Phrase-based Models, Phrase Extraction

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(adapted from slides by Barry Haddow)

(and before that from ones by Philipp Koehn)

(and before ...)

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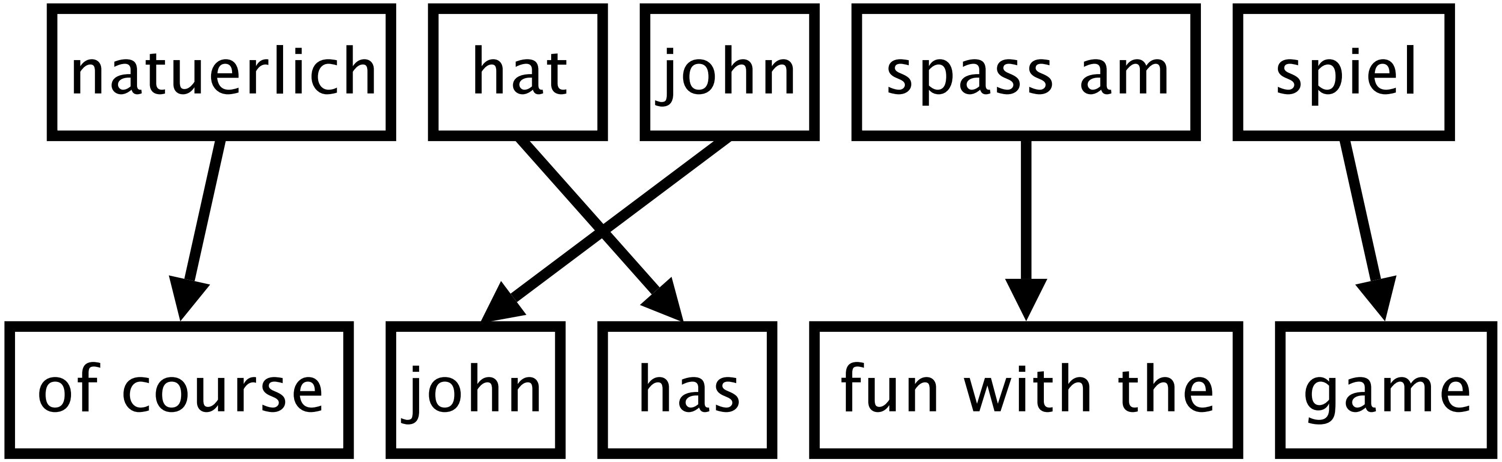
Outline

- From word-based to phrase-based
- Creating the phrase table
- The log-linear model and the “standard” phrase-based MT features

Motivation

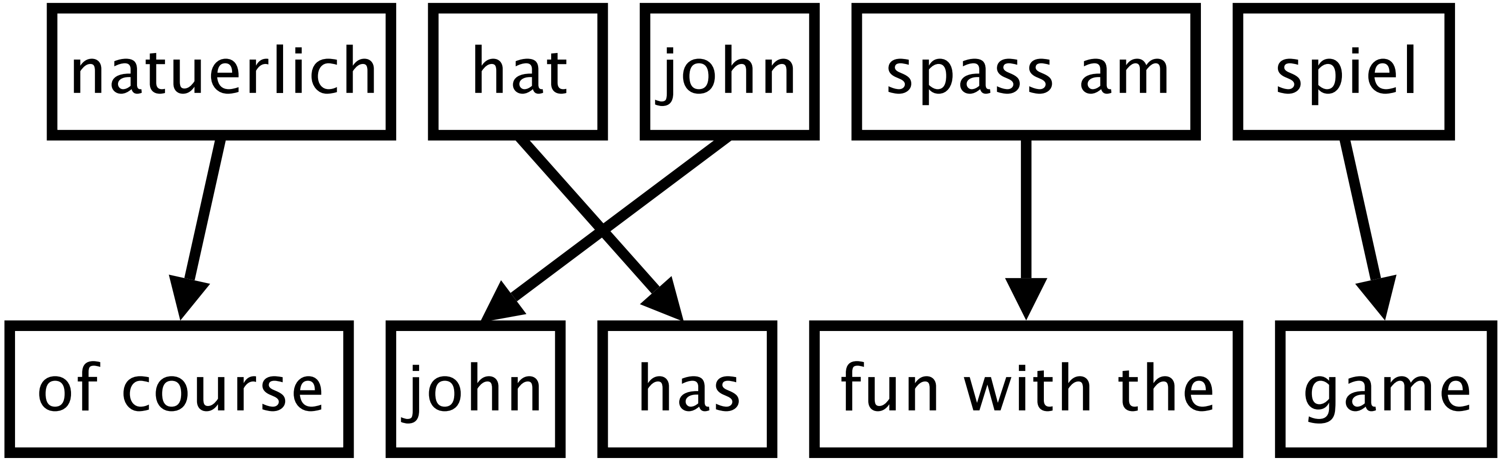
- Phrase-Based Models translate *phrases* instead of *words* as atomic units
- Advantages:
  - many-to-many translation can handle non-compositional phrases
  - use of local context in translation
  - the more data, the longer phrases can be learned
- "Standard Model", used by Google Translate and others

Phrase-Based Model



- Foreign input is segmented in phrases
- Each phrase is translated into English
- Phrases are reordered

Phrase-Based Model



- Simpler generative story
- No fertility or NULL-insertion

Big Picture

$$\begin{aligned}\hat{\mathbf{e}} &= \text{argmax}_{\mathbf{e}}\, p(\mathbf{e}|\mathbf{f}) \\ &= \text{argmax}_{\mathbf{e}}\, p_{\text{TM}}(\mathbf{f}|\mathbf{e})\, p_{\text{LM}}(\mathbf{e})\end{aligned}$$

p_{TM} can be estimated in different ways:

- Word-based IBM model:

$$p_{\text{TM}}(\mathbf{f}|\mathbf{e}) = p_{lex}(\mathbf{f}|\mathbf{e}) \cdot p_{dist}(\mathbf{f}|\mathbf{e}) \cdot p_{fert}(\mathbf{f}|\mathbf{e}) \cdots$$

- Let us define how it is estimated in phrase-based translation

Phrase Translation Table

- Main knowledge source: table with phrase translations and their probabilities

- Example: phrase translations for natuerlich

Translation	**Probability** $\phi(\bar{e}\|\bar{f})$
of course	0.5
naturally	0.3
of course ,	0.15
, of course ,	0.05

Real Example

- Phrase translations for den Vorschlag learned from the Europarl corpus:

English	$\phi(\bar{e}\|\bar{f})$	English	$\phi(\bar{e}\|\bar{f})$
the proposal	0.6227	the suggestions	0.0114
's proposal	0.1068	the proposed	0.0114
a proposal	0.0341	the motion	0.0091
the idea	0.0250	the idea of	0.0091
this proposal	0.0227	the proposal ,	0.0068
proposal	0.0205	its proposal	0.0068
of the proposal	0.0159	it	0.0068
the proposals	0.0159	...	...

  - lexical variation (proposal vs suggestions)
  - morphological variation (proposal vs proposals)
  - included function words (the, a, ...)
  - noise (it)

Linguistic Phrases?

- Model is not limited to linguistic phrases
  (syntactic sub-tree spans: noun phrases, verb phrases, prep. phrases, . . .)

- Example non-linguistic phrase pair

$$\text{spass am} \rightarrow \text{fun with the}$$

- Prior noun often helps with translation of preposition

- Experiments show that limitation to linguistic phrases hurts quality

Learning a Phrase Translation Table

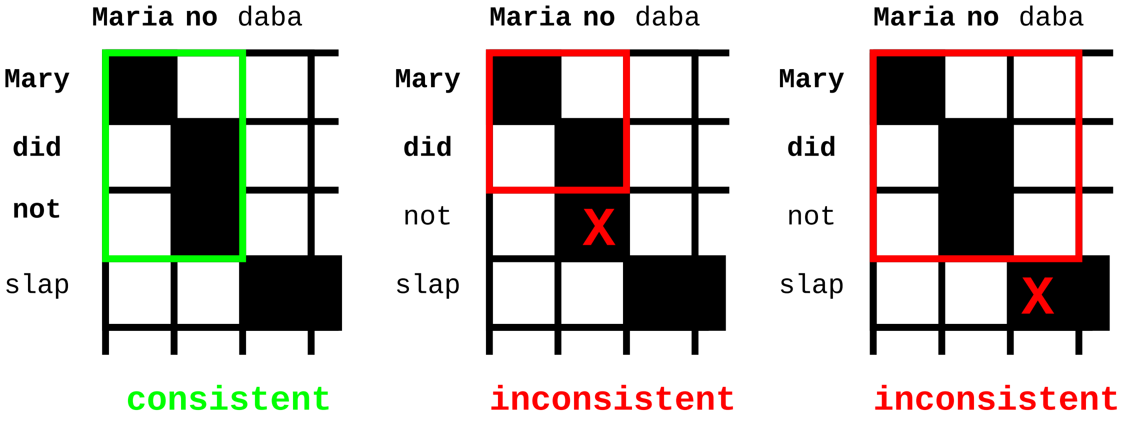
- Task: learn the model from a parallel corpus

- Three stages:
  - word alignment: using IBM models or other method
  - extraction of phrase pairs
  - scoring phrase pairs

Word Alignment

	María	no	daba	una	bofetada	a	la	bruja	verde
Mary	■								
did		■							
not		■							
slap			■	■	■				
the						■	■		
green									■
witch								■	

Phrase Extraction Criteria



- Phrase alignment has to *contain all alignment points* for all covered words
- Phrase alignment has to *contain at least one alignment point*

Phrase Extraction Criteria, Formalised

A phrase pair $(\overline{e}, \overline{f})$ is *consistent* with an alignment A if and only if:

1. No English words in the phrase pair are aligned to words outside it.

$$\forall e_i \in \overline{e}, (e_i, f_j) \in A \Rightarrow f_j \in \overline{f}$$

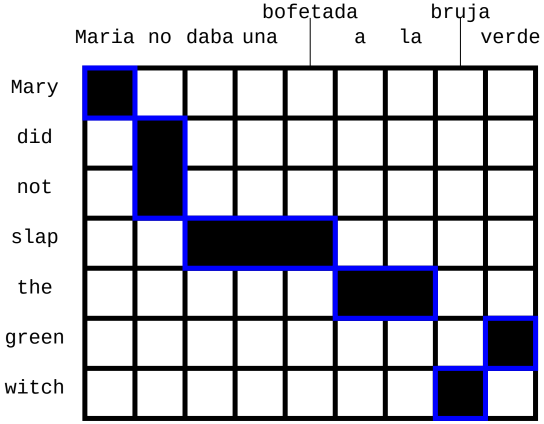
2. No Foreign words in the phrase pair are aligned to words outside it.

$$\forall f_j \in \overline{f}, (e_i, f_j) \in A \Rightarrow e_i \in \overline{e}$$

3. The phrase pair contains at least one alignment point.

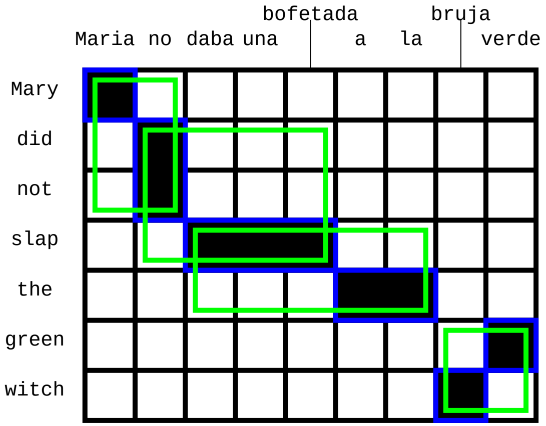
$$\exists e_i \in \bar{e}, f_j \in \bar{f} \; s.t. \; (e_i, f_j) \in A$$

Word alignment induced phrases



(Maria, Mary), (no, did not), (slap, daba una bofetada), (a la, the), (bruja, witch), (verde, green)

Word alignment induced phrases



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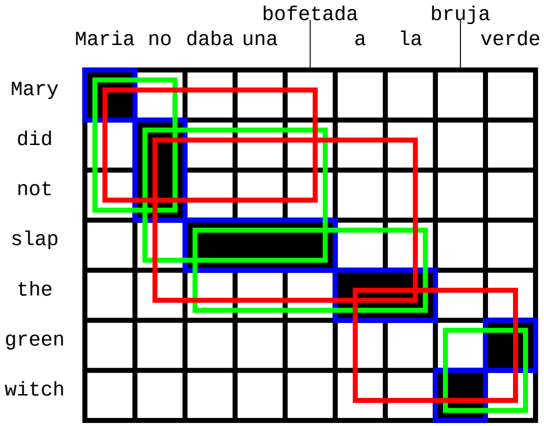

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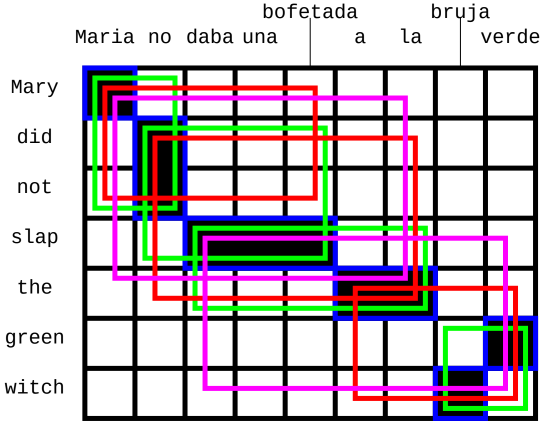

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(bruja verde, green witch), (Maria no daba una bofetada, Mary did not slap),

(no daba una bofetada a la, did not slap the), (a la bruja verde, the green witch),

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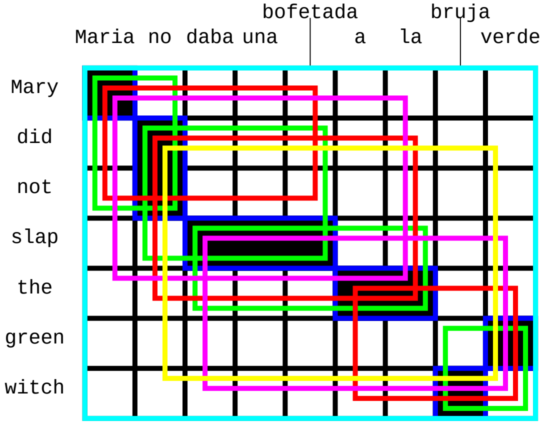

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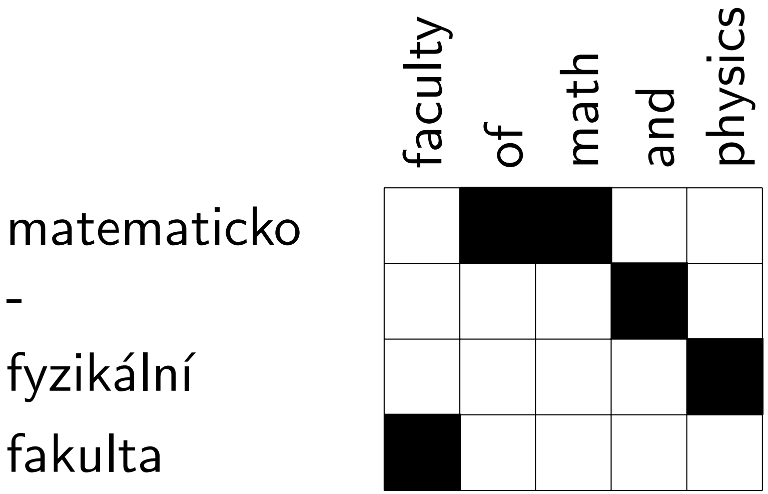
Word alignment can be wrong



	faculty	of	math	and	physics
matematicko		■	■		
-				■	
fyzikální					■
fakulta	■				

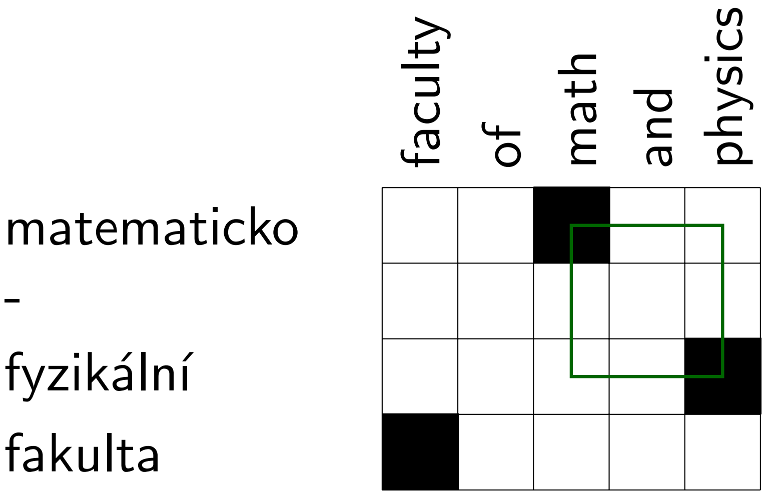
(fakulta, faculty), (matematicko - fyzikální, of math and physics), (fyzikální, physics),

(matematicko, of math), (-, and), (- fyzikální, and physics), etc.

Word alignment can be wrong

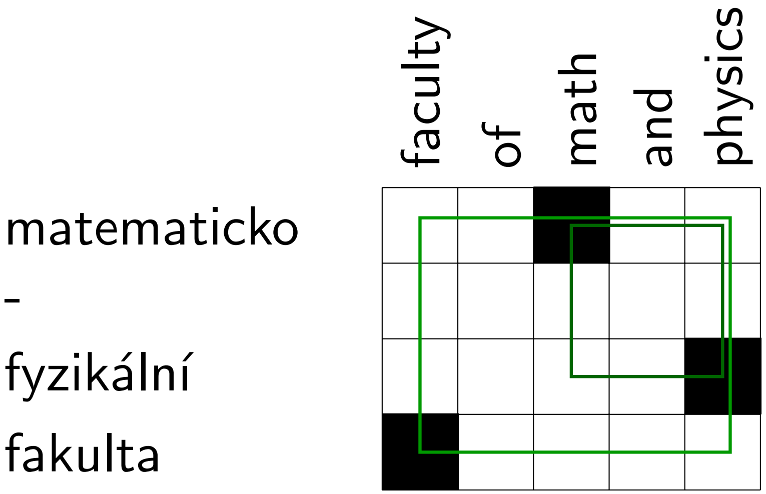
	faculty	of	math	and	physics
matematicko			■		
-					
fyzikální					■
fakulta	■				

Word alignment can be wrong



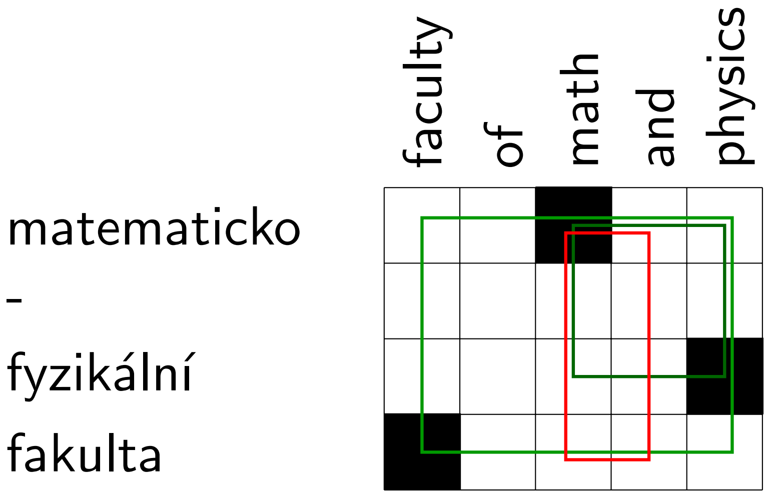
	faculty	of	math	and	physics
matematicko			■		
-					
fyzikální					■
fakulta	■				

Word alignment can be wrong

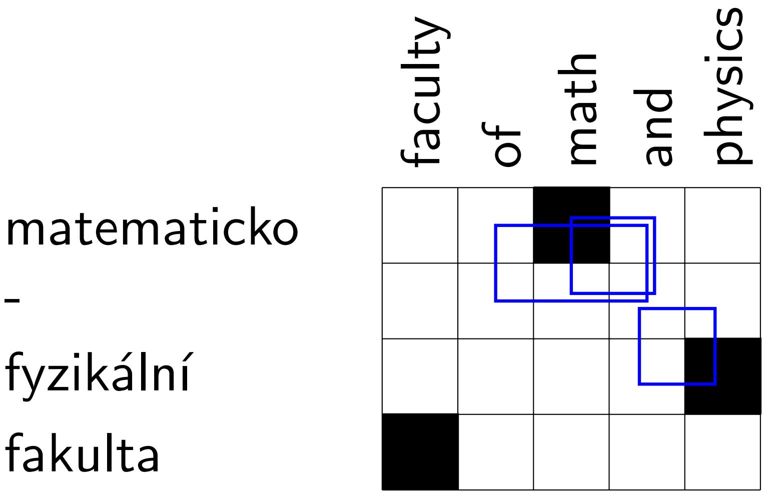


	faculty	of	math	and	physics
matematicko			■		
-					
fyzikální					■
fakulta	■				

Word alignment can be wrong



Word alignment can be wrong



Are these allowed?

Word alignment can be wrong

	the	faculty	of	math	and	physics
matematicko				■		
-						
fyzikální						■
fakulta		■				

This allows for extracting both (fakulta, faculty) and (fakulta, the faculty) = more flexible

Word alignment vs phrase extraction

A word alignment **restricts** the extracted phrase pairs to it

- A dense word alignment
  - will result in fewer phrase pairs
  - might bring wrong phrases in case of wrong or uncertain word alignment points

- A sparse word alignment
  - will result in more phrases, many of which might be noisy
  - but is preferred to an uncertain dense word alignment, since it can also include the correct phrase pairs
  - scoring can bring up the correct phrase pairs

Scoring Phrase Translations

- Phrase pair extraction: collect all phrase pairs from the data
- Phrase pair scoring: assign probabilities to phrase translations
- Score by relative frequency:

$$\phi(\bar{f}|\bar{e}) = \frac{\text{count}(\bar{e}, \bar{f})}{\sum_{\bar{f}_i} \text{count}(\bar{e}, \bar{f}_i)}$$

Scoring Translations

- Searching for the most likely output

$$\mathbf{e}_{\text{best}} = \text{argmax}_{\mathbf{e}}\, p(\mathbf{e}|\mathbf{f}) = \text{argmax}_{\mathbf{e}}\, p_{\text{TM}}(\mathbf{f}|\mathbf{e})\; p_{\text{LM}}(\mathbf{e})$$

  - translation model $p_{\text{TM}}(\mathbf{f}|\mathbf{e})$, language model $p_{\text{LM}}(\mathbf{e})$

- Decomposition of the translation model

$$p_{\text{TM}}(\mathbf{f}|\mathbf{e}) = p(\bar{f}_1^I|\bar{e}_1^I) = \prod_{i=1}^{I} \phi(\bar{f}_i|\bar{e}_i)$$

Log-linear Model

$$\frac{\partial \ln f(x)}{\partial x} = \frac{1}{x} \cdot \frac{\partial f(x)}{\partial x} \implies \text{argmax}_x f(x) = \text{argmax}_x \ln f(x)$$

which means that we can replace

$$score(\mathbf{e}) = p_{\mathrm{TM}}(\mathbf{f}|\mathbf{e}) \cdot p_{\mathrm{LM}}(\mathbf{e})$$

with

$$logscore(\mathbf{e}) = \ln score(\mathbf{e}) = \ln p_{\mathrm{TM}}(\mathbf{f}|\mathbf{e}) + \ln p_{\mathrm{LM}}(\mathbf{e})$$

and search for its maximum instead

Weighted Log-linear Model

We can weight the models differently

$$logscore(\mathbf{e}) = \lambda_{\text{TM}} \log p_{\text{TM}}(\mathbf{f}|\mathbf{e}) + \lambda_{\text{LM}} \log p_{\text{LM}}(\mathbf{e})$$

and actually add any number of models, called *feature functions*:

$$logscore(\mathbf{e}) = \sum_{k=1}^{n} \lambda_k h_k(\mathbf{e}, \mathbf{f})$$

Weights $\vec{\lambda}$ determined automatically via tuning (MERT/PRO/MIRA/. . .)

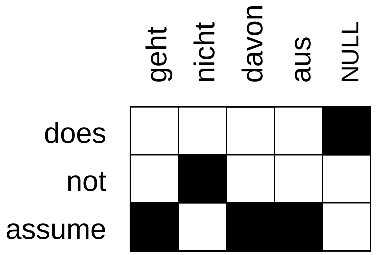
Adding features

- Reverse phrase translation probability (i.e. $p_{\text{TM}}(\mathbf{e}|\mathbf{f})$)
- Lexical translation probabilities (in both directions)
- Phrase count
- Word count
- Distortion cost
- Reordering score

Adding features

- Rare phrase pairs have unreliable phrase translation probability estimates

  → lexical weighting with word translation probabilities



	geht	nicht	davon	aus	NULL
does					■
not		■			
assume	■		■	■	

$$\text{lex}(\bar{e}|\bar{f},a) = \prod_{i=1}^{\text{length}(\bar{e})} \frac{1}{|\{j|(i,j) \in a\}|} \sum_{\forall (i,j) \in a} w(e_i|f_j)$$

Adding features

- Language model has a bias towards short translations

  → word count: $\text{wc}(e) = \log |\mathbf{e}|^{\omega}$

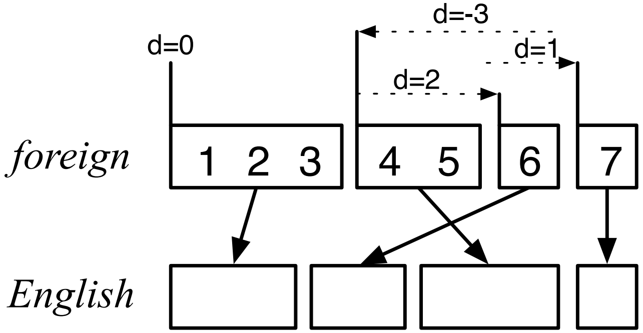
- We may prefer finer or coarser segmentation

  → phrase count $\text{pc}(e) = \log |I|^{\rho}$

- Multiple language models

- Multiple translation models

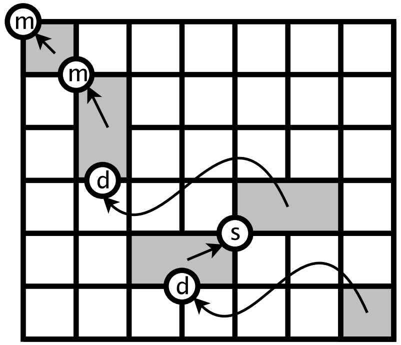
Distance-Based Reordering



phrase	translates	movement	distance
1	1–3	start at beginning	0
2	6	skip over 4–5	+2
3	4–5	move back over 4–6	-3
4	7	skip over 6	+1

Scoring function: $d(x) = \alpha^{|x|}$ — exponential with distance

Lexicalized Reordering



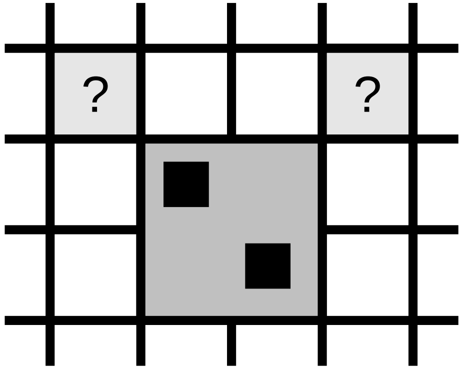
- Distance-based reordering model is weak
  → learn reordering preference for each phrase pair

- Three orientations types: (m) monotone, (s) swap, (d) discontinuous

$$\text{orientation} \in \{m, s, d\}$$

$$p_o(\text{orientation}|\bar{f}, \bar{e})$$

Learning Lexicalized Reordering



- Collect orientation information during phrase pair extraction
  - if word alignment point to the top left exists → **monotone**
  - if a word alignment point to the top right exists→ **swap**
  - if neither a word alignment point to top left nor to the top right exists → neither monotone nor swap → **discontinuous**

Learning Lexicalized Reordering

- Estimation by relative frequency

$$p_o(\text{orientation}) = \frac{\sum_{\bar{f}} \sum_{\bar{e}} count(\text{orientation}, \bar{e}, \bar{f})}{\sum_o \sum_{\bar{f}} \sum_{\bar{e}} count(o, \bar{e}, \bar{f})}$$

- Smoothing with unlexicalized orientation model $p(\text{orientation})$ to avoid zero probabilities for unseen orientations

$$p_o(\text{orientation}|\bar{f}, \bar{e}) = \frac{\sigma\ p(\text{orientation}) + count(\text{orientation}, \bar{e}, \bar{f})}{\sigma + \sum_o count(o, \bar{e}, \bar{f})}$$

In Practice:

Phrase table (phrase probability, lexical weight, reverse probability, reverse weight):

```
Maria no             ||| Mary did not ||| 0.1   0.01  0.12  0.02
no daba una bofetada ||| did not slap ||| 0.23  0.009  0.29  0.08
daba una bofetada    ||| slap         ||| 0.16  0.027  0.04  0.06
...
```

Lexicalized reordering table (monotone/swap/discont for both directions):

```
Maria no             ||| Mary did not ||| 0.2 0.2 0.6 0.6 0.2 0.2
no daba una bofetada ||| did not slap ||| 0.4 0.3 0.3 0.3 0.2 0.5
daba una bofetada    ||| slap         ||| 0.3 0.1 0.6 0.6 0.3 0.1
...
```

EM Training of the Phrase Model

- We presented a heuristic set-up to build phrase translation table (word alignment, phrase extraction, phrase scoring)

- Alternative: align phrase pairs directly with EM algorithm
  - initialization: uniform model, all $\phi(\bar{e}, \bar{f})$ are the same
  - expectation step:
    - estimate likelihood of all possible phrase alignments for all sentence pairs
  - maximization step:
    - collect counts for phrase pairs $(\bar{e}, \bar{f})$, weighted by alignment probability
    - update phrase translation probabilties $p(\bar{e}, \bar{f})$

- However: method easily overfits (learns very large phrase pairs, spanning entire sentences)

Summary

- Phrase Model
- Training the model
  - word alignment
  - phrase pair extraction
  - phrase pair scoring
- Log linear model
  - sub-models as feature functions
  - lexical weighting
- Lexicalized reordering model
- EM training of the phrase model