Statistical Machine Translation
Part III – Many-to-Many Alignments

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- Last time, we discussed Model 1 and Expectation Maximization
- Today we will discuss getting useful alignments for translation and a translation model

IBM Model 1

- *Generative model*: break up translation process into smaller steps
  - **IBM Model 1** only uses *lexical translation*

- Translation probability
  - for a foreign sentence $\mathbf{f} = (f_1, ..., f_{l_f})$ of length l_f
  - to an English sentence $\mathbf{e} = (e_1, ..., e_{l_e})$ of length l_e
  - with an alignment of each English word e_j to a foreign word f_i according to the alignment function $a : j \rightarrow i$

$$p(\mathbf{e}, a|\mathbf{f}) = \frac{\epsilon}{(l_f + 1)^{l_e}} \prod_{j=1}^{l_e} t(e_j|f_{a(j)})$$

  - parameter ϵ is a *normalization constant*

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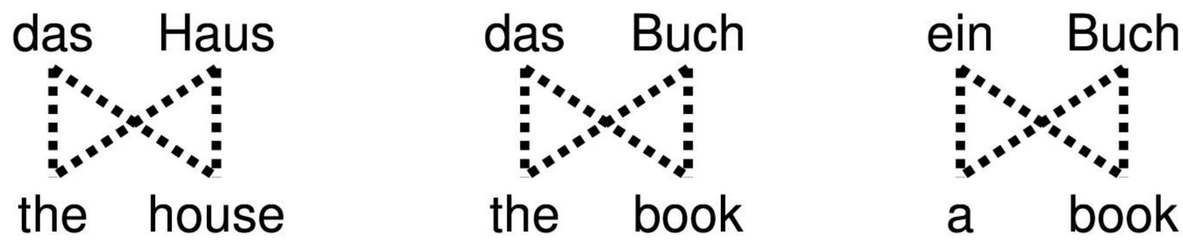
Convergence



e	f	initial	1st it.	2nd it.	3rd it.	...	final
the	das	0.25	0.5	0.6364	0.7479	...	1
book	das	0.25	0.25	0.1818	0.1208	...	0
house	das	0.25	0.25	0.1818	0.1313	...	0
the	buch	0.25	0.25	0.1818	0.1208	...	0
book	buch	0.25	0.5	0.6364	0.7479	...	1
a	buch	0.25	0.25	0.1818	0.1313	...	0
book	ein	0.25	0.5	0.4286	0.3466	...	0
a	ein	0.25	0.5	0.5714	0.6534	...	1
the	haus	0.25	0.5	0.4286	0.3466	...	0
house	haus	0.25	0.5	0.5714	0.6534	...	1

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Higher IBM Models

IBM Model 1	lexical translation
IBM Model 2	adds absolute reordering model
IBM Model 3	adds fertility model
IBM Model 4	relative reordering model
IBM Model 5	fixes deficiency

- Only IBM Model 1 has global maximum
  - training of a higher IBM model builds on previous model
- Compuationally biggest change in Model 3
  - trick to simplify estimation does not work anymore
  - $\rightarrow$ exhaustive count collection becomes computationally too expensive
  - sampling over high probability alignments is used instead

HMM Model

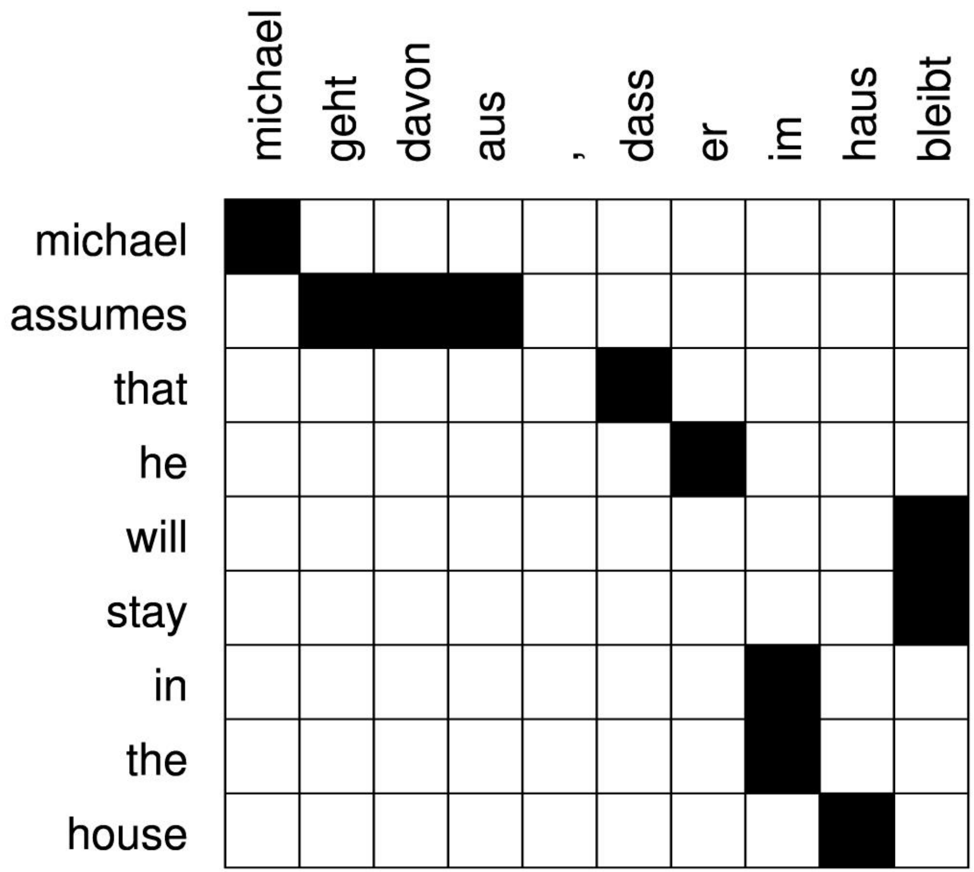
- Model 4 requires local search (making small changes to an initial alignment and rescoring)
- Another popular model is the HMM model, which is similar to Model 2 except that it uses relative alignment positions (like Model 4)
- Popular because it supports inference via the forward-backward algorithm

Overcoming 1-to-N

- We'll now discuss overcoming the poor assumption behind alignment functions

Word Alignment

Given a sentence pair, which words correspond to each other?



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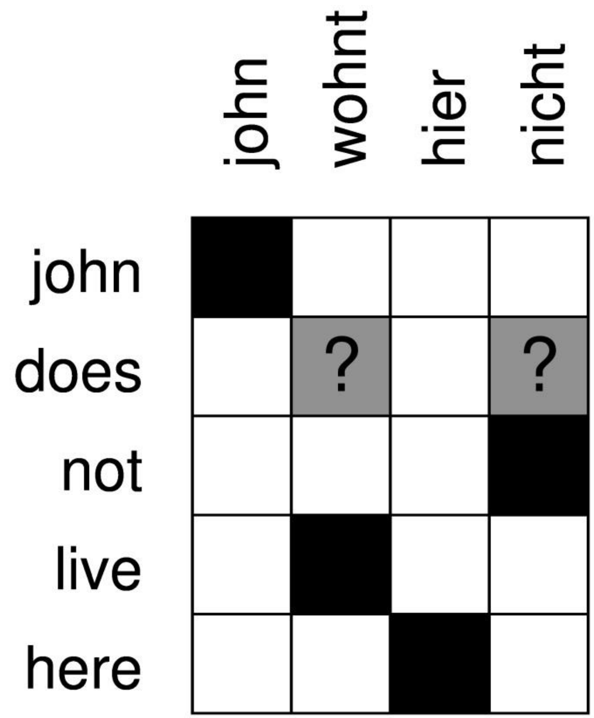
Word Alignment?



Is the English word does aligned to the German wohnt (verb) or nicht (negation) or neither?

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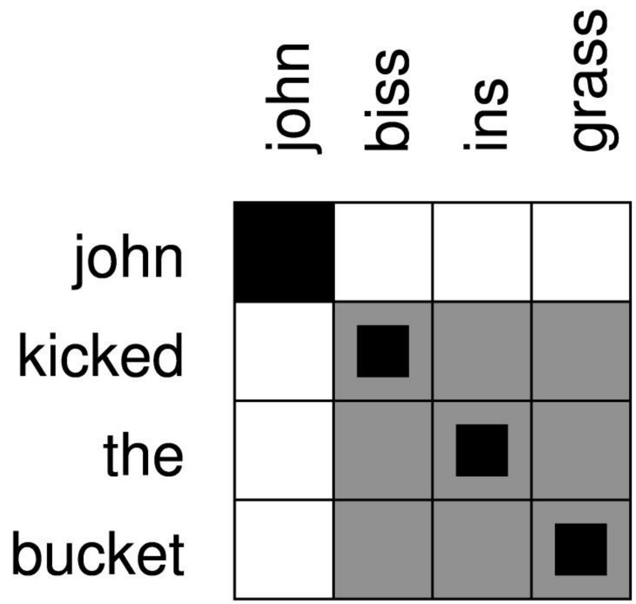
Word Alignment?

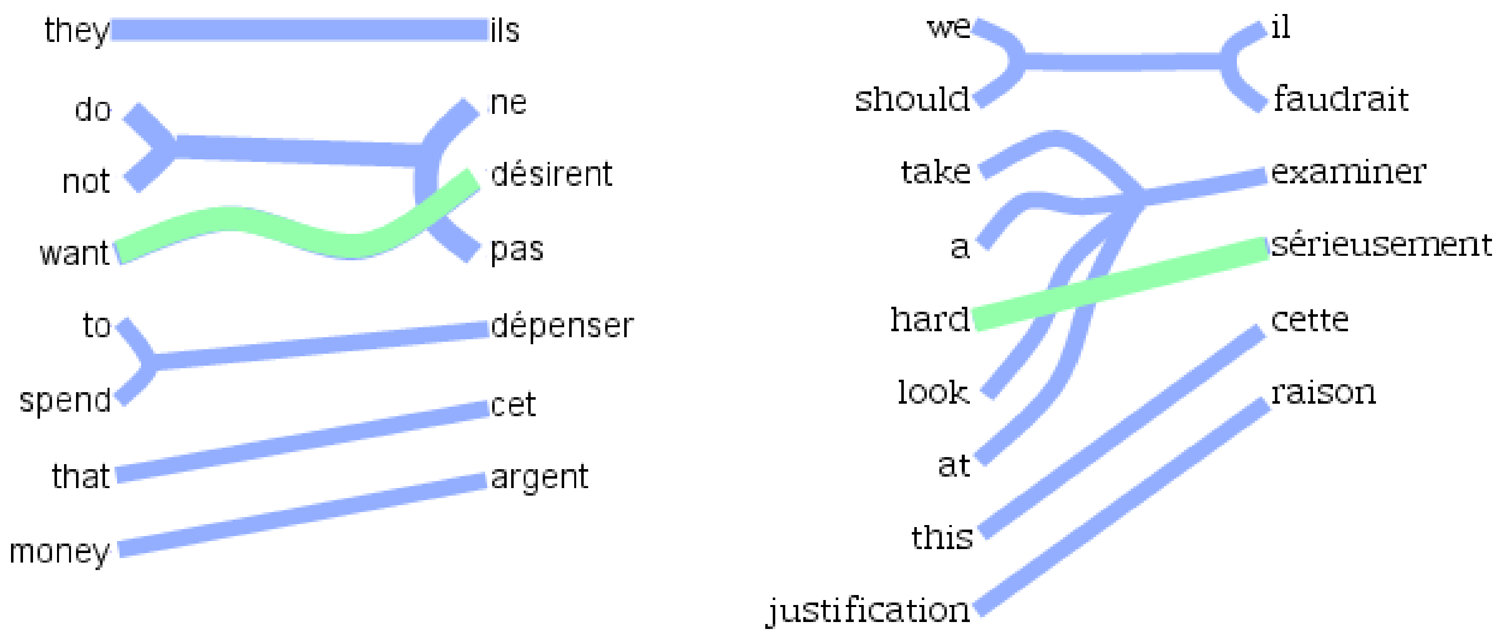


How do the idioms kicked the bucket and biss ins grass match up?
Outside this exceptional context, bucket is never a good translation for grass

Word Alignment with IBM Models

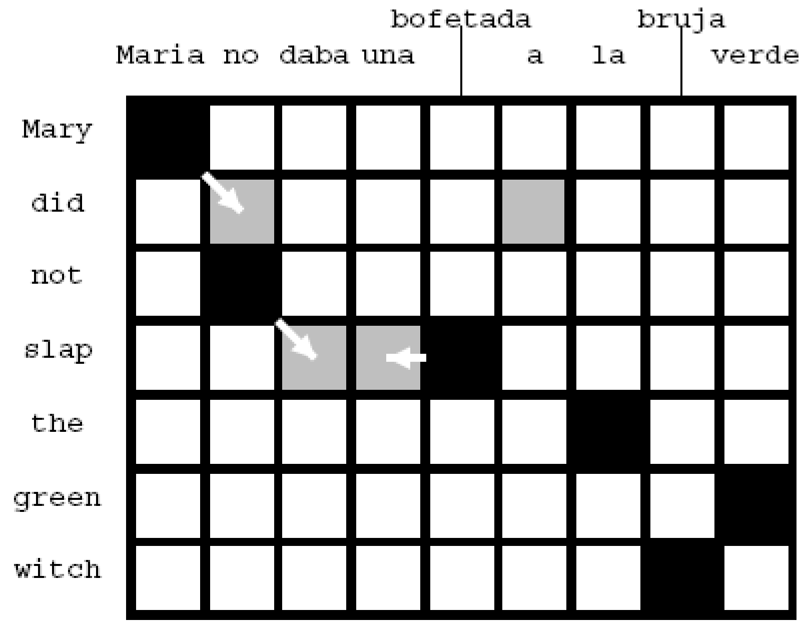
- IBM Models create a **many-to-one** mapping
  - words are aligned using an alignment function
  - a function may return the same value for different input (one-to-many mapping)
  - a function can not return multiple values for one input (no many-to-one mapping)
- Real word alignments have **many-to-many** mappings

IBM Models: 1-to-N Assumption



- 1-to-N assumption
  - Multi-word “cepts” (words in one language translated as a unit) only allowed on target side. Source side limited to single word “cepts”.
  - Forced to create M-to-N alignments using heuristics

Symmetrizing word alignments



- *Grow* additional alignment points [Och and Ney, CompLing2003]

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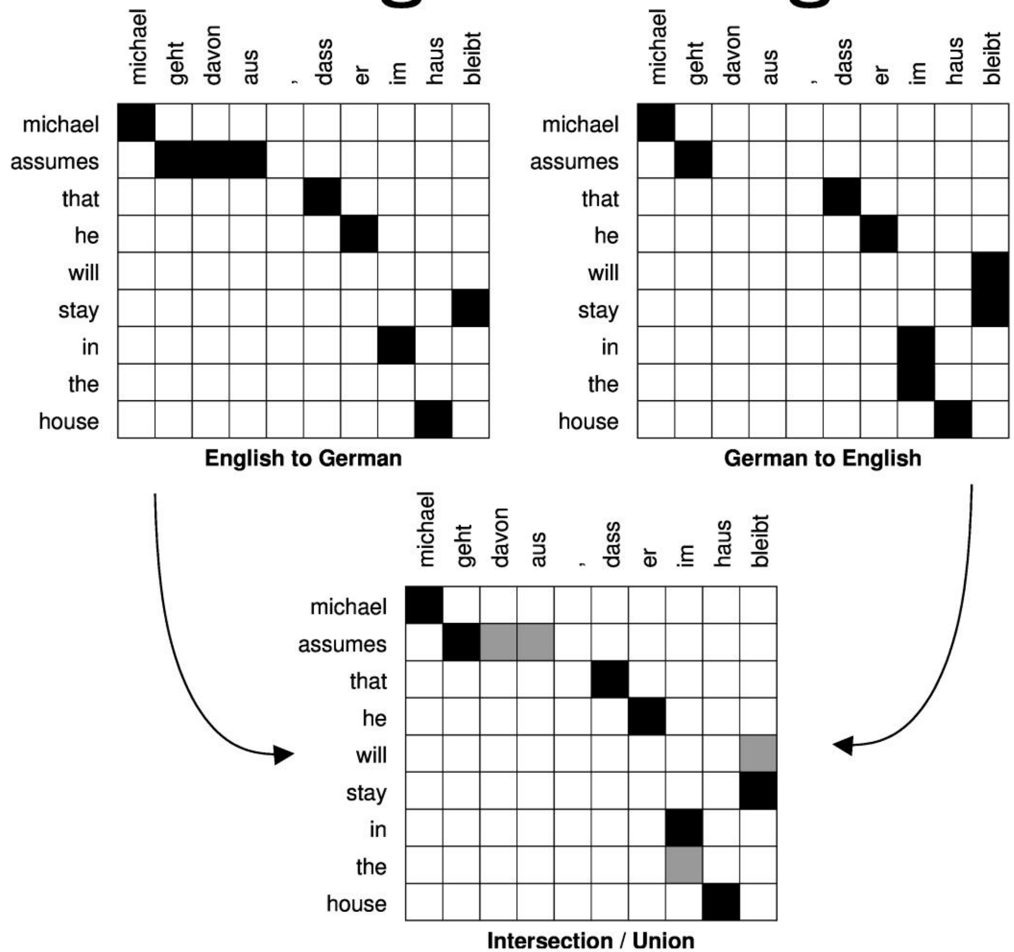
Symmetrizing Word Alignments



- Intersection of GIZA++ bidirectional alignments
- Grow additional alignment points [Och and Ney, CompLing2003]

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Growing heuristic

grow-diag-final(e2f,f2e)

neighboring = {(-1,0),(0,-1),(1,0),(0,1),(-1,-1),(-1,1),(1,-1),(1,1)}
alignment A = intersect(e2f,f2e); grow-diag(); final(e2f); final(f2e);

grow-diag()

while new points added **do**
  for all English word $e \in [1...e_n]$, foreign word $f \in [1...f_n]$, $(e, f) \in A$ **do**
    for all neighboring alignment points $(e_{\text{new}}, f_{\text{new}})$ **do**
      if (e_{new} unaligned OR f_{new} unaligned) AND $(e_{\text{new}}, f_{\text{new}}) \in$ union(e2f,f2e) **then**
        add $(e_{\text{new}}, f_{\text{new}})$ to A
      end if
    end for
  end for
end while

final()

for all English word $e_{\text{new}} \in [1...e_n]$, foreign word $f_{\text{new}} \in [1...f_n]$ **do**
  if (e_{new} unaligned OR f_{new} unaligned) AND $(e_{\text{new}}, f_{\text{new}}) \in$ union(e2f,f2e) **then**
    add $(e_{\text{new}}, f_{\text{new}})$ to A
  end if
end for

Discussion

- Most state of the art SMT systems are built as I presented
- Use IBM Models to generate both:
  - one-to-many alignment
  - many-to-one alignment
- Combine these two alignments using symmetrization heuristic
  - output is a many-to-many alignment
  - used for building decoder
- Moses toolkit for implementation: www.statmt.org
  - Uses Och and Ney GIZA++ tool for Model 1, HMM, Model 4

- However, there is newer work on alignment that is interesting!

Where we have been

- We defined the overall problem and talked about evaluation
- We have now covered word alignment
  - IBM Model 1, true Expectation Maximization
  - Briefly mentioned: IBM Model 4, approximate Expectation Maximization
  - Symmetrization Heuristics (such as Grow)
    - Applied to two Viterbi alignments (typically from Model 4)
    - Results in final word alignment

Where we are going

- We will discuss the "traditional" phrase-based model (which noone actually uses, but gives a good intuition)
- Then we will define a high performance translation model (next slide set)
- Finally, we will show how to solve the search problem for this model (= decoding)

Outline

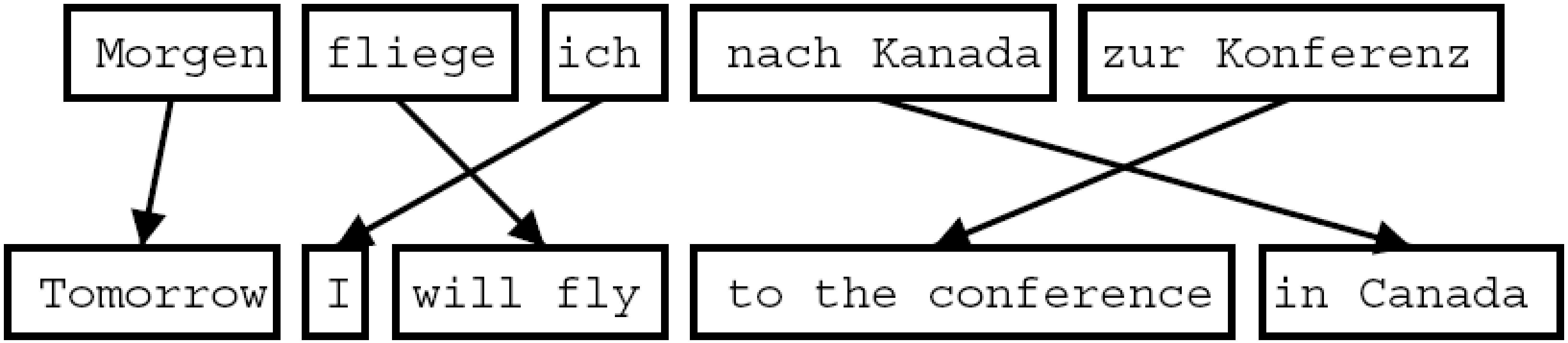
- Phrase-based translation
  - Model
  - Estimating parameters
- Decoding

- We could use IBM Model 4 in the direction p(f|e), together with a language model, p(e), to translate

$$\underset{e}{\operatorname{argmax}}\ P(e \mid f) = \underset{e}{\operatorname{argmax}}\ P(f \mid e)\ P(e)$$

- However, decoding using Model 4 doesn't work well in practice
  - One strong reason is the bad 1-to-N assumption
  - Another problem would be defining the search algorithm
    - If we add additional operations to allow the English words to vary, this will be very expensive
  - Despite these problems, Model 4 decoding was briefly state of the art
- We will now define a better model…

Phrase-based translation



- Foreign input is segmented in phrases
  - any sequence of words, not necessarily linguistically motivated
- Each phrase is translated into English
- Phrases are reordered

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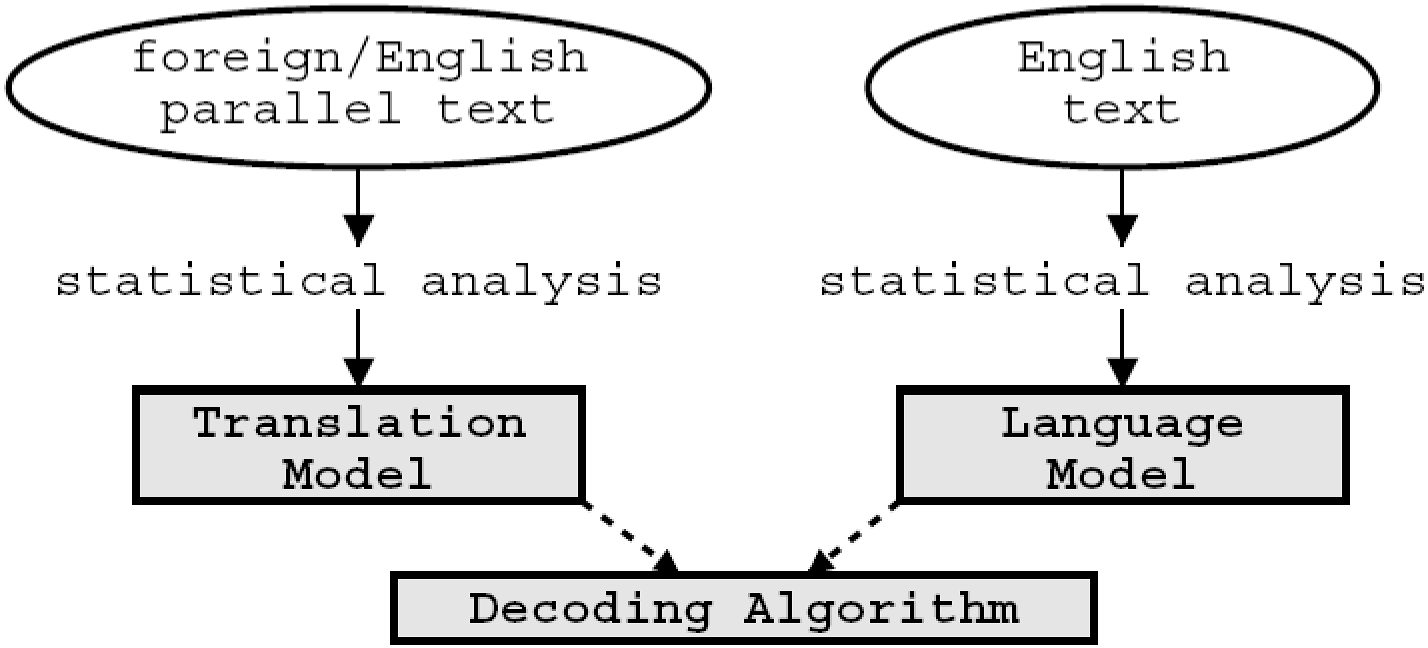
Statistical Machine Translation

- Components: Translation model, language model, decoder



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Language Model

- Often a trigram language model is used for p(e)
  - P(the man went home) = p(the | START) p(man | START the) p(went | the man) p(home | man went)
- Language models work well for comparing the grammaticality of strings of the same length
  - However, when comparing short strings with long strings they favor short strings
  - For this reason, an important component of the language model is the length bonus
    - This is a constant > 1 multiplied for each English word in the hypothesis
    - It makes longer strings competitive with shorter strings

Phrase-based translation model

- Major components of phrase-based model
  - **phrase translation model** $\phi(\mathbf{f}|\mathbf{e})$
  - **reordering model** d
  - **language model** $p_{\text{LM}}(\mathbf{e})$
- Bayes rule

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

- Sentence $\mathbf{f}$ is decomposed into I phrases $\bar{f}_1^I = \bar{f}_1, ..., \bar{f}_I$
- Decomposition of $\phi(\mathbf{f}|\mathbf{e})$

$$\phi(\bar{f}_1^I|\bar{e}_1^I) = \prod_{i=1}^{I} \phi(\bar{f}_i|\bar{e}_i) d(a_i - b_{i-1})$$

Modified from Koehn 2008

Advantages of phrase-based translation

- *Many-to-many* translation can handle non-compositional phrases
- Use of *local context* in translation
- The more data, the *longer phrases* can be learned

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Phrase translation table

- Phrase translations for *den Vorschlag*

English	$\phi(e\|f)$	English	$\phi(e\|f)$
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	...	...

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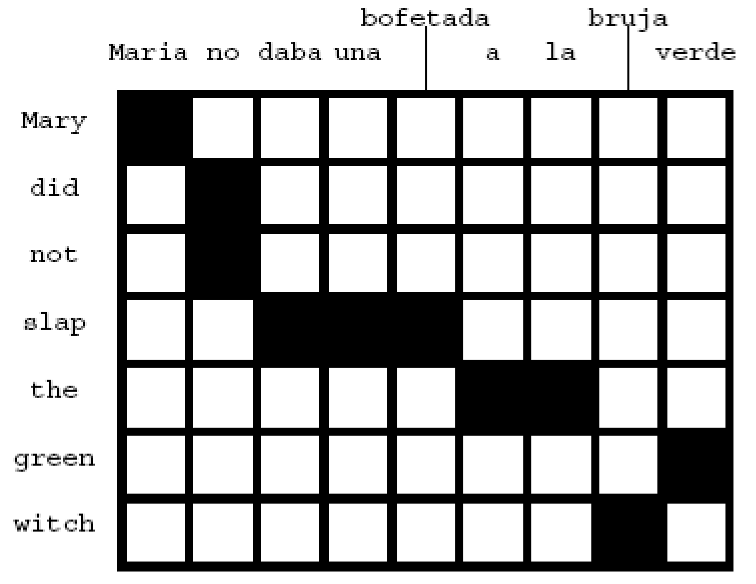
How to learn the phrase translation table?

- Start with the *word alignment*:



- Collect all phrase pairs that are **consistent** with the word alignment

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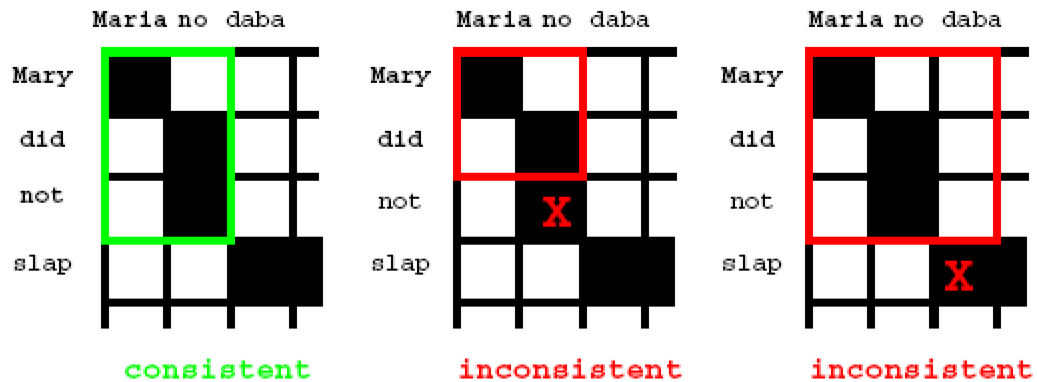
Consistent with word alignment



- **Consistent with the word alignment** :=

  phrase alignment has to *contain all alignment points* for all covered words

$$(\overline{e}, \overline{f}) \in BP \Leftrightarrow \quad \forall e_i \in \overline{e} : (e_i, f_j) \in A \rightarrow f_j \in \overline{f}$$
$$\text{AND} \quad \forall f_j \in \overline{f} : (e_i, f_j) \in A \rightarrow e_i \in \overline{e}$$

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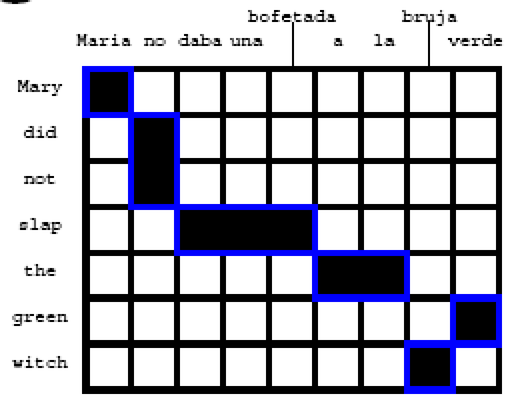
Word alignment induced phrases



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

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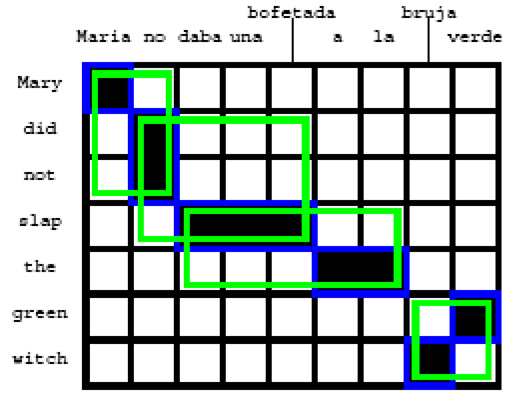
Word alignment induced phrases



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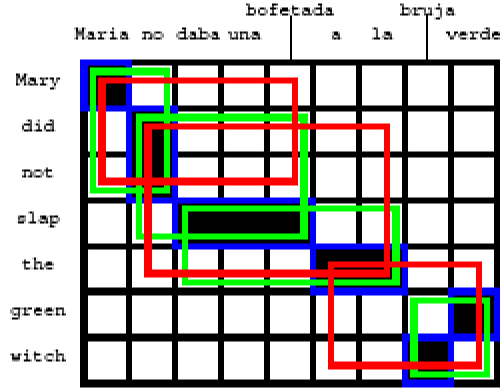

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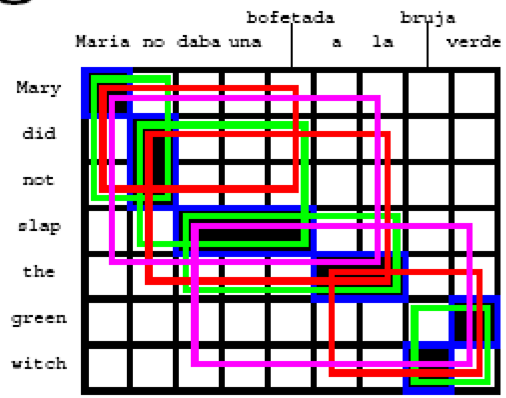
Word alignment induced phrases



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

(Maria no daba una bofetada a la, Mary did not slap the),

(daba una bofetada a la bruja verde, slap the green witch)

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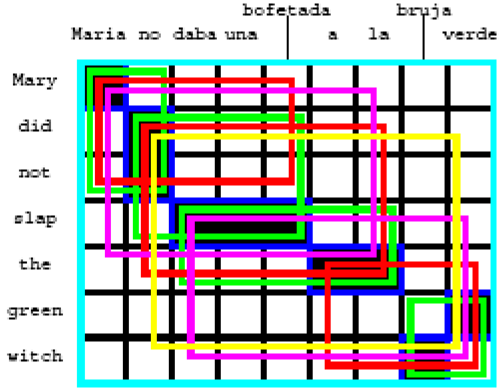
Word alignment induced phrases (5)



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Probability distribution of phrase pairs

- We need a **probability distribution** $\phi(\bar{f}|\bar{e})$ over the collected phrase pairs

$\Rightarrow$ Possible *choices*

- *relative frequency* of collected phrases: $\phi(\bar{f}|\bar{e}) = \frac{\text{count}(\bar{f},\bar{e})}{\sum_{\bar{f}} \text{count}(\bar{f},\bar{e})}$
- or, conversely $\phi(\bar{e}|\bar{f})$
- use *lexical translation probabilities*

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Reordering

- *Monotone* translation
  - do not allow any reordering
  - $\rightarrow$ worse translations
- *Limiting* reordering (to movement over max. number of words) helps
- *Distance-based* reordering cost
  - moving a foreign phrase over n words: cost z^n
- *Lexicalized* reordering model

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