Machine Translation
Phrase-based Models 1 (Training)

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(slides by Philipp Koehn and Barry Haddow)

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School of informatics

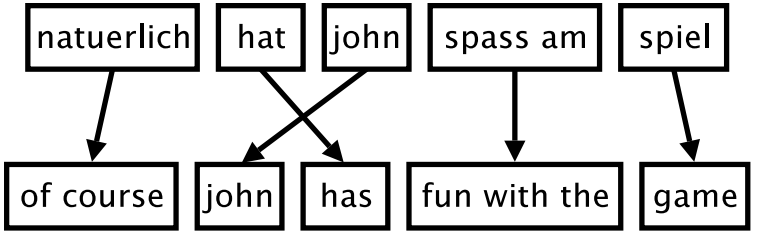
Outline

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

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

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	...	...

Real Example: Observations

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

Linguistic Phrases?

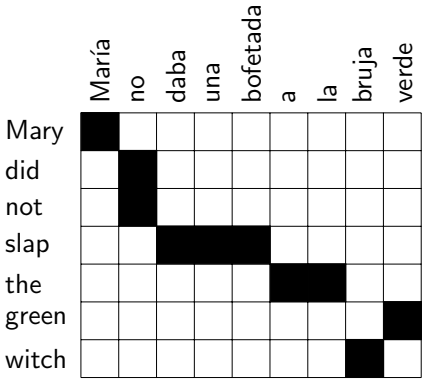
- Model is not limited to linguistic phrases
  (noun phrases, verb phrases, prepositional phrases, ...)
- Example non-linguistic phrase pair

  spass am → fun with the
- Prior noun often helps with translation of preposition
- Experiments show that limitation to linguistic phrases hurts quality

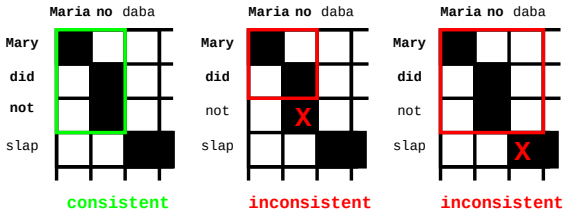
Learning a Phrase Translation Table

- 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



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.

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

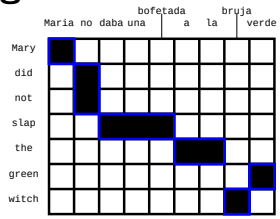
2. No Foreign words in the phrase pair are aligned to words outside it.

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

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

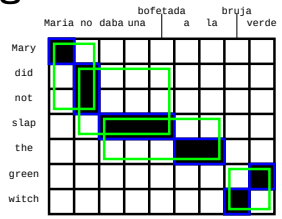
$$\exists e_i \in \overline{e}, f_j \in \overline{f} \; s.t. \; (e_i, f_j) \in A$$

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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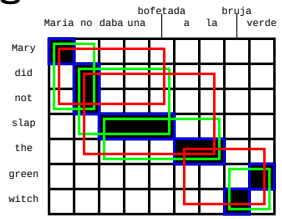

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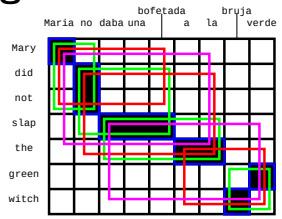

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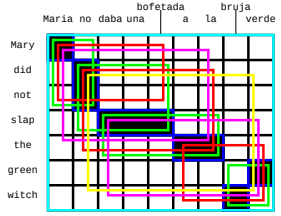
Word alignment induced phrases (5)



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

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

- Bayes rule

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

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

- Decomposition of the translation model

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

Linear Model

We always work in log space, so translations are scored as follows:

$$score(\mathbf{e})\ (\equiv logp(\mathbf{e}|\mathbf{f})) = \log p_{\text{TM}}(\mathbf{f}|\mathbf{e}) + \log p_{\text{LM}}(\mathbf{e})$$

This suggests that we could weight the models differently

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

So why not just go the whole way and use a linear (log-linear?) model

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

But where do the weights come from? (Lecture 10!)

Expanding the Model

- Now we can add more feature functions
  - Reverse phrase translation probability (i.e. $p_{\mathrm{TM}}(\mathbf{e}|\mathbf{f})$)
  - Lexical translation probabilities (from IBM models)
  - Phrase count
  - Word count
  - Distortion cost (Lecture 11)
  - Reordering score (Lecture 11)
- Why might these be useful?

Using the Model

To translate a foreign sentence $\mathbf{f}$, we have to solve

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

In reality what we do is (Viterbi approximation)

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

- This is known as *decoding*
- It's a search problem
- The search space is huge

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

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
- EM training of the phrase model