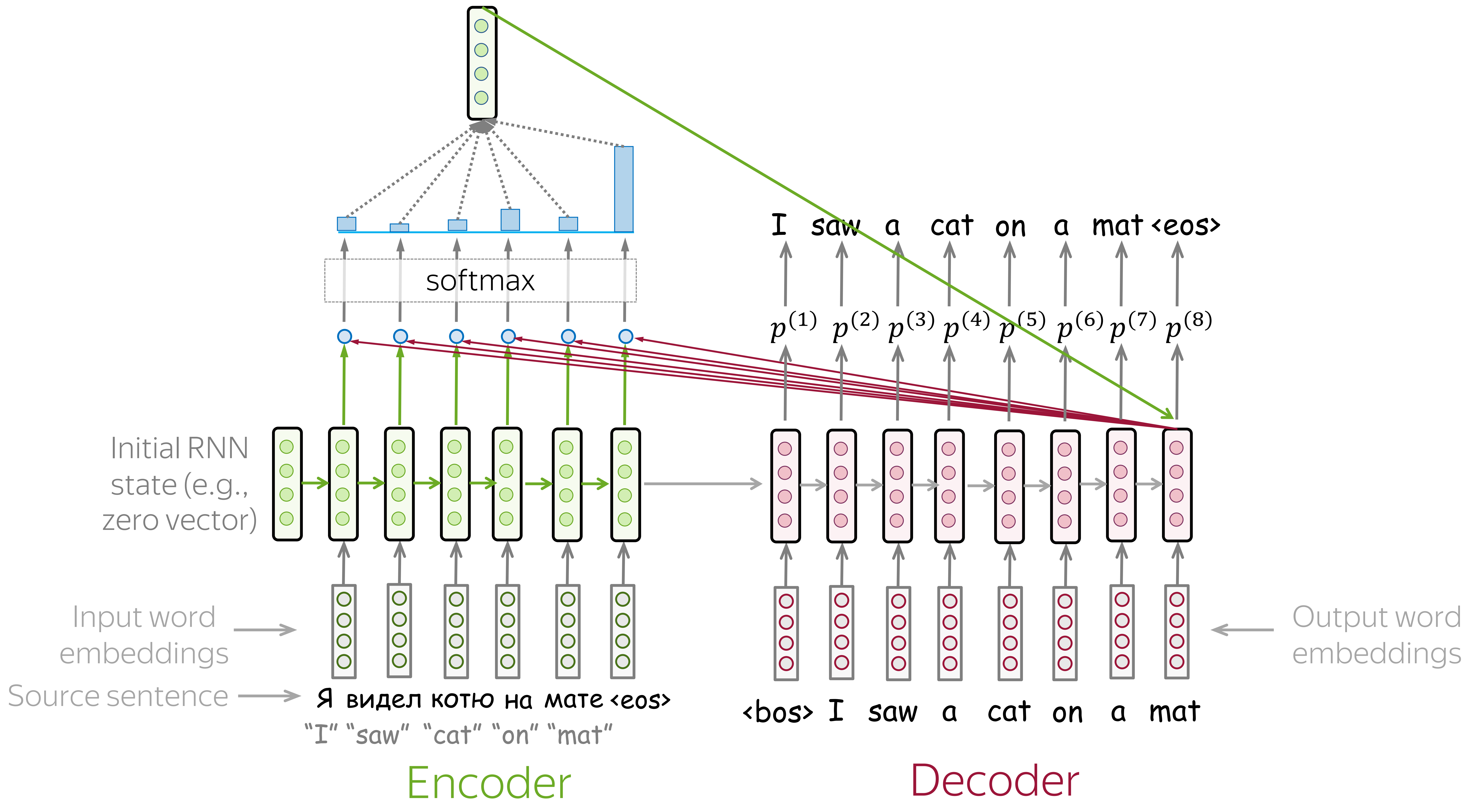
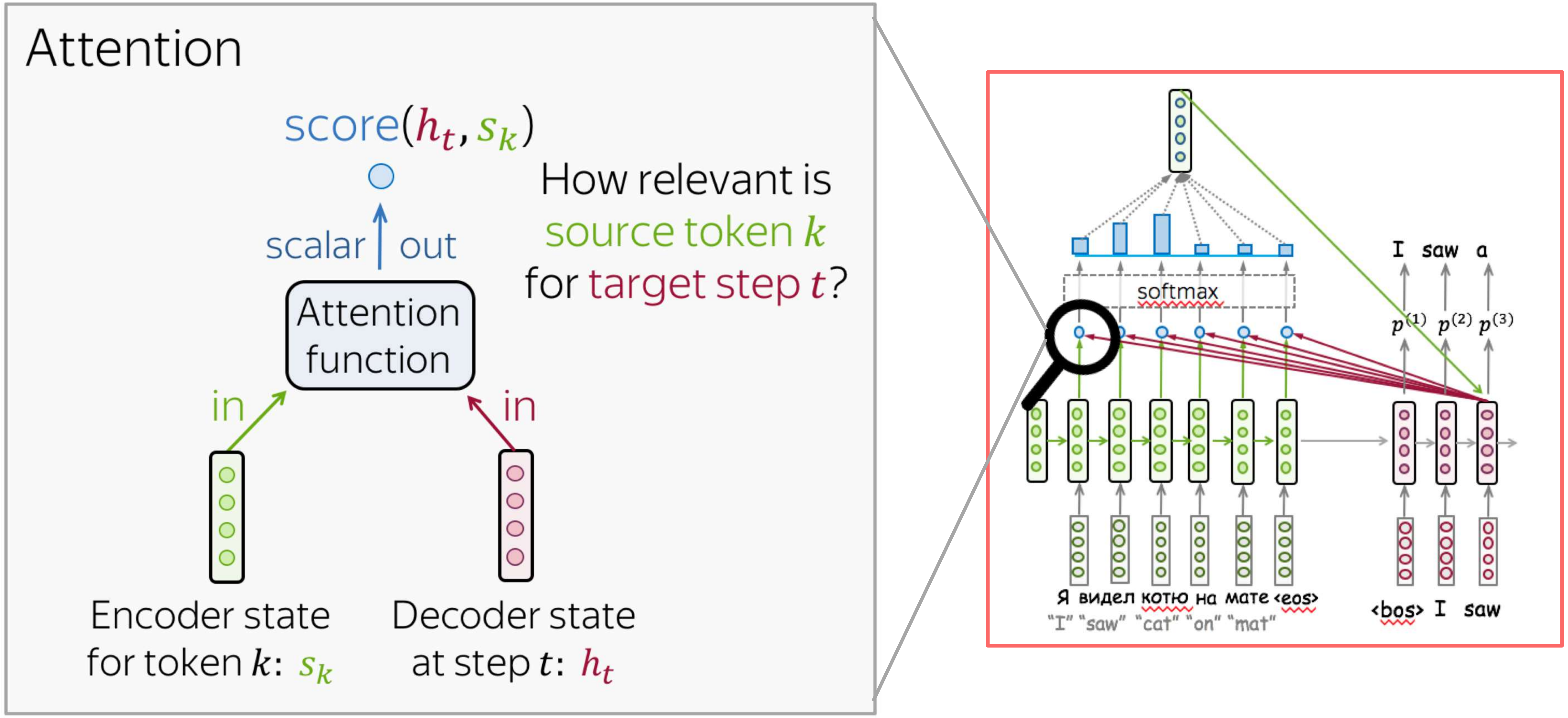
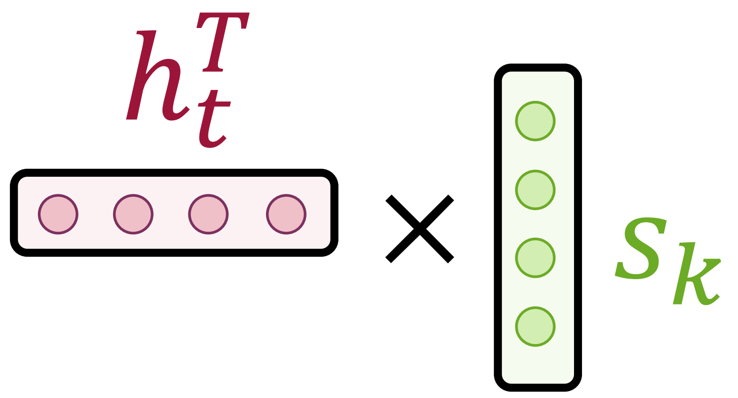


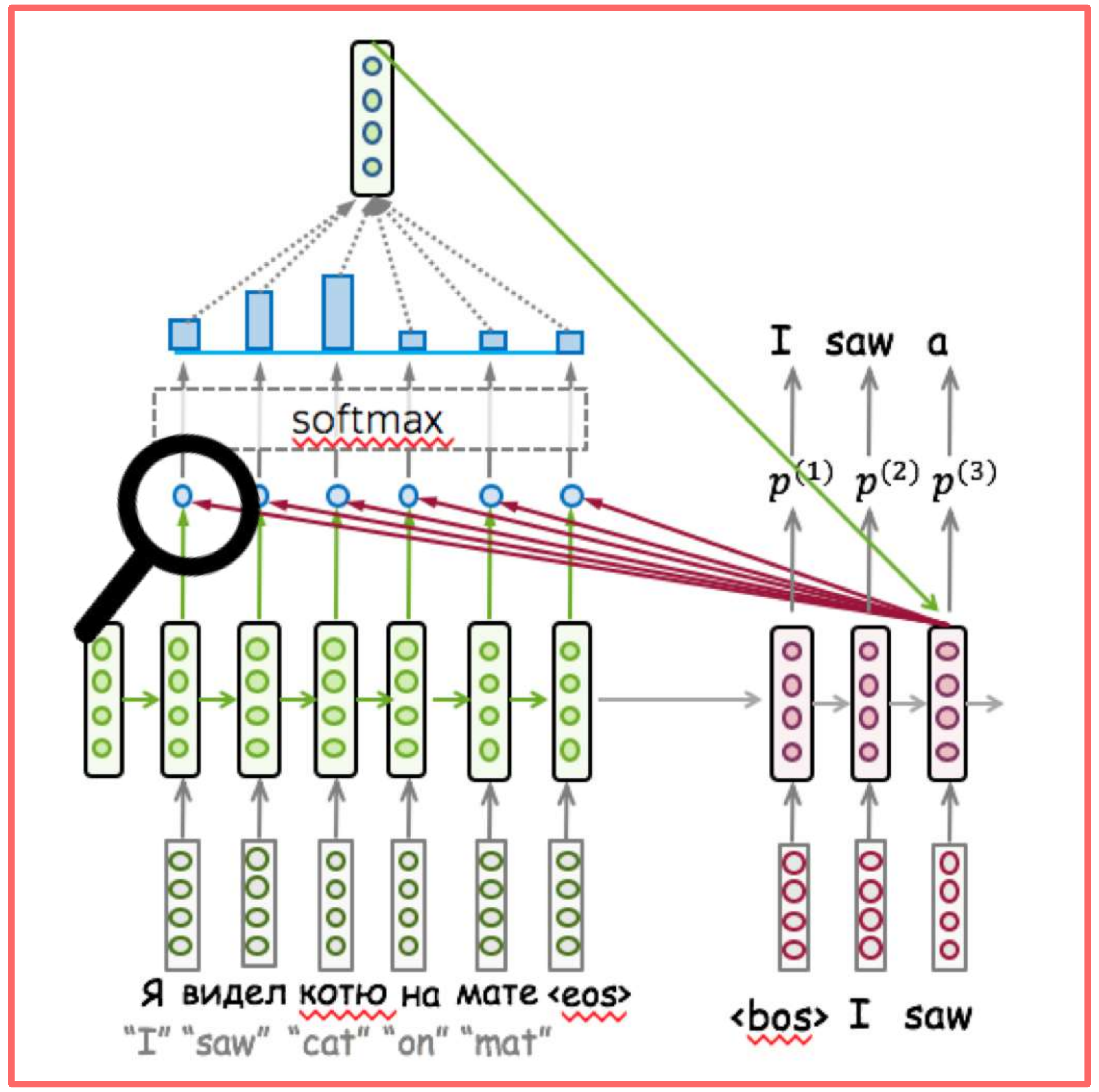
Attention Score Functions



Attention Score Functions

- Dot-product: $\text{score}(h_t, s_k) = h_t^T\ s_k$





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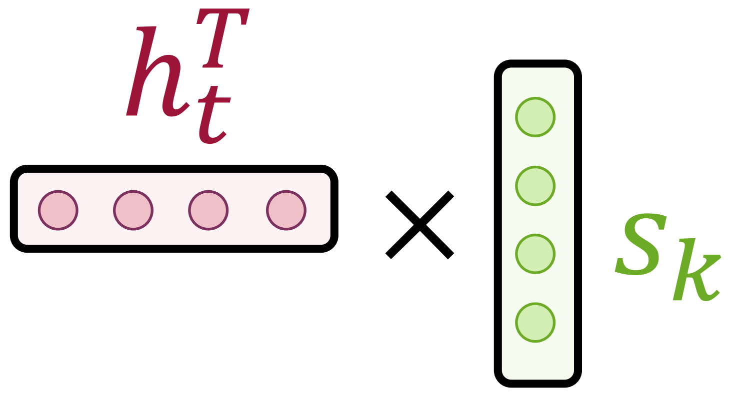
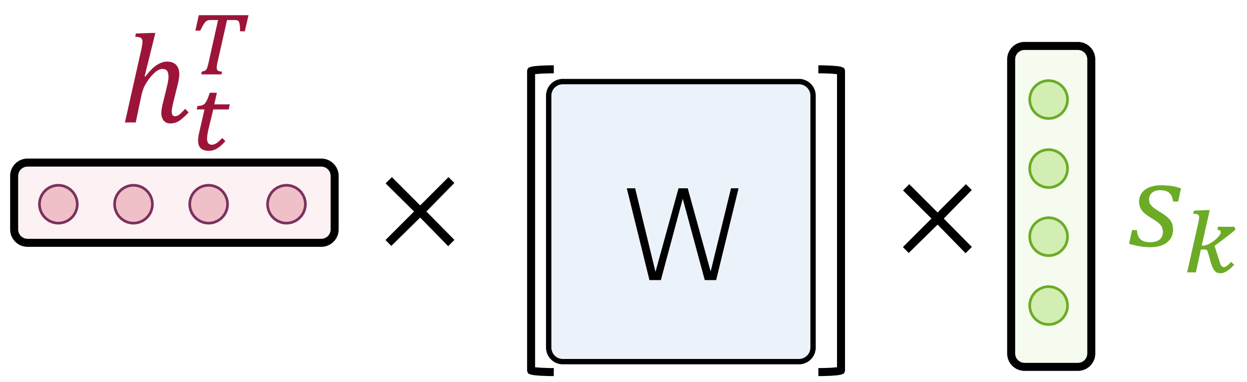
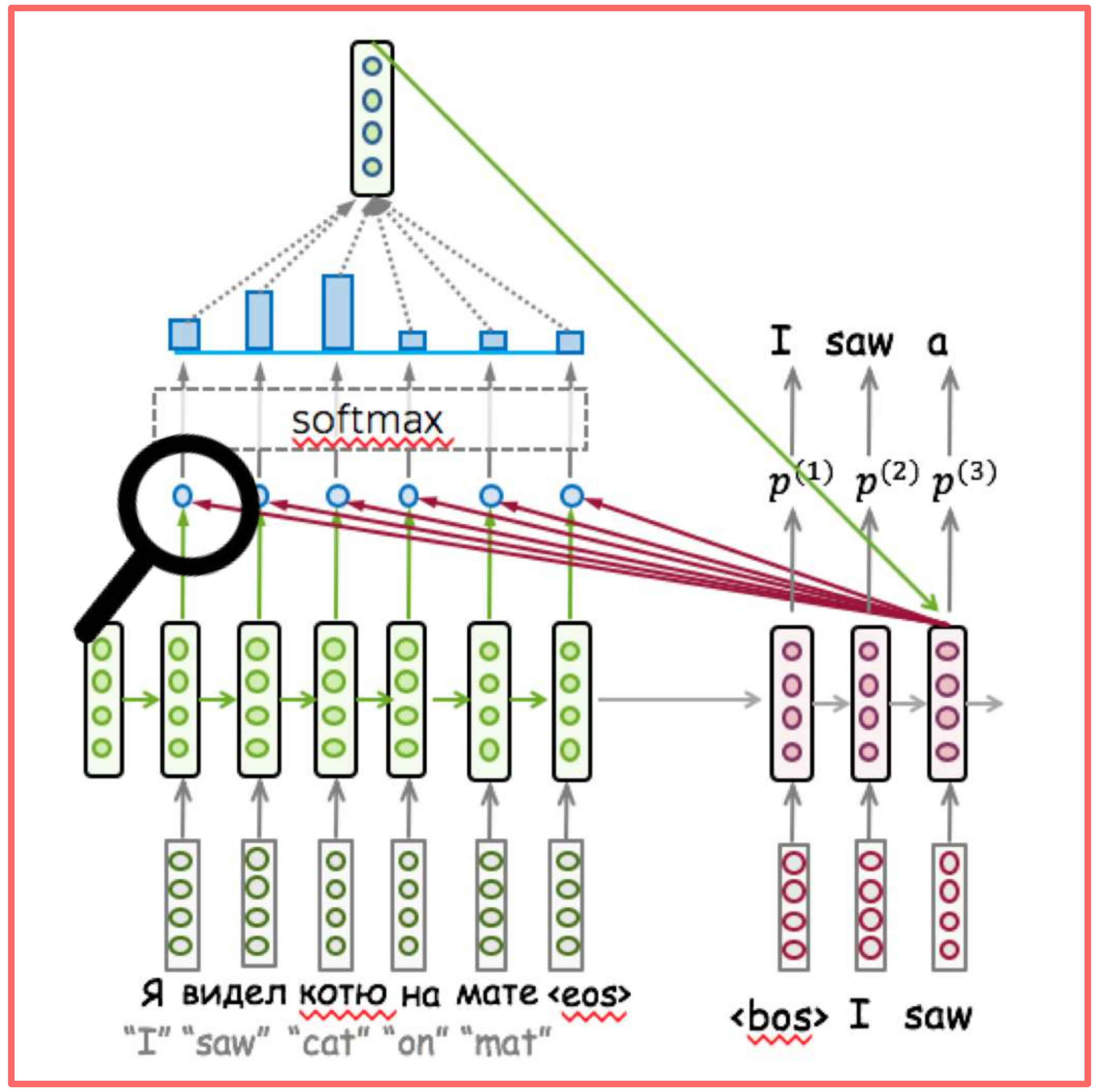


- Bilinear: $\text{score}(h_t, s_k) = h_t^T W s_k$





Attention Score Functions

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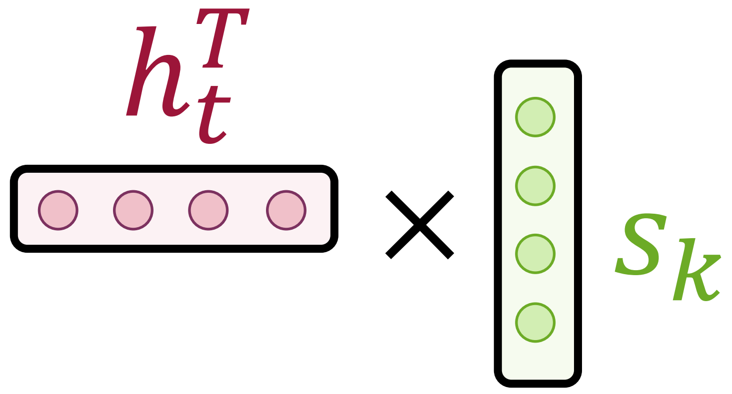
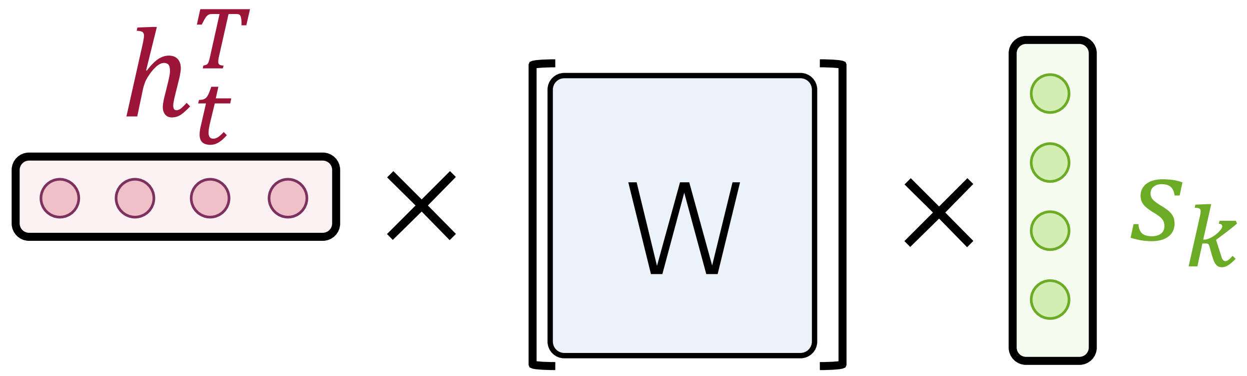
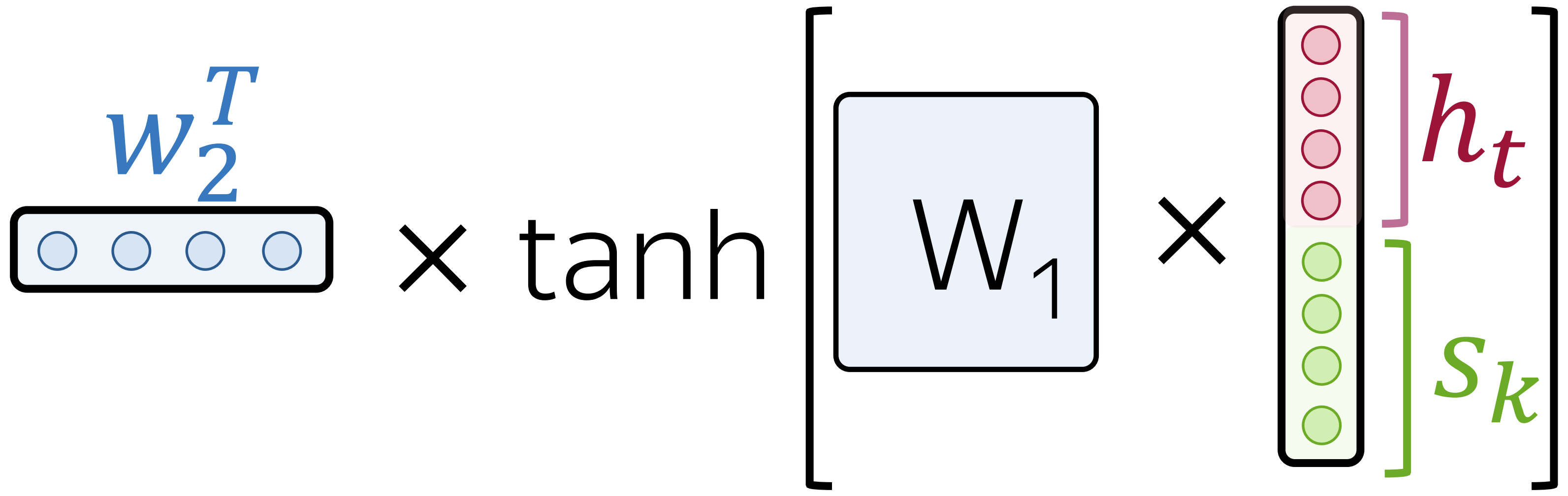
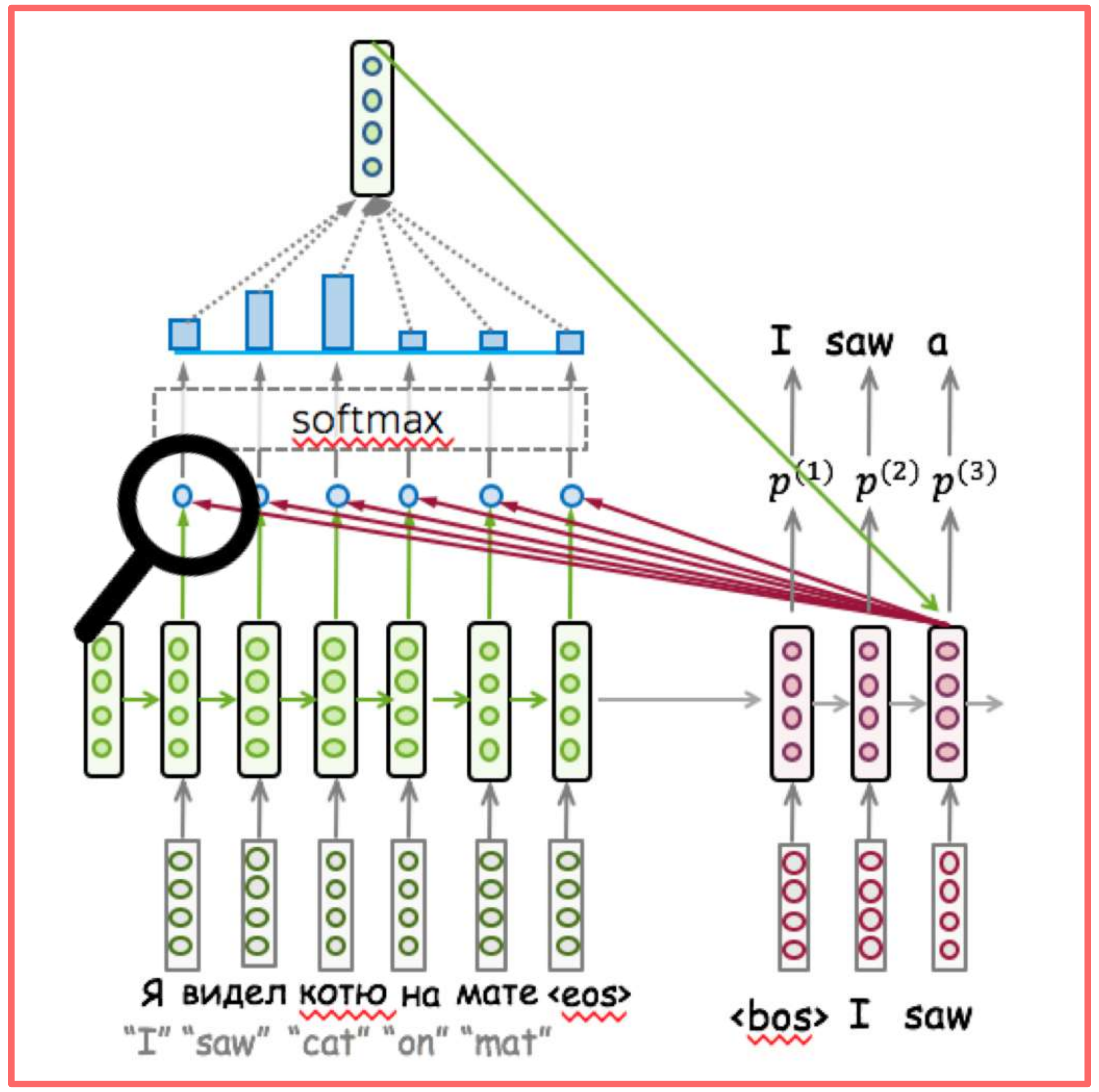


- Bilinear: $\text{score}(h_t, s_k) = h_t^T \; W s_k$



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





What is going to happen:

- Seq2seq Basics
- Attention
  - Why do we need it?
  - Attention: High-Level
  - Attention Score Functions
  - Models: Bahdanau vs Luong
- Transformer
- Subword Segmentation: BPE
- Analysis and Interpretability

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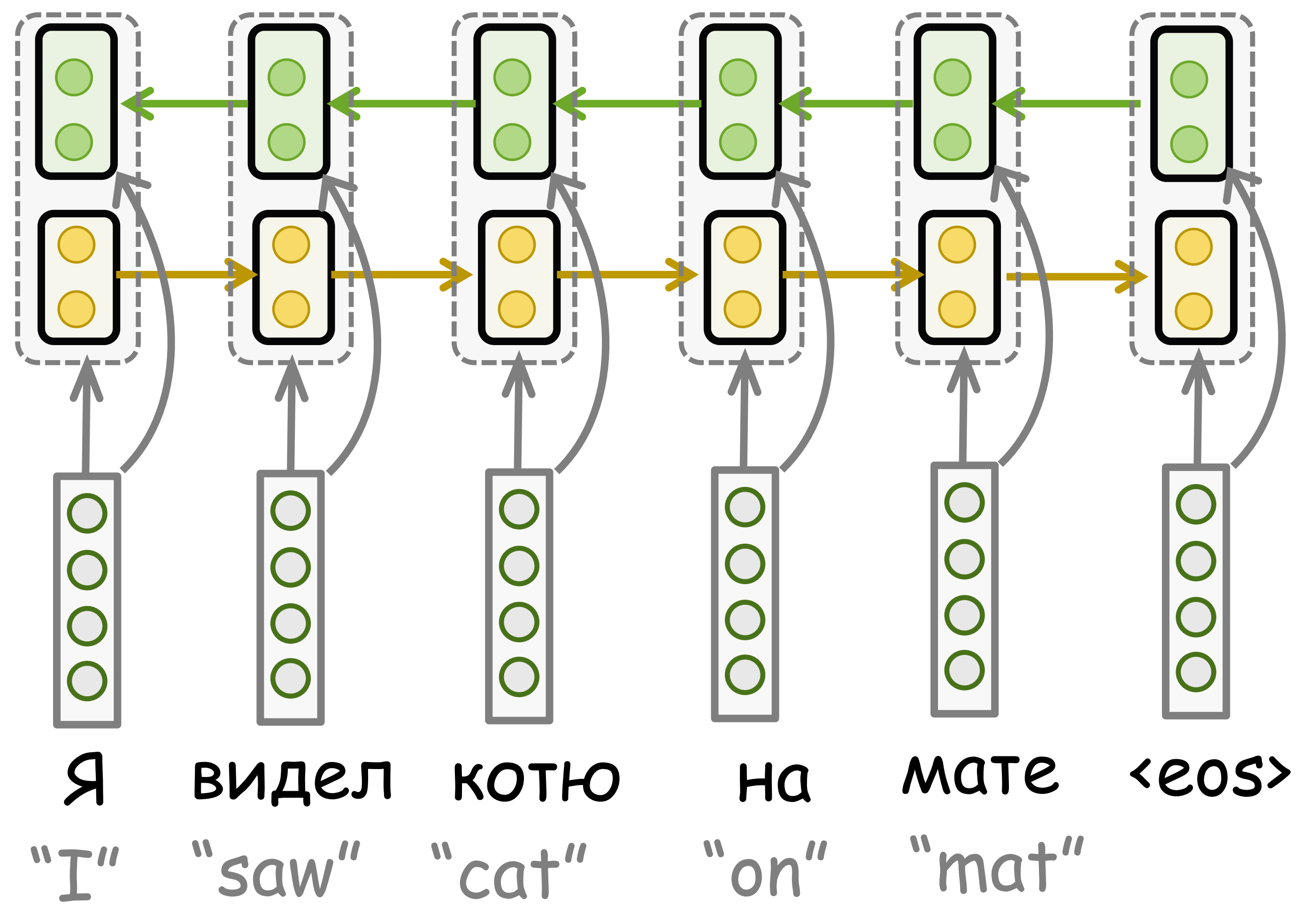
Bahdanau Model (the original attention model)

Bidirectional encoder
Concatenate states from
forward and backward RNNs



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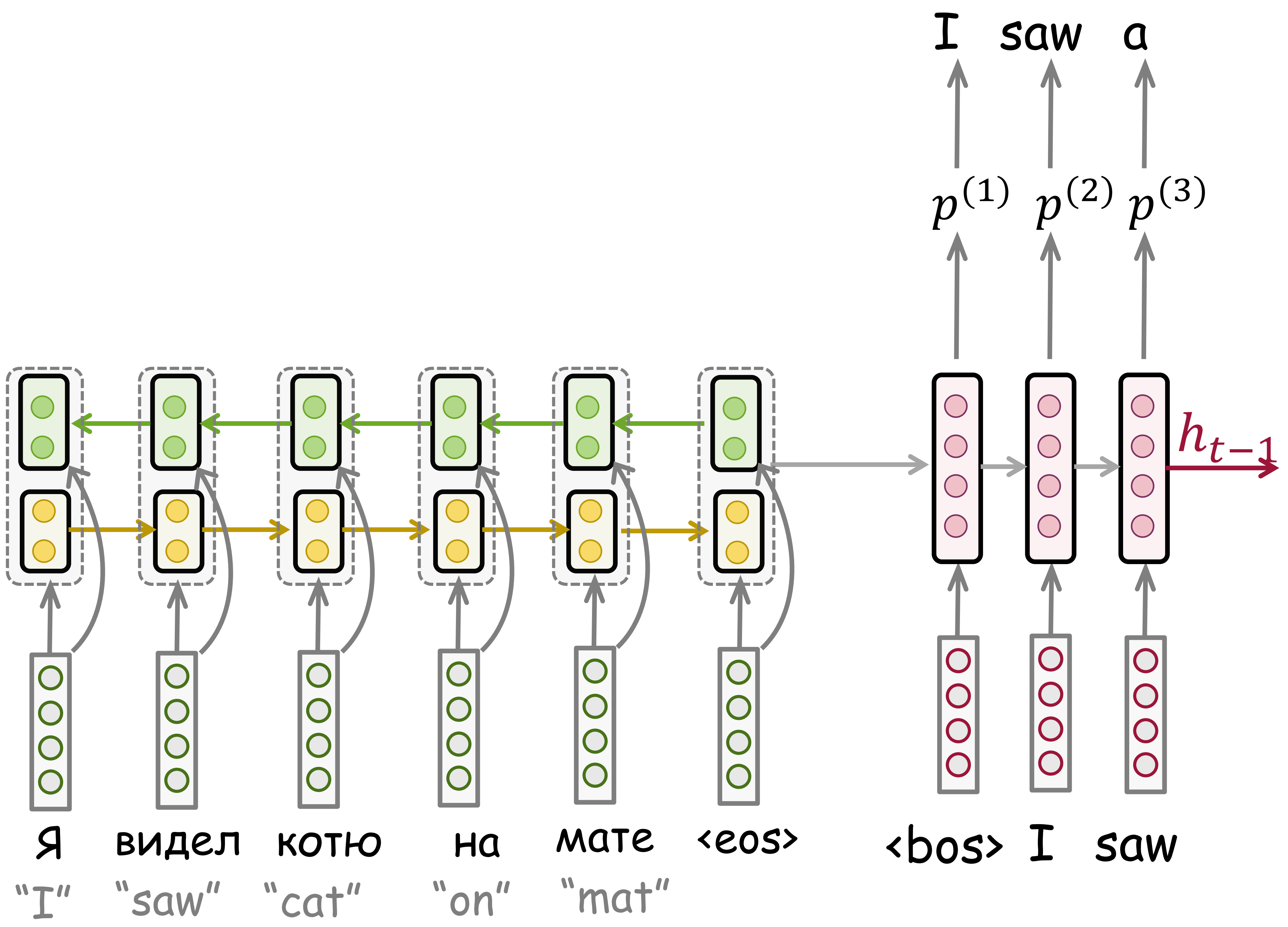

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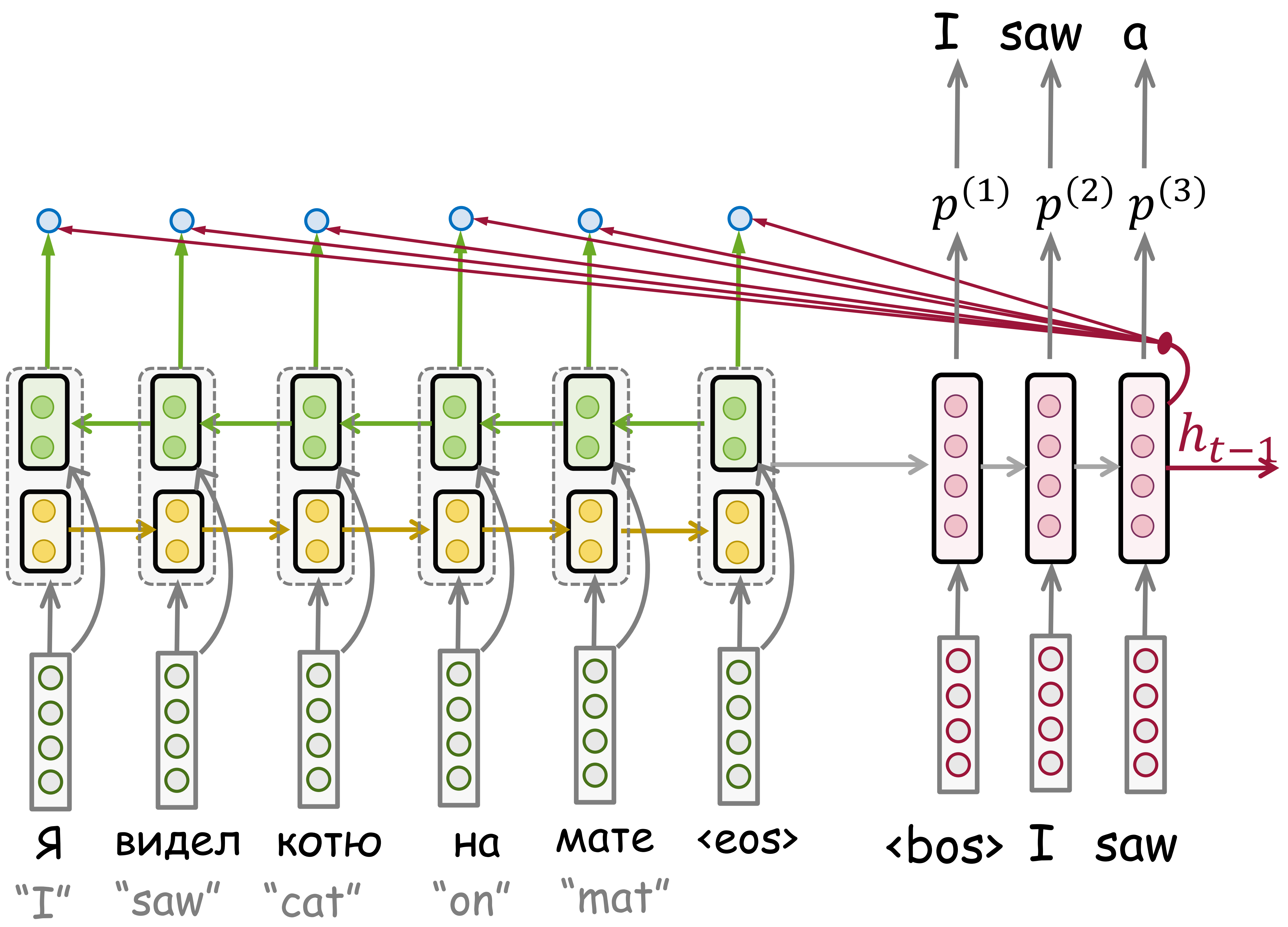

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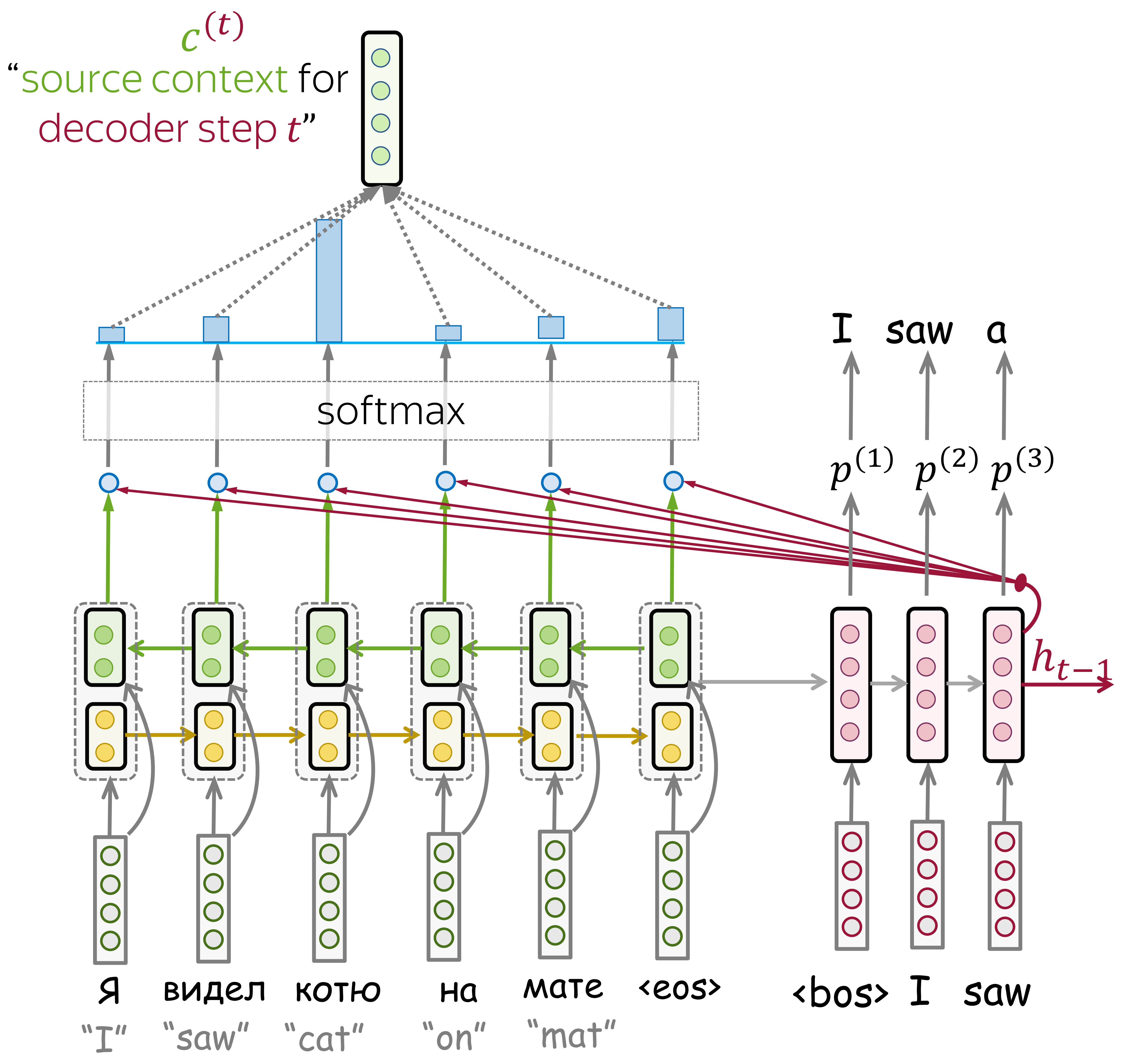

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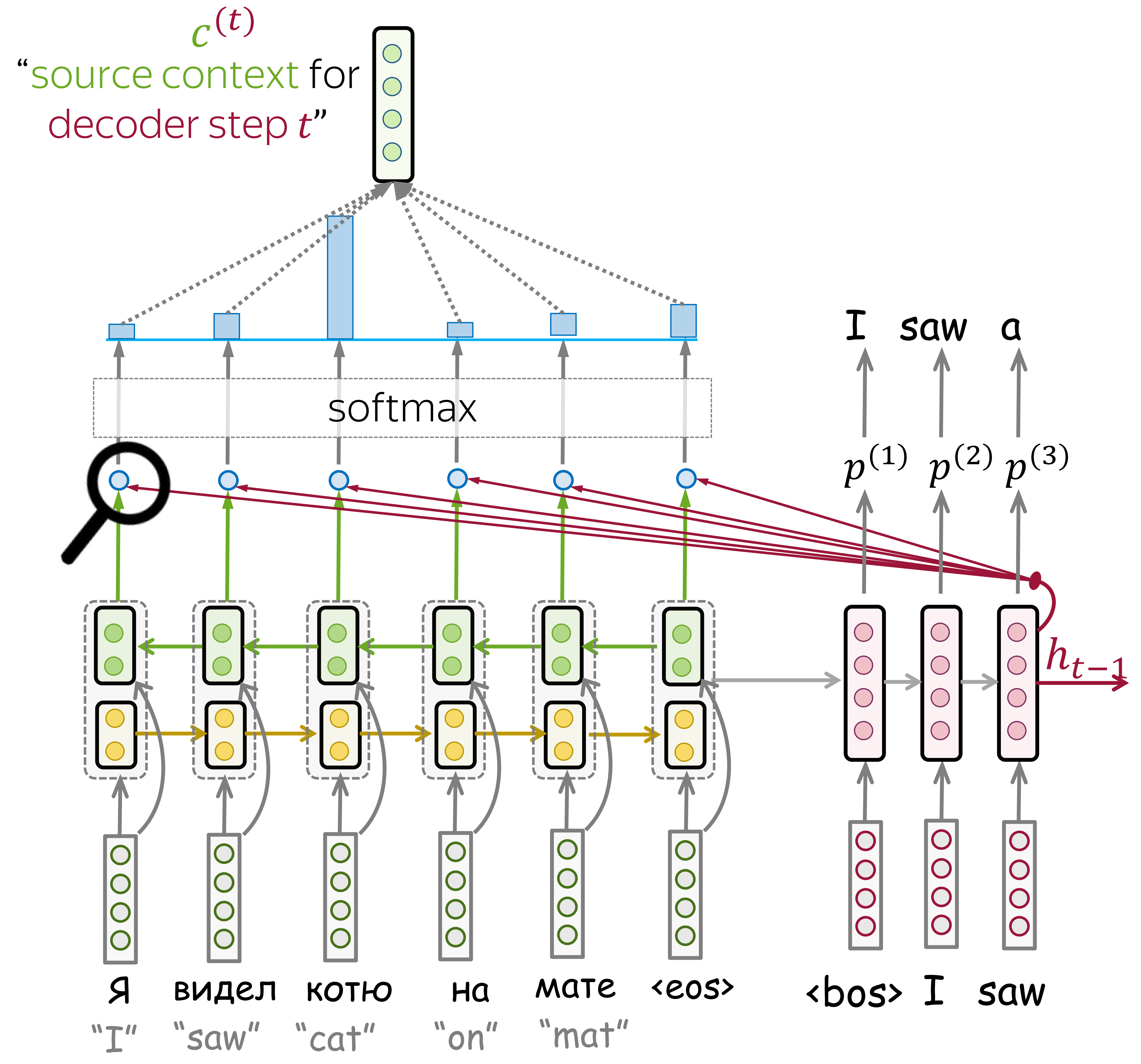

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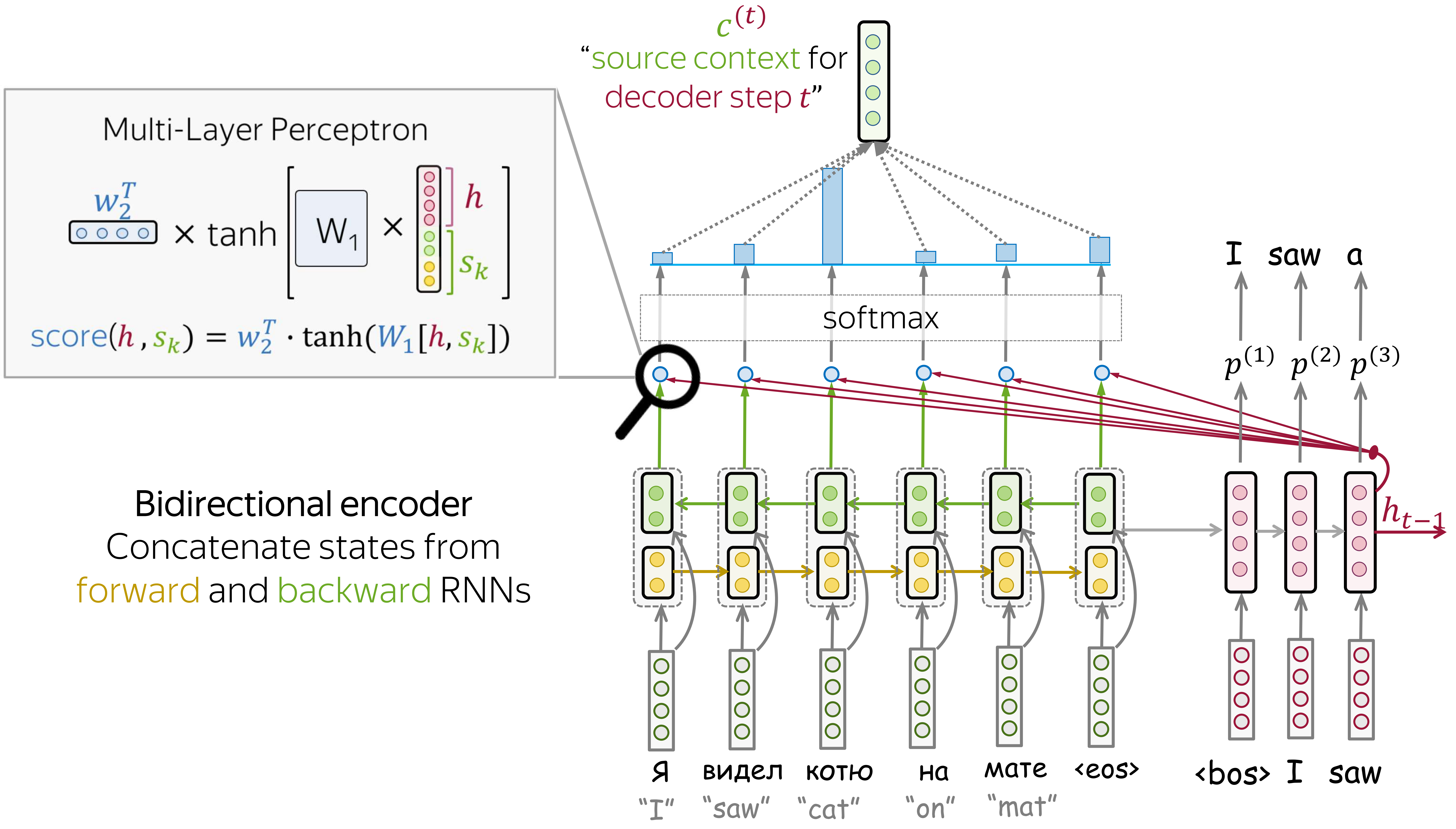

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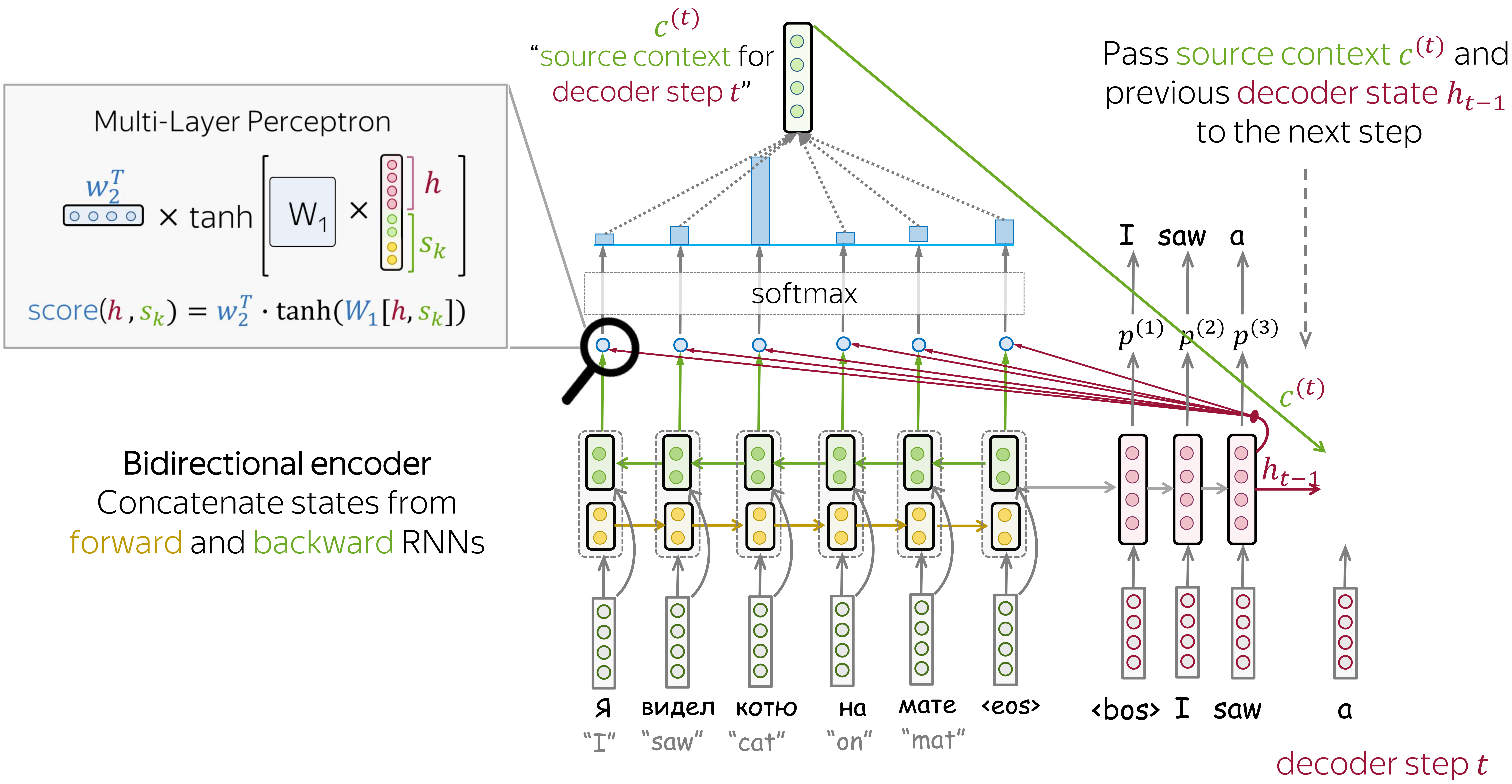

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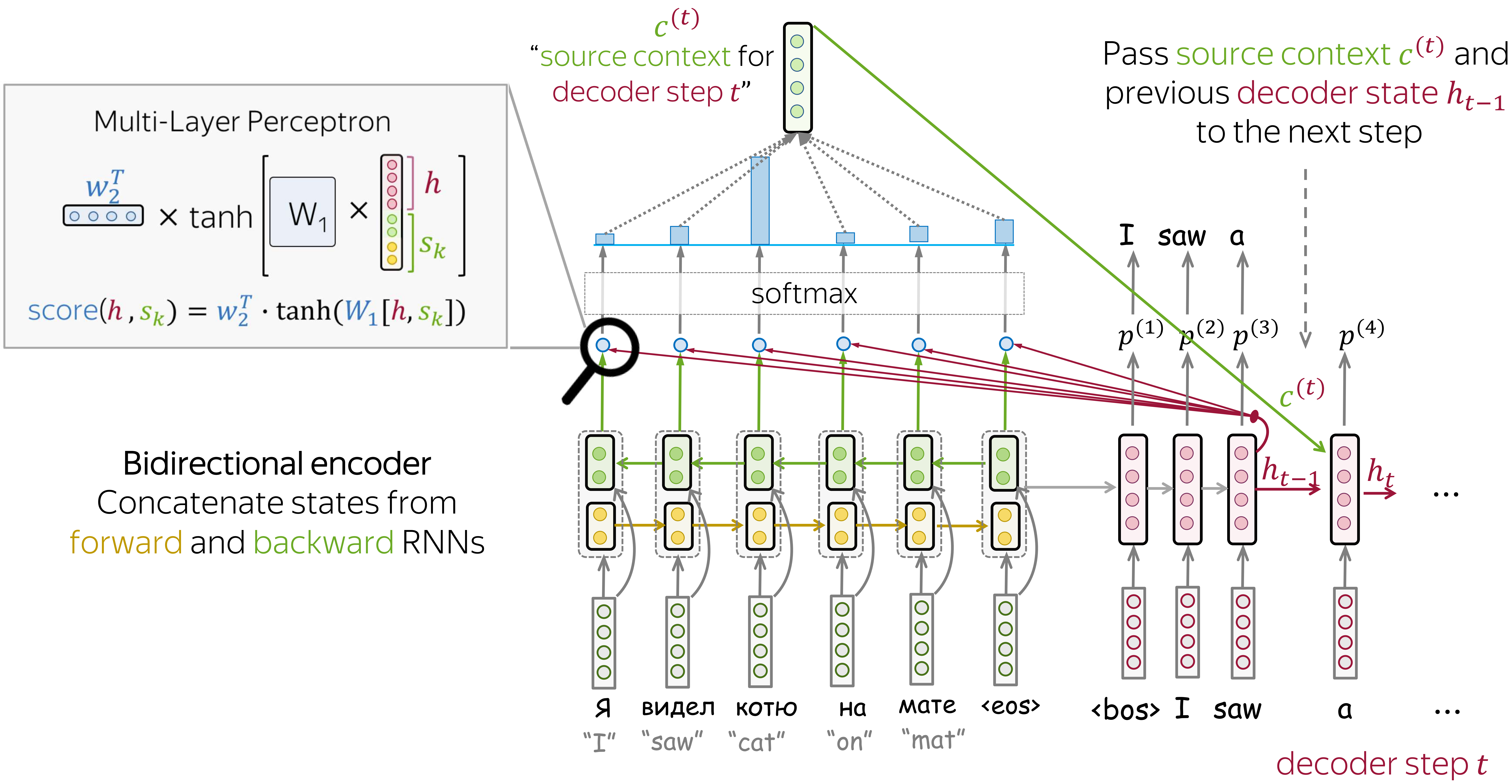
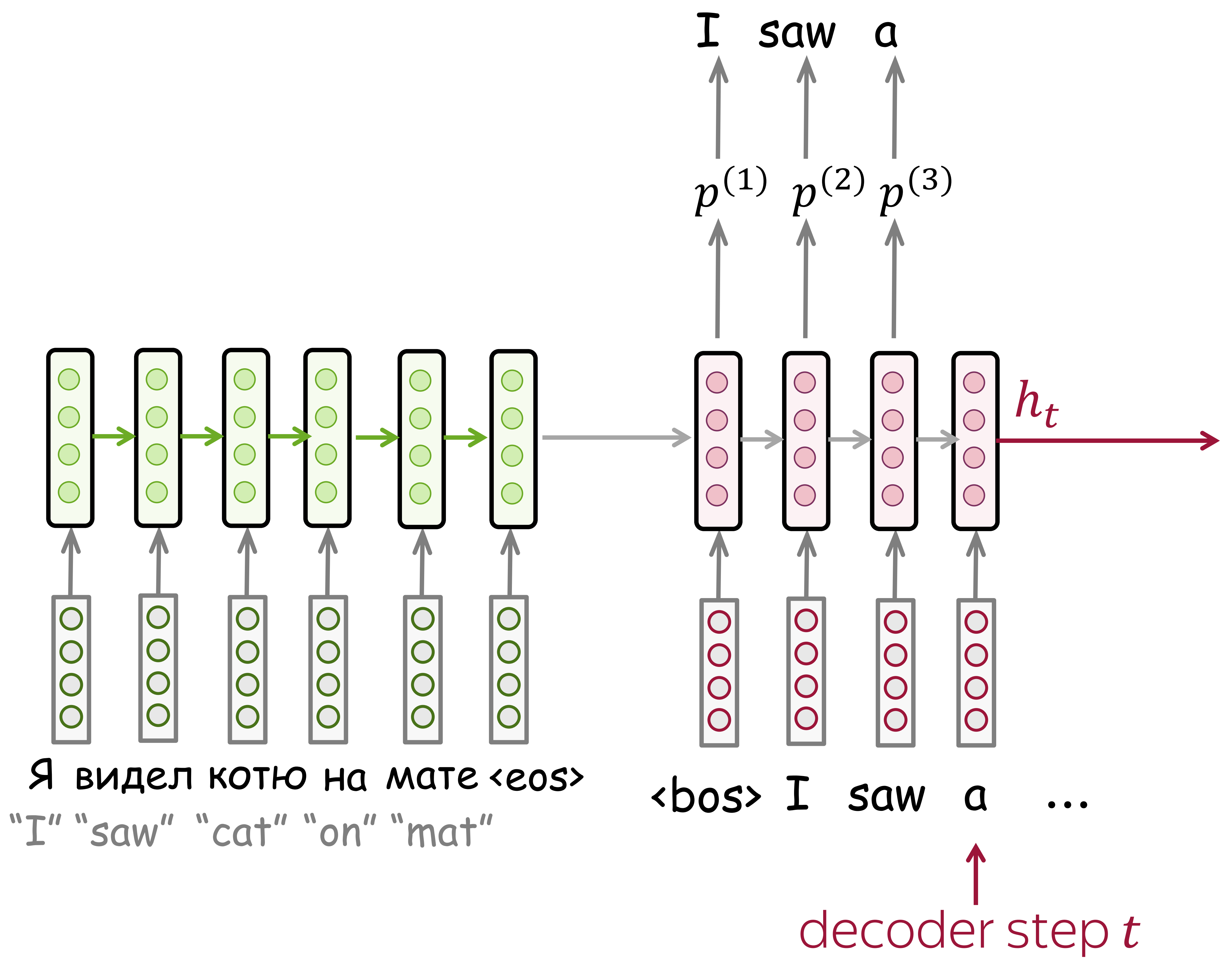
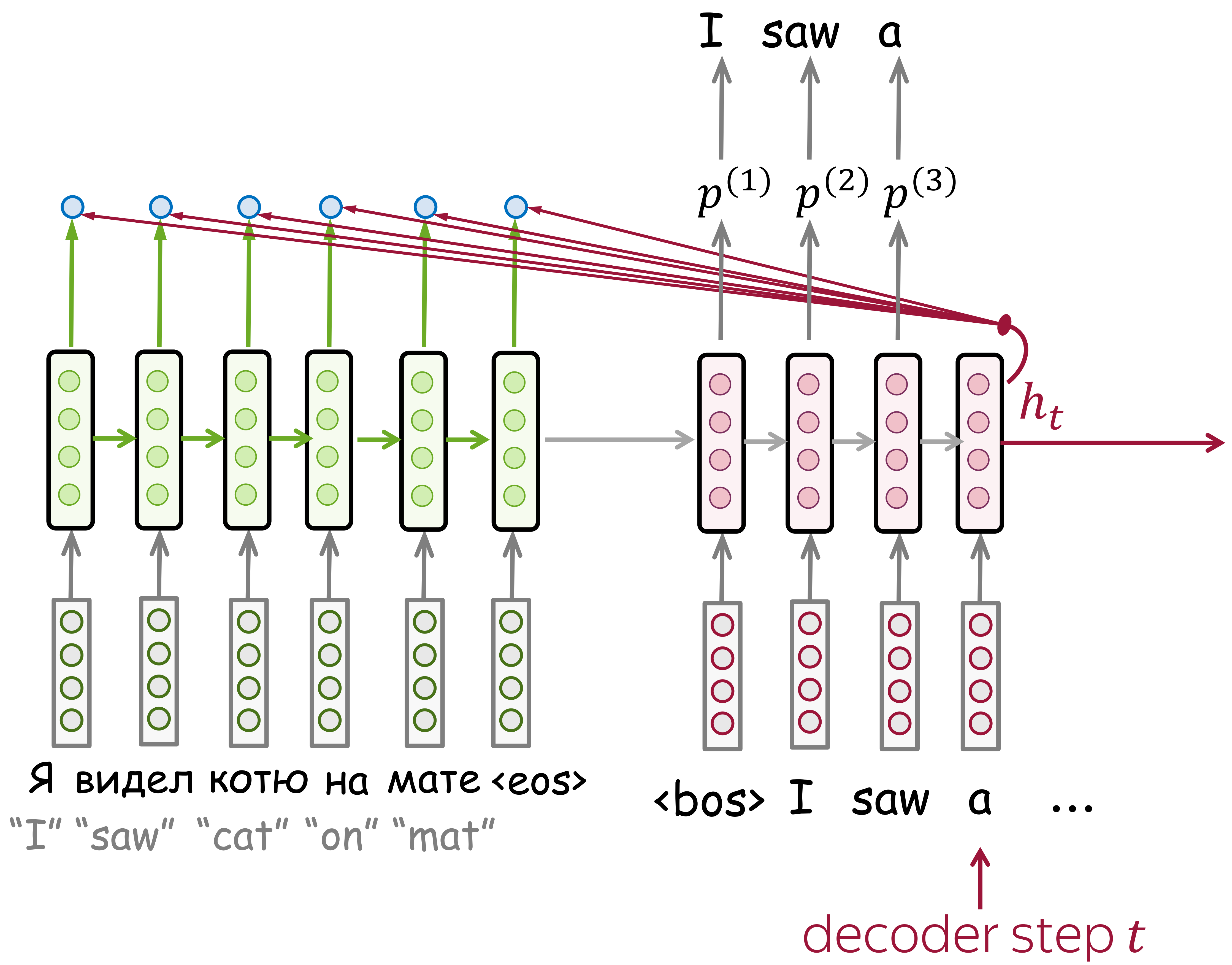


Luong Model

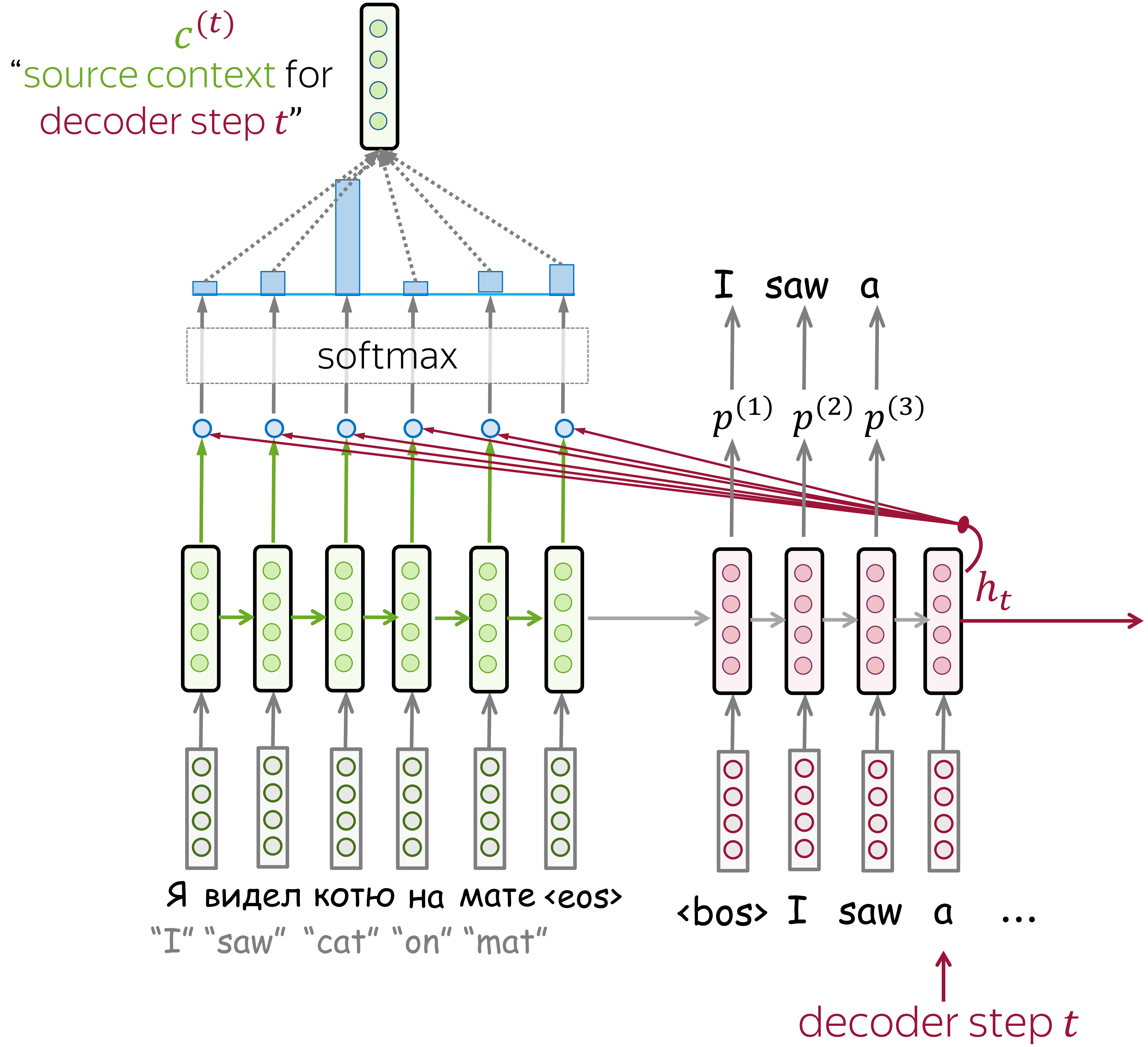


I saw a
$p^{(1)}$ $p^{(2)}$ $p^{(3)}$
h_t
Я видел котю на мате <eos>
"I" "saw" "cat" "on" "mat"
<bos> I saw a ...
decoder step t

Luong Model

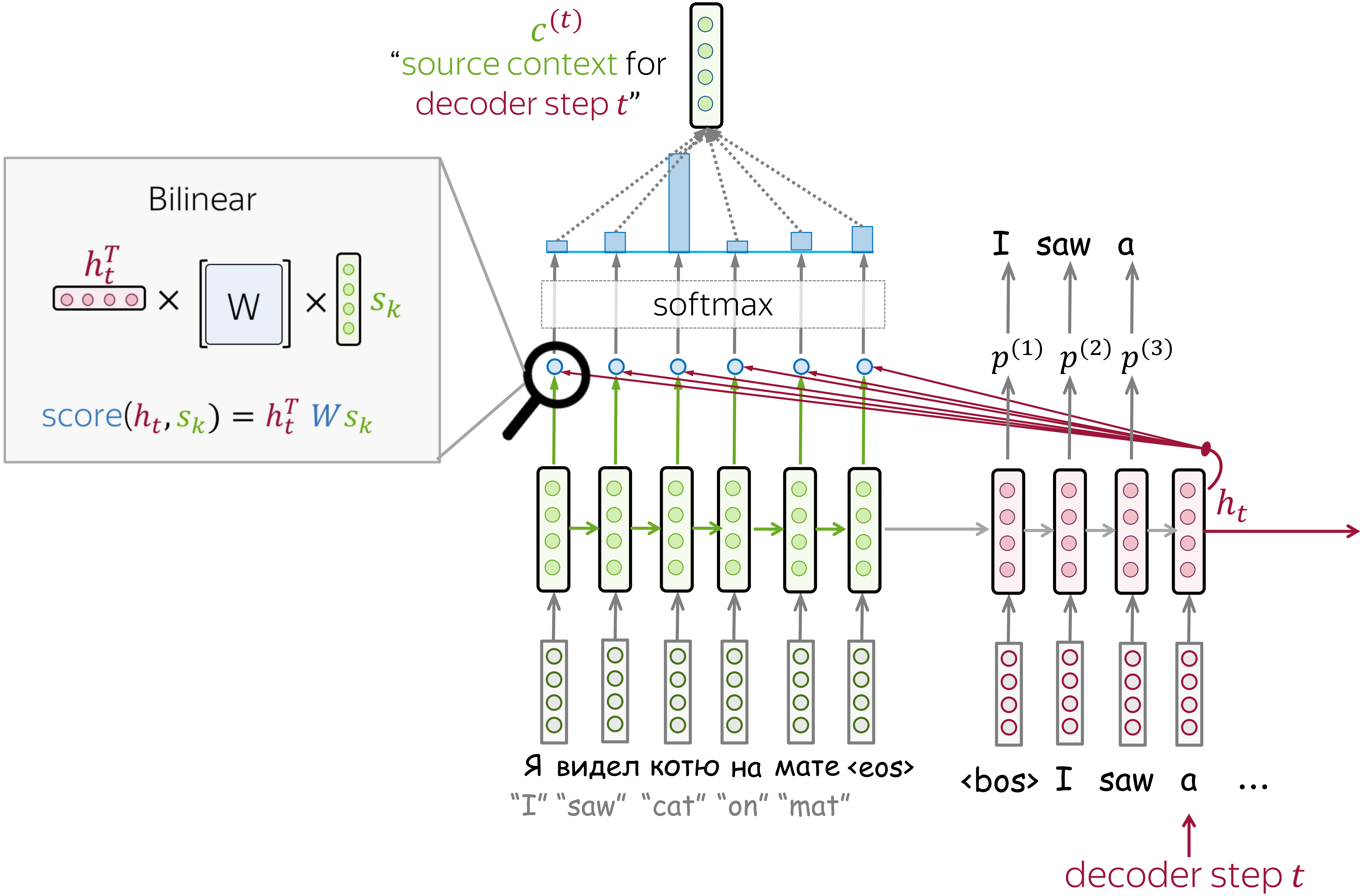

I saw a
$p^{(1)}$ $p^{(2)}$ $p^{(3)}$
h_t
Я видел котю на мате <eos>
"I" "saw" "cat" "on" "mat"
<bos> I saw a ...
decoder step t

Luong Model



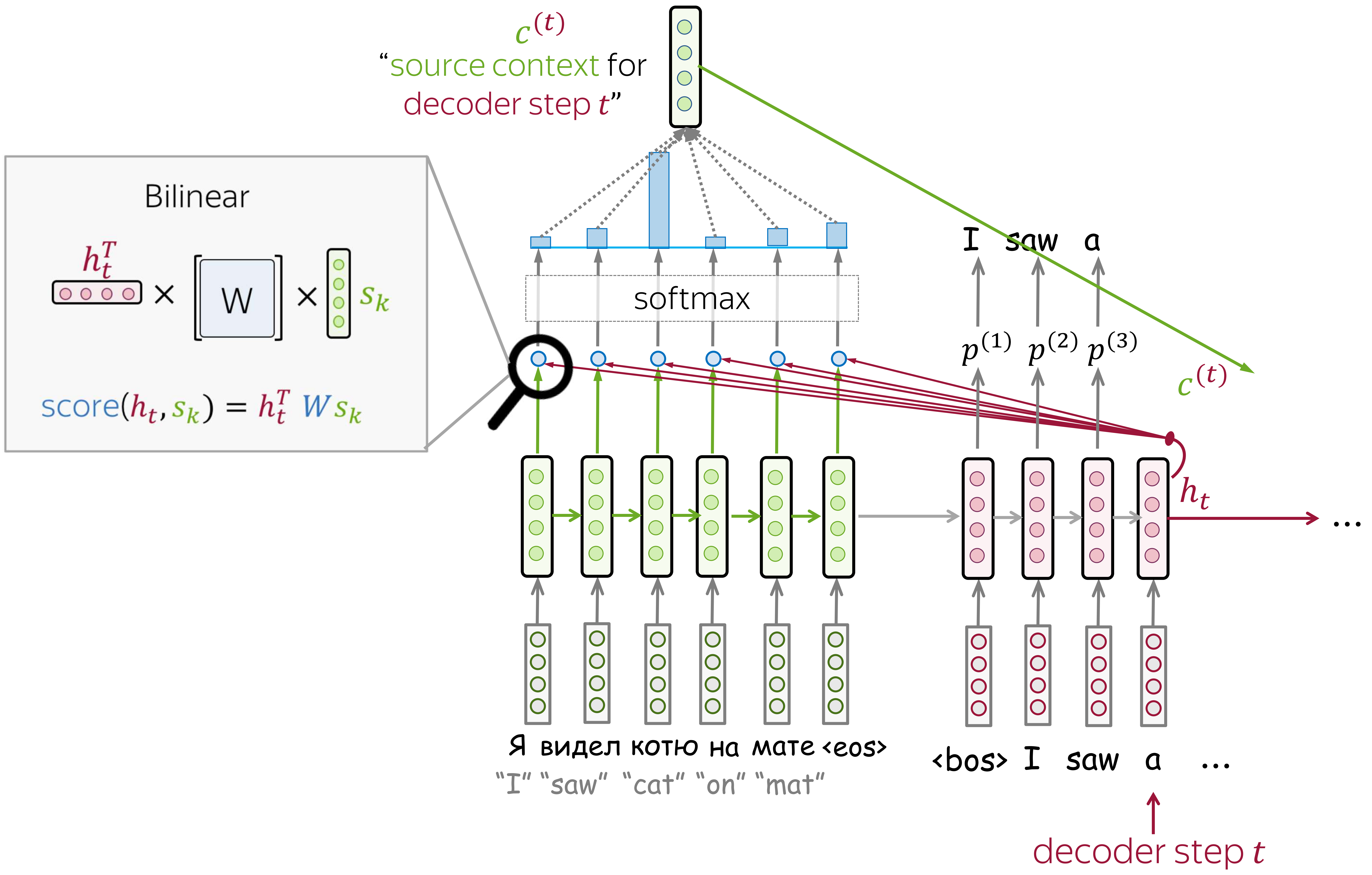
$c^{(t)}$
"source context for decoder step t"
softmax
I saw a
$p^{(1)}$ $p^{(2)}$ $p^{(3)}$
h_t
Я видел котю на мате <eos>
"I" "saw" "cat" "on" "mat"
<bos> I saw a ...
decoder step t

Luong Model



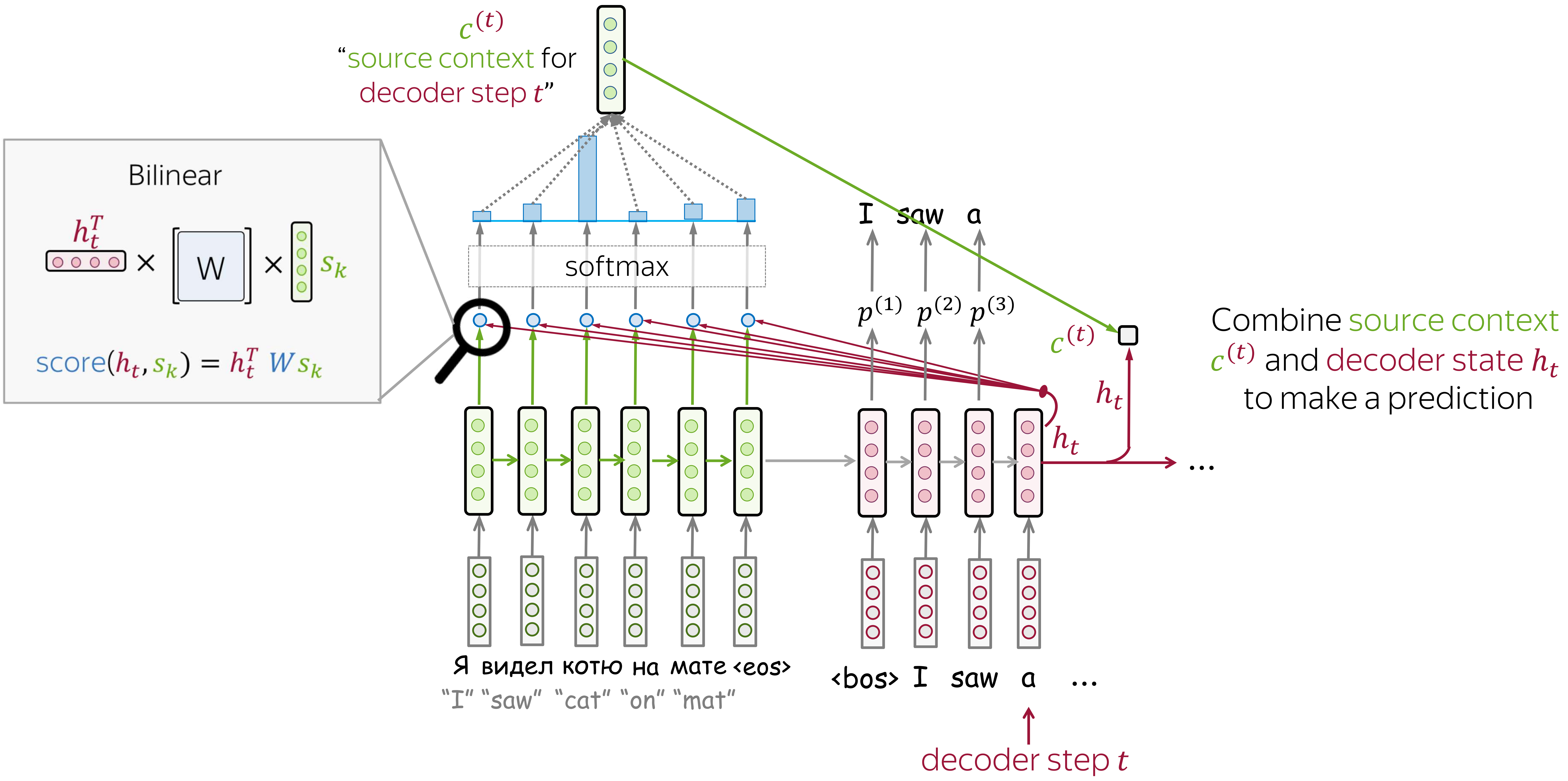
$c^{(t)}$
"source context for decoder step t"
Bilinear
h_t^T
W
s_k
$\text{score}(h_t, s_k) = h_t^T W s_k$
softmax
I saw a
$p^{(1)}$ $p^{(2)}$ $p^{(3)}$
h_t
Я видел котю на мате <eos>
"I" "saw" "cat" "on" "mat"
<bos> I saw a ...
decoder step t

Luong Model



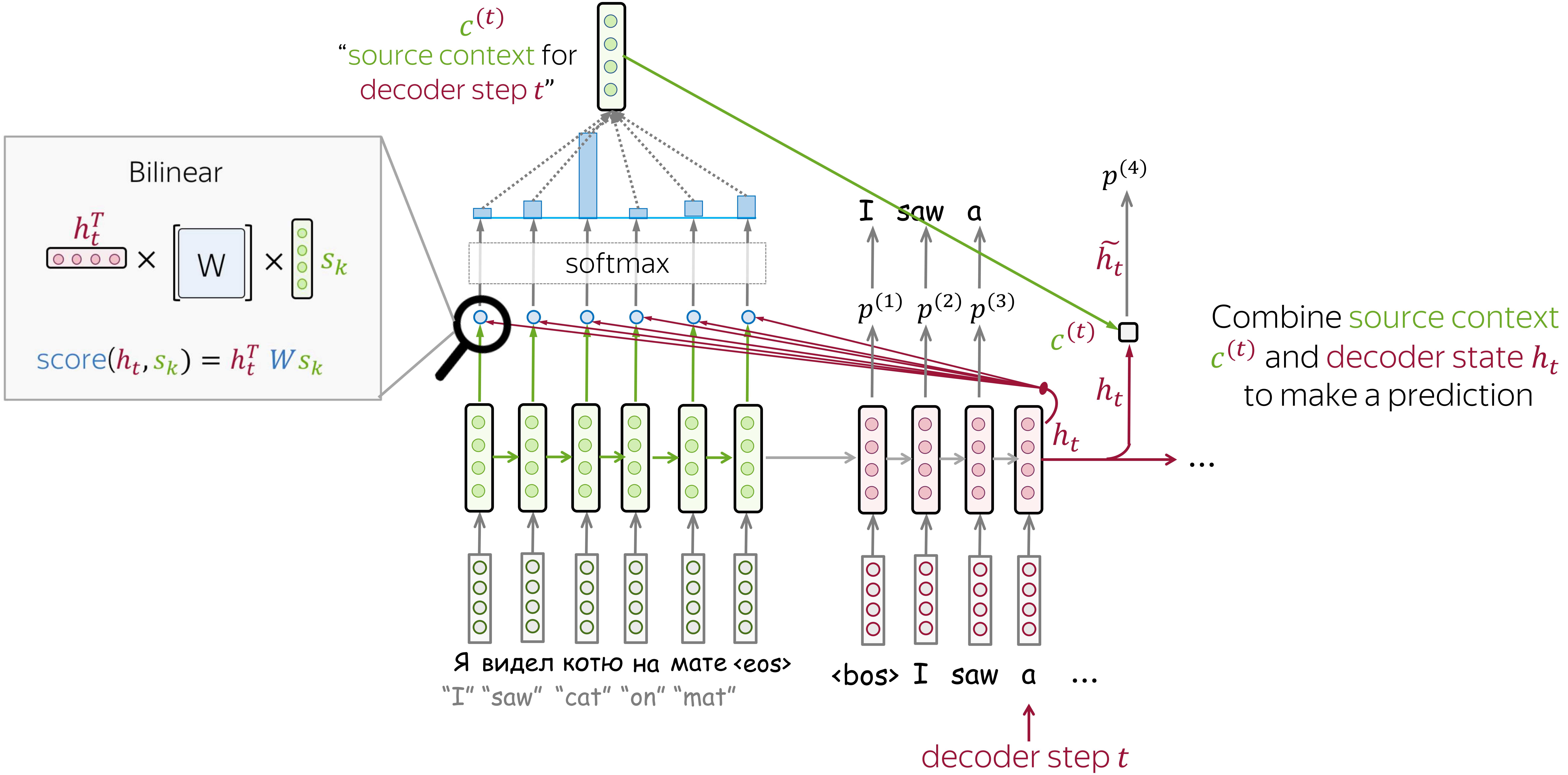
$c^{(t)}$
"source context for decoder step t"
Bilinear
h_t^T × W × s_k
score$(h_t, s_k) = h_t^T\, W s_k$
softmax
I saw a
$p^{(1)}$ $p^{(2)}$ $p^{(3)}$
$c^{(t)}$
h_t
...
Я видел котю на мате <eos>
"I" "saw" "cat" "on" "mat"
<bos> I saw a ...
decoder step t

Luong Model



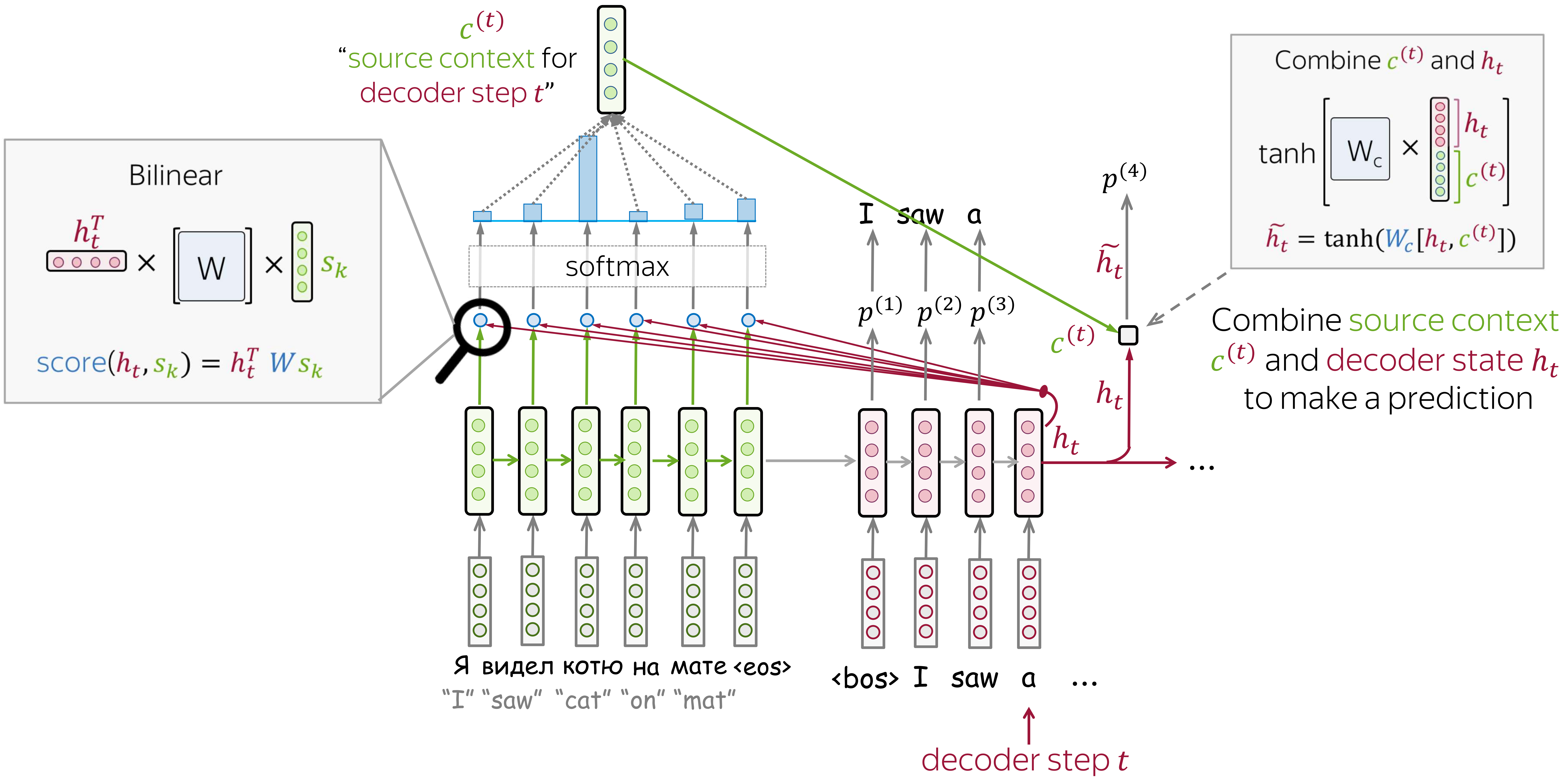
$c^{(t)}$
"source context for decoder step t"
Bilinear
h_t^T
$\times$ W $\times$ s_k
score$(h_t, s_k) = h_t^T W s_k$
softmax
I saw a
$p^{(1)}$ $p^{(2)}$ $p^{(3)}$
$c^{(t)}$
h_t
h_t
...
Combine source context $c^{(t)}$ and decoder state h_t to make a prediction
Я видел котю на мате <eos>
"I" "saw" "cat" "on" "mat"
<bos> I saw a ...
decoder step t

Luong Model



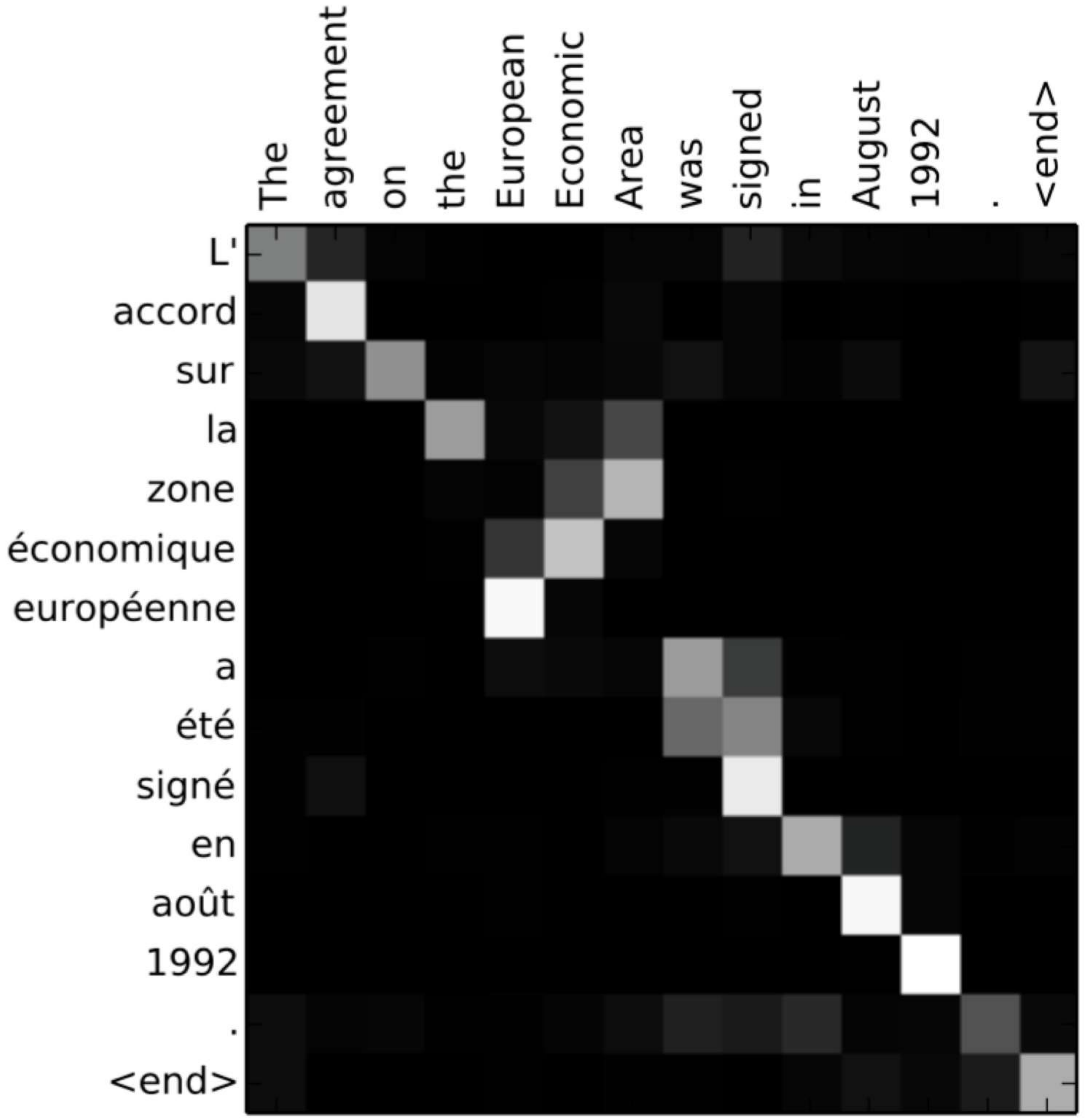
$c^{(t)}$
"source context for decoder step t"
Bilinear
h_t^T
$\times$ W $\times$ s_k
score(h_t, s_k) = h_t^T $W s_k$
softmax
I saw a
$p^{(1)}$ $p^{(2)}$ $p^{(3)}$
$p^{(4)}$
$\tilde{h}_t$
$c^{(t)}$
h_t
h_t
...
Я видел котю на мате <eos>
"I" "saw" "cat" "on" "mat"
<bos> I saw a ...
decoder step t
Combine source context $c^{(t)}$ and decoder state h_t to make a prediction

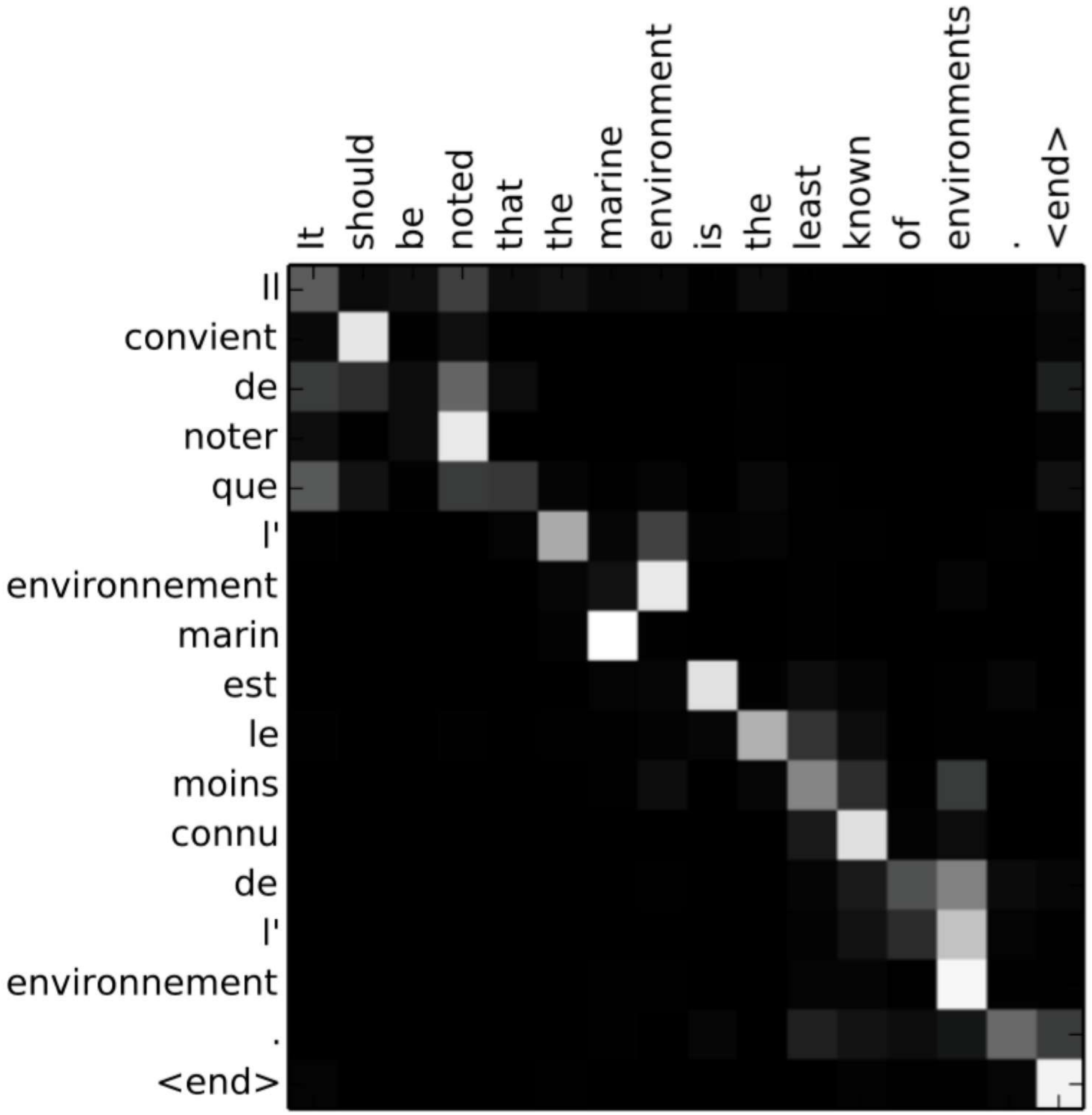
Luong Model



Bilinear
h_t^T
W
s_k
score$(h_t, s_k) = h_t^T\ W s_k$
$c^{(t)}$
"source context for decoder step t"
softmax
Я видел котю на мате <eos>
"I" "saw" "cat" "on" "mat"
<bos> I saw a ...
decoder step t
I saw a
$p^{(1)}$ $p^{(2)}$ $p^{(3)}$
$p^{(4)}$
$\tilde{h}_t$
$c^{(t)}$
h_t
h_t
...
Combine $c^{(t)}$ and h_t
tanh
W$_c$
h_t
$c^{(t)}$
$\tilde{h}_t = \tanh(W_c[h_t, c^{(t)}])$
Combine source context $c^{(t)}$ and decoder state h_t to make a prediction

Attention Learned (almost) Alignment





The examples are from the paper Neural Machine Translation by Jointly Learning to Align and Translate.