Phrase-based models

Hasso Plattner Institut
IT Systems Engineering | Universität Potsdam

Dr. Mariana Neves
(adapted from the original slides
of Prof. Philipp Koehn)

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Motivation

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

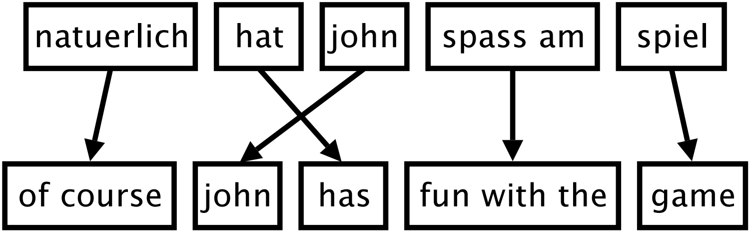
Motivation

- 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

Phrase-Based Model

- "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 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, ...)

- fun with the game: fun is a noun phrase and with the game is a prepositional phrase

Linguistic Phrases?

- Example non-linguistic phrase pair:

  spass am → fun with the

- Prior noun often helps with translation of preposition:
  - am is usually translated to on the or at the, but with the is rather unusual.
- Experiments show that limitation to linguistic phrases hurts quality.

Benefits of phrases over words for translations

- Words may not be the best atomic units, due to one-to-many mappings (and vice-versa).
- Translating words groups helps to resolve ambiguities.
- It is possible to learn longer and longer phrases based on large training corpora.
- We do not need to deal with the complex notions of fertility, insertion and deletions.

Probabilistic Model

- Bayes rule

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

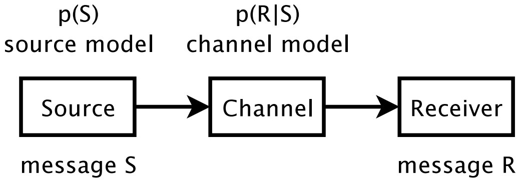
  - translation model $p(\mathbf{e}|\mathbf{f})$
  - language model $p_{\mathrm{LM}}(\mathbf{e})$

Recap Word-based models: Noisy Channel Model

- We would like to integrate a language model.
- We look for the best translation e for the input foreign sentence f.
- Use use Bayes rule to include $p(e)$:

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

Recap Word-based models: 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**)

Probabilistic Model

- 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

- Segmentation is not modeled explicitly and any segmentation is equally likely.

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

- Each foreign phrase f is broken up into I phrases $\bar{f}_i$.
- Each foreign sentence $\bar{f}_i$ is translated into an English sentence $\bar{e}_i$.

Distance-Based Reordering

- Reordering is relative to the previous phrase:

$$d(start_i - end_{i-1} - 1)$$

  - $start_i$ is the position of the first word of the foreign phrase that translates to the ith English phrase.
  - end_i is the position of the last word of that foreign phrase.
  - end_{i-1} is the position of the last word of the foreign phrase that translates to the $(i-1)$th English phrase.
  - reordering distance is computed as $start_i - end_{i-1} - 1$

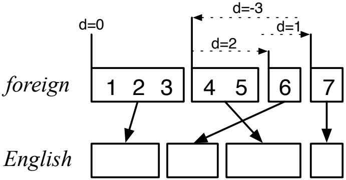
Distance-Based Reordering

- The reordering distance is the number of phrases skipped (forward or backward):

$$d(start_i - end_{i-1} - 1)$$

  - If two phrases are translated in sequence: $start_i = end_{i-1} - 1$ (reordering cost $d(0)$)

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

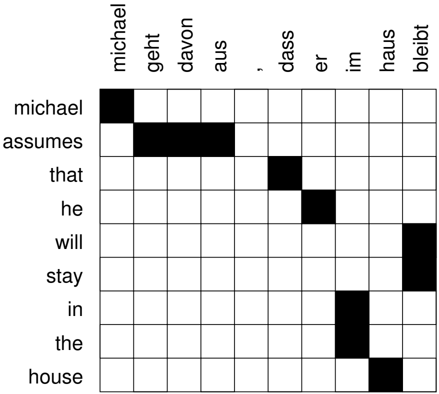
Distance-Based Reordering

- Scoring function: $d(x) = \alpha^{|x|}$ — exponential with distance
- Movements of phrases over large distances are more expensive than short distances or no movement at all.
- $\alpha \in [0, 1]$

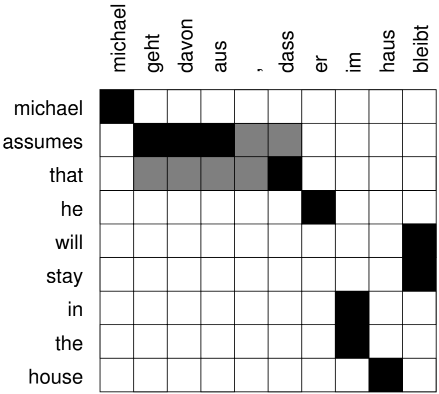
Learning a Phrase Translation Table

- 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

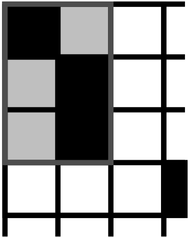


extract phrase pair consistent with word alignment:
assumes that / geht davon aus , dass

Extracting Phrase Pairs

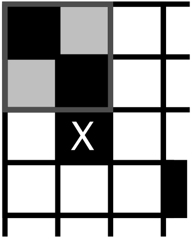
- Phrases can be shorter or longer:
  - Shorter phrases occur frequently and are more often applicable to unseen sentences.
  - Longer phrases capture more local context and can be used to translate large chunks of text at one time.

Consistency



consistent

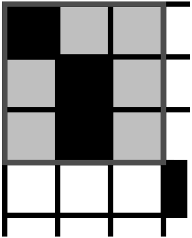
ok



inconsistent

violated

one alignment point outside



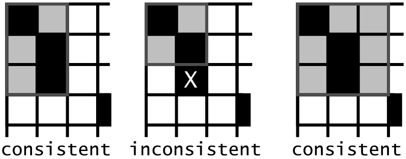
consistent

ok

unaligned word is fine

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

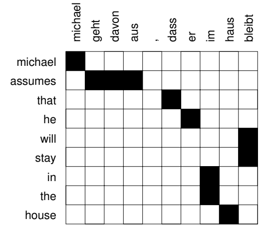
Consistency



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:

$$
\begin{aligned}
(\bar{e}, \bar{f}) \text{ consistent with } A \Leftrightarrow& \\
&\forall e_i \in \bar{e} : (e_i, f_j) \in A \rightarrow f_j \in \bar{f} \\
\text{AND } &\forall f_j \in \bar{f} : (e_i, f_j) \in A \rightarrow e_i \in \bar{e} \\
\text{AND } &\exists e_i \in \bar{e}, f_j \in \bar{f} : (e_i, f_j) \in A
\end{aligned}
$$

Phrase Pair Extraction



Smallest phrase pairs:

michael — michael

assumes — geht davon aus / geht davon aus ,

that — dass / , dass

he — er

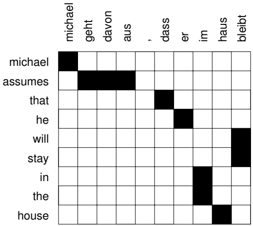
will stay — bleibt

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

Remarks on Phrase Pair Extraction

- We cannot extract matching German phrases for some English phrases
  - e.g., im is mapped to both in and the

Remarks on Phrase Pair Extraction

- We cannot extract matching German phrases for some English phrases
  - e.g., he will stay cannot be mapped to er ... bleibt

Remarks on Phrase Pair Extraction

- Unaligned words can lead to multiple matches
  - e.g., the comma can be aligned or not together with dass

Remarks on Phrase Pair Extraction

- Some statistics:
  - 9 English words, 10 German words: 11 alignment points
  - 36 English phrases, 45 German phrases: 24 pairs extracted
- The number of extracted phrases can be quadratic in the number of words.
- Limiting the length of the phrases is recommended.

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:

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

Standard model

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

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

Weighted Model

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

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

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 $h_1 = \log \phi$
  - feature function $h_2 = \log d$
  - feature function $h_3 = \log p_{\mathrm{LM}}$

Weighted Model as Log-Linear Model

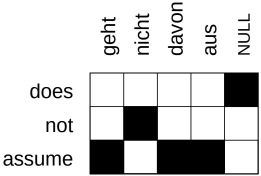
$$p(e, a|f) = \exp(\lambda_\phi \sum_{i=1}^{I} \log \phi(\bar{f}_i|\bar{e}_i) +$$
$$\lambda_d \sum_{i=1}^{I} \log d(a_i - b_{i-1} - 1) +$$
$$\lambda_{LM} \sum_{i=1}^{|\mathbf{e}|} \log p_{LM}(e_i|e_1 \ldots e_{i-1}))$$

Bidirectional translation probabilities

- Situation: A rare long English phrase $\bar{e}$ gets mapped to a common foreign phrase $\bar{f}$.
- Bidirectional alignment probabilities: $\phi(\bar{e}|\bar{f})$ and $\phi(\bar{f}|\bar{e})$.
- A model using both translation directions usually outperforms a model using only one of them.

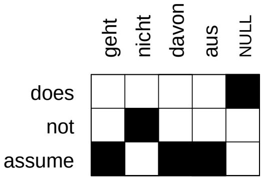
Lexical weighting

- Situation: rare phrase pairs have unreliable phrase translation probability estimates
  $\rightarrow$ lexical weighting with word translation probabilities



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

Lexical weighting



$$\begin{aligned}\text{lex}(\bar{e}|\bar{f}, a) = & w(does|NULL)\times \\ & w(not|nicht)\times \\ & \frac{1}{3}(w(assume|geht) + w(assume|davon) + w(assume|aus))\end{aligned}$$

Word penalty

- Language model has a bias towards short translations:
  $\rightarrow$ word count (output length): $\mathrm{wc}(e) = \log |\mathbf{e}|^{\omega}$

- $\omega < 1$: preference for shorter translations.
- $\omega > 1$: preference for longer translations.

Phrase penalty

- We may prefer finer (many short phrases) or coarser (few longer phrases) segmentation:
  $\rightarrow$ phrase count: $\mathrm{pc}(e) = \log |I|^{\rho}$

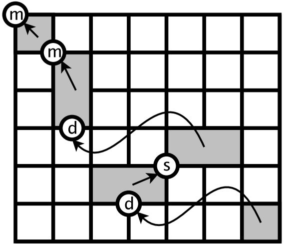
- $\rho < 1$: preference for fewer (longer) phrases.
- $\rho > 1$: preference for more (shorter) phrases.

Reordering

- Different language pairs need different types of reordering:
  - local: French, Arabian, Chinese to English
  - distant: German, Japanese to English

- Our reordering model generally punishes movement and it is up to the language model (usually based on trigrams) to justify the placement of words in a different order.

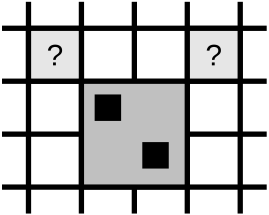
Lexicalized Reordering



- Distance-based reordering model is weak
  $\rightarrow$ 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 based on the maximum likelihood principle:

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

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

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

EM Training of the Phrase Model

- What if we do not have the word alignment for the sentences?
- Could we align the phrases directly from the sentence pairs?

- 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

EM Training of the Phrase Model

- 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 $p(\bar{e}, \bar{f})$

Drawbacks of EM for Phrase Model

- There are many possibilities of phrases (input and output).
  - We might want to limit the phrases space: minimum occurrences for a phrase or phrase pair.
- Greedy search heuristic: can find high-probability phrase alignments in a reasonable time.
- Results are usually no better than using word alignments as input.
  - The 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

Suggested reading

- Statistical Machine Translation, Philipp Koehn (chapter 5).