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?

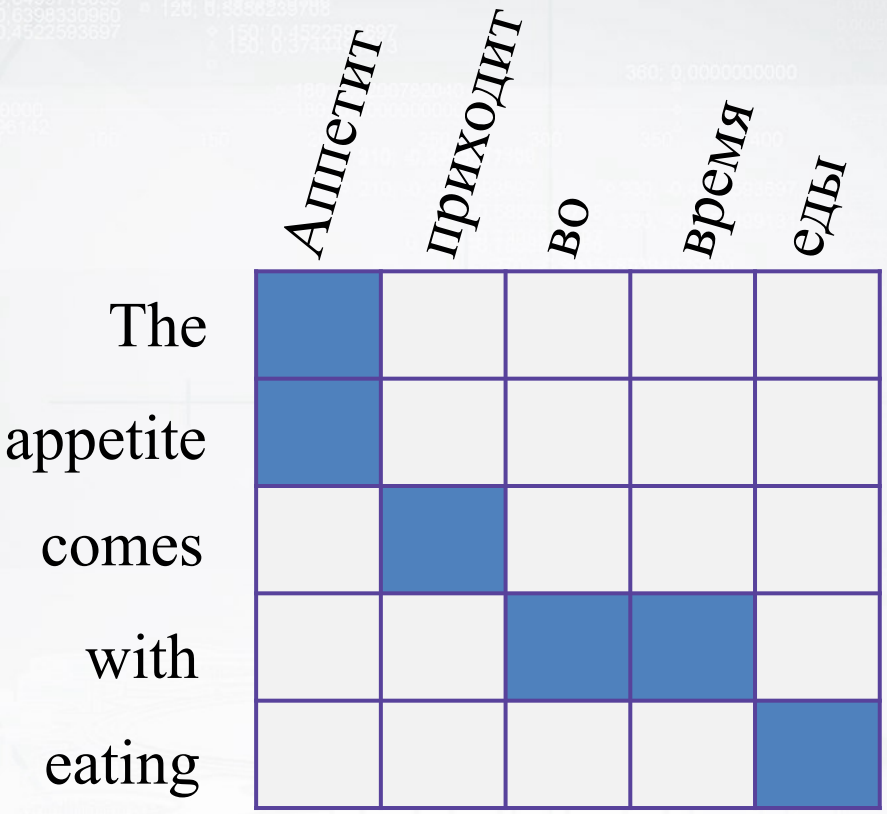
f: Аппетит приходит во время еды.

Recap: Bayes' rule

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

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

Word alignment matrix



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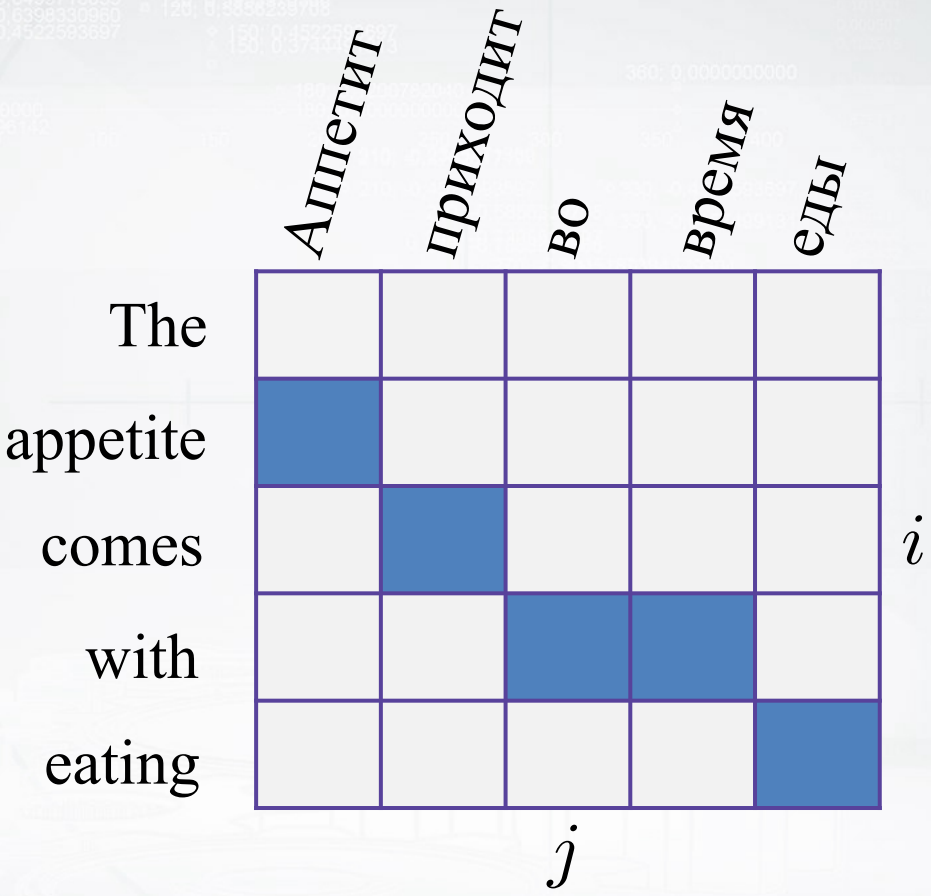

Each target word is allowed to have only one source!

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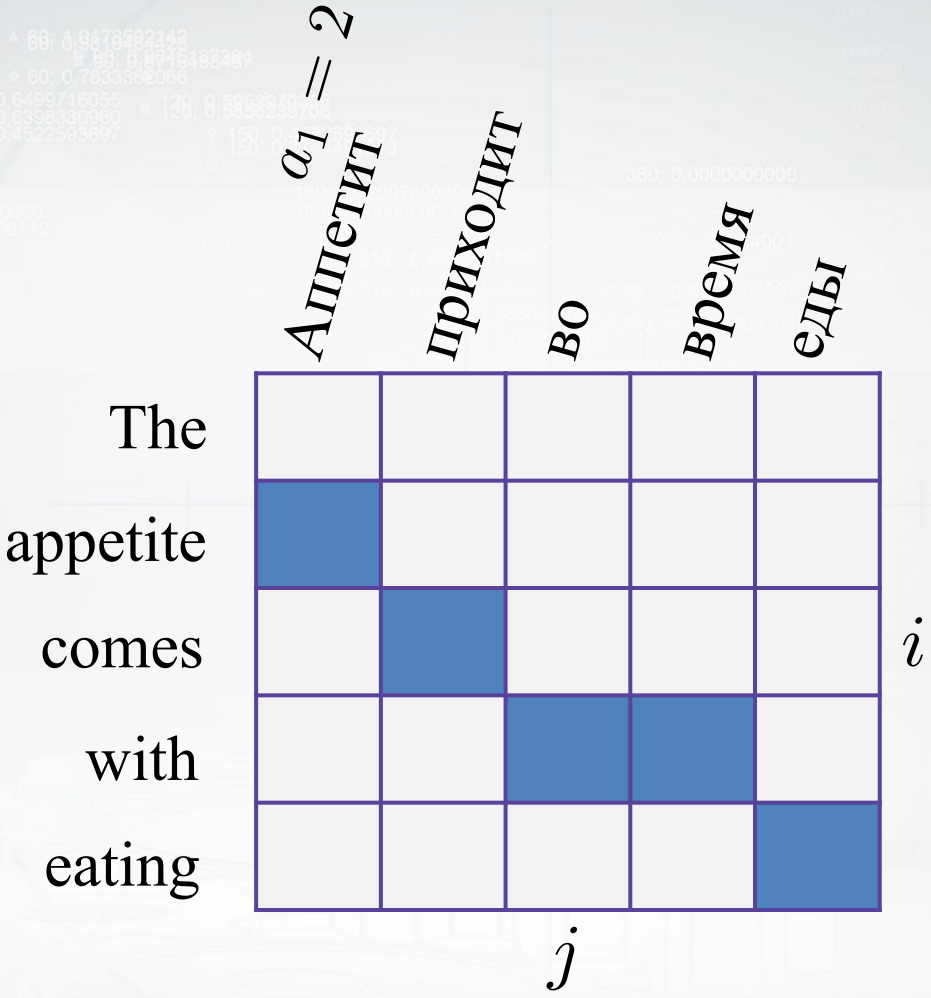

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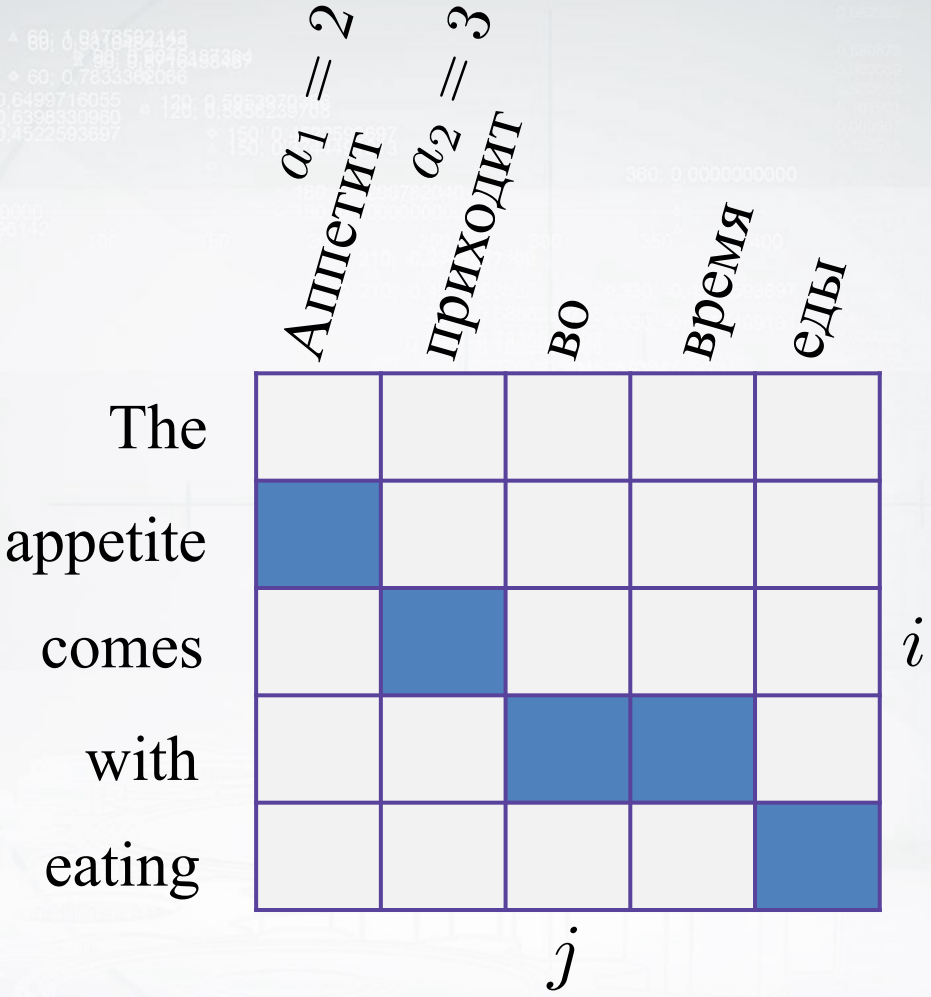

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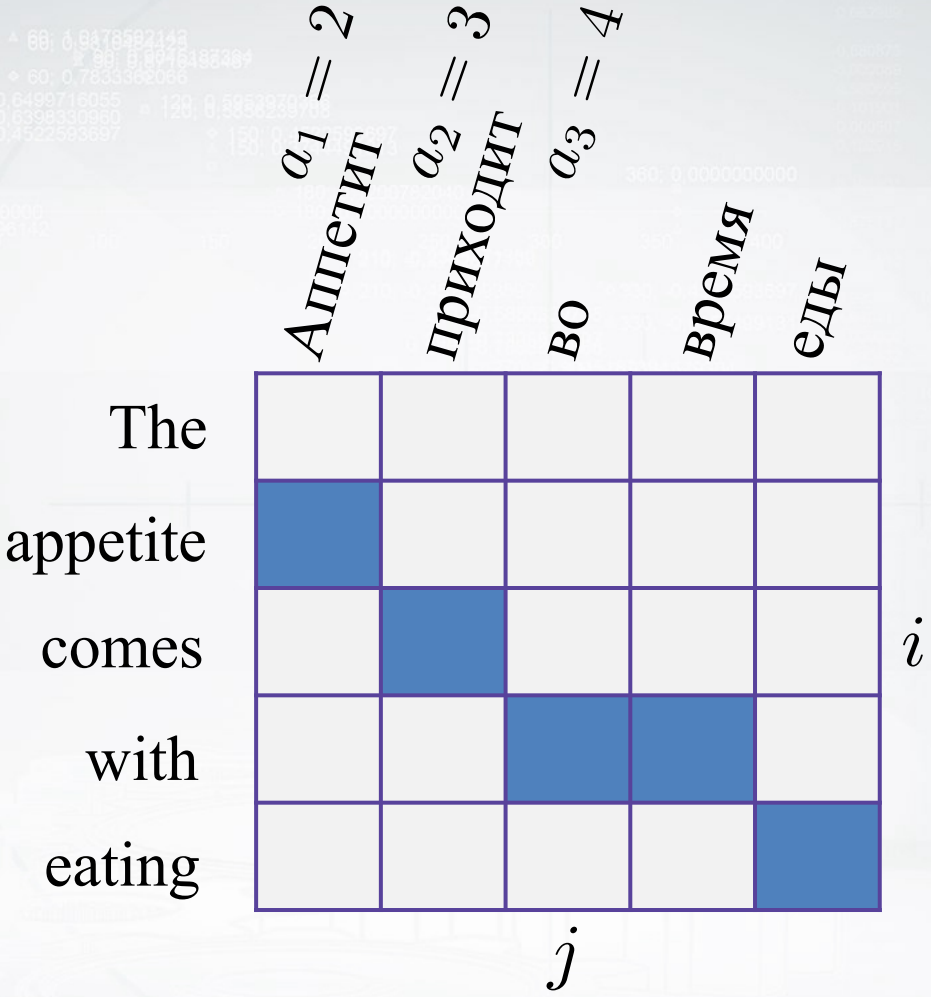

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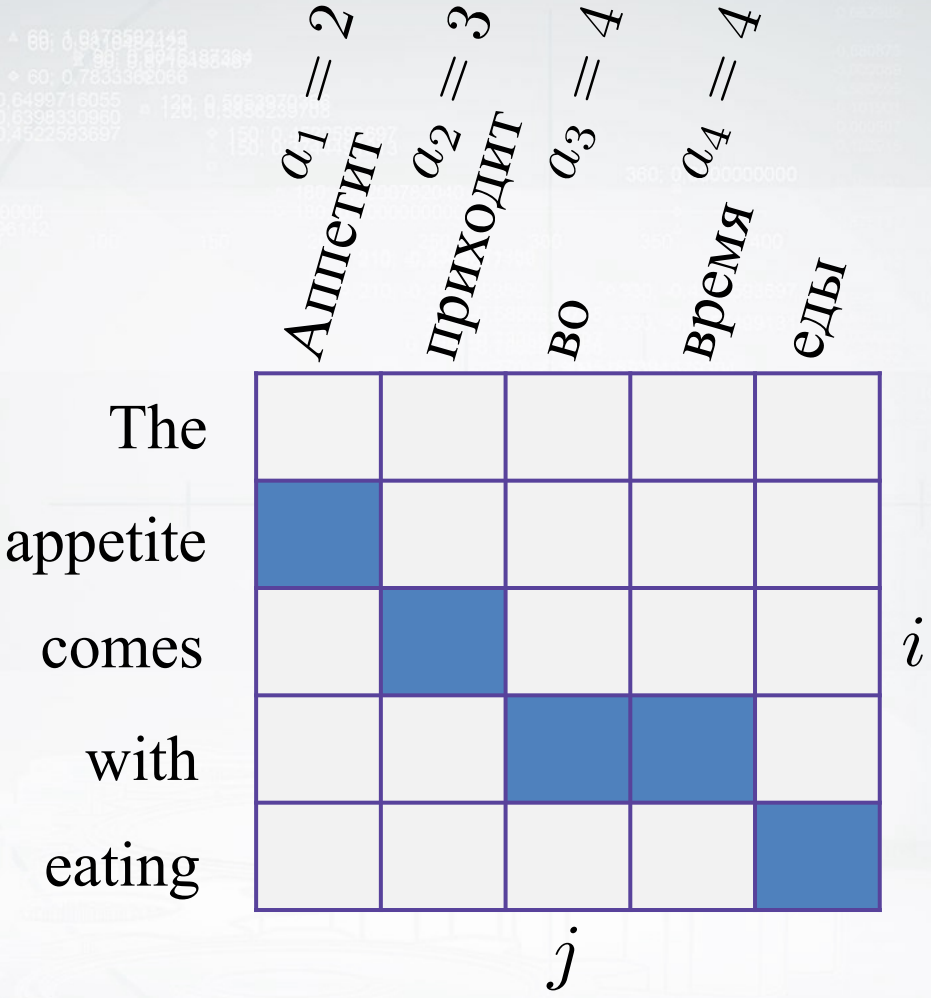

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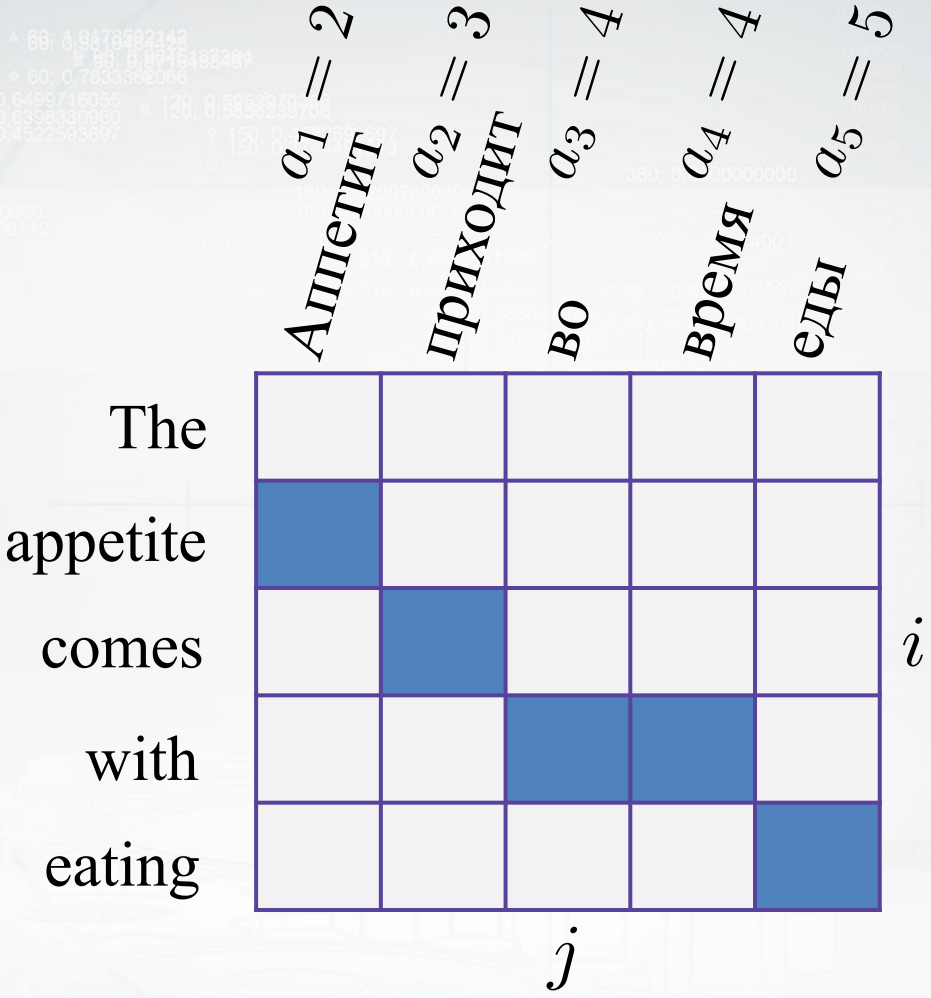

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Sketch of learning algorithm

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?

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observable variables

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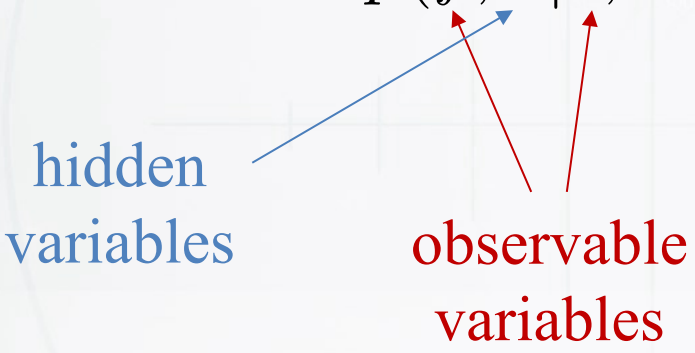

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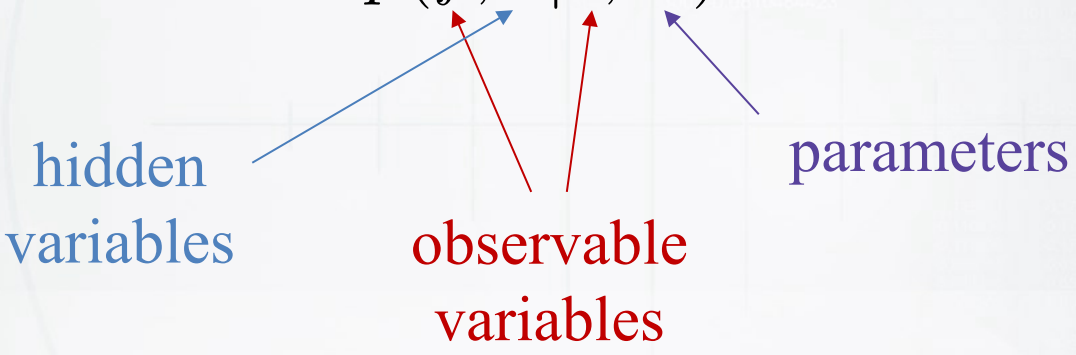

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Sketch of learning algorithm

2. Likelihood maximization for the incomplete data:

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

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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

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

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$$\times p(f_j|a_j, a_1^{j-1}, f_1^{j-1}, J, e)$$

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

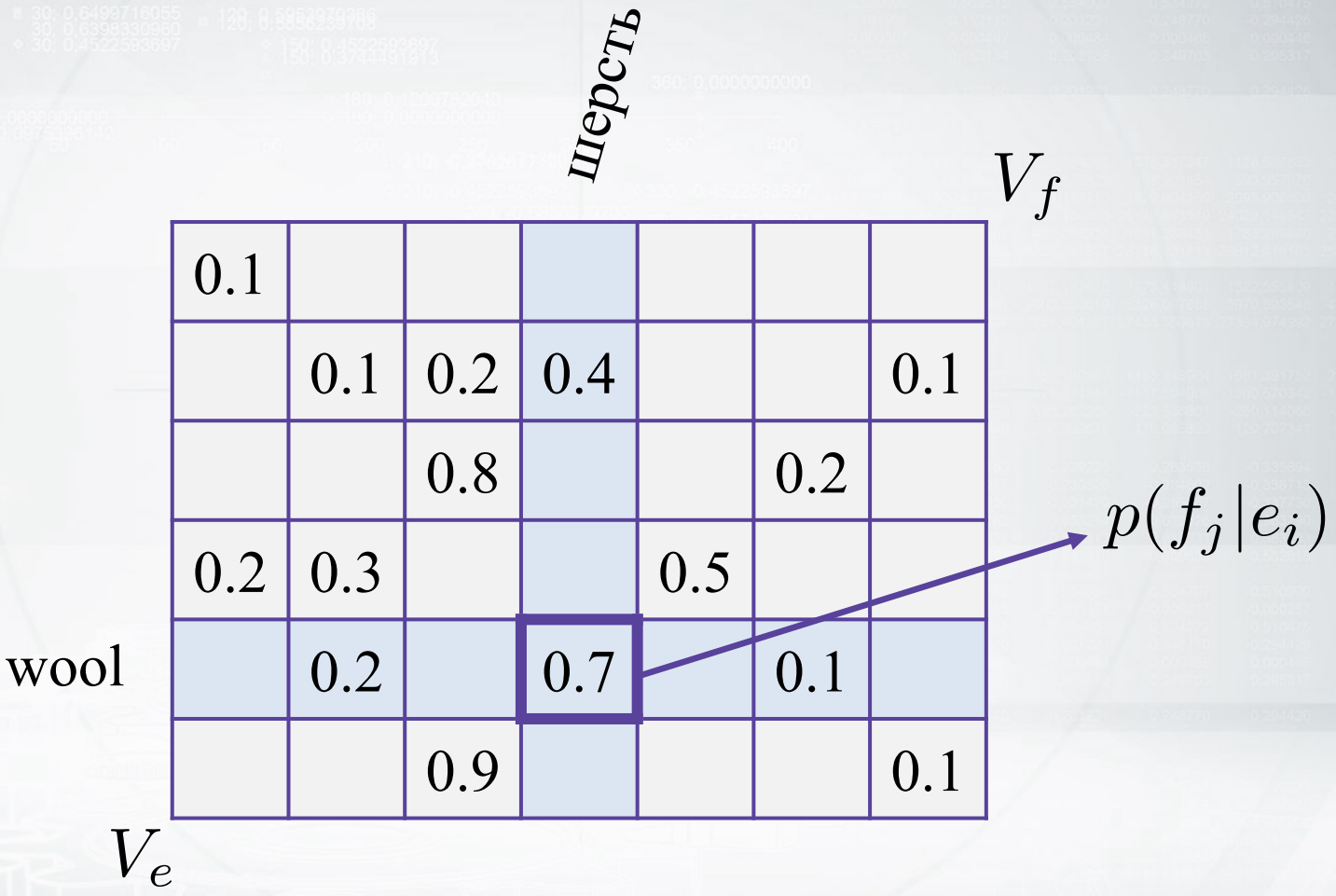
$$p(f, a|e) = p(J|e) \prod_{j=1}^{J} p(a_j) p(f_j|a_j, e)$$

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

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

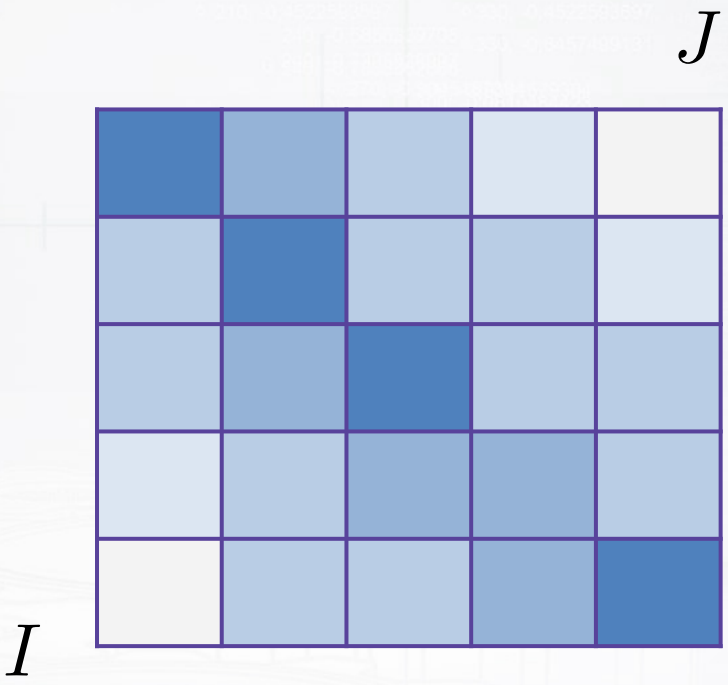
Position-based prior $d(a_j|j, I, J)$

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

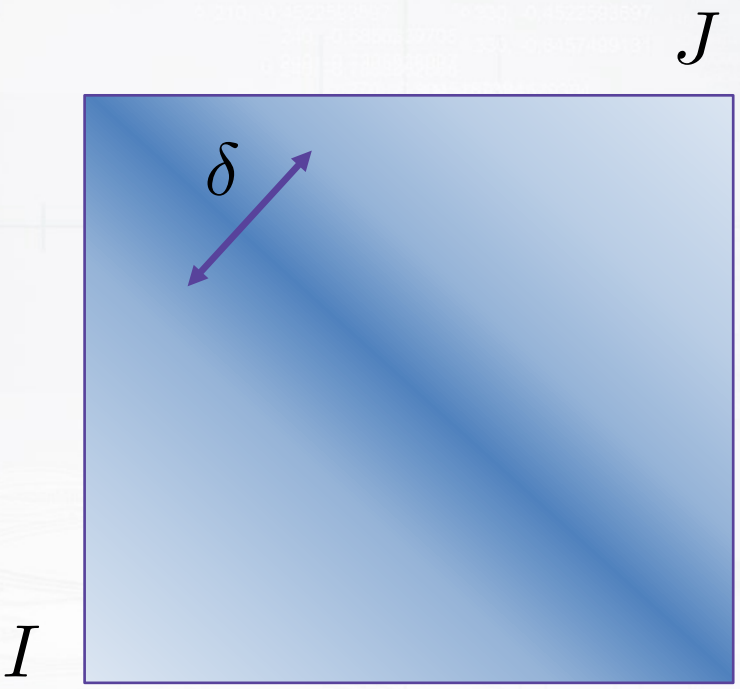
- For each pair of the **lengths** of the sentences:
  - $I \times J$ matrix of probabilities



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*
  - ....
- How to do many-to-many alignments?
  - Phrase-based machine translation