Phrase-Based Models

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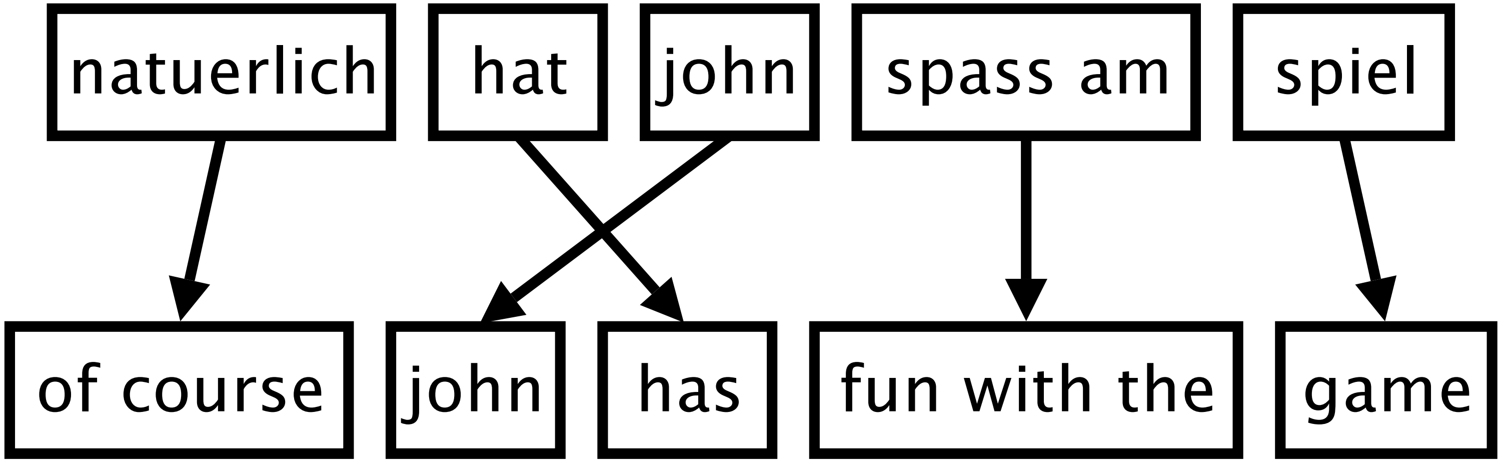
Motivation

- Word-Based Models translate *words* as atomic units
- Phrase-Based Models translate *phrases* 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 until about 2017

Phrase-Based Model



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

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
  (noun phrases, verb phrases, prepositional phrases, ...)

- Example non-linguistic phrase pair

spass am → fun with the

- Prior noun often helps with translation of preposition

- Experiments show that limitation to linguistic phrases hurts quality

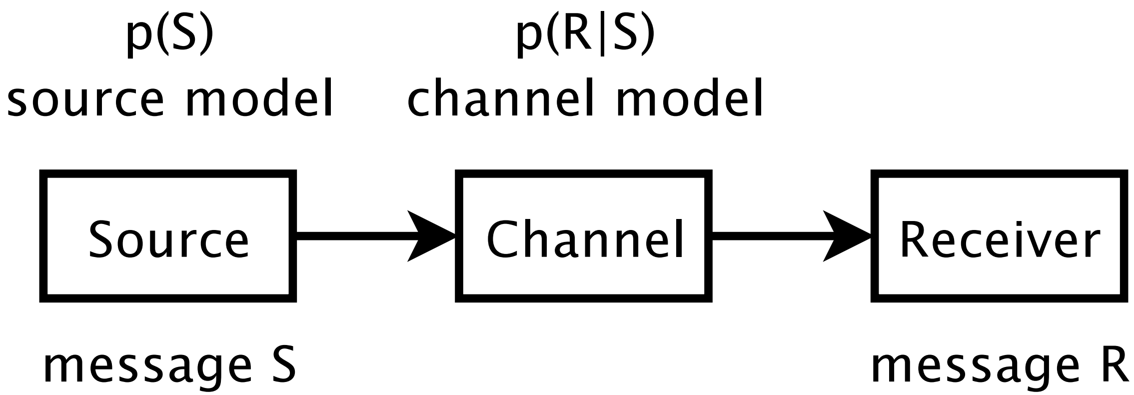
modeling

Noisy Channel Model

- We would like to integrate a language model
- Bayes rule

$$\begin{aligned}\text{argmax}_{\mathbf{e}}\, p(\mathbf{e}|\mathbf{f}) &= \text{argmax}_{\mathbf{e}} \frac{p(\mathbf{f}|\mathbf{e})\; p(\mathbf{e})}{p(\mathbf{f})} \\ &= \text{argmax}_{\mathbf{e}}\, p(\mathbf{f}|\mathbf{e})\; p(\mathbf{e})\end{aligned}$$

Noisy Channel Model



- Applying Bayes rule also called noisy channel model
  - we observe a distorted message R (here: a foreign string **f**)
  - we have a model on how the message is distorted (here: translation model)
  - we have a model on what messages are probably (here: language model)
  - we want to recover the original message S (here: an English string **e**)

More Detail

- Bayes rule

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

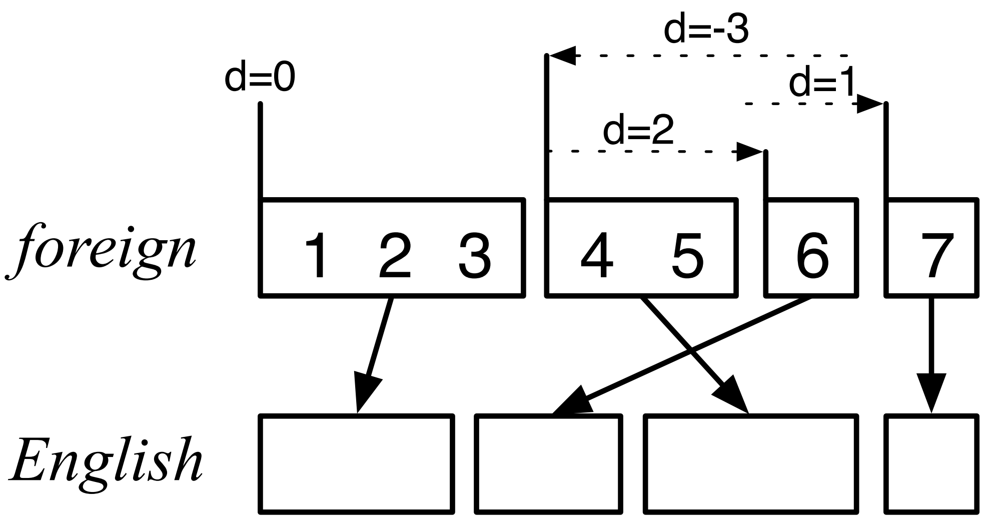
  - translation model $p(\mathbf{f}|\mathbf{e})$
  - language model $p_{\mathsf{LM}}(\mathbf{e})$

- Decomposition of the translation model

$$p(\bar{f}_1^I|\bar{e}_1^I) = \prod_{i=1}^{I} \phi(\bar{f}_i|\bar{e}_i)\; d(start_i - end_{i-1} - 1)$$

  - phrase translation probability ϕ
  - reordering probability d

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

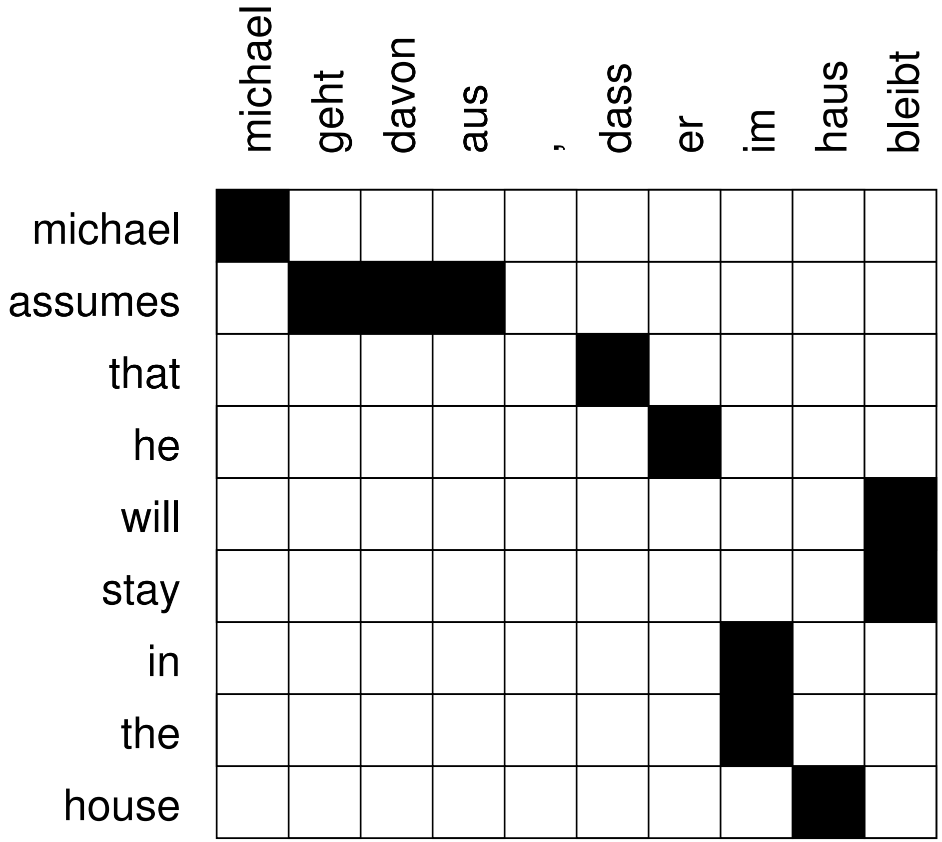
training

Learning a Phrase Translation Table

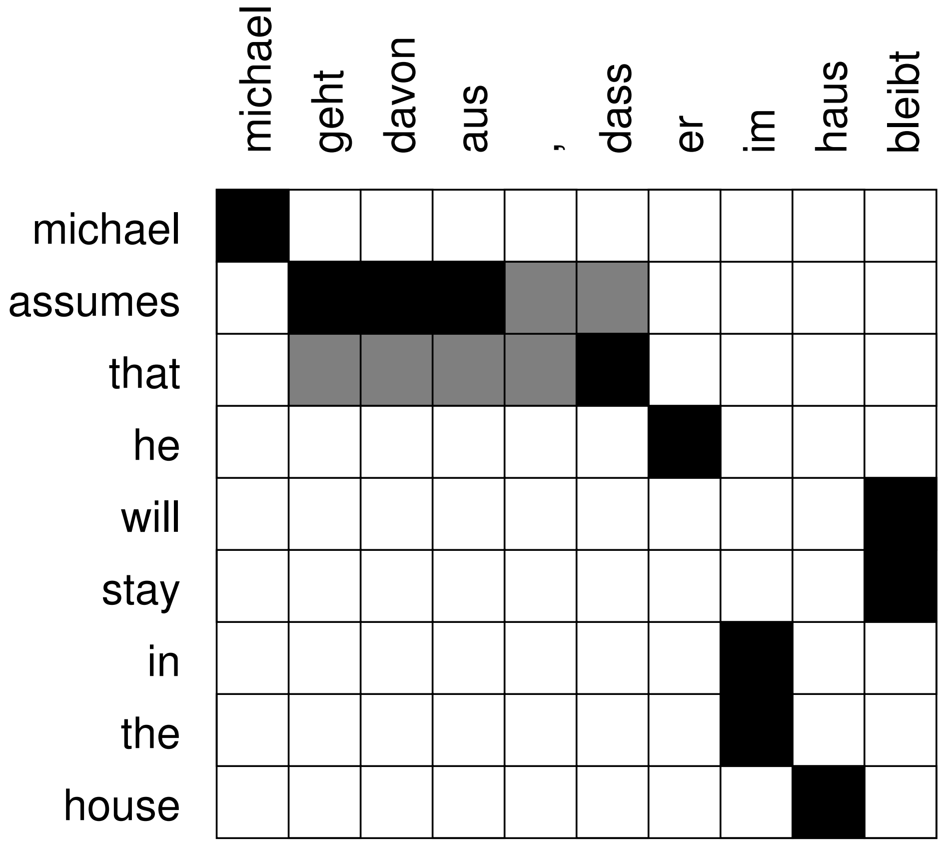
- Task: learn the model from a parallel corpus

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

Word Alignment



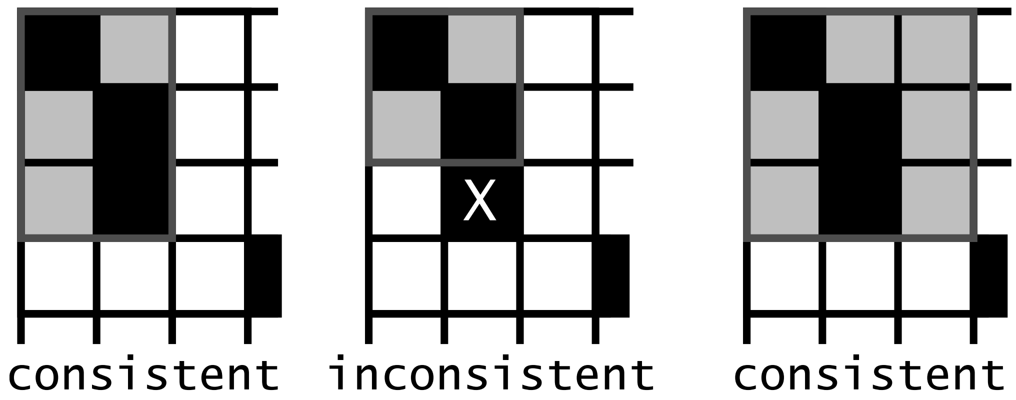
Extracting Phrase Pairs



extract phrase pair consistent with word alignment:

assumes that / geht davon aus , dass

Consistent



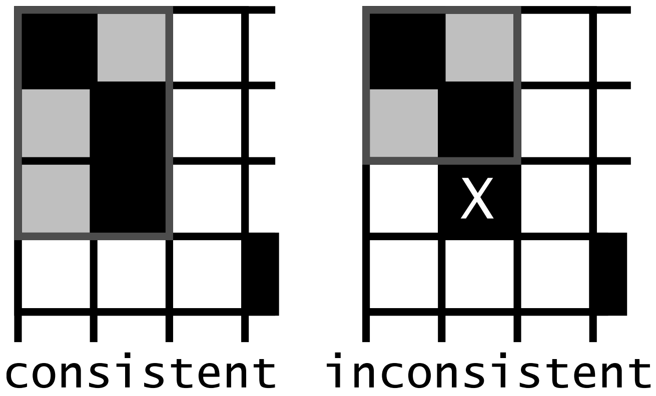
ok

violated
one alignment point outside

ok
unaligned word is fine

All words of the phrase pair have to align to each other.

Consistent



Phrase pair $(\bar{e}, \bar{f})$ consistent with an alignment A, if all words $f_1, ..., f_n$ in $\bar{f}$ that have alignment points in A have these with words $e_1, ..., e_n$ in $\bar{e}$ and vice versa:

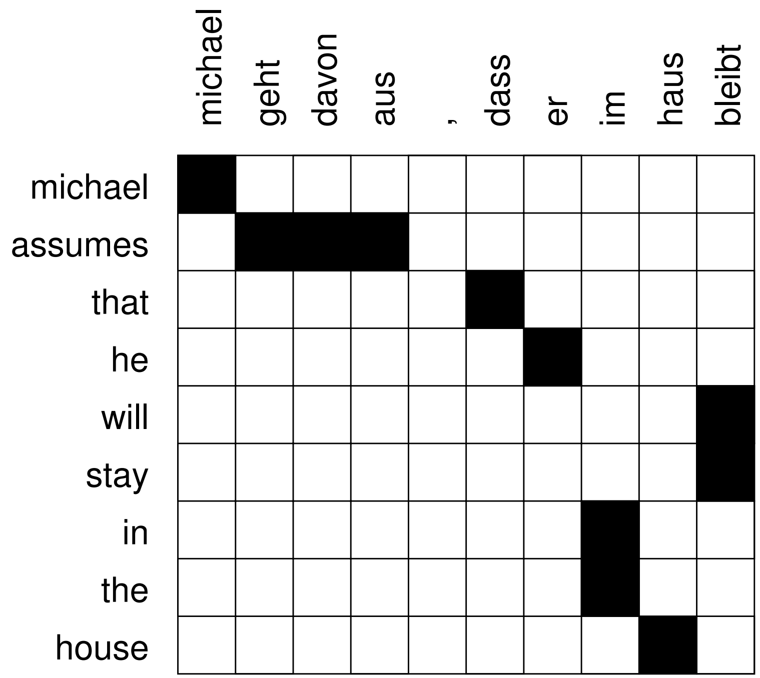
$$(\bar{e}, \bar{f}) \text{ consistent with } A \Leftrightarrow$$

$$\forall e_i \in \bar{e} : (e_i, f_j) \in A \rightarrow f_j \in \bar{f}$$

$$\text{AND } \forall f_j \in \bar{f} : (e_i, f_j) \in A \rightarrow e_i \in \bar{e}$$

$$\text{AND } \exists e_i \in \bar{e}, f_j \in \bar{f} : (e_i, f_j) \in A$$

Phrase Pair Extraction



Smallest phrase pairs:

michael — michael

assumes — geht davon aus / geht davon aus ,

that — dass / , dass

he — er

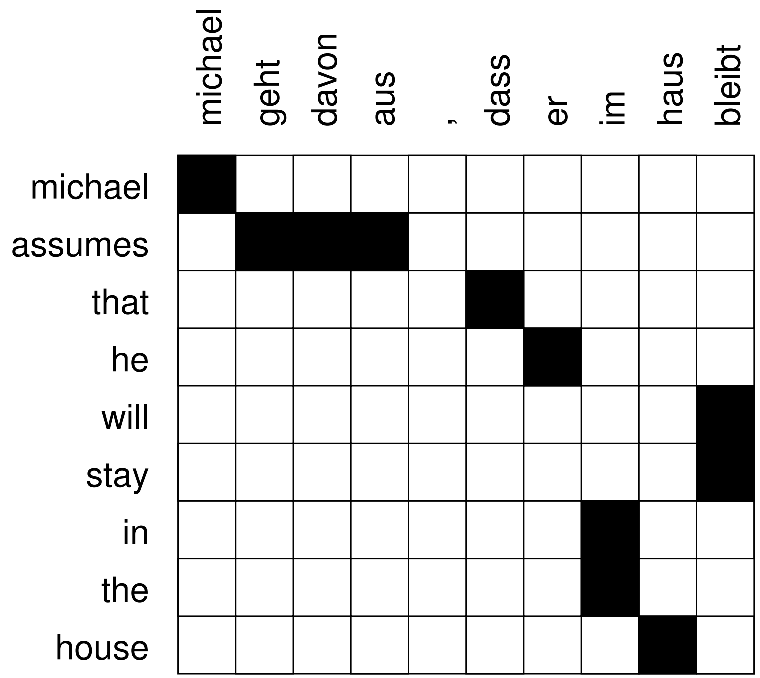
will stay — bleibt

in the — im

house — haus

unaligned words (here: German comma) lead to multiple translations

Larger Phrase Pairs



michael assumes — michael geht davon aus / michael geht davon aus ,
assumes that — geht davon aus , dass ; assumes that he — geht davon aus , dass er
that he — dass er / , dass er ; in the house — im haus
michael assumes that — michael geht davon aus , dass
michael assumes that he — michael geht davon aus , dass er
michael assumes that he will stay in the house — michael geht davon aus , dass er im haus bleibt
assumes that he will stay in the house — geht davon aus , dass er im haus bleibt
that he will stay in the house — dass er im haus bleibt ; dass er im haus bleibt ,
he will stay in the house — er im haus bleibt ; will stay in the house — im haus bleibt

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:

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

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)

Size of the Phrase Table

- Phrase translation table typically bigger than corpus

  ... even with limits on phrase lengths (e.g., max 7 words)

→ Too big to store in memory?

- Solution for training
  - extract to disk, sort, construct for one source phrase at a time

- Solutions for decoding
  - on-disk data structures with index for quick look-ups
  - suffix arrays to create phrase pairs on demand

advanced modeling

Weighted Model

- Described standard model consists of three sub-models
  - phrase translation model $\phi(\bar{f}|\bar{e})$
  - reordering model d
  - language model $p_{LM}(e)$

$$e_{\text{best}} = \text{argmax}_e \prod_{i=1}^{I} \phi(\bar{f}_i|\bar{e}_i)\ d(start_i - end_{i-1} - 1)\ \prod_{i=1}^{|\mathbf{e}|} p_{LM}(e_i|e_1...e_{i-1})$$

- Some sub-models may be more important than others

- Add weights λ_ϕ, λ_d, λ_{LM}

$$e_{\text{best}} = \text{argmax}_e \prod_{i=1}^{I} \phi(\bar{f}_i|\bar{e}_i)^{\lambda_\phi}\ d(start_i - end_{i-1} - 1)^{\lambda_d}\ \prod_{i=1}^{|\mathbf{e}|} p_{LM}(e_i|e_1...e_{i-1})^{\lambda_{LM}}$$

Log-Linear Model

- Such a weighted model is a log-linear model:

$$p(x) = \exp \sum_{i=1}^{n} \lambda_i h_i(x)$$

- Our feature functions
  - number of feature function $n = 3$
  - random variable $x = (e, f, start, end)$
  - feature function $h_1 = \log \phi$
  - feature function $h_2 = \log d$
  - feature function $h_3 = \log p_{\text{LM}}$

Weighted Model as Log-Linear Model

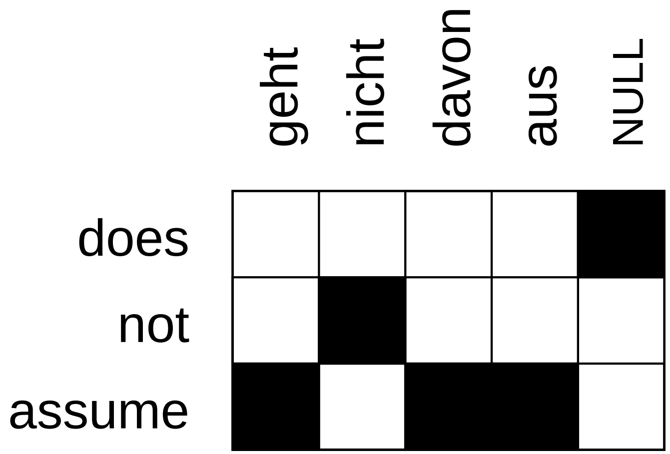
$$p(e,a|f) = \exp(\lambda_\phi \sum_{i=1}^{I} \log \phi(\bar{f}_i|\bar{e}_i) +$$

$$\lambda_d \sum_{i=1}^{I} \log d(a_i - b_{i-1} - 1) +$$

$$\lambda_{LM} \sum_{i=1}^{|\mathbf{e}|} \log p_{LM}(e_i|e_1...e_{i-1}))$$

More Feature Functions

- Bidirectional alignment probabilities: $\phi(\bar{e}|\bar{f})$ and $\phi(\bar{f}|\bar{e})$
- Rare phrase pairs have unreliable phrase translation probability estimates
  $\rightarrow$ lexical weighting with word translation probabilities



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

More Feature Functions

- Language model has a bias towards short translations

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

- We may prefer finer or coarser segmentation

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

- Multiple language models

- Multiple translation models

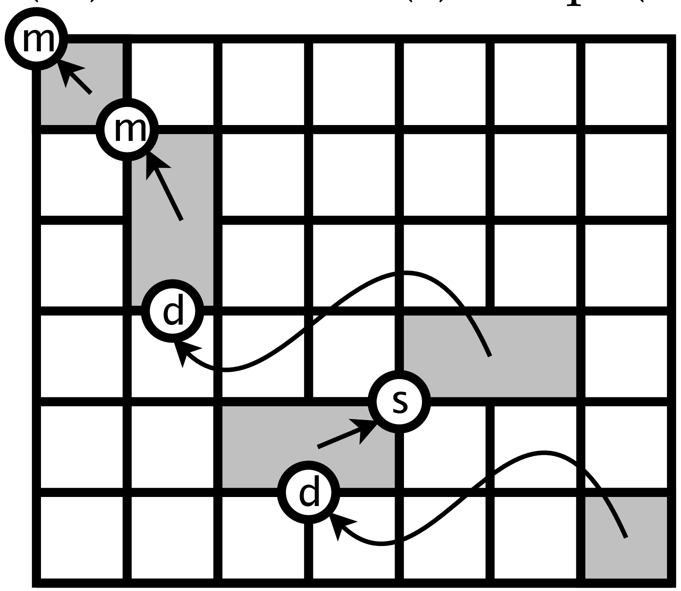
- Other knowledge sources

reordering

Lexicalized Reordering

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

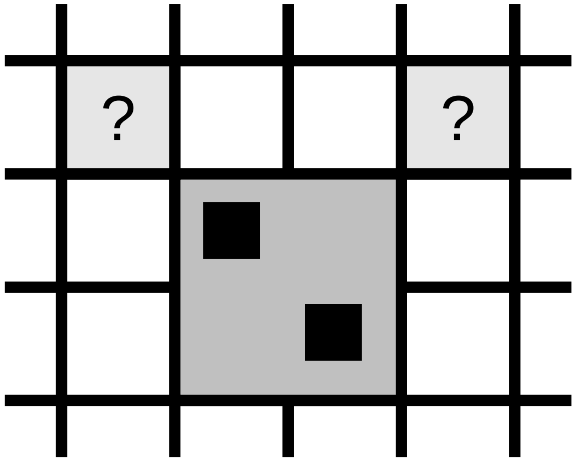
- Three orientations types: (m) monotone, (s) swap, (d) discontinuous



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

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

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

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

operation sequence model

A Critique: Phrase Segmentation is Arbitrary

- If multiple segmentations possible - why chose one over the other?

  | spass am | spiel | vs. | spass | am spiel |

- When choose larger phrase pairs or multiple shorter phrase pairs?

  | spass am | spiel | vs. | spass | am | spiel | vs. | spass am spiel |

- None of this has been properly addressed

A Critique: Strong Independence Assumptions

- Lexical context considered only within phrase pairs

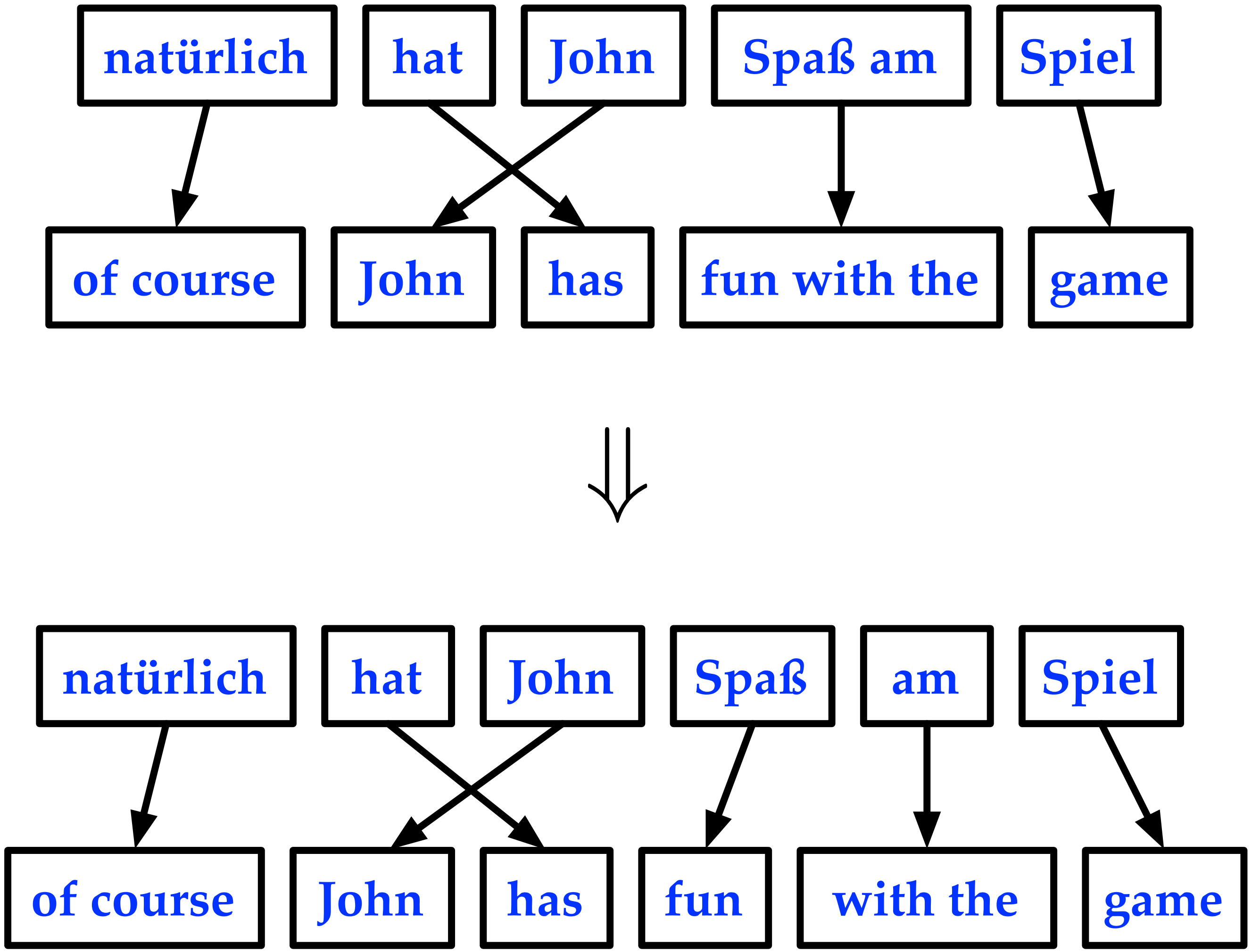
  $\boxed{\text{spass am}} \rightarrow \boxed{\text{fun with}}$

- No context considered between phrase pairs

  ? $\boxed{\text{spass am}}$? $\rightarrow$? $\boxed{\text{fun with}}$?

- Some phrasal context considered in lexicalized reordering model
  ... but not based on the identity of neighboring phrases

Segmentation? Minimal Phrase Pairs



Independence?
Consider Sequence of Operations

o_1	Generate(natürlich, of course)	natürlich ↓ of course
o_2 o_3	Insert Gap Generate (John, John)	natürlich ↓ $\boxed{}$ John of course John
o_4 o_5	Jump Back (1) Generate (hat, has)	natürlich hat ↓ John of course John has
o_6	Jump Forward	natürlich hat John ↓ of course John has
o_7	Generate(natürlich, of course)	natürlich hat John Spaß ↓ of course John has fun
o_8 o_9	Generate(am, with) GenerateTargetOnly(the)	natürlich hat John Spaß am ↓ of course John has fun with the
o_{10}	Generate(Spiel, game)	natürlich hat John Spaß am Spiel ↓ of course John has fun with the game

Operation Sequence Model

- Operations
  - generate (phrase translation)
  - generate target only
  - generate source only
  - insert gap
  - jump back
  - jump forward

- N-gram sequence model over operations, e.g., 5-gram model:

$$p(o_1)\ p(o_2|o_1)\ p(o_3|o_1, o_2)\ ...\ p(o_{10}|o_6, o_7, o_8, o_9)$$

In Practice

- Operation Sequence Model used as additional feature function

- Significant improvements over phrase-based baseline

$\rightarrow$ State-of-the-art systems include such a model

Summary

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