Анализ неструктурированных данных

Introduction to machine translation

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31 октября 2018 г.

Machine Translation

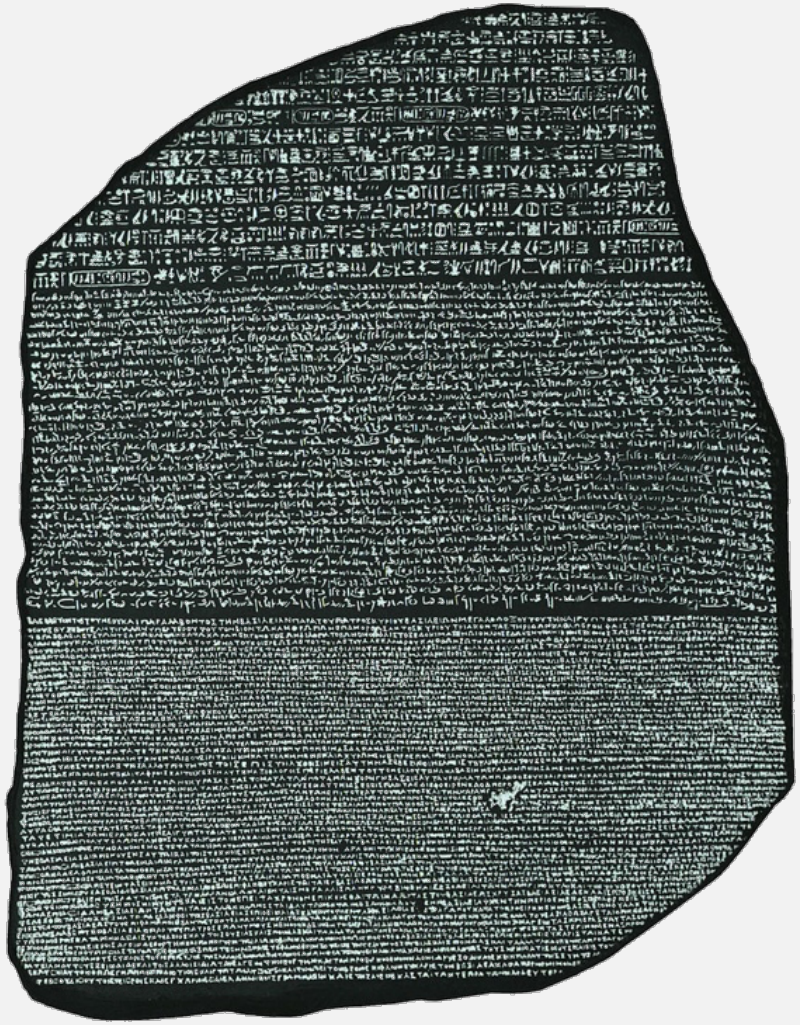
Parallel data

Parallel corpora:

- Europarl
- Movie subtitles
- Translated news, books
- Wikipedia (comparable)
- http://opus.lingfil.uu.se/

Lot's of problems with data:

- Noisy
- Specific domain
- Rare language pairs
- Not aligned, not enough



Evaluation

- How to compare two arbitrary translations?
- Low agreement rate even between reviewers
- BLEU score – a popular automatic technique

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3-grams: 2 / 4

4-grams: 1 / 3

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Brevity penalty : min(1, 6 / 5)

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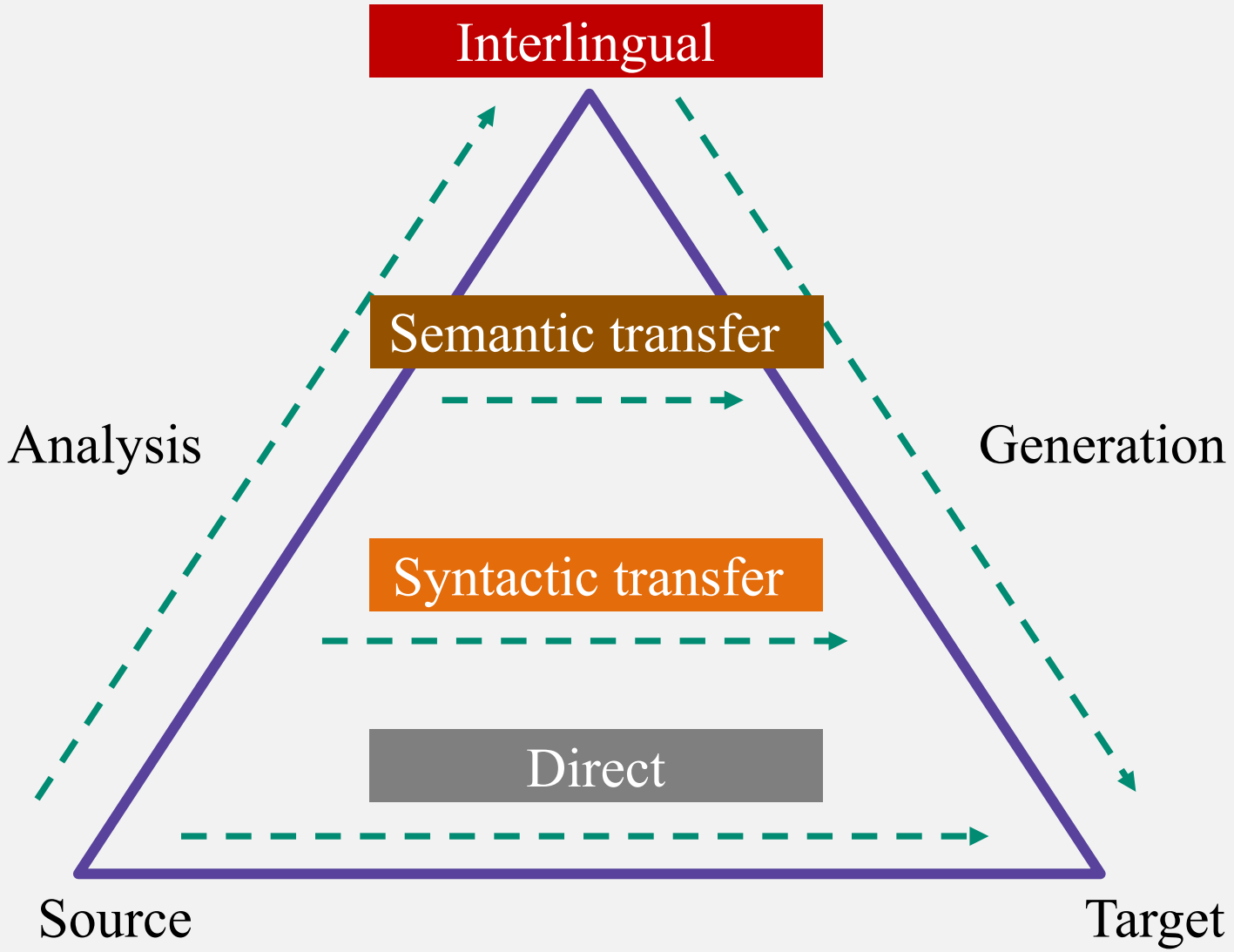
$$\mathrm{BLEU} = 1 \cdot \sqrt[4]{\frac{4}{6} \cdot \frac{3}{5} \cdot \frac{2}{4} \cdot \frac{1}{3}}$$

Brevity penalty : min(1, 6 / 5)

The mandatory slide



Henry S. Thompson, https://www.inf.ed.ac.uk/teaching/courses/anlp/lectures/30/

Roller-coaster of machine translation

1954 Georgetown IBM experiment Russian to English:

- Claimed that MT would be solved **within 3-5 years.**

1966 ALPAC report:

- Concluded that MT was **too expensive and ineffective.**

Two main paradigms

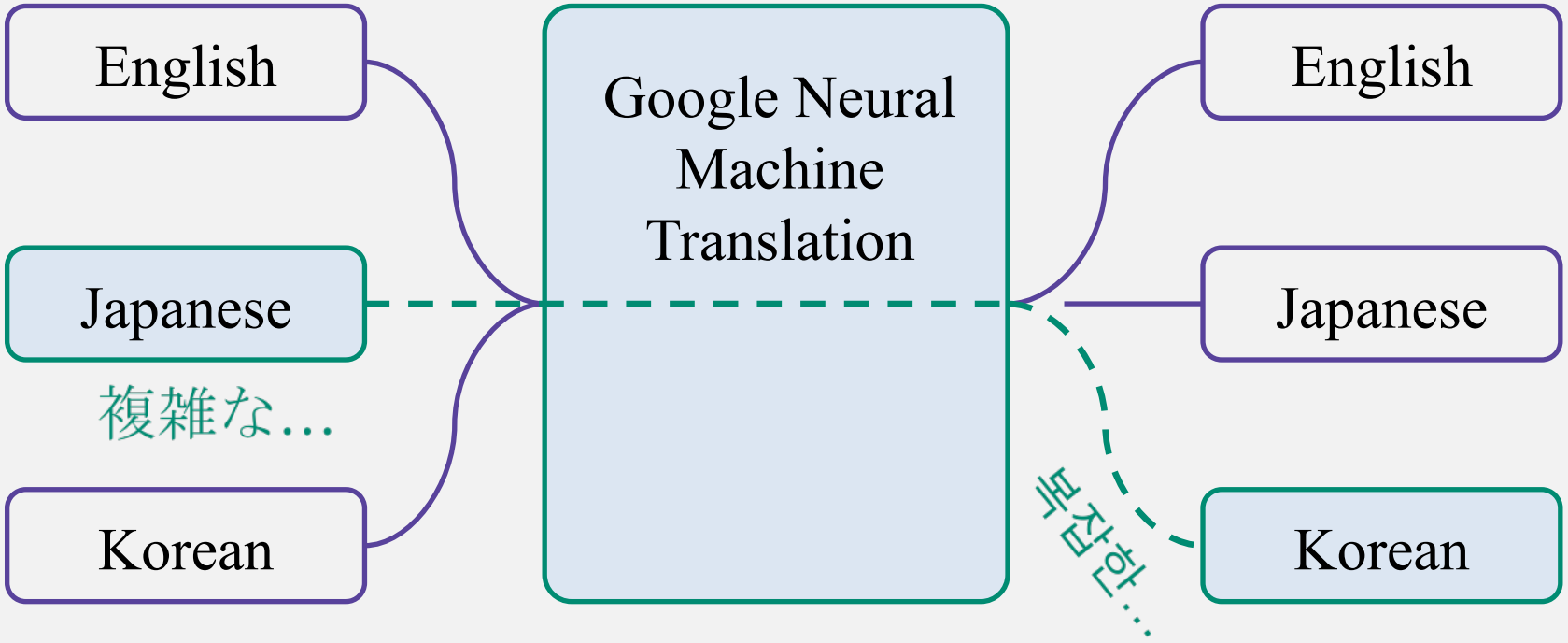
Statistical Machine Translation (SMT):

- 1988 – Word-based models (IBM models)
- 2003 – Phrase-based models (Philip Koehn)
- 2006 – Google Translate (and Moses, next year)

Neural Machine Translation (NMT):

- 2013 – First papers on pure NMT
- 2015 – NMT enters shared tasks (WMT, IWSLT)
- 2016 – Launched in production in companies

Zero-shot translation



https://research.googleblog.com/2016/11/zero-shot-translation-with-googles.html

Noisy channel:
said in English, received in French

The main equation

- **Given:** French (foreign) sentence *f*,
- **Find:** English translation *e*:

$$e^* = \underset{e \in E}{\operatorname{argmax}}\ p(e|f)$$

1993 Brown et al., “The mathematics of statistical machine translation”

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$$= \underset{e \in E}{\operatorname{argmax}}\ p(e)p(f|e)$$

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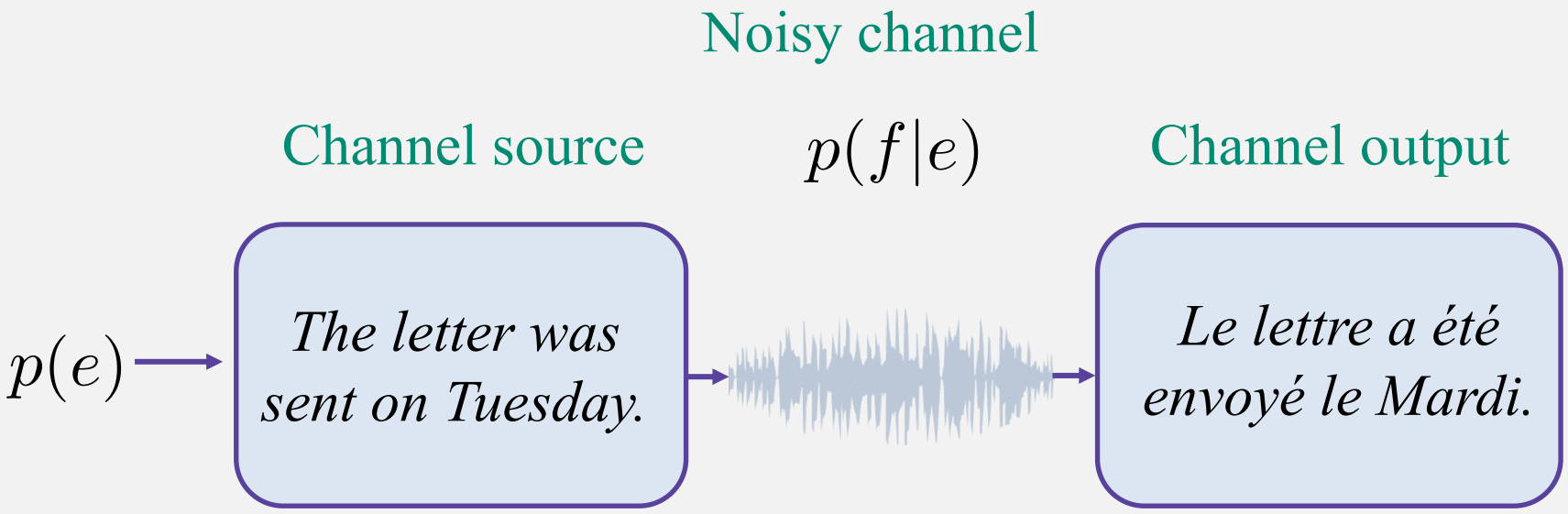
Why is it easier to deal with?

$$e^* = \underset{e \in E}{\operatorname{argmax}} \underbrace{p(e)}_{\text{Language model}} \underbrace{p(f|e)}_{\text{Translation model}}$$

- $p(e)$ models the *fluency* of the translation
- $p(f|e)$ models the *adequacy* of the translation
- argmax is the search problem implemented by a *decoder*

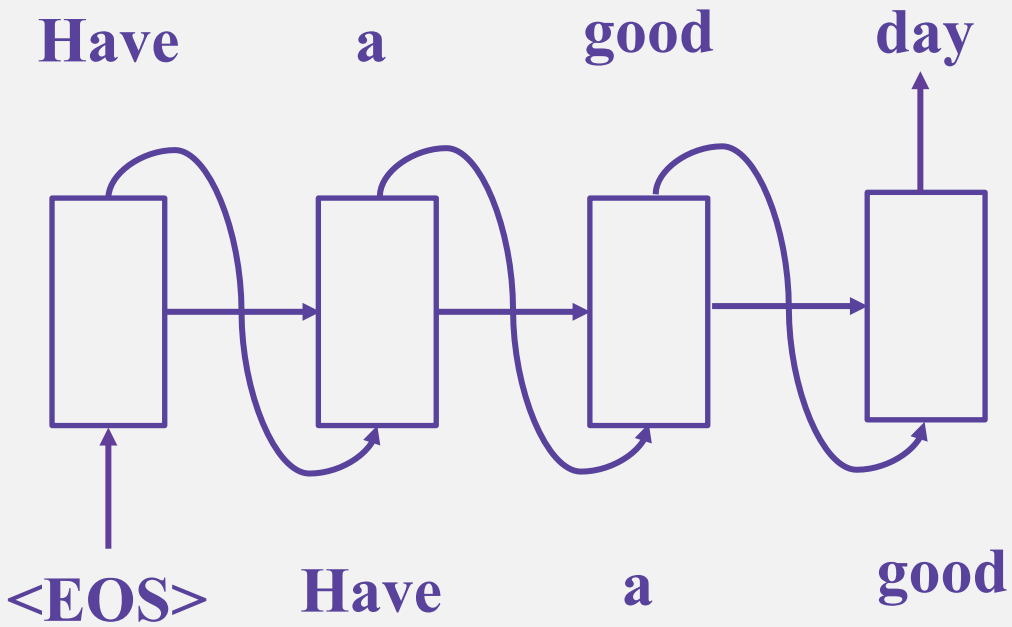
Noisy Chanel



Language model: p(e)

$$p(\mathbf{e}) = p(e_1)p(e_2|e_1)\dots p(e_k|e_1\dots e_{k-1})$$

N-gram models or neural networks:



Translation model: p(f|e)

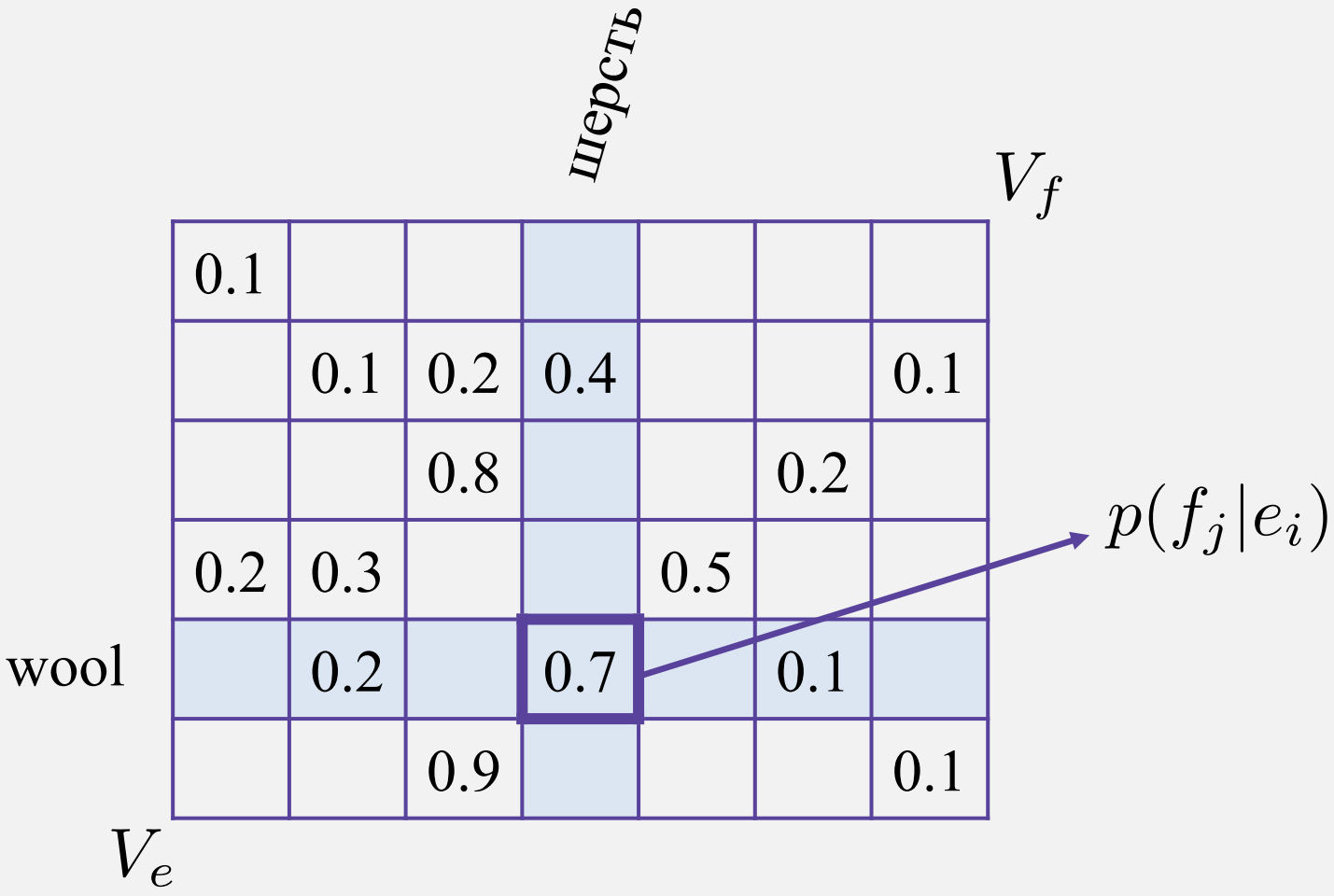
$$p(f|e) = p(f_1, f_2, \ldots f_J|e_1, e_2, \ldots e_I)$$

f (Foreign): Крику много, а шерсти мало.

e (English): Great cry and little wool.

Translation model: p(f|e)

We could learn translation probabilities for separate words:



Translation model: p(f|e)

But how to build the probability for the whole sentences?

$$p(f|e) = \begin{array}{c}\text{Some Magic} \\ \text{Factorization}\end{array} \left[\; p(f_j|e_i) \; \right]$$

Translation model: p(f|e)

But how to build the probability for the whole sentences?

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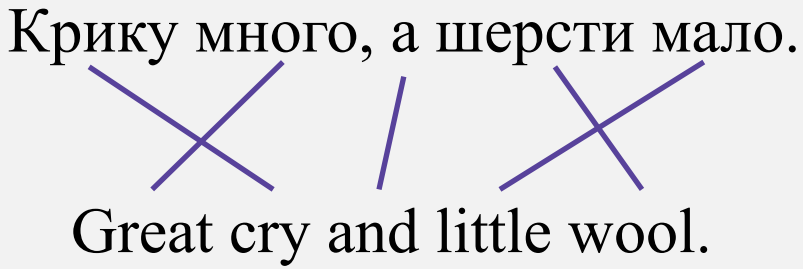
Reorderings:



Word Alignments

One-to-many and many-to-one:

Words can disappear or appear from nowhere:

Word Alignment Models

Word Alignments

“As English not all languages words in the same order put. Hmmmmmm.» - Yoda

Word alignment task

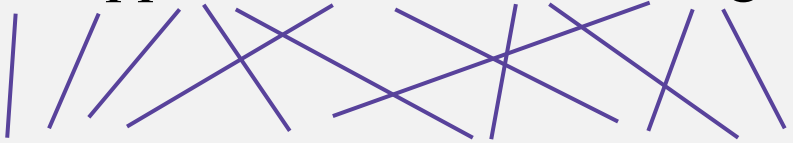
Given a corpus of **(e, f)** sentence pairs:

- English, source: $e = (e_1, e_2, \ldots e_I)$
- Foreign, target: $f = (f_1, f_2, \ldots f_J)$

Predict:

- Alignments **a** between **e** and **f**:

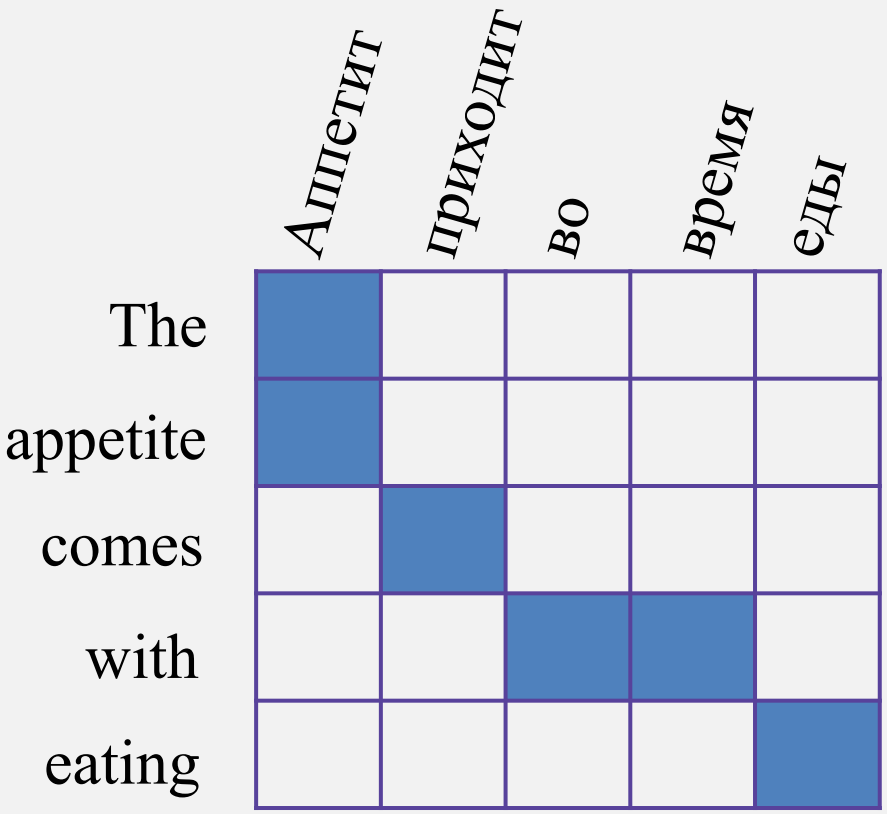
e: The appetite comes with eating.



a?

f: Аппетит приходит во время еды.

Word alignment matrix



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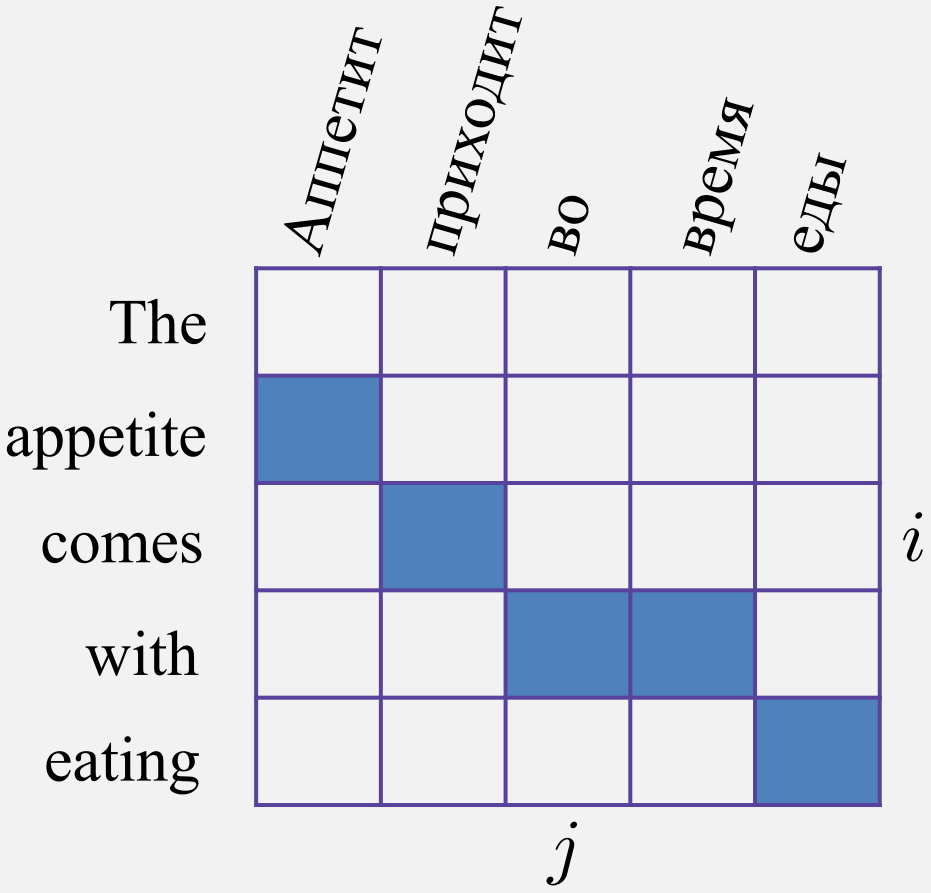
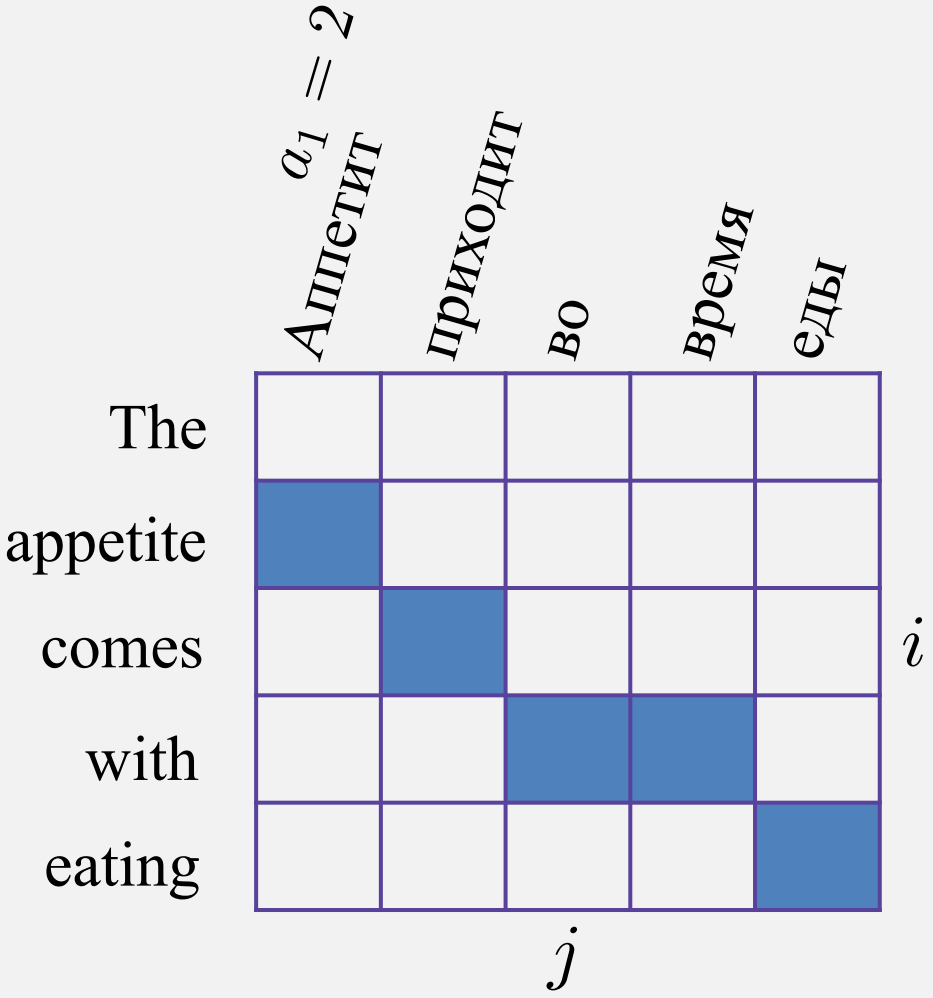


Each target word is allowed to have only one source!

Word alignment matrix



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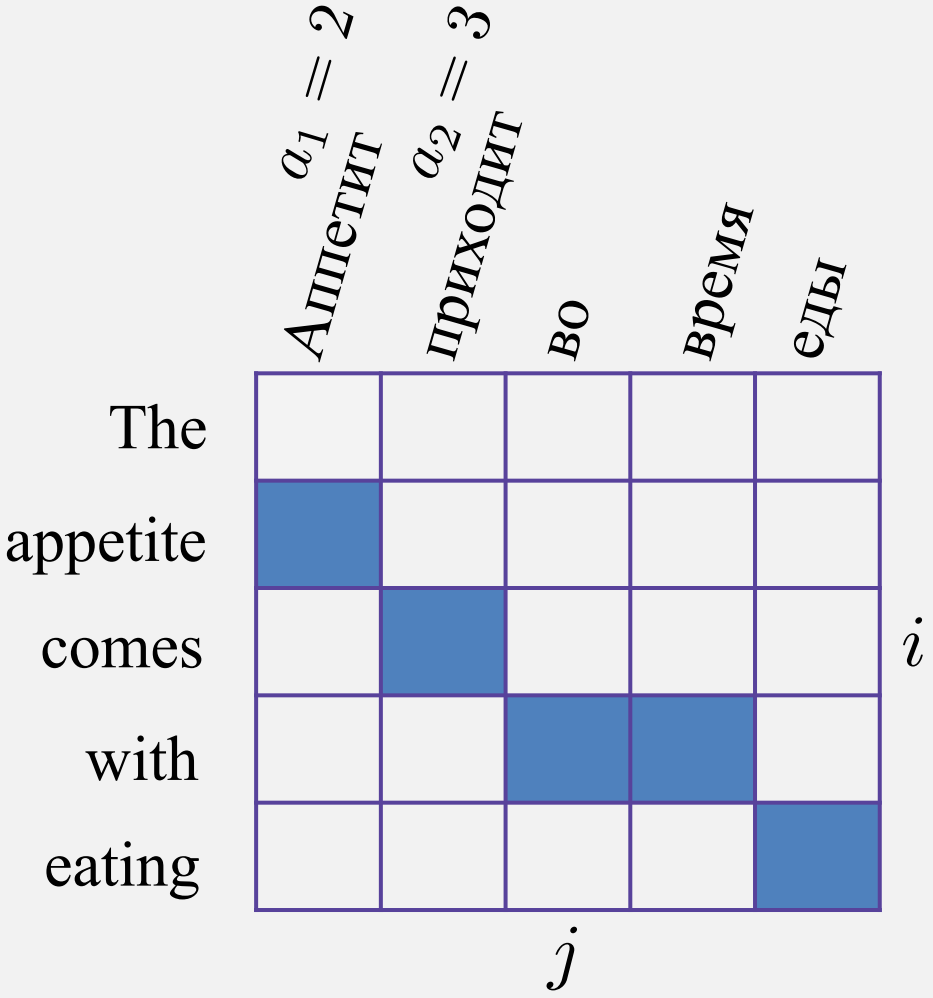

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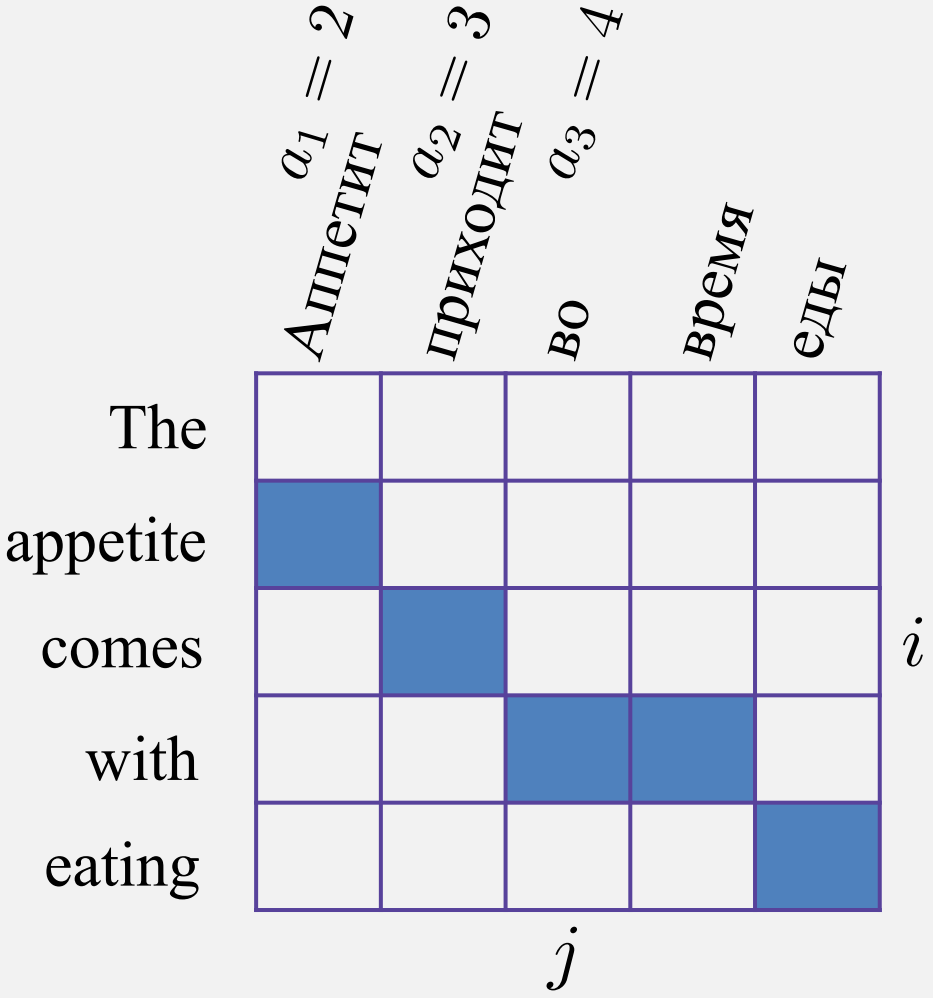

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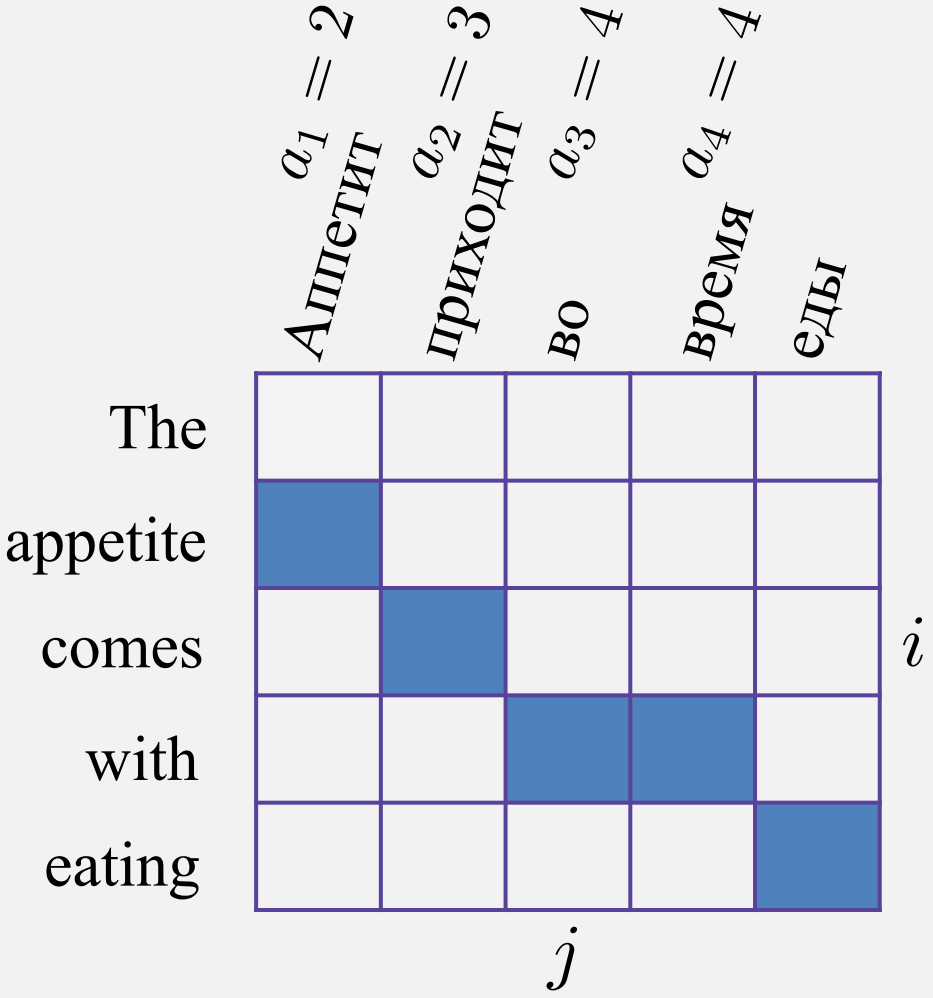

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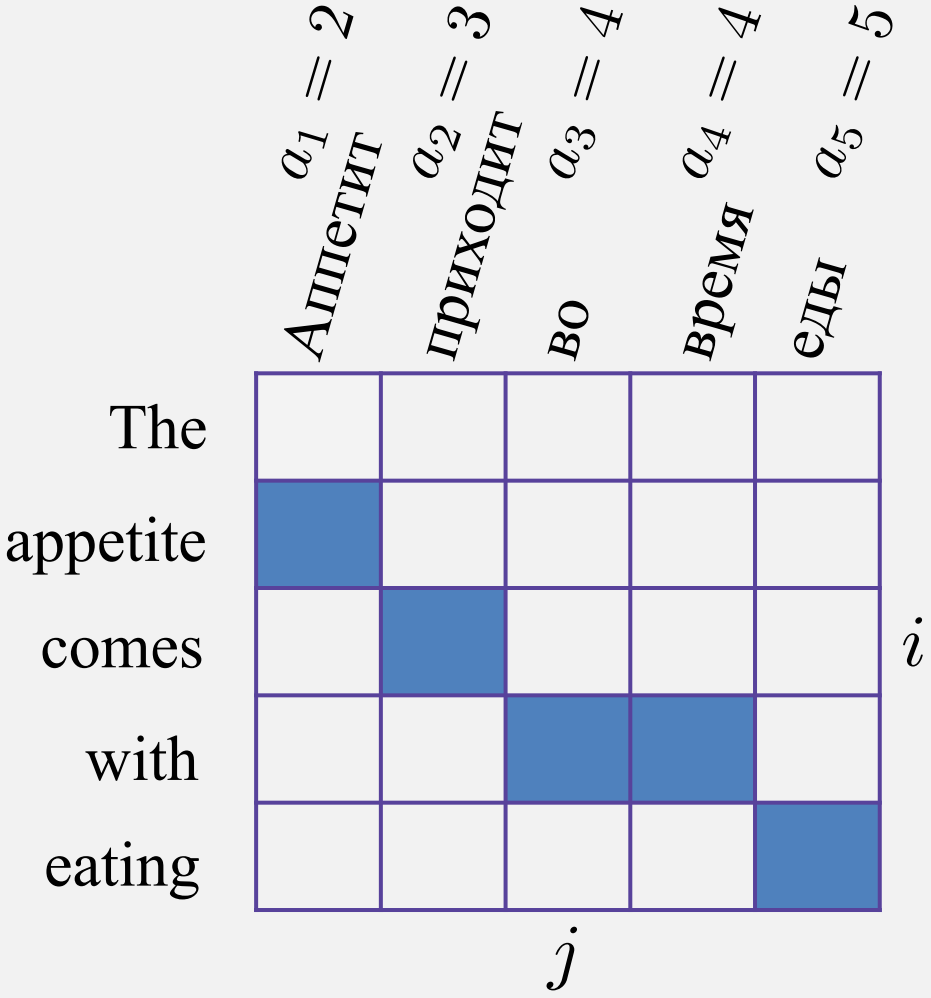

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Sketch of learning algorithm

1. **Probabilistic model (generative story)**

   Given **e**, model the generation of **f**:

$$p(f, a|e, \Theta) = ?$$

The most creative step:

- How do we parametrize the model?
- Is it too complicated or too unrealistic?

Sketch of learning algorithm

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observable variables

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observable variables

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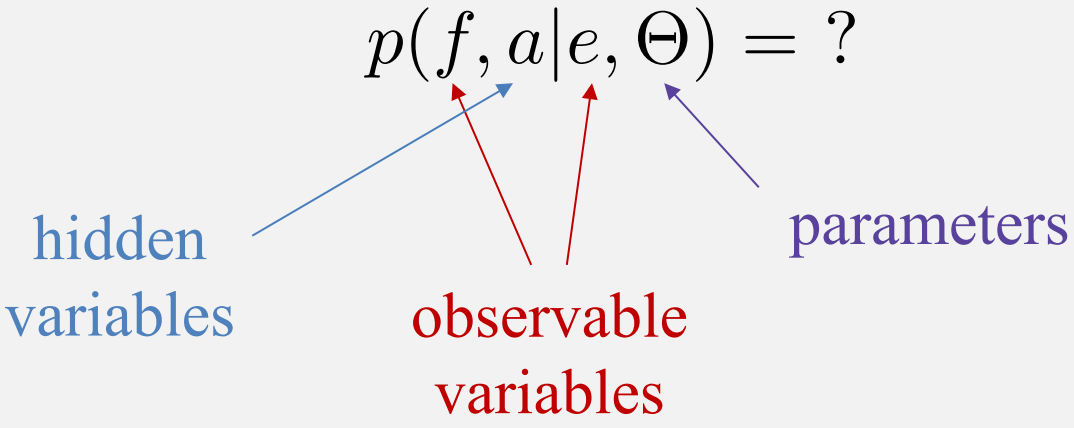

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Sketch of learning algorithm

2. Likelihood maximization for the incomplete data:

$$p(f|e,\Theta) = \sum_{a} p(f,a|e,\Theta) \to \max_{\Theta}$$

Sketch of learning algorithm

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$$p(f|e,\Theta) = \sum_{a} p(f,a|e,\Theta) \rightarrow \max_{\Theta}$$

3. EM-algorithm to the rescue!

Iterative process:

- E-step: estimates posterior probabilities for alignments
- M-step: updates Θ – parameters of the model

Generative story

$$p(f, a|e) = p(J|e)$$

1. Choose the length of the foreign sentence

Generative story

$$p(f, a|e) = p(J|e) \prod_{j=1}^{J} p(a_j|a_1^{j-1}, f_1^{j-1}, J, e) \times$$

1. Choose the length of the foreign sentence
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1. Choose the length of the foreign sentence
2. Choose an alignment for each word (given lots of things)
3. Choose the word (given lots of things)

IBM model 1

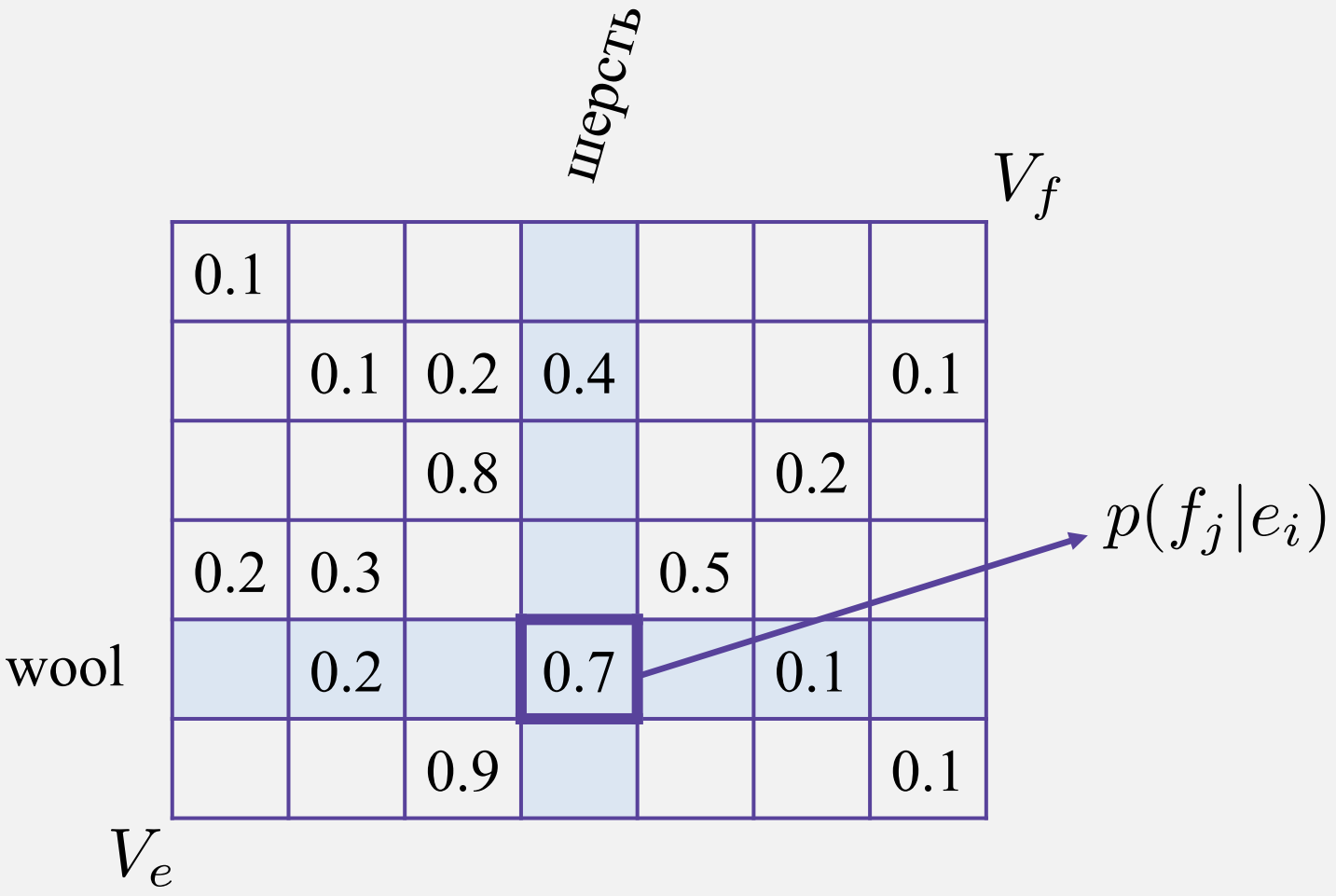
$$p(f, a|e) = p(J|e) \prod_{j=1}^{J} p(a_j) p(f_j|a_j, e)$$

Uniform prior ε

Translation table $t(f_j|e_{a_j})$

+ The model is simple and has not too many parameters
– The alignment prior does not depend on word positions

Translation table



IBM model 2

$$p(f, a|e) = p(J|e) \prod_{j=1}^{J} p(a_j|j, I, J) p(f_j|a_j, e)$$

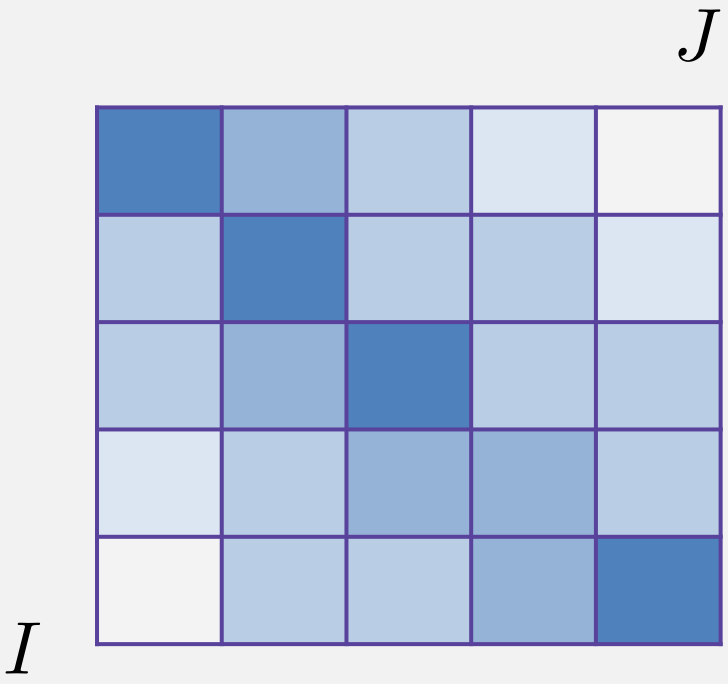
Position-based prior
$d(a_j|j, I, J)$

Translation table
$t(f_j|e_{a_j})$

+ The alignments depend on position-based prior
– Quite a lot of parameters for the alignments

Position-based prior

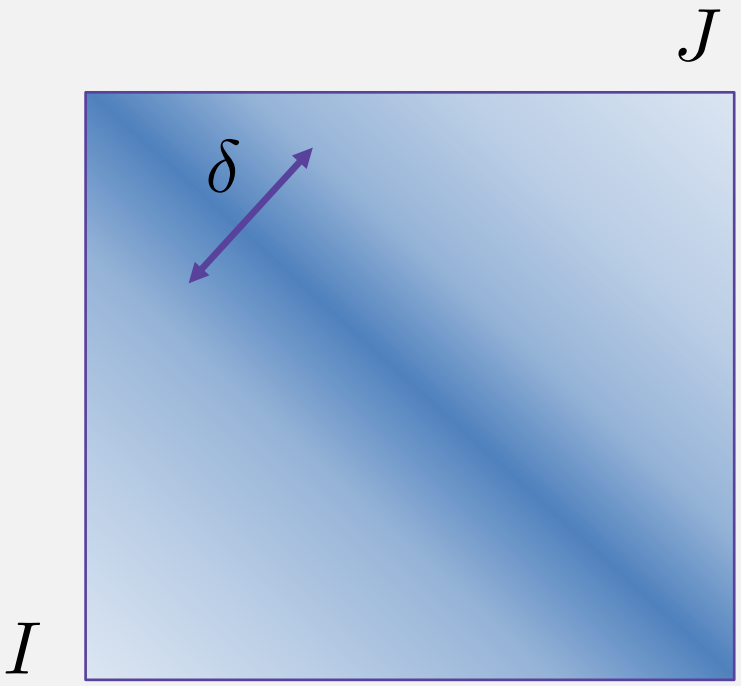
- For each pair of the **lengths** of the sentences:
  - $I \times J$ matrix of probabilities



Dyer et al. A Simple, Fast, and Effective Reparameterization of IBM Model 2, 2013

Re-parametrization, Dyer et. al 2013

- If we know, it's going to be diagonal – let's model it diagonal!
- Much less parameters, easier to train on small data



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HMM for the prior

$$p(f, a|e) = \prod_{j=1}^{J} p(a_j|a_{j-1}, I, J)p(f_j|a_j, e)$$

Transition probabilities
$d(a_j|a_{j-1}, I, J)$

Translation table
$t(f_j|e_{a_j})$

e: All cats are grey in the dark.

f: В темноте все кошки серы.

Resume

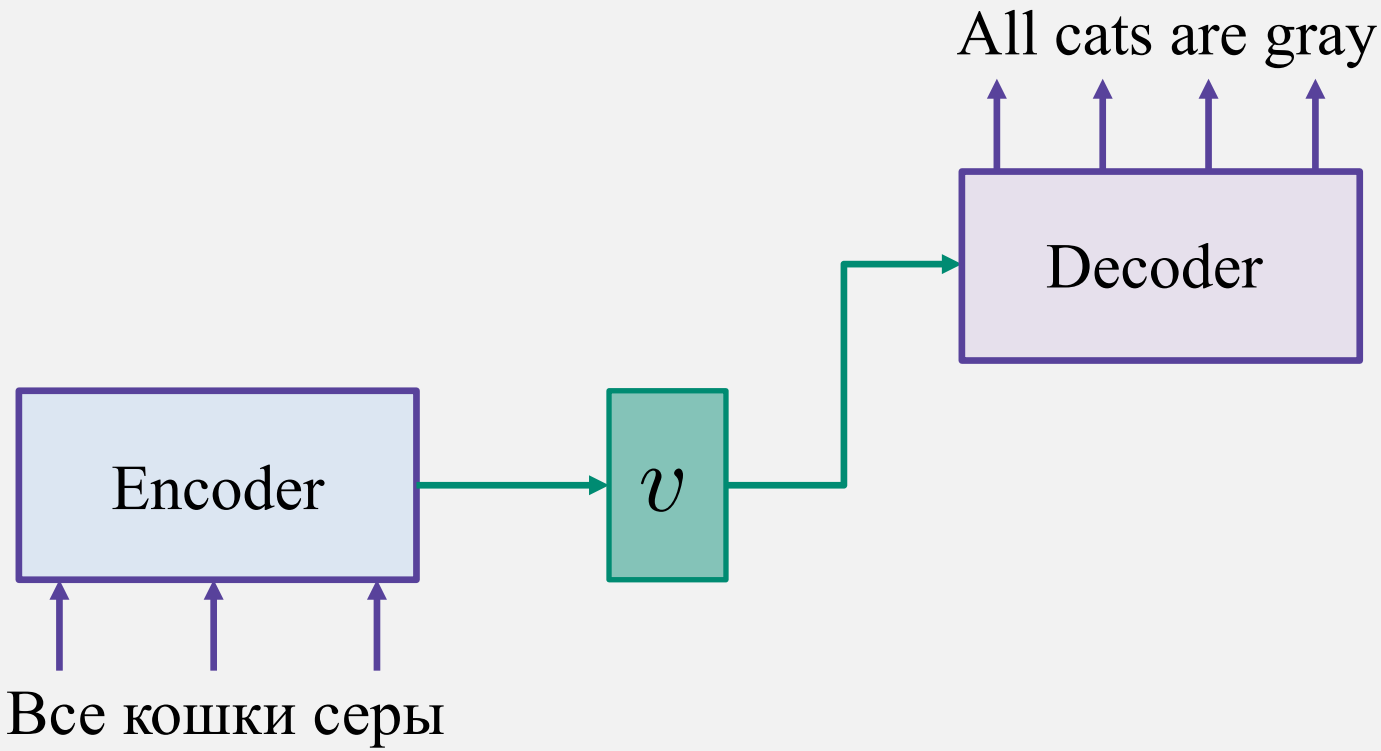
- IBM models – first working systems of MT

- Lot's of problems with models 1 and 2:
  - How to deal with *spurious words*
  - How to control *fertility*
  - ....

- Most importantly, how to do many-to-many alignments?
  - Phrased-based machine translation (Koehn's book)

Encoder-decoder architecture

Sequence to sequence



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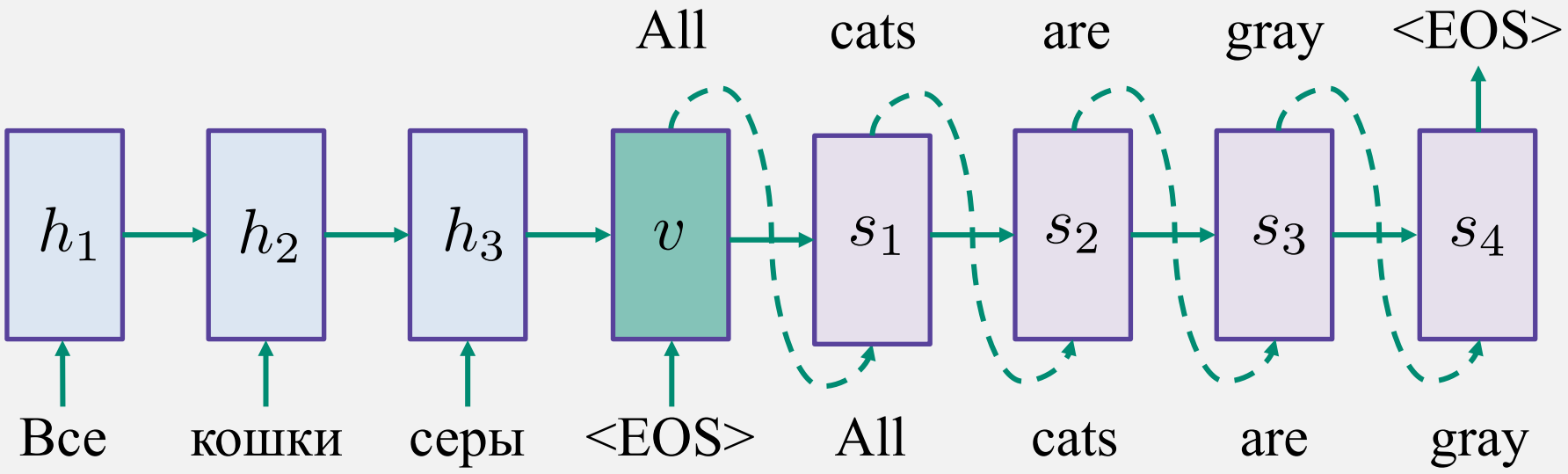
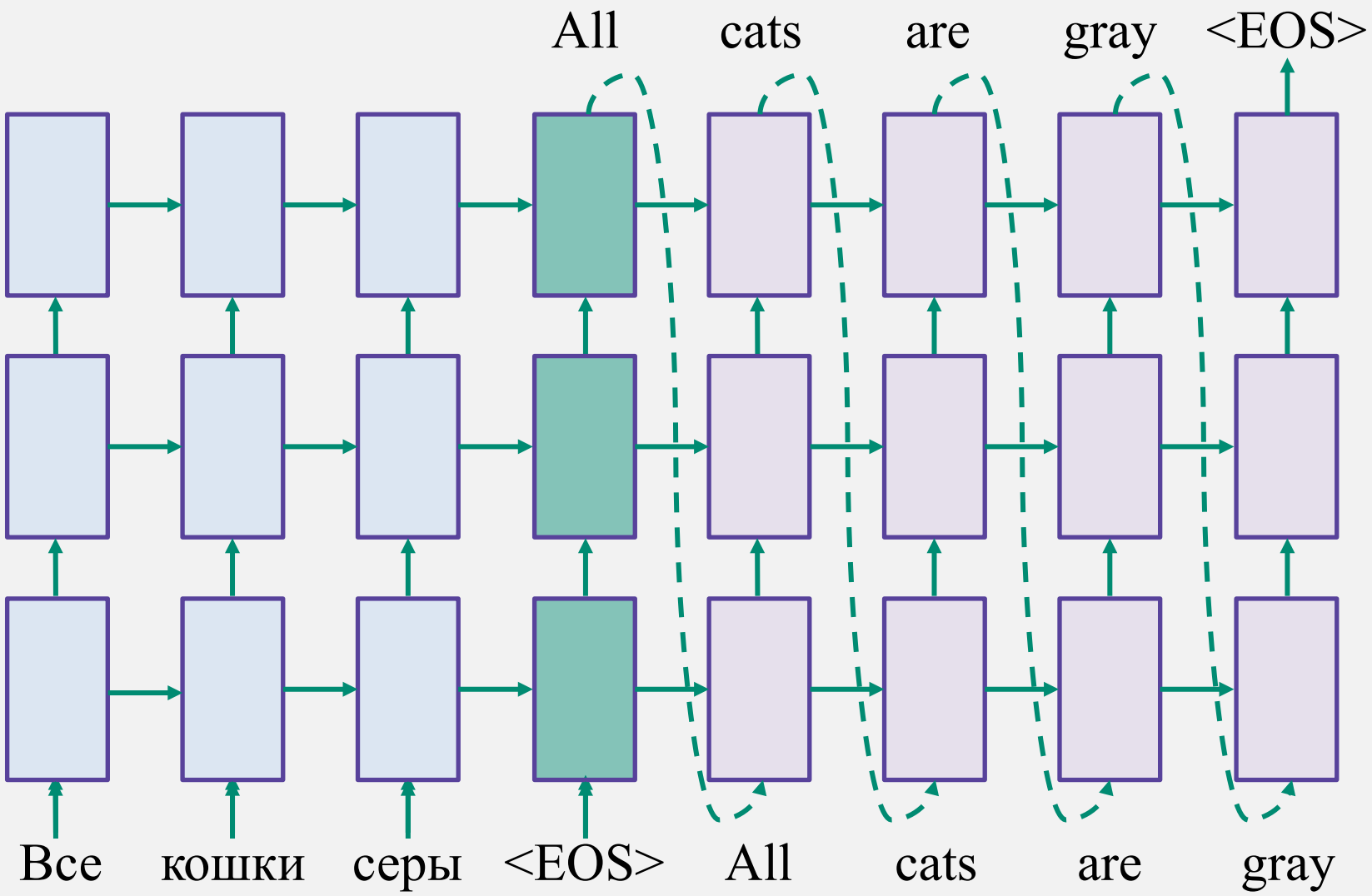


Ilya Sutskever, Oriol Vinyals, Quoc V. Le. Sequence to Sequence Learning with Neural Network, 2014.

Sequence to sequence



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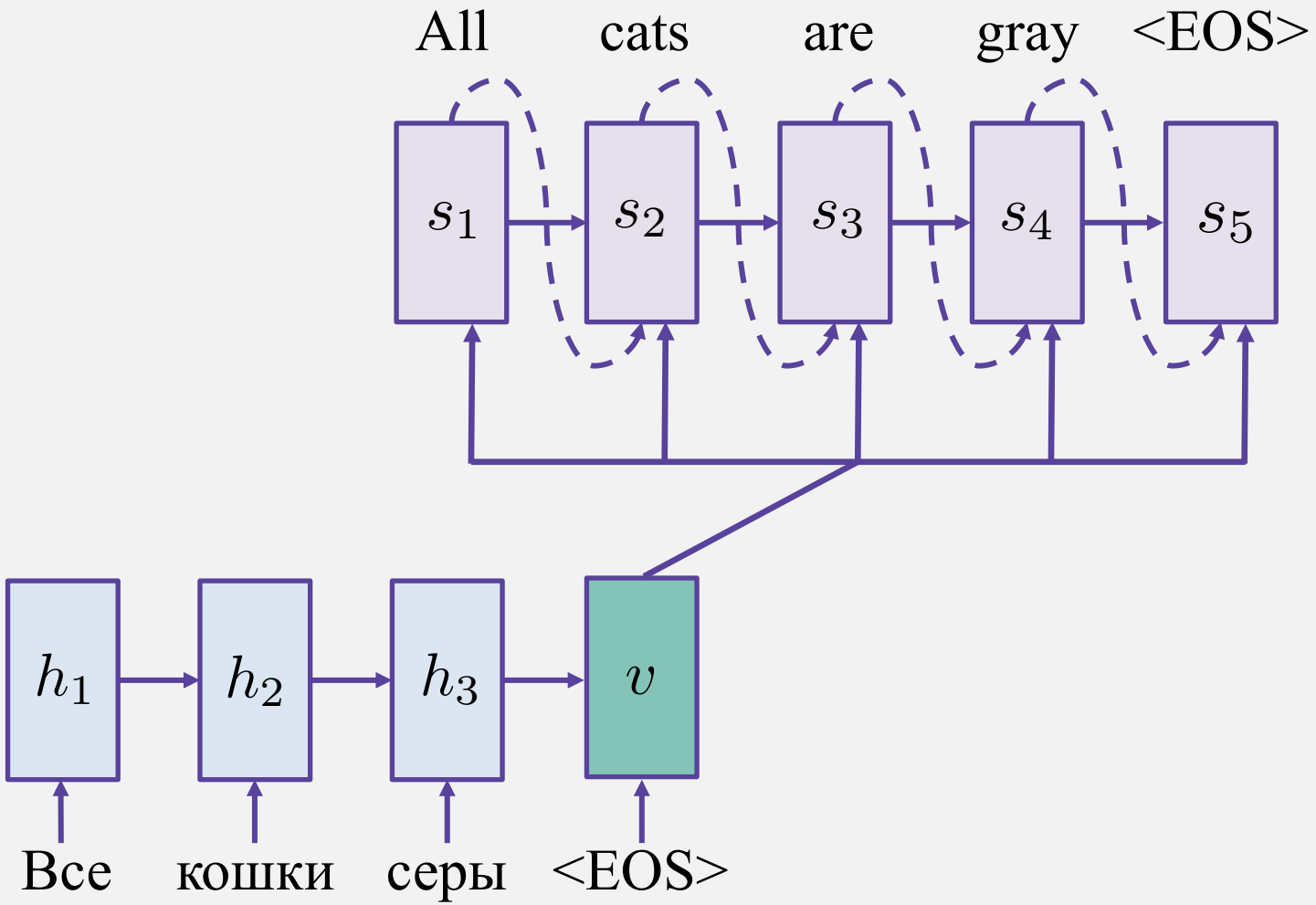


Cho et. al. Learning Phrase Representations using RNN Encoder-Decoder for Statistical Machine Translation, 2014.

Sequence to sequence

$$p(y_1, \dots y_J | x_1, \dots x_I) = \prod_{j=1}^{J} p(y_j | v, y_1, \dots y_{j-1})$$

- **Encoder:** maps the source sequence to the hidden vector

  RNN: $h_i = f(h_{i-1}, x_i)$ $\qquad\qquad$ $v = h_I$

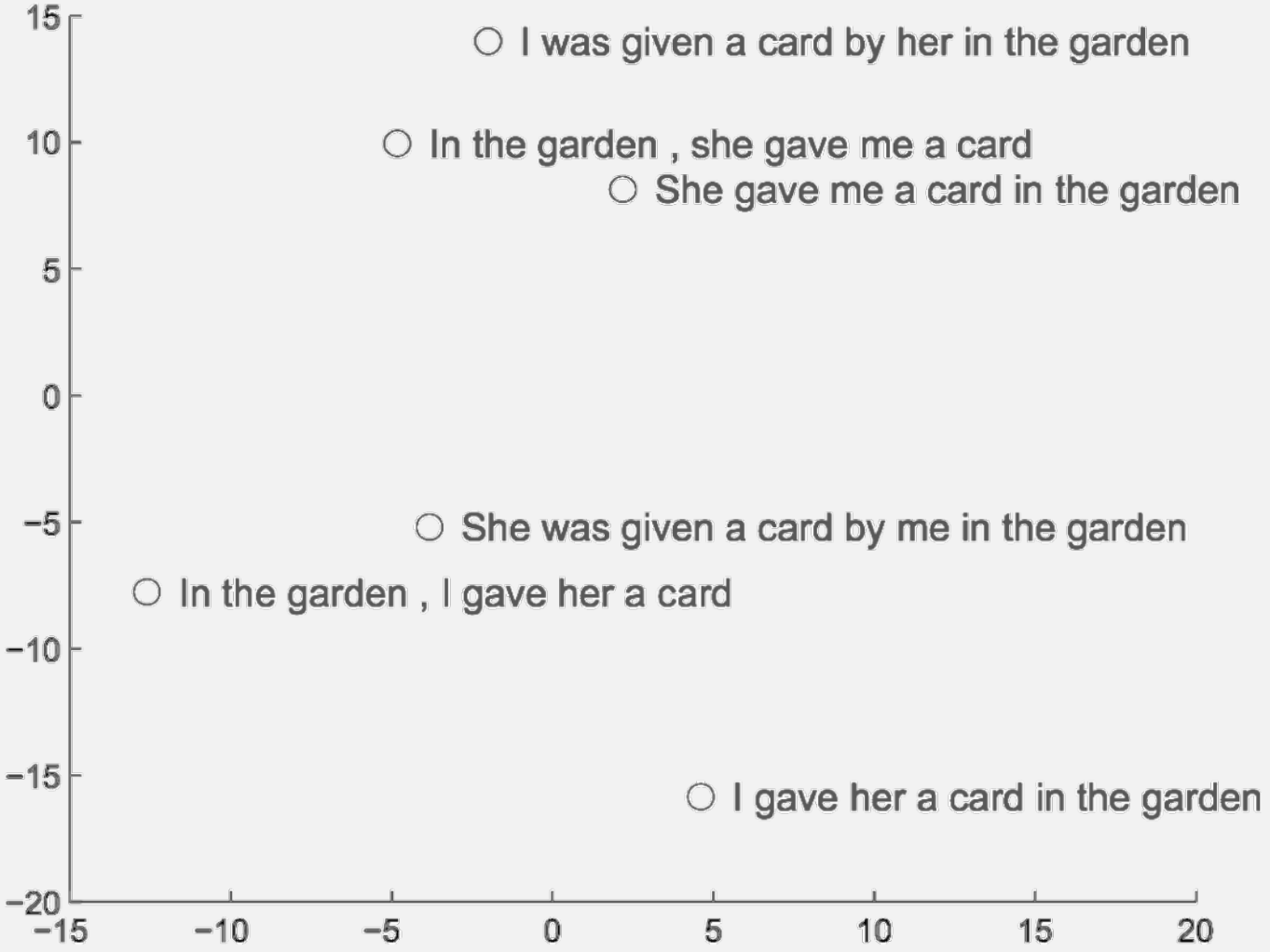
- **Decoder:** performs language modeling given this vector

  RNN: $\quad s_j = g(s_{j-1}, [y_{j-1}, v])$

- **Prediction** (the simplest way):

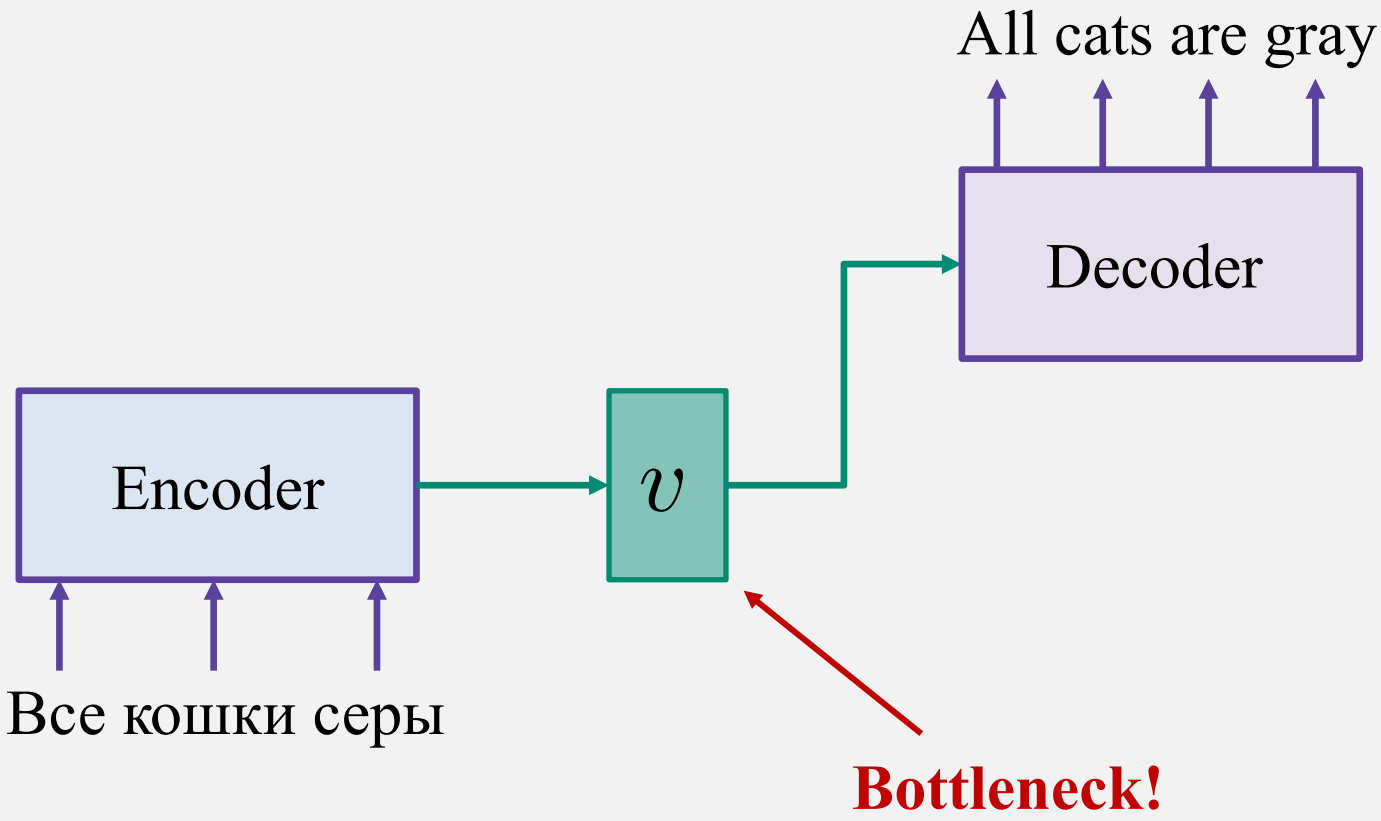
  $p(y_j | v, y_1, \dots y_{j-1}) = softmax\,(U s_j + b)$

Hidden representations are good…



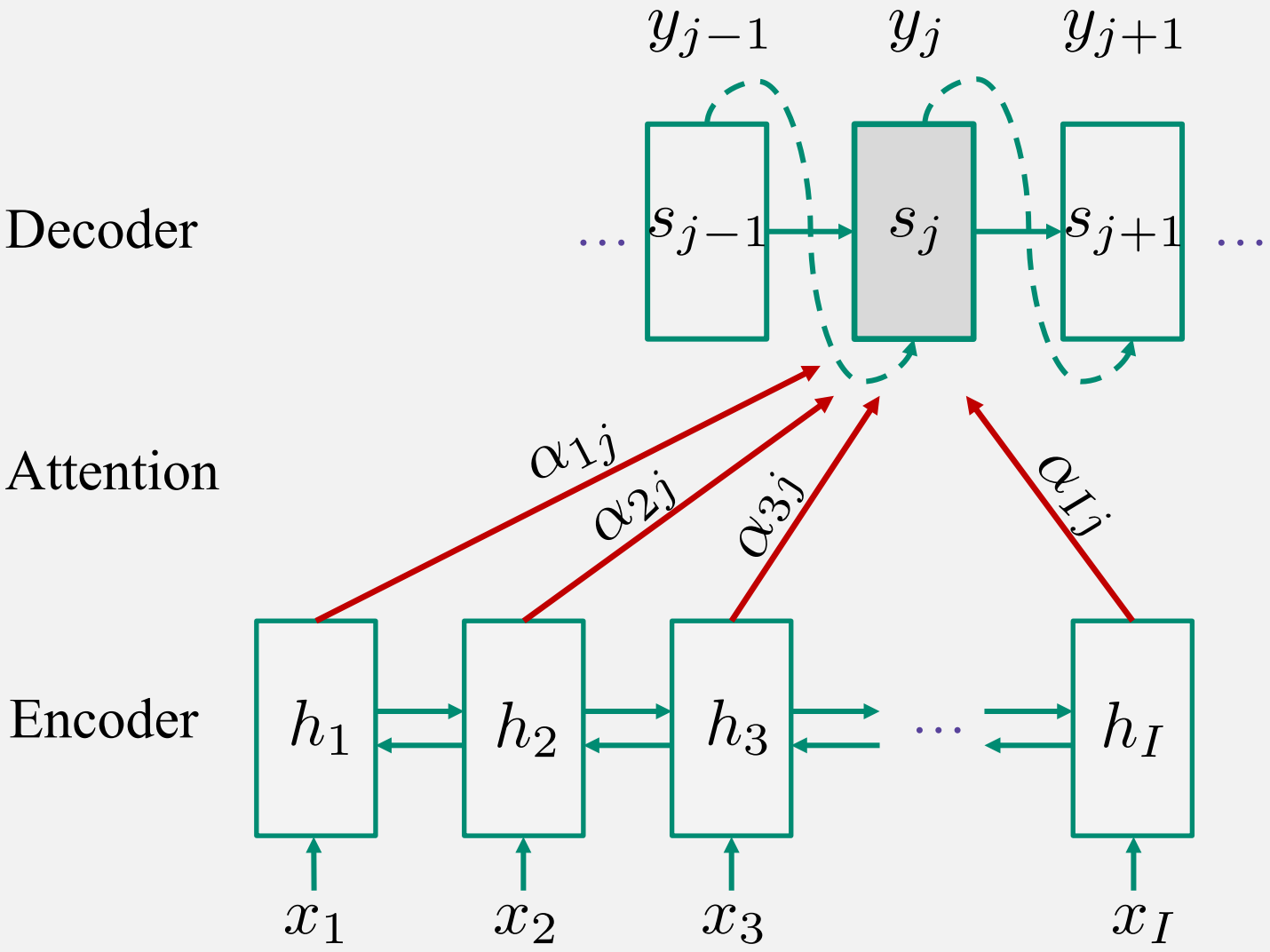
Ilya Sutskever, Oriol Vinyals, Quoc V. Le. Sequence to Sequence Learning with Neural Network, 2014.

… but still a bottleneck



Attention mechanism

Attention mechanism



Bahdanau et. al - Neural Machine Translation by jointly learning to align and translate, 2015.

Attention mechanism

- Encoder states are weighted to obtain the representation relevant to the decoder state:

$$v_j = \sum_{i=1}^{I} \alpha_{ij} h_i$$

- The weights are learnt and should find the most relevant encoder positions:

$$\alpha_{ij} = \frac{\exp(sim(h_i, s_{j-1}))}{\sum_{i'=1}^{I} \exp(sim(h_{i'}, s_{j-1}))}$$

How to compute attention weights?

- **Additive attention:**

$$sim(h_i, s_j) = w^T \tanh(W_h h_i + W_s s_j)$$

- **Multiplicative attention:**

$$sim(h_i, s_j) = h_i^T W s_j$$

- **Dot product also works:**

$$sim(h_i, s_j) = h_i^T s_j$$

Put all together

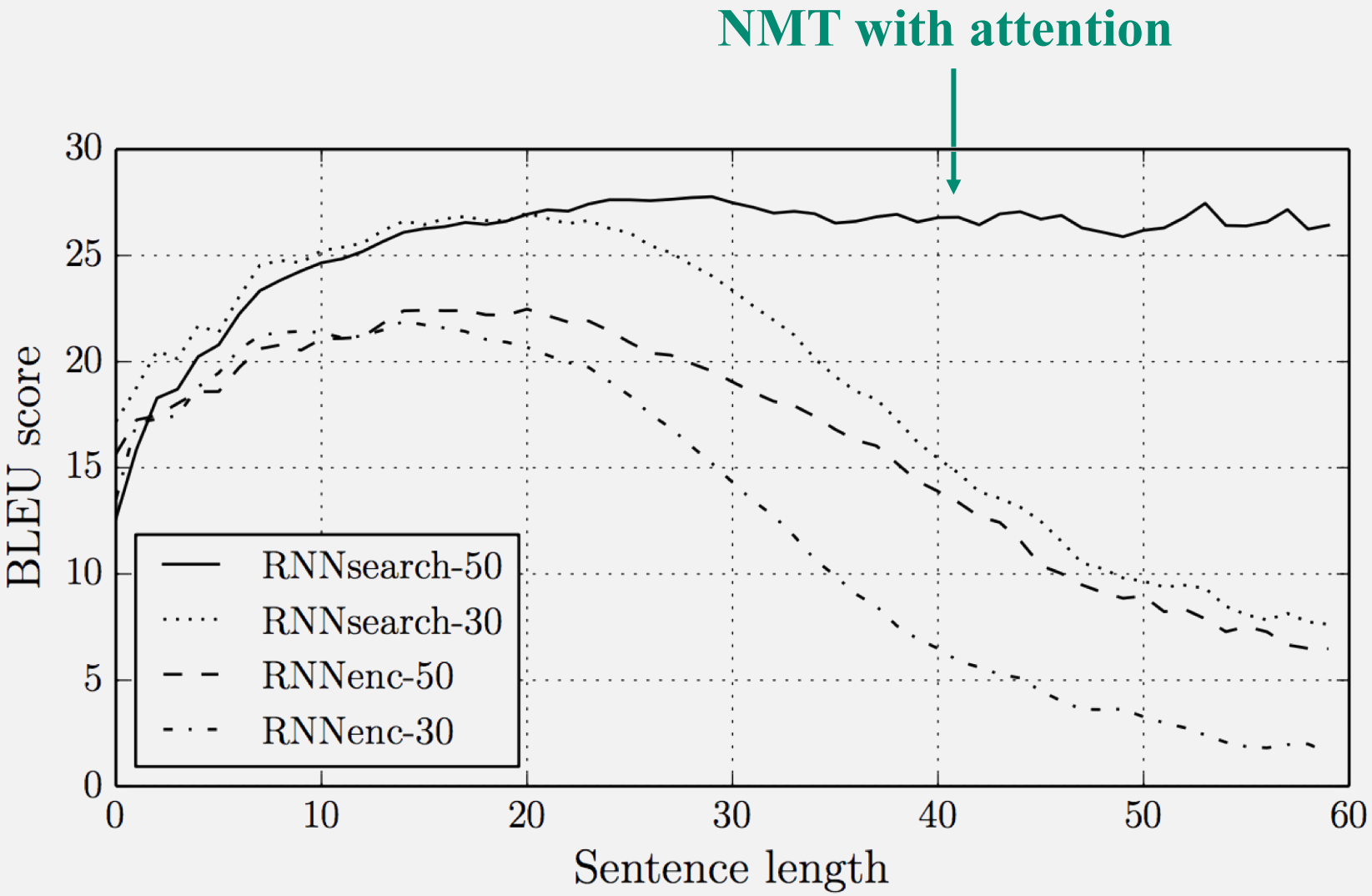
$$p(y_1, \ldots y_J | x_1, \ldots x_I) = \prod_{j=1}^{J} p(y_j | v_j, y_1, \ldots y_{j-1})$$

- Still encoder-decoder architecture with RNNs:

$$h_i = f(h_{i-1}, x_i) \qquad s_j = g(s_{j-1}, [y_{j-1}, v_j])$$

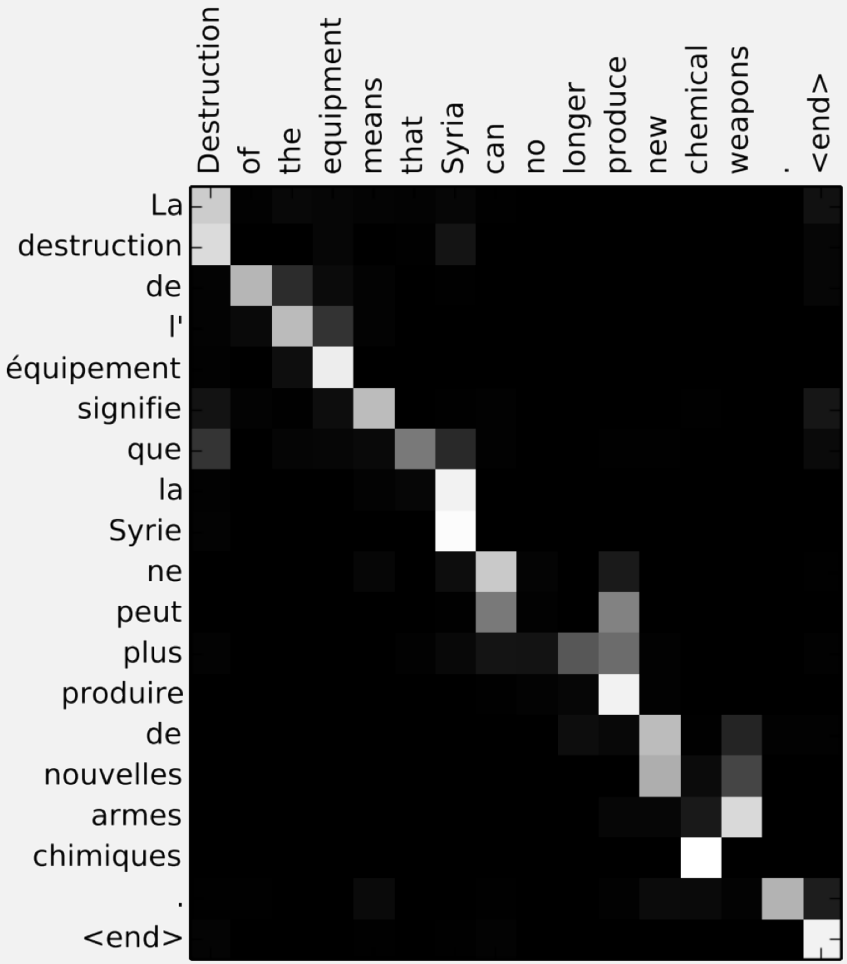
- But the source representations differ for each position j of the decoder.

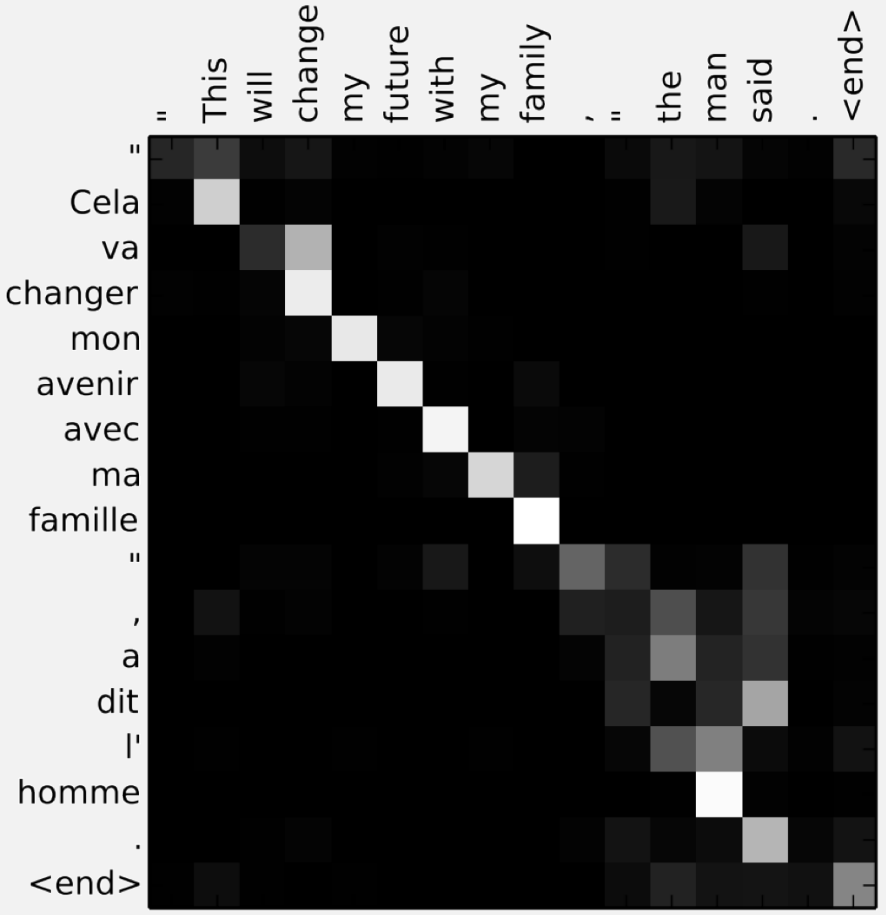
Helps for long sentences



Bahdanau et. al. Neural Machine Translation by jointly learning to align and translate, 2015.

Example: attention (alignments)





Bahdanau et. al. Neural Machine Translation by jointly learning to align and translate, 2015.

Is the attention similar to what humans do?

- *For humans:* **saves time**

Attention saves time when reading (i.e. we look only to the relevant parts of the sentence).

- *For machines:* **wastes time**

To compute the attention weights, the model carefully examines ALL the positions, thus wastes even more time.

Local attention

1. **Find the most relevant position $\mathbf{a_j}$ in the source**

- Monotonic alignments: $a_j = j$
- Predictive alignments: $a_j = I \cdot \sigma(b^T \tanh(W s_j))$

2. **Attend only positions within a window $[\mathbf{a_j} - \mathbf{h}; \mathbf{a_j} + \mathbf{h}]$**

- Compute scores as usual
- Probably multiply by a Gaussian centered in a_j

Luong et. al. Effective Approaches to Attention-based Neural Machine Translation, 2015.

Global vs local attention

System	Perplexity	BLEU
global (location)	6.4	19.3
global (dot)	6.1	20.5
global (mult)	6.1	19.5
local-m (dot)	>7.0	x
local-m (mult)	6.2	20.4
local-p (dot)	6.6	19.6
local-p (mult)	**5.9**	**20.9**

Luong et. al. Effective Approaches to Attention-based Neural Machine Translation, 2015.

Global vs local attention

	System	Perplexity	BLEU
Ws_j →	global (location)	6.4	19.3
$h_i^T s_j$ →	global (dot)	6.1	20.5
$h_i^T W s_j$ →	global (mult)	6.1	19.5
	local-m (dot)	>7.0	x
	local-m (mult)	6.2	20.4
	local-p (dot)	6.6	19.6
	local-p (mult)	**5.9**	**20.9**

Luong et. al. Effective Approaches to Attention-based Neural Machine Translation, 2015.

How to deal with a vocabulary?

Outline

- Computing *softmax* for a large vocabulary is slow!
  - Hierarchical softmax
- Even a large vocabulary has *OOV words*:
  - Copy mechanism
  - Sub-word modeling
    - Word-character hybrid models
    - Byte-pair encoding

Outline

- Computing *softmax* for a large vocabulary is slow!
  - **Hierarchical softmax**
- Even a large vocabulary has *OOV words*:
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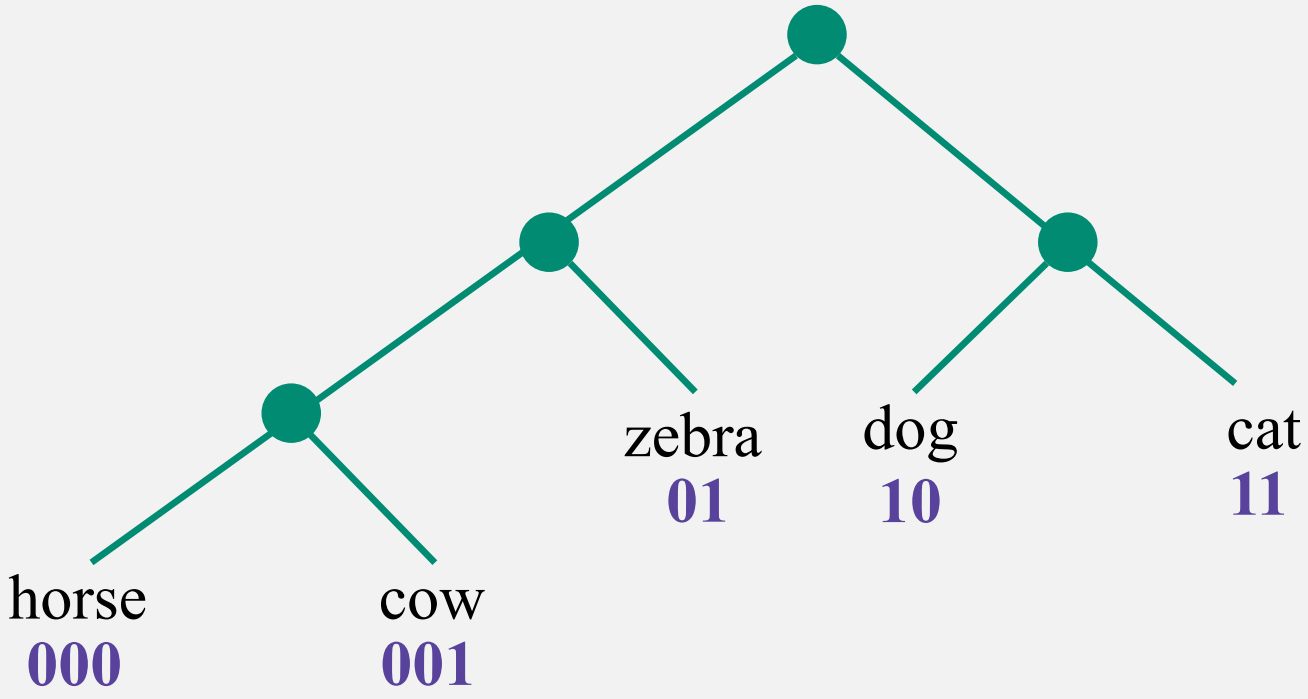
Hierarchical softmax

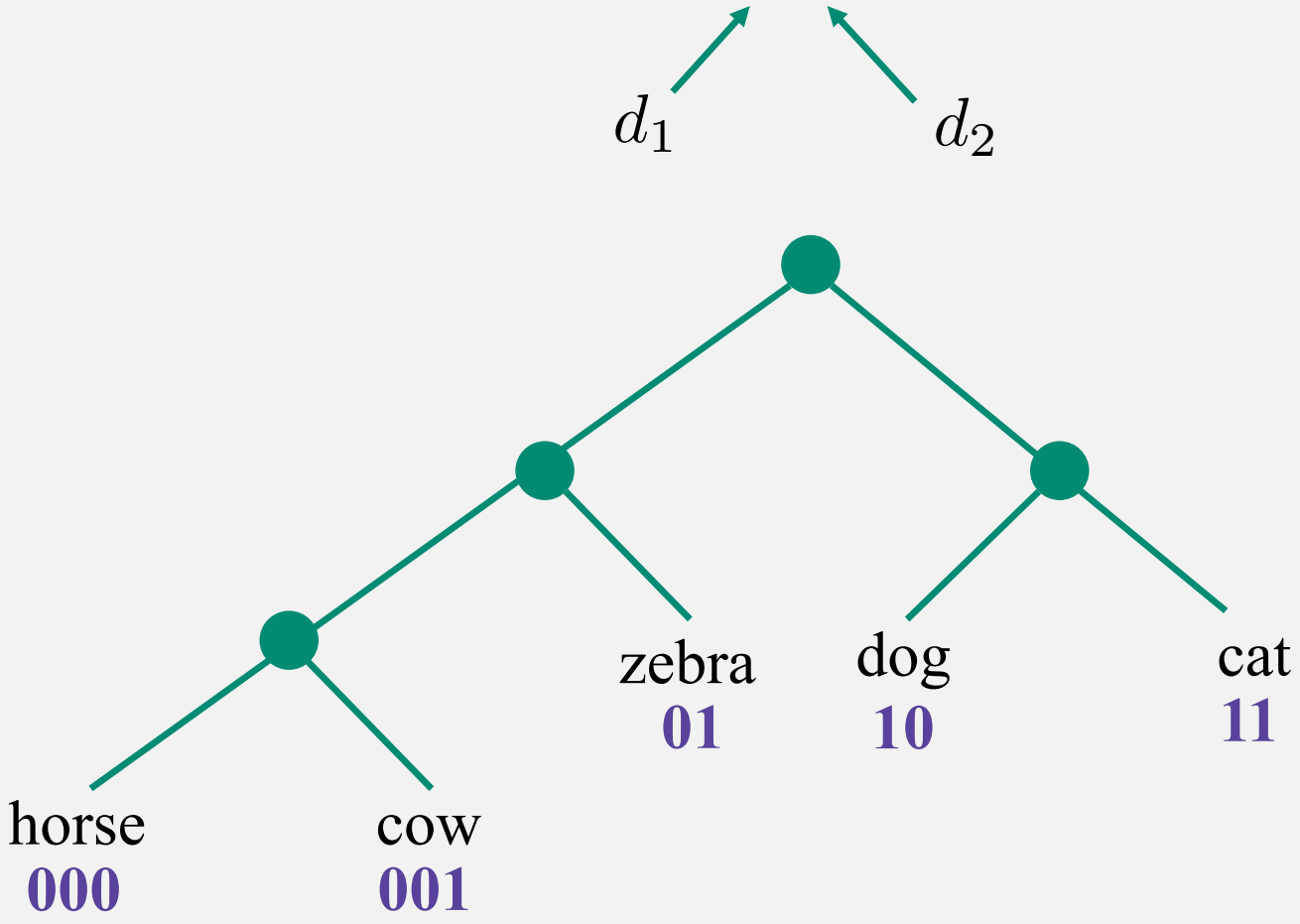
Each word is uniquely represented by a binary code:

- 0 means “go left”, 1 means “go right”



Hierarchical softmax

E.g. for **zebra** the code is $d = (0, 1)$



Scaling softmax

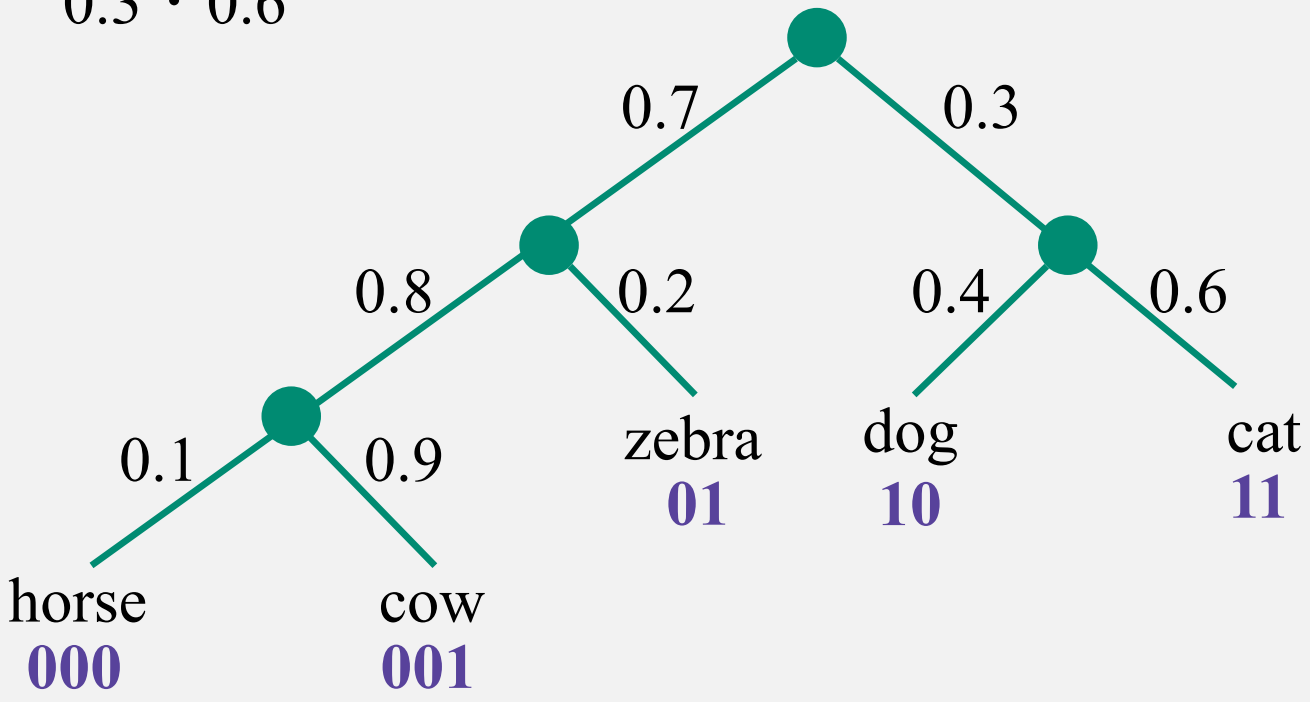
Express the probability of a word (zebra) as a product of probabilities of the binary decisions along the path (d_1 d_2).

$$p(w_n = w|w_1^{n-1}) = \prod_i p(d_i|w_1^{n-1})$$

Do you believe that it sums to 1?

Hierarchical softmax

$$
\begin{aligned}
& 0.7 \cdot 0.8 \cdot 0.1 \\
& 0.7 \cdot 0.8 \cdot 0.9 \\
+ \quad & 0.7 \cdot 0.2 \\
& 0.3 \cdot 0.4 \\
& 0.3 \cdot 0.6
\end{aligned}
$$



Hierarchical softmax

$$
\begin{aligned}
& 0.7 \cdot 0.8 \cdot 0.1 \\
& 0.7 \cdot 0.8 \cdot 0.9 \\
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& 0.3 \cdot 0.4 \\
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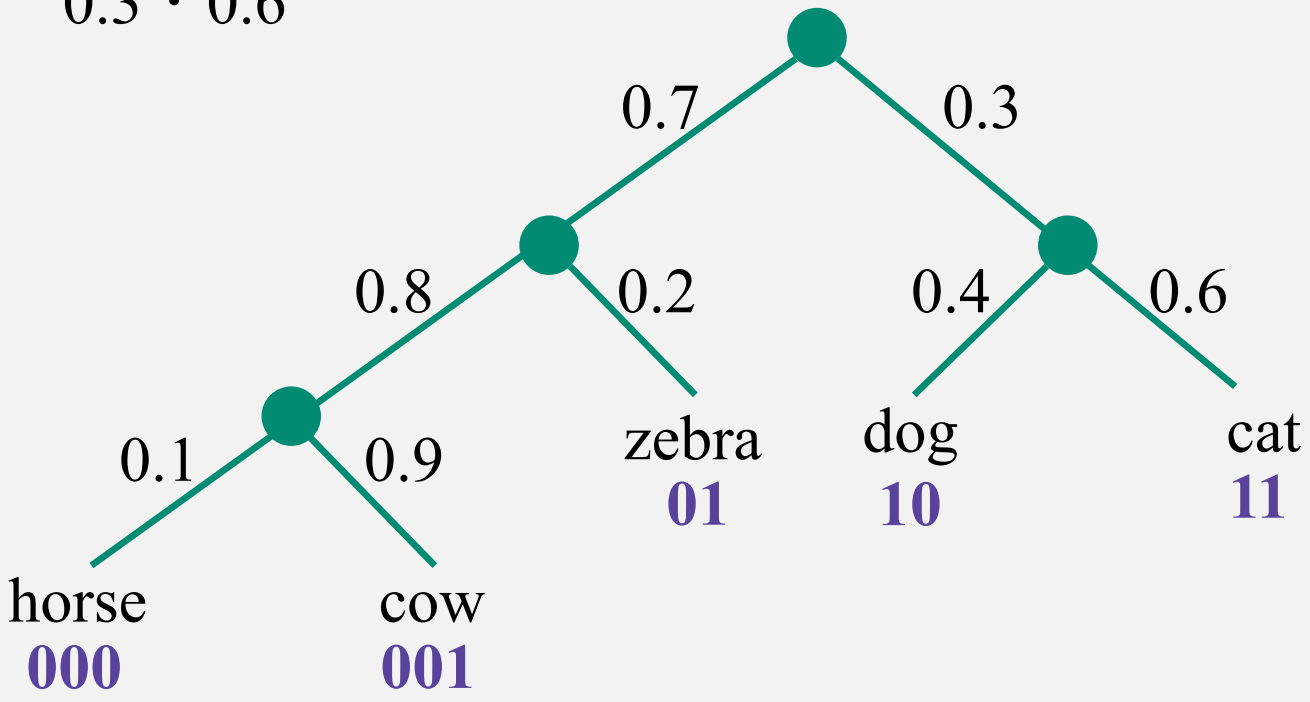
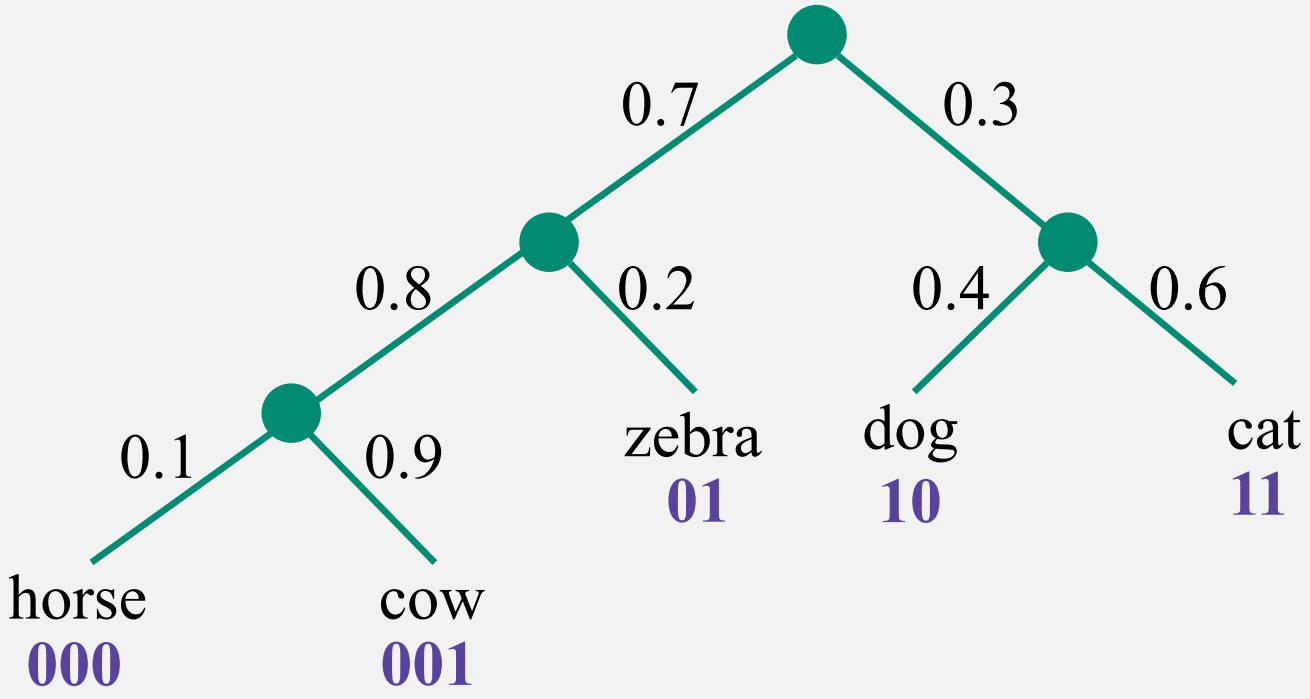
$$



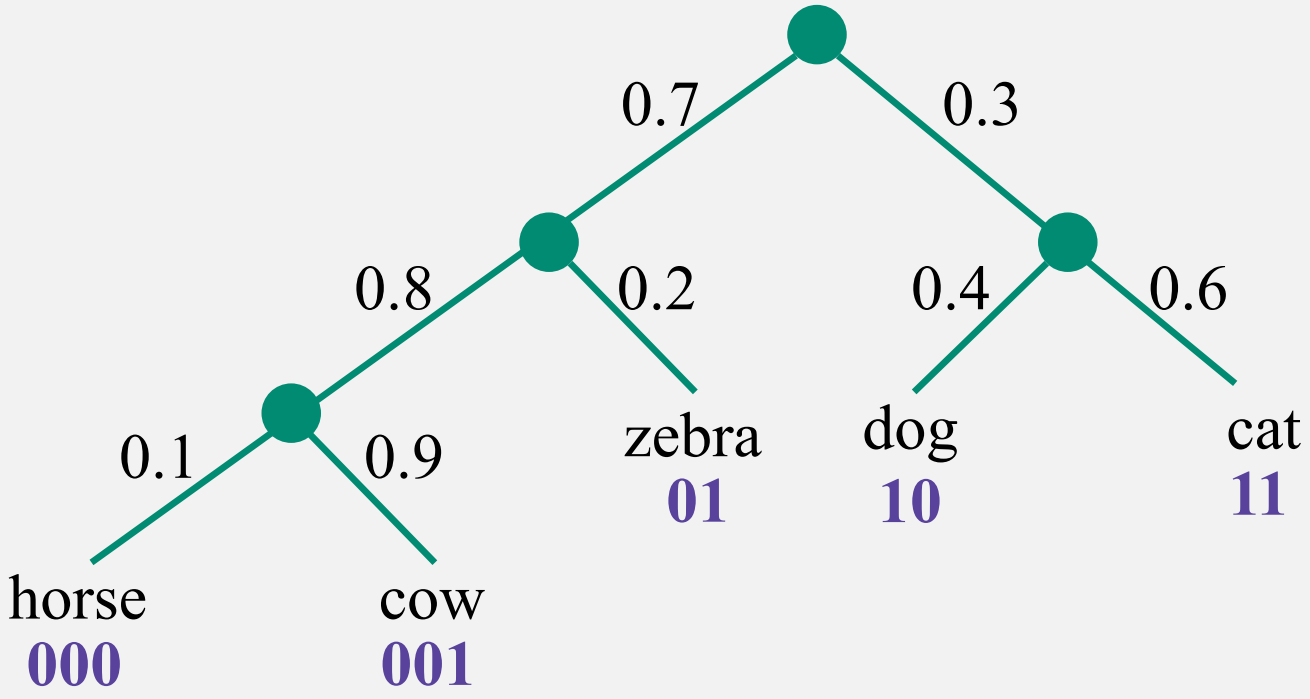
Hierarchical softmax

$$+ \begin{matrix} 0.7 \cdot 0.8 \\ 0.7 \cdot 0.2 \\ 0.3 \cdot 0.4 \\ 0.3 \cdot 0.6 \end{matrix}$$



Hierarchical softmax

$$
\begin{aligned}
& 0.7 \cdot 0.8 \\
& 0.7 \cdot 0.2 \\
+ \quad & 0.3 \cdot 0.4 \\
& 0.3 \cdot 0.6
\end{aligned}
$$



Hierarchical softmax

$$
\begin{aligned}
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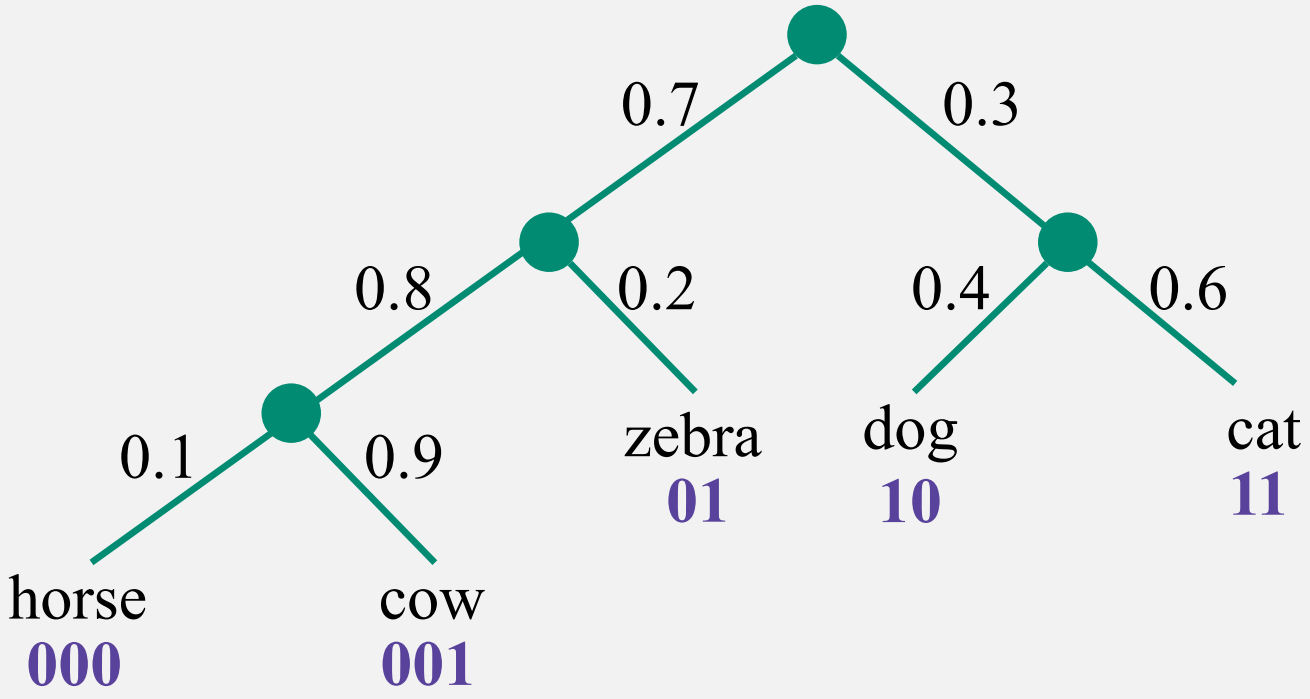
$$



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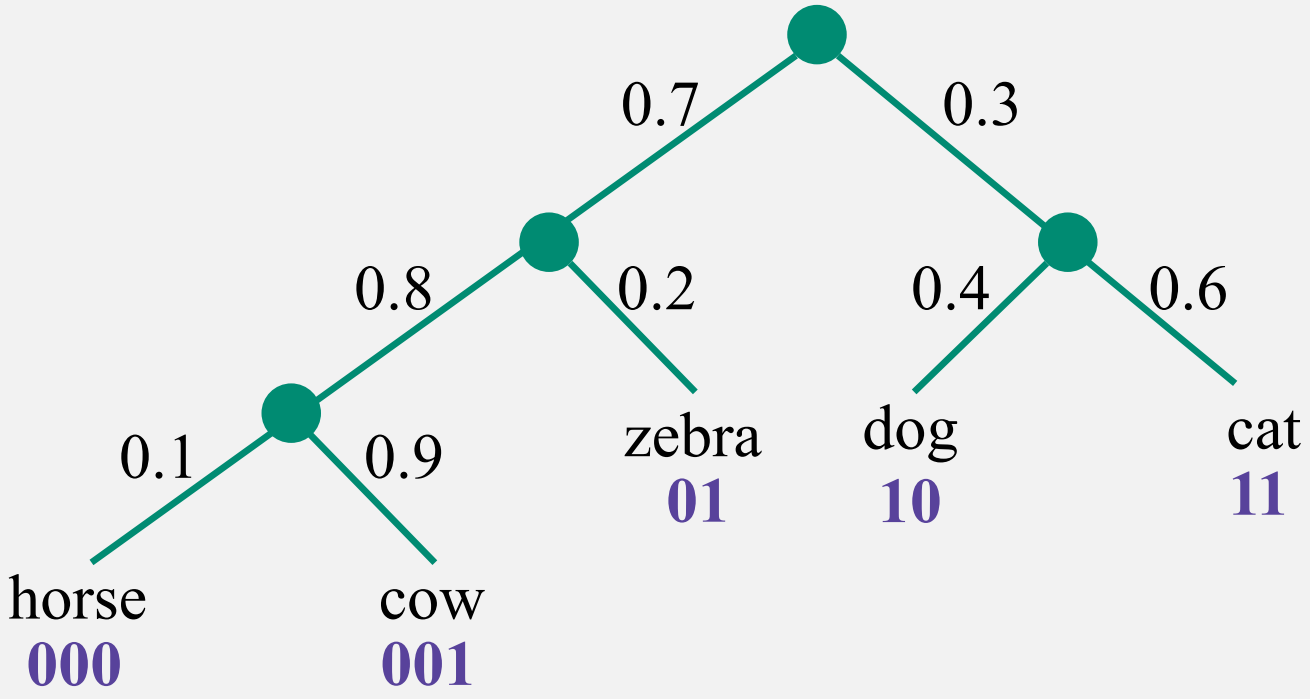
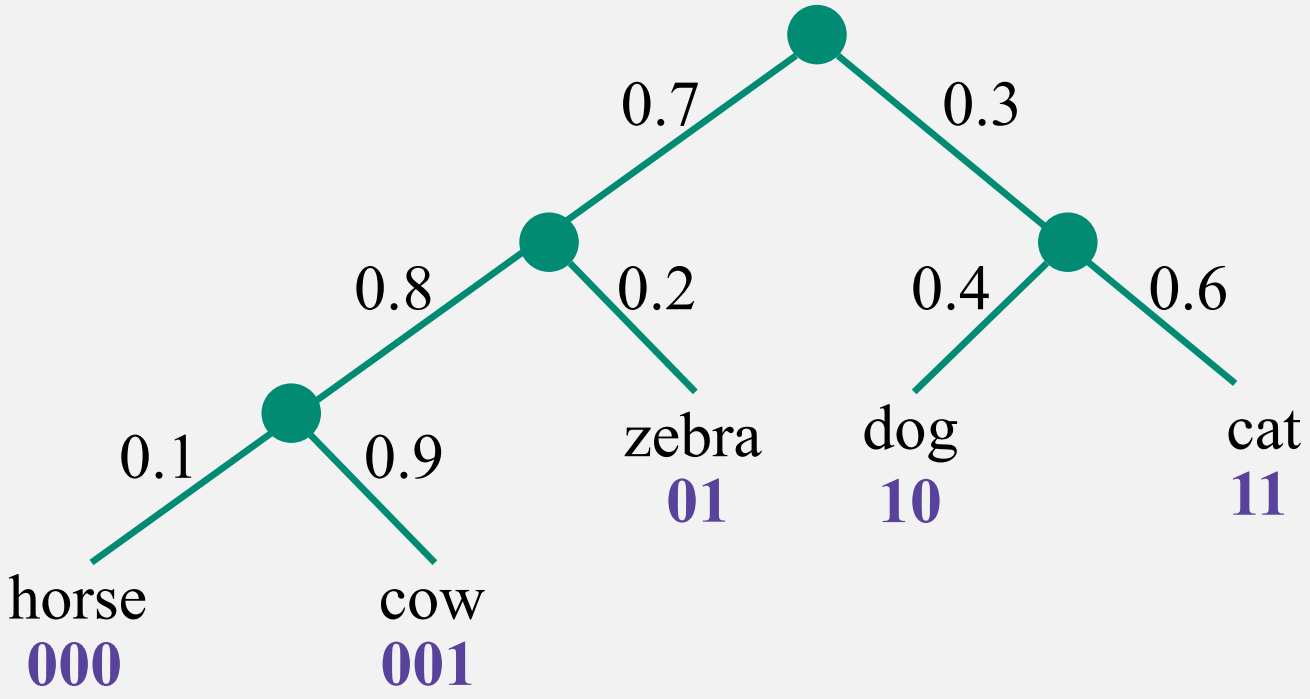


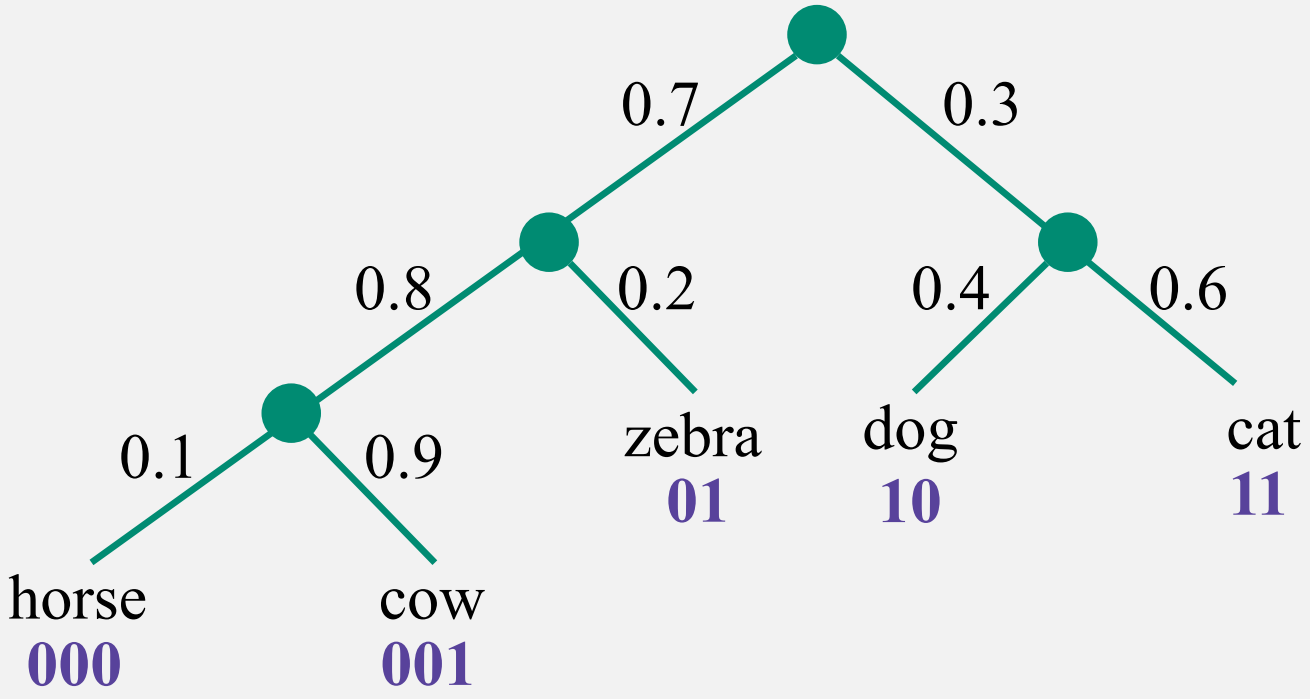
Hierarchical softmax

0.7
0.3
+



Hierarchical softmax

0.7
0.3
+

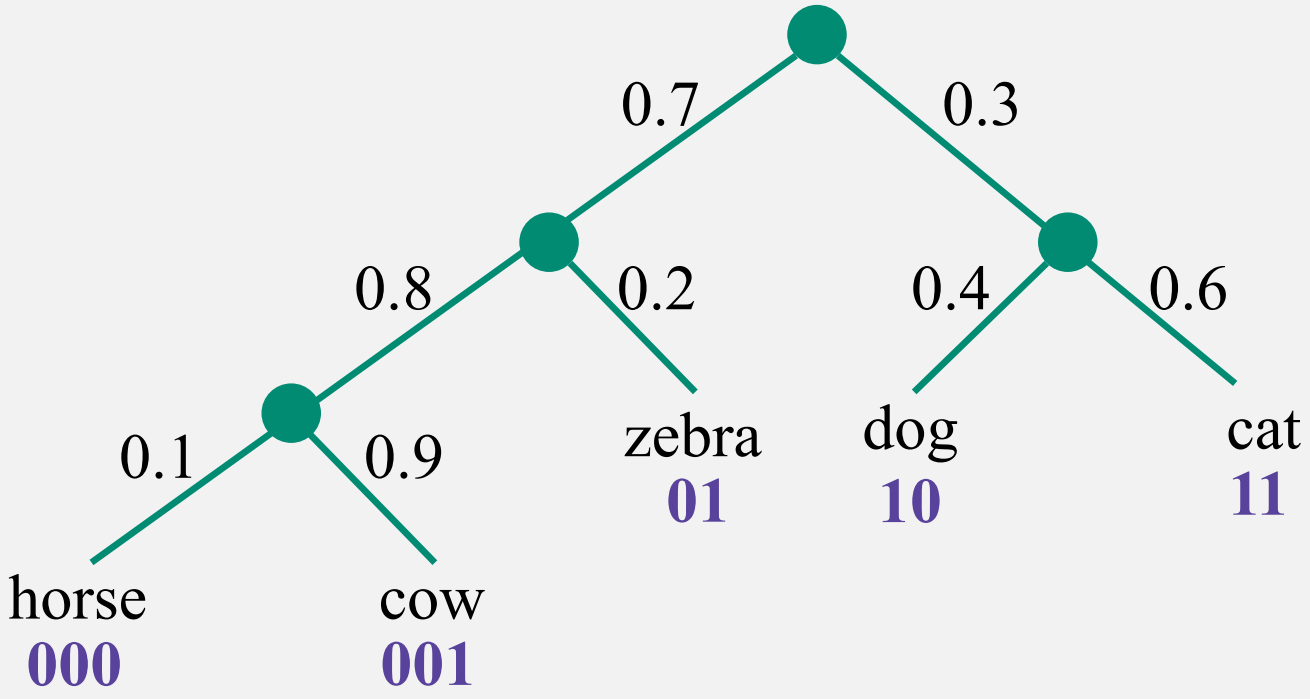


Hierarchical softmax

1.0

+

Congratulations!



Hierarchical softmax

Model binary decisions along the path in the tree:

$$p(w_n = w | w_1^{n-1}) = \prod_i p(d_i | w_1^{n-1})$$

How to construct a tree (balanced vs. semantic):

- Based on some pre-built ontology
- Based on semantic clustering from data
- Huffman tree
- Random

Outline

- Computing *softmax* for a large vocabulary is slow!
  - Hierarchical softmax
- Even a large vocabulary has *OOV words*:
  - **Copy mechanism**
  - Sub-word modeling
    - Word-character hybrid models
    - Byte-pair encoding

Copy mechanism

- Scaling *softmax* is insufficient!
- What do we do with OOV words?
  - Names, numbers, rare words…

	ecotax			*Pont-de-Buis*
The	UNK	portico	in	UNK

Copy mechanism

- Scaling *softmax* is insufficient!
- What do we do with OOV words?
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	ecotax				*Pont-de-Buis*
The	UNK	portico	in	UNK	
Le	portique	UNK	de	UNK	

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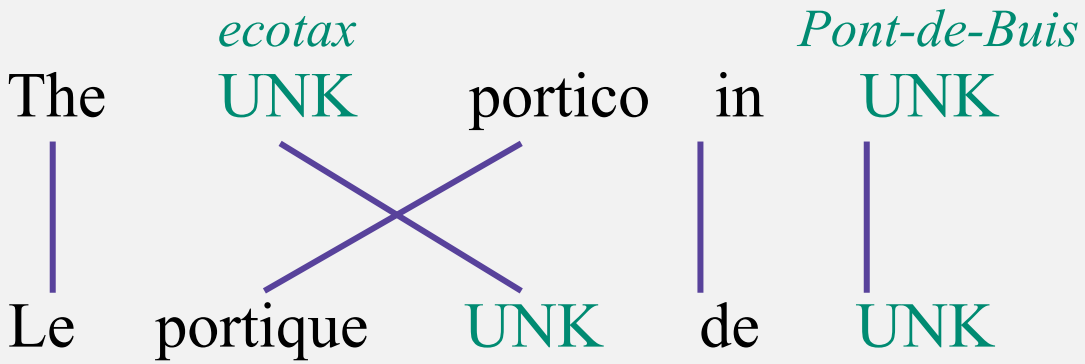

Copy mechanism

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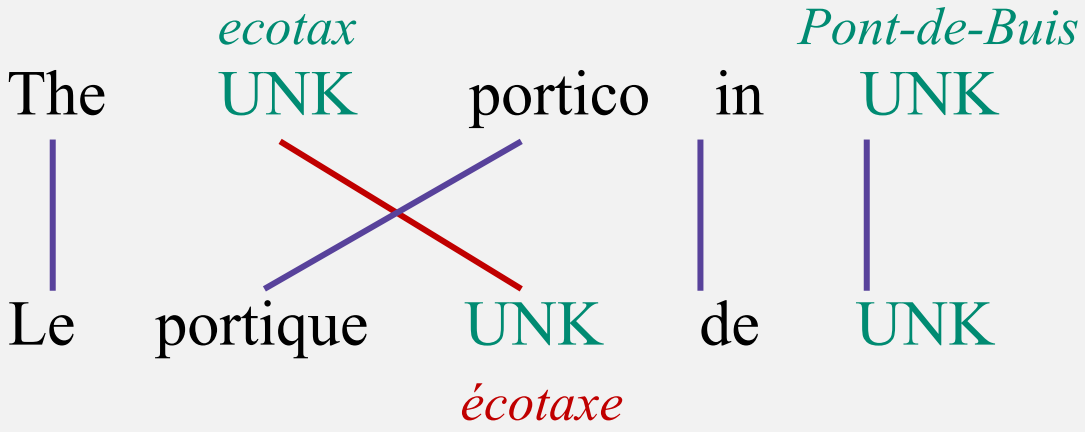
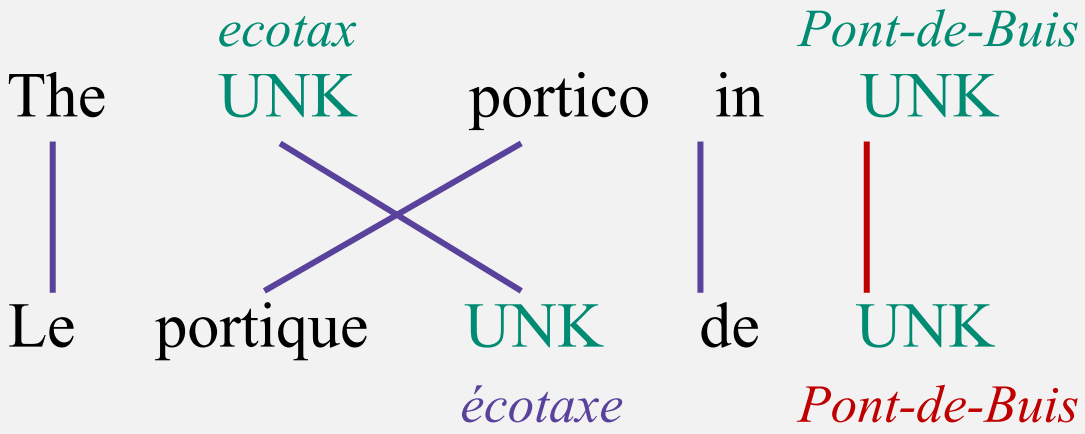
Look-up in a dictionary



Copy mechanism

- Scaling *softmax* is insufficient!
- What do we do with OOV words?
  - Names, numbers, rare words…

Look-up in a dictionary **Copy name**



Copy mechanism

Algorithm:

- Provide word alignments in train time
- Learn relative positions for UNK tokens with NMT
- Post-process the translation:
  - Copy the source word
  - Look up in a dictionary

Simple, but super useful technique!

Towards open vocabulary

Still problems:

- Transliteration: Christopher ↦ Kryštof
- Multi-word alignment: Solar system ↦ Sonnensystem
- Rich morphology: nejneobhospodařovávatelnějšímu
- Informal spelling: goooooood morning !!!!!

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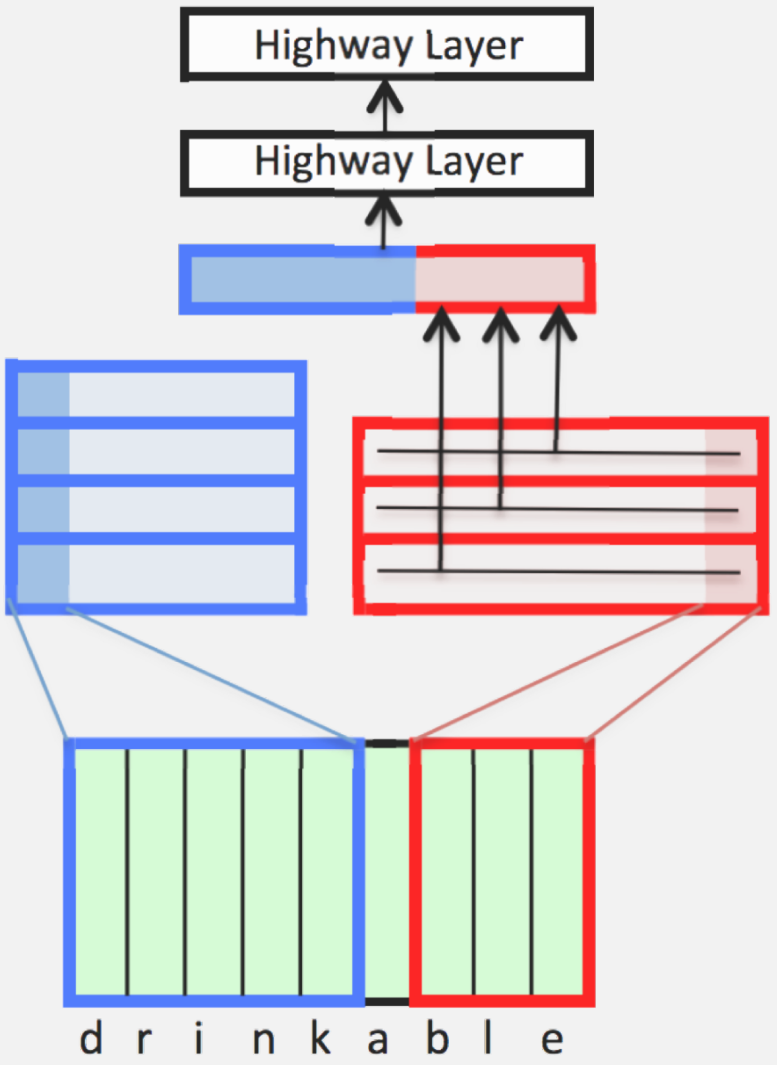
Character-based models

Character-based encoder is good for source languages with rich morphology!

- Bi-LSTMs to build word embeddings from characters
- CNNs on characters



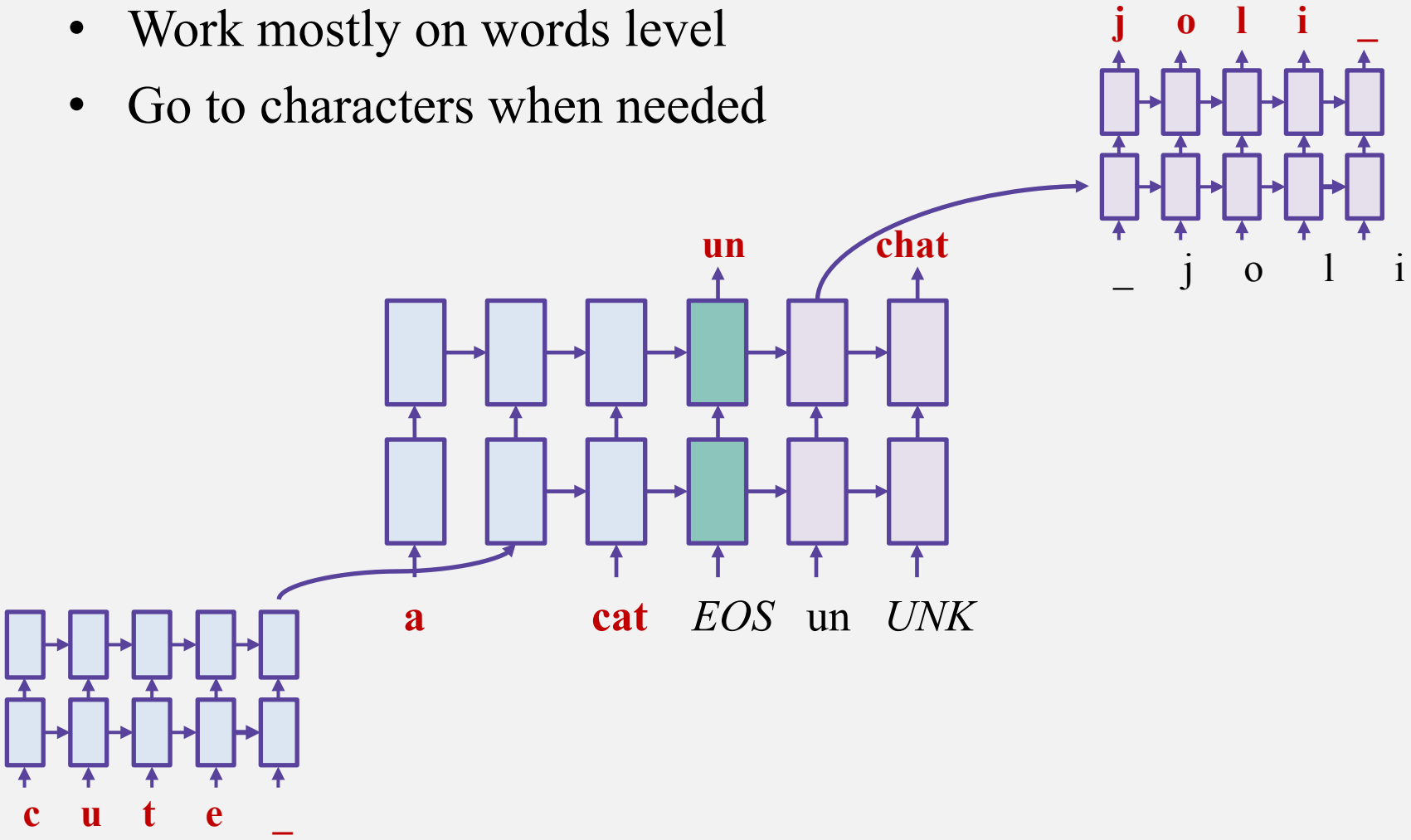
Ling, et. al. Finding Function in Form: Compositional Character Models for Open Vocabulary Word Representation. EMNLP 2015.

Kim, et. al. Character-Aware Neural Language Models. AAAI 2016.

Marta R. Costa-jussà and José A. R. Fonollosa. Character-based Neural Machine Translation. ACL 2016.

Hybrid models: the best of two worlds

- Work mostly on words level
- Go to characters when needed



Thang Luong and Chris Manning. Achieving Open Vocabulary Neural Machine Translation with Hybrid Word-Character Models. ACL 2016.

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Byte-pair encoding

- Simple way to handle open vocabulary:
  - Start with characters
  - Iteratively replace the most frequent pair with one unit

Byte-pair encoding

- Simple way to handle open vocabulary:
  - Start with characters
  - Iteratively replace the most frequent pair with one unit

She sells seashells by the seashore

Byte-pair encoding

- Simple way to handle open vocabulary:
  - Start with characters
  - Iteratively replace the most frequent pair with one unit

S h e _ s e l l s _ s e a s h e l l s _ b y _ t h e _ s e a s h o r e _

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Sh e _ se ll s _ se a sh e ll s _ b y _ t h e _ se a sh o r e _

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Sh e _ se ll s _ sea sh e ll s _ b y _ t h e _ sea sh o r e _

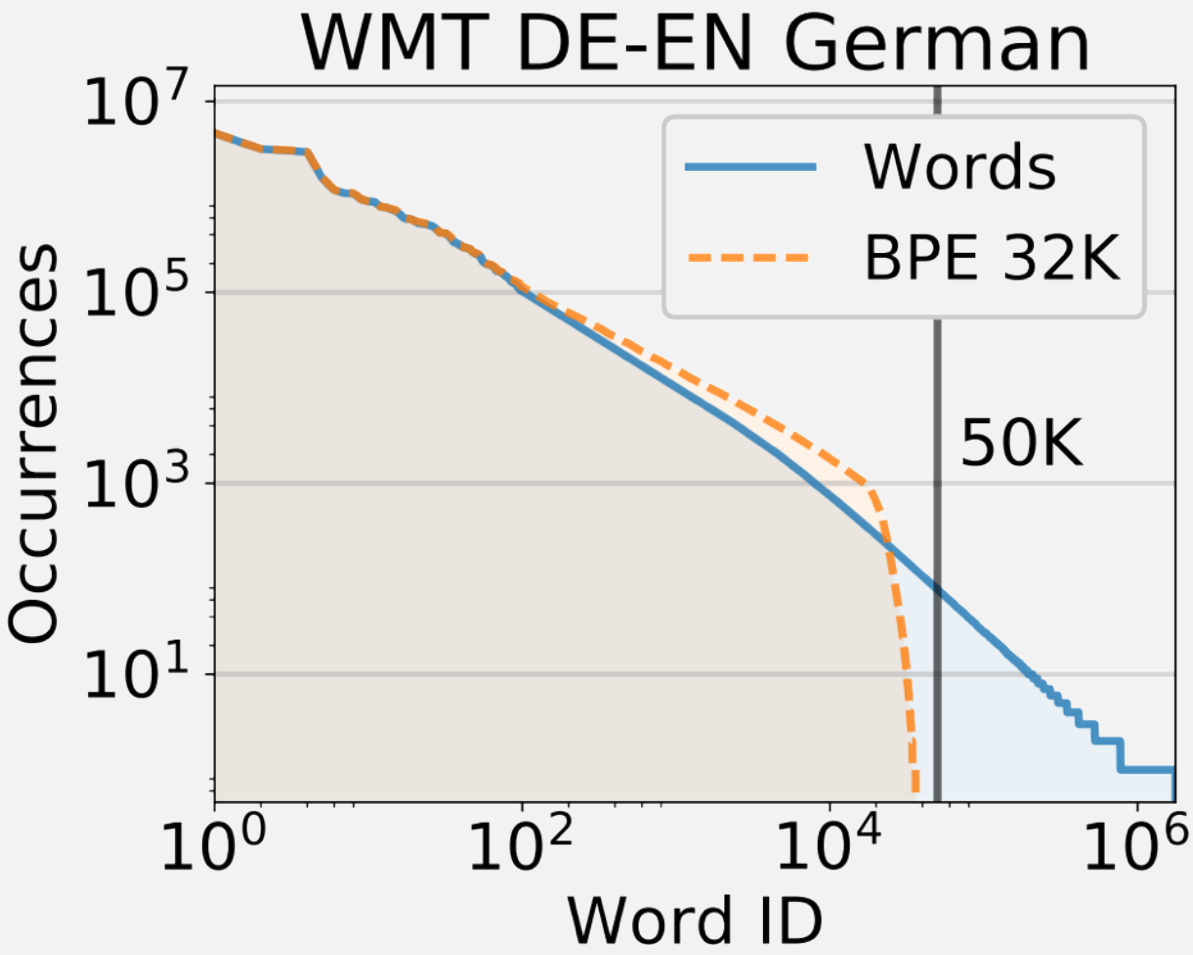
Byte-pair encoding

- Simple way to handle open vocabulary:
  - Start with characters
  - Iteratively replace the most frequent pair with one unit

Sh e _ se ll s _ sea sh e ll s _ b y _ t h e _ sea sh o r e _

- End whenever you reach the vocabulary size limit
- Stick to that vocabulary of sub-word units
- Apply the same algorithm to test sentences

Why is it so useful?



Denkowski, Neubig. Stronger Baselines for Trustable Results in Neural Machine Translation, 2017.

BLEU score comparison

	WMT			IWSLT	
	DE-EN	EN-FI	RO-EN	EN-FR	CS-EN
Words 50K	31.6	12.6	27.1	33.6	21.0
BPE 32K	**33.5**	**14.7**	**27.8**	34.5	22.6
BPE 16K	33.1	**14.7**	**27.8**	**34.8**	**23.0**

- Byte-pair encoding improves BLEU score
- It is a nice and simple way to handle the vocabulary
- Very common trick in modern NMT

Denkowski, Neubig. Stronger Baselines for Trustable Results in Neural Machine Translation, 2017.