Machine Translation

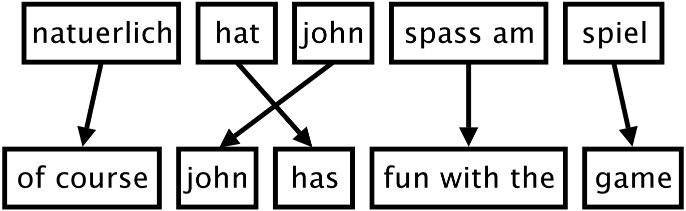
Computational Linguistics: Jordan Boyd-Graber
University of Maryland
PHRASE-BASED MODELS

Adapted from material by Philipp Koehn

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" until recently

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**

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	$\phi(\bar{e}\vert\bar{f})$	English	$\phi(\bar{e}\vert\bar{f})$
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

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

- Prior noun often helps with translation of preposition
- Experiments show that limitation to linguistic phrases hurts quality

Probabilistic Model

- Bayes rule

$$\mathbf{e}_{\mathbf{best}} = \mathbf{argmax}_{\mathbf{e}}\, p(\mathbf{e}|\mathbf{f}) = \mathbf{argmax}_{\mathbf{e}}\, p(\mathbf{f}|\mathbf{e})\, p_{\mathrm{lm}}(\mathbf{e})$$

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

Probabilistic Model

- Bayes rule

$$\mathbf{e}_{\text{best}} = \textbf{argmax}_{\mathbf{e}}\, p(\mathbf{e}|\mathbf{f}) = \textbf{argmax}_{\mathbf{e}}\, p(\mathbf{f}|\mathbf{e})\, p_{\text{lm}}(\mathbf{e})$$

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

Probabilistic Model

- Bayes rule

$$\mathbf{e}_{\text{best}} = \textbf{argmax}_{\mathbf{e}}\, p(\mathbf{e}|\mathbf{f}) = \textbf{argmax}_{\mathbf{e}}\, p(\mathbf{f}|\mathbf{e})\, p_{\text{lm}}(\mathbf{e})$$

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

- 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

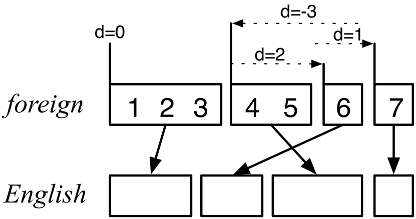
Good to use context, but . . .

- Phrases are mostly independent (LM is glue)
- Would like to use wider context
- And have fuzzy phrase boundaries

Good to use context, but . . .

- Phrases are mostly independent (LM is glue)
- Would like to use wider context
- And have fuzzy phrase boundaries
- Neural models!

Distance-Based Reordering



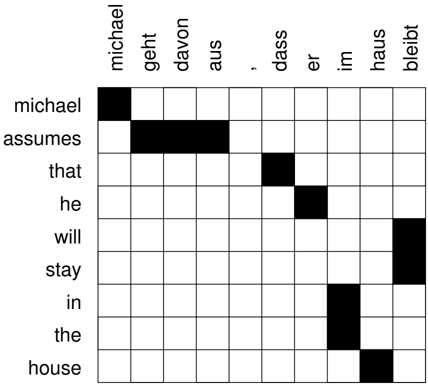
phrase	translates	movement	distance
1	1–3	start at beginning	0
2	6	skip over 4–5	+2
3	4–5	move back over 4–6	-3
4	7	skip over 6	+1

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

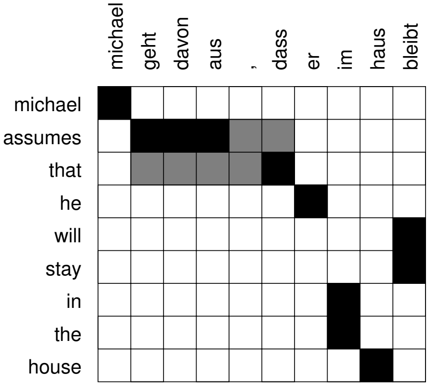
Learning a Phrase Translation Table

- 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



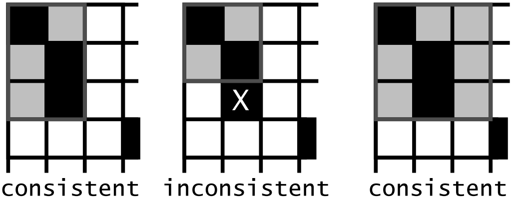
Extracting Phrase Pairs



extract phrase pair consistent with word alignment:

assumes that / geht davon aus , dass

Consistent

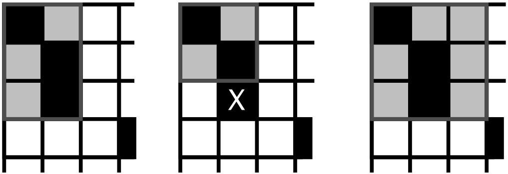


ok	violated	ok
	one alignment point outside	unaligned word is fine

Bottom line:

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:

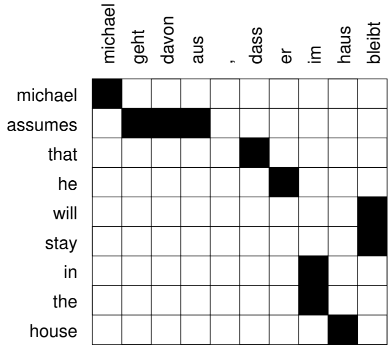
$$(\bar{e}, \bar{f}) \textbf{ consistent with } A \Leftrightarrow$$

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

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

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

Phrase Pair Extraction



Smallest phrase pairs:

michael — michael

assumes — geht davon aus / geht davon aus

,

that — dass / , dass

he — er

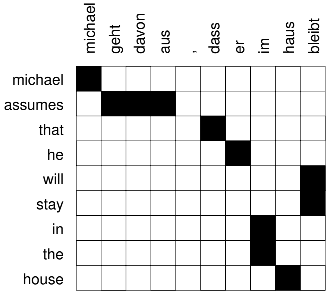
will stay — bleibt

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:

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

Size of the Phrase Table

- Phrase translation table typically bigger than corpus

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

$\longrightarrow$ 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

Weighted Model

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

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

- Some sub-models may be more important than others
- Add weights λ_ϕ, λ_d, λ_{LM}

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

Log-Linear Model

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

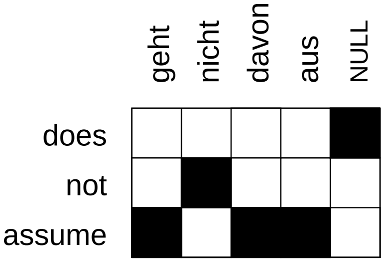
$$p(x) = \exp \sum_{i=1}^{n} \lambda_i h_i(x)$$

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

Weighted Model as Log-Linear Model

$$
\begin{aligned}
p(e, a|f) = \mathbf{exp}(\lambda_\phi \sum_{i=1}^{I} \mathbf{log}\, \phi(\bar{f}_i|\bar{e}_i) + \\
\lambda_d \sum_{i=1}^{I} \mathbf{log}\, d(a_i - b_{i-1} - 1) + \\
\lambda_{LM} \sum_{i=1}^{|\mathbf{e}|} \mathbf{log}\, p_{LM}(e_i|e_1 ... e_{i-1}))
\end{aligned}
$$

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

$\longrightarrow$ lexical weighting with word translation probabilities

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

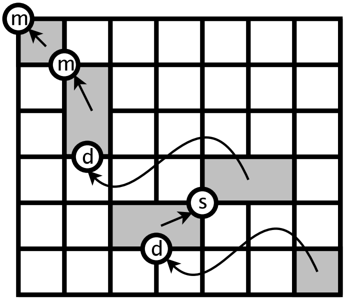
More Feature Functions

- Language model has a bias towards short translations

  $\longrightarrow$ word count: $\mathbf{wc}(e) = \log |\mathbf{e}|^{\omega}$
- We may prefer finer or coarser segmentation

  $\longrightarrow$ phrase count $\mathbf{pc}(e) = \log |I|^{\rho}$
- Multiple language models
- Multiple translation models
- Other knowledge sources

Lexicalized Reordering



- Distance-based reordering model is weak

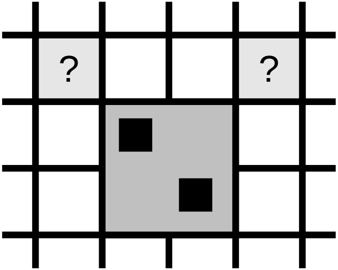
  $\longrightarrow$ learn reordering preference for each phrase pair

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

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

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

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

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

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

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

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
  - word and phrase count features
- Lexicalized reordering model
- EM training of the phrase model