AERFAI Summer School

Phrase-Based and Factored Statistical Machine Translation

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Machine translation

- Task: make sense of foreign text like

毒品

本册子爲家長們提供實際和有用的關于毒品
的信息，包括如何減少使用非法毒品的危險。
它有助於您和您的家人討論有關毒品的問題。
這本小册子的主要内容已錄在磁帶上。如果您
想索取一盒免費的磁帶(中文)，請在下面的

- One of the oldest problems in Artificial Intelligence
- AI-hard: reasoning and world knowledge required

The Rosetta stone

- Egyptian language was a mystery for centuries
- 1799 a stone with Egyptian text and its translation into Greek was found

⇒ Humans *could learn* how to translated Egyptian

Parallel data

- Lots of translated text available: 100s of million words of translated text for some language pairs
  - a book has a few 100,000s words
  - an educated person may read 10,000 words a day

  $\rightarrow$ 3.5 million words a year

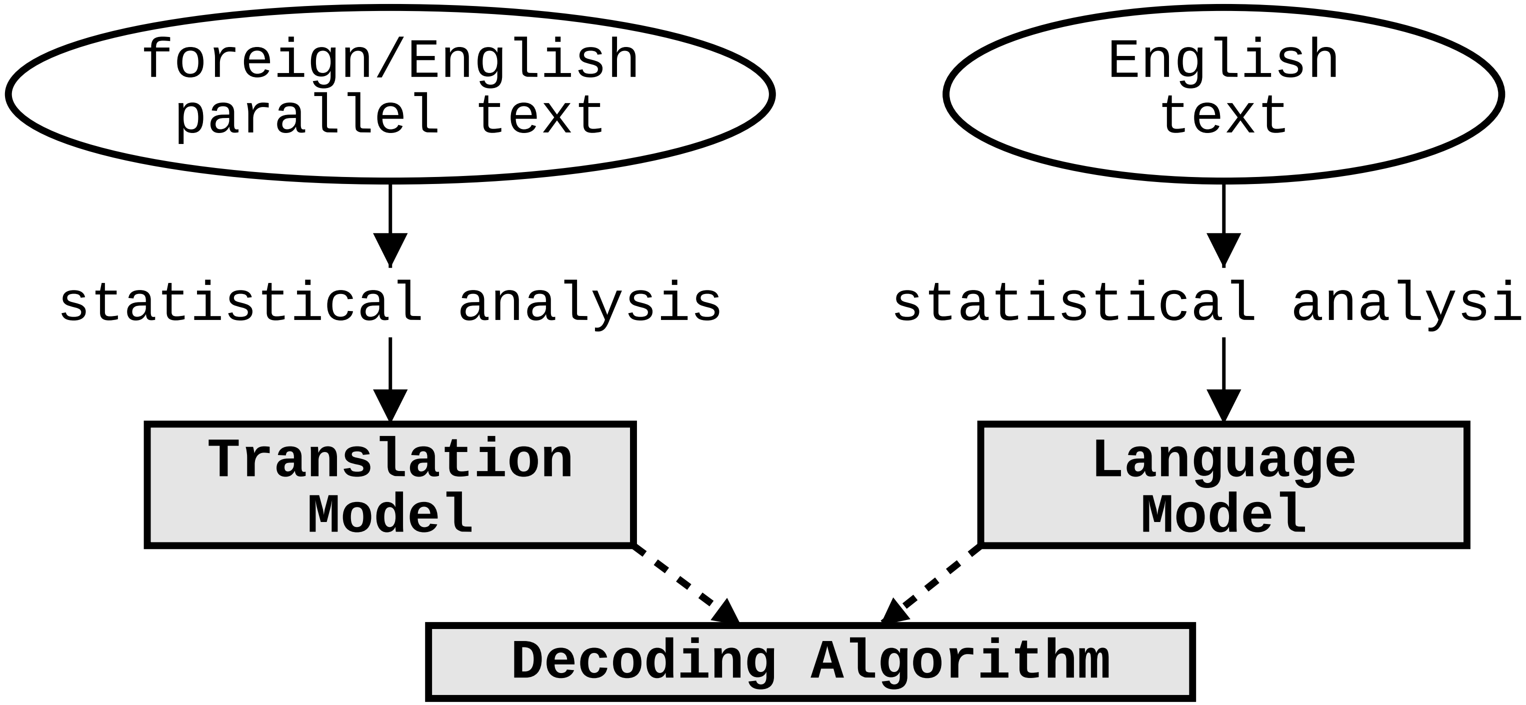
  $\rightarrow$ *300 million a lifetime*

  $\rightarrow$ soon computers will be able to see more translated text than humans read in a lifetime

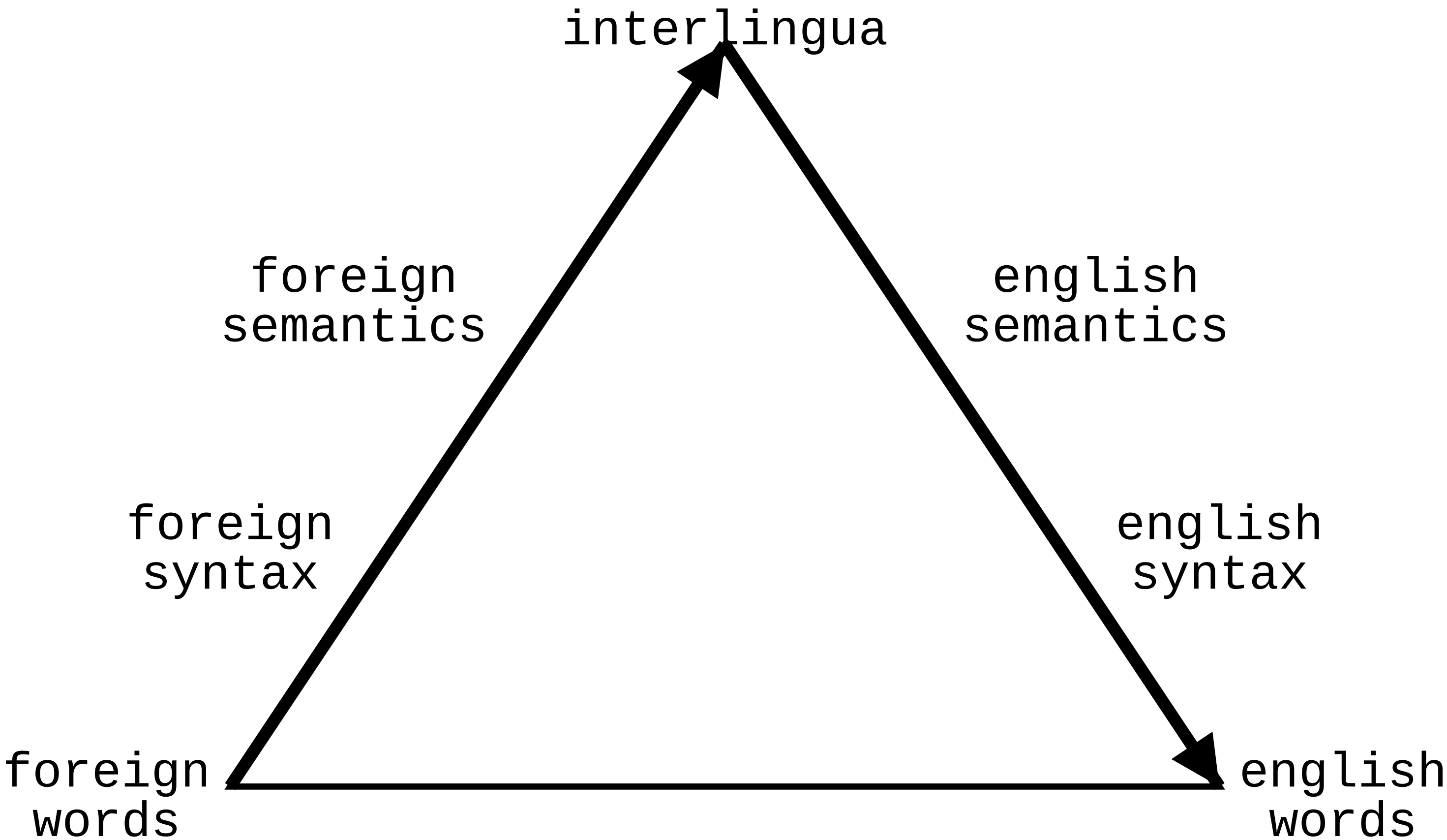
$\Rightarrow$ Machine *can learn* how to translated foreign languages

Statistical machine translation

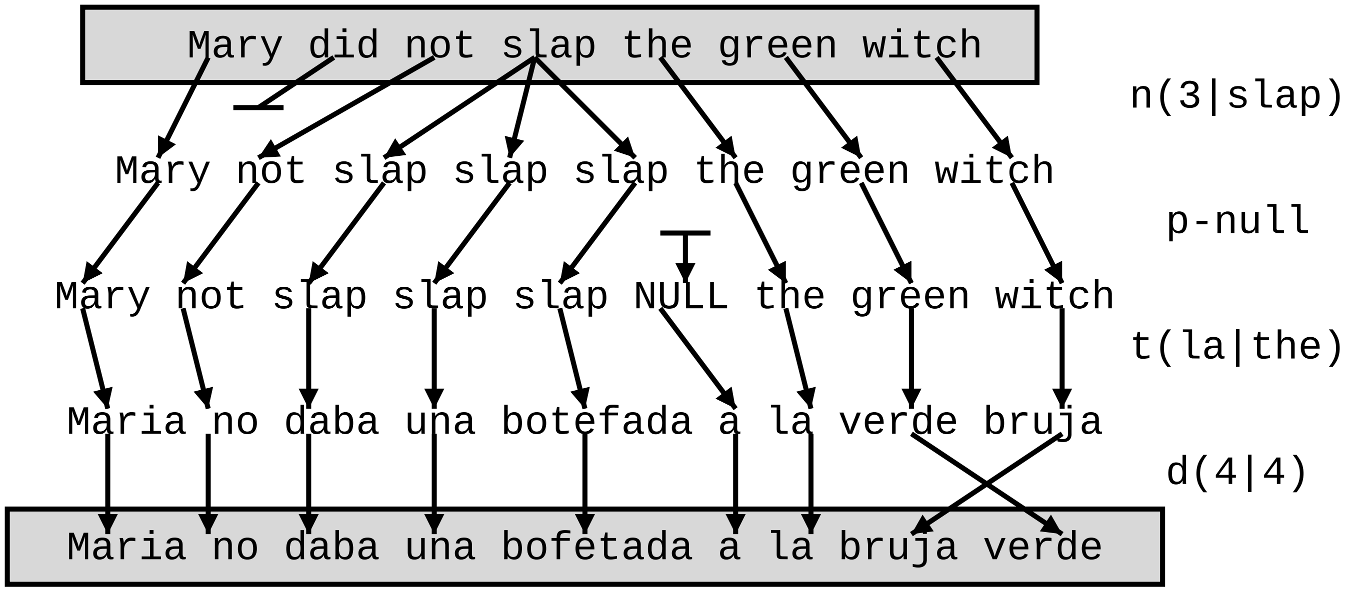
- Components: **Translation model**, **language model**, **decoder**



The machine translation pyramid



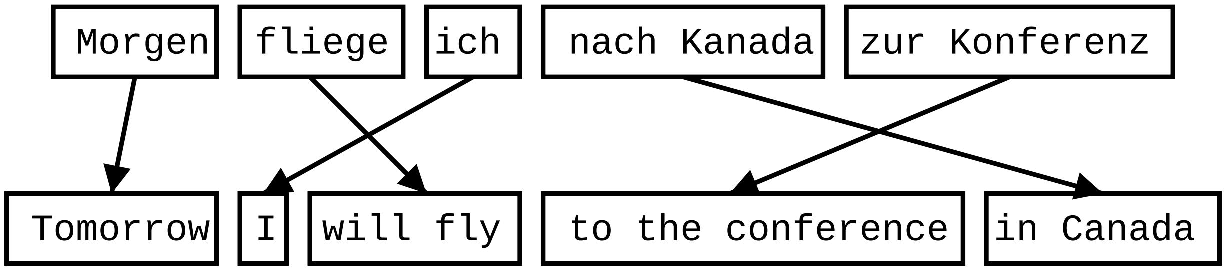
Word-based models



[from Knight, 1997]

- Translation process is *decomposed into smaller steps*, each is tied to words
- Original models for statistical machine translation [Brown et al., 1993]

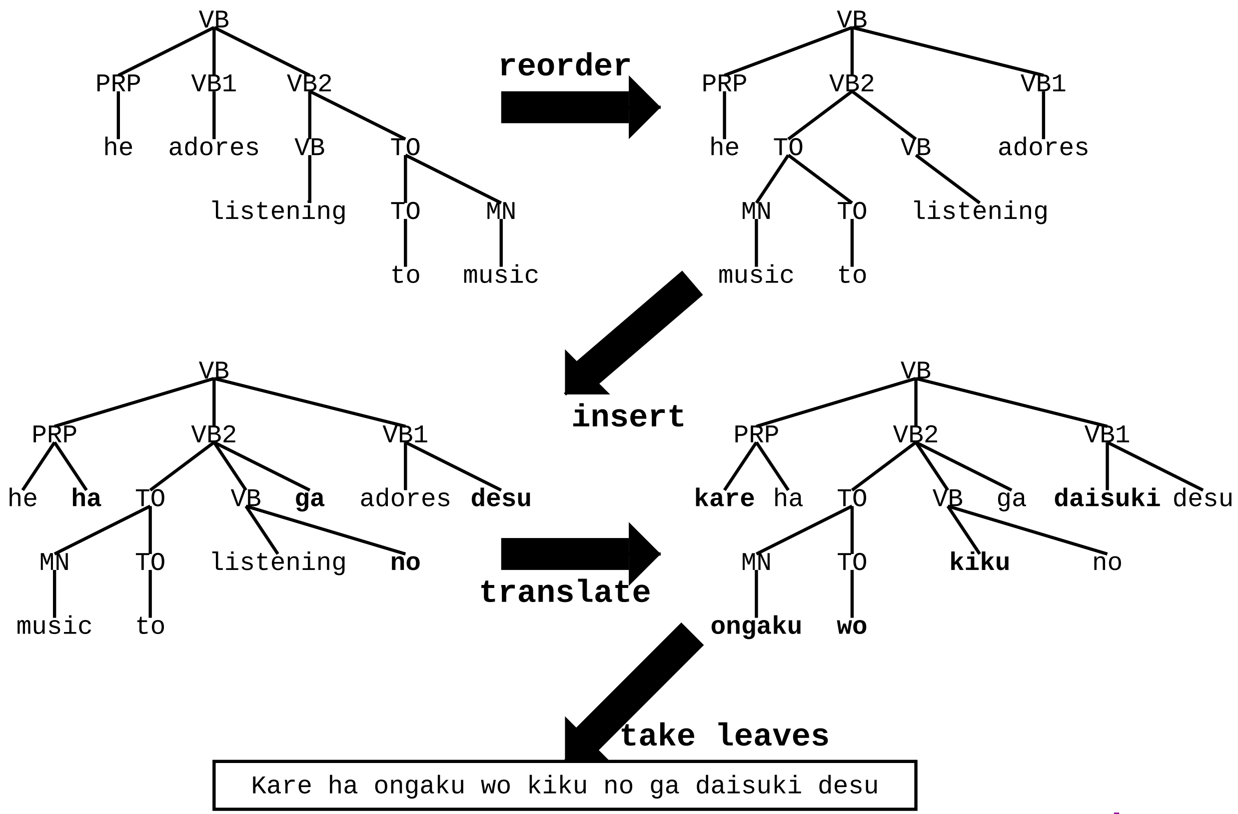
Phrase-based models



[from Koehn et al., 2003, NAACL]

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

Syntax-based models



[from Yamada and Knight, 2001]

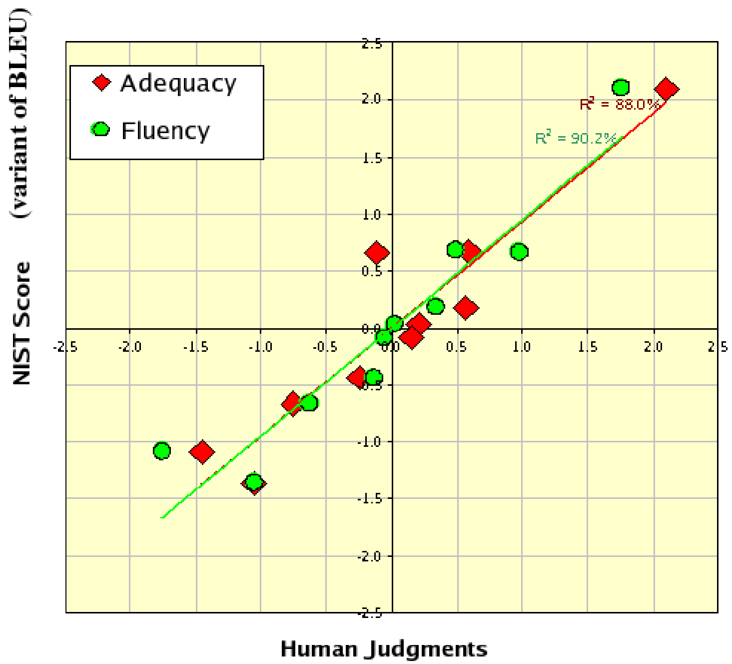
Automatic evaluation

- Why **automatic evaluation** metrics?
  - Manual evaluation is *too slow*
  - Evaluation on large test sets *reveals minor improvements*
  - **Automatic tuning** to improve machine translation performance
- History
  - Word Error Rate
  - **BLEU** since 2002
- BLEU in short: *Overlap with reference* translations

Automatic evaluation

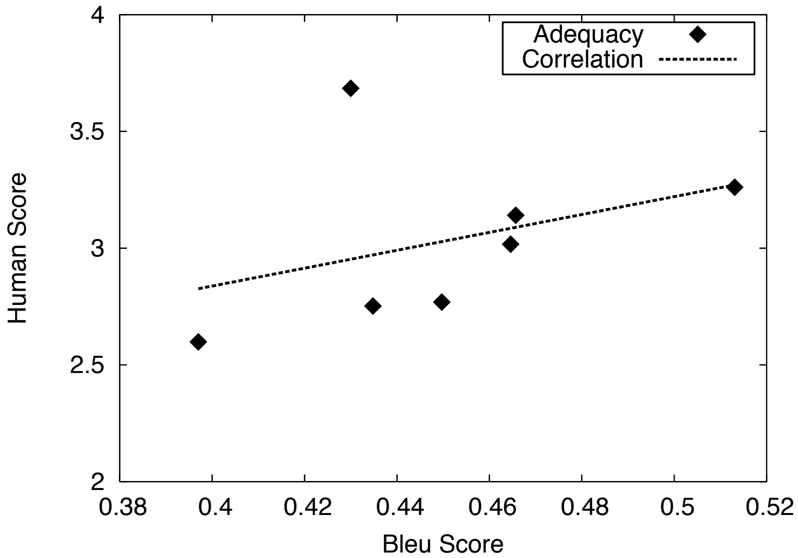
- Reference Translation
  - the gunman was shot to death by the police .
- System Translations
  - **the gunman was police kill .**
  - **wounded police jaya of**
  - **the gunman was shot dead by the police .**
  - **the gunman arrested by police kill .**
  - **the gunmen were killed .**
  - **the gunman was shot to death by the police .**
  - **gunmen were killed by police ?SUB>0 ?SUB>0**
  - **al by the police .**
  - **the ringer is killed by the police .**
  - **police killed the gunman .**
- Matches
  - green = 4 gram match (good!)
  - red = word not matched (bad!)

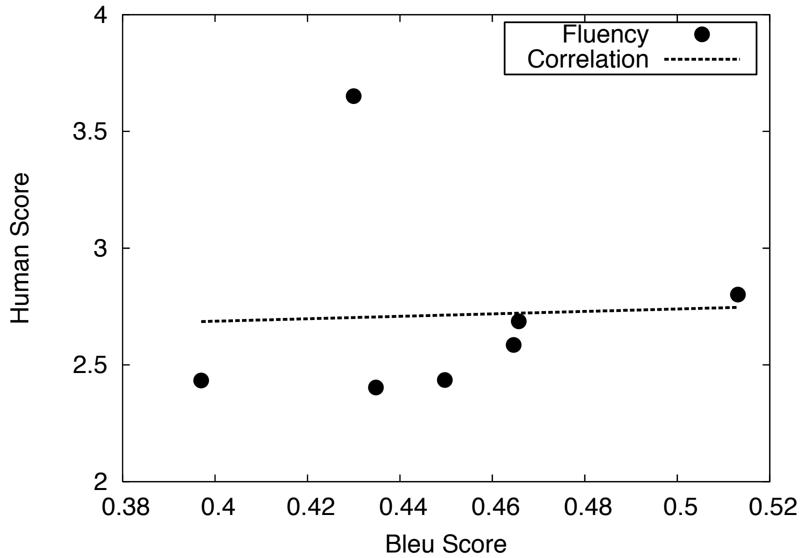
Automatic evaluation



- BLEU **correlates** with human judgement [from George Doddington, NIST]
  - **multiple reference translations** may be used

Correlation? [Callison-Burch et al., 2006]



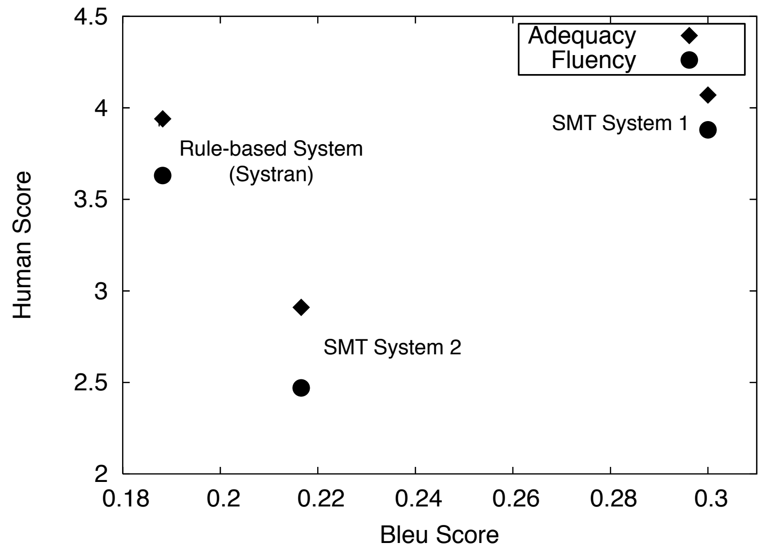


[from Callison-Burch et al., 2006, EACL]

- DARPA/NIST MT Eval 2005
  - Mostly statistical systems (all but one in graphs)
  - One submission **manual post-edit** of statistical system's output

→ Good adequacy/fluency scores *not reflected* by BLEU

Correlation? [Callison-Burch et al., 2006]



[from Callison-Burch et al., 2006, EACL]

- Comparison of
  - *good statistical* system: high BLEU, high adequacy/fluency
  - *bad statistical* sys. (trained on less data): low BLEU, low adequacy/fluency
  - *Systran*: lowest BLEU score, but high adequacy/fluency

Automatic evaluation: outlook

- Research questions
  - why does BLEU *fail* Systran and manual post-edits?
  - how can this *overcome* with novel evaluation metrics?
- Future of automatic methods
  - automatic metrics too *useful* to be abandoned
  - evidence still supports that during *system development*, a better BLEU indicates a better system
  - *final assessment* has to be human judgement

Euromatrix

- Proceedings of the European Parliament
  - translated into *11 official languages*
  - entry of new members in May 2004: more to come...
- Europarl corpus
  - collected 20-30 million words per language
  - → *110 language pairs*
- 110 Translation systems
  - 3 weeks on 16-node cluster computer
  - → *110 translation systems*

Quality of translation systems

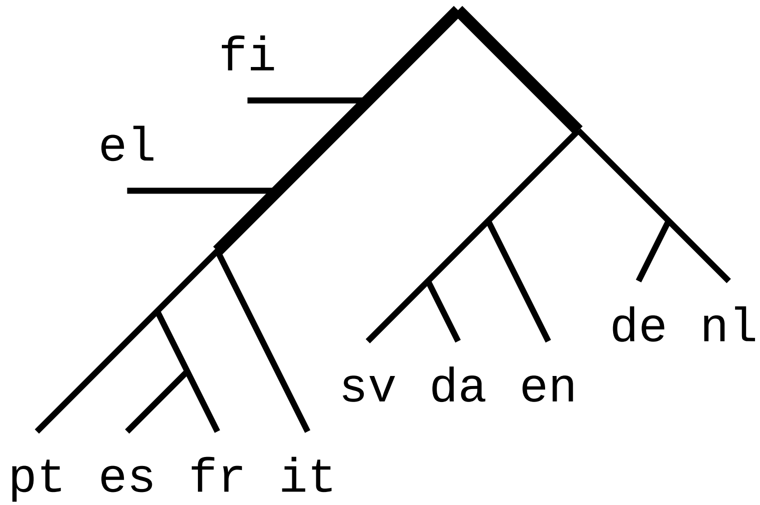
- *Scores* for all 110 systems

	da	de	el	en	es	fr	fi	it	nl	pt	sv
da	-	18.4	21.1	28.5	26.4	28.7	14.2	22.2	21.4	24.3	28.3
de	22.3	-	20.7	25.3	25.4	27.7	11.8	21.3	23.4	23.2	20.5
el	22.7	17.4	-	27.2	31.2	32.1	11.4	26.8	20.0	27.6	21.2
en	25.2	17.6	23.2	-	30.1	31.1	13.0	25.3	21.0	27.1	24.8
es	24.1	18.2	28.3	30.5	-	40.2	12.5	32.3	21.4	35.9	23.9
fr	23.7	18.5	26.1	30.0	38.4	-	12.6	32.4	21.1	35.3	22.6
fi	20.0	14.5	18.2	21.8	21.1	22.4	-	18.3	17.0	19.1	18.8
it	21.4	16.9	24.8	27.8	34.0	36.0	11.0	-	20.0	31.2	20.2
nl	20.5	18.3	17.4	23.0	22.9	24.6	10.3	20.0	-	20.7	19.0
pt	23.2	18.2	26.4	30.1	37.9	39.0	11.9	32.0	20.2	-	21.9
sv	30.3	18.9	22.8	30.2	28.6	29.7	15.3	23.9	21.9	25.9	-

[from Koehn, 2005: Europarl]

- Online evaluation at `http://matrix.statmt.org/`

Clustering languages



[from Koehn, 2005, MT Summit]

- **Clustering** languages based on how easy they translate into each other

⇒ Approximation of language families

Translate into vs. out of a language

- Some languages are *easier* to translate into that out of

Language	From	Into	Diff
da	23.4	23.3	0.0
de	**22.2**	**17.7**	**-4.5**
el	23.8	22.9	-0.9
en	**23.8**	**27.4**	**+3.6**
es	26.7	29.6	+2.9
fr	26.1	31.1	+5.1
fi	19.1	12.4	-6.7
it	24.3	25.4	+1.1
nl	19.7	20.7	+1.1
pt	26.1	27.0	+0.9
sv	24.8	22.1	-2.6

[from Koehn, 2005: Europarl]

- *Morphologically rich languages* harder to generate (German, Finnish)

Backtranslations

- Checking translation quality by **back-translation**
- *The spirit is willing, but the flesh is weak*
- English → Russian → English
- *The vodka is good but the meat is rotten*

Backtranslations II

- *Does not correlate* with unidirectional performance

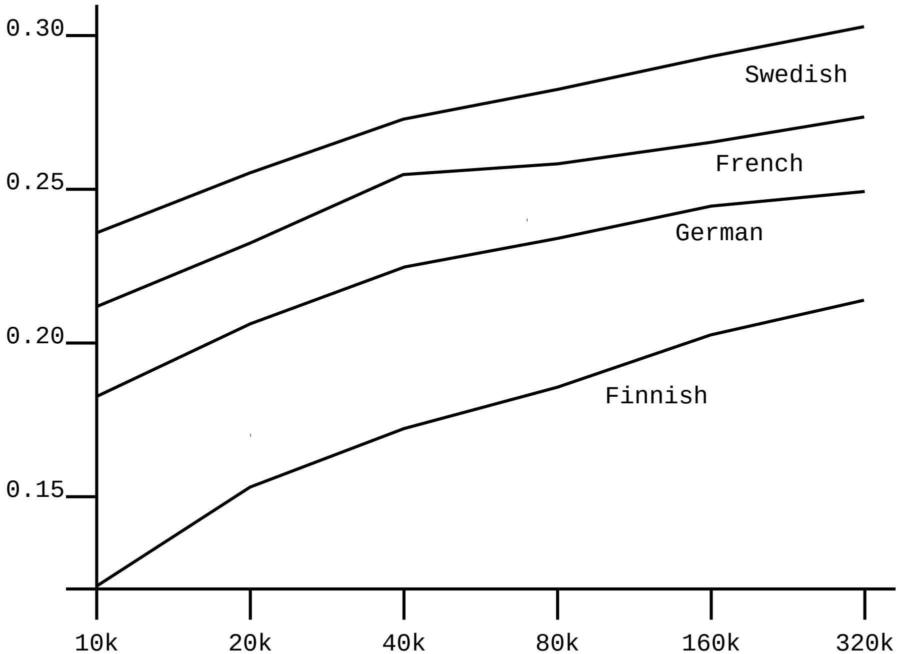
Language	From	Into	Back
da	28.5	25.2	56.6
de	25.3	17.6	48.8
el	27.2	23.2	**56.5**
es	30.5	30.1	52.6
fi	21.8	13.0	44.4
it	27.8	25.3	49.9
nl	23.0	21.0	46.0
pt	30.1	27.1	**53.6**
sv	30.2	24.8	54.4

[from Koehn, 2005: Europarl]

Available data

- Available *parallel text*
  - **Europarl**: *30 million words* in 11 languages http://www.statmt.org/europarl/
  - **Acquis Communitaire**: *8-50 million words* in 20 EU languages
  - **Canadian Hansards**: *20 million words* from Ulrich Germann, ISI
  - Chinese/Arabic to English: *over 100 million words* from **LDC**
  - lots more French/English, Spanish/French/English from **LDC**
- Available monolingual text (for language modeling)
  - *2.8 billion words* of English from **LDC**
  - *100s of billions, trillions* on the web

More data, better translations



[from Koehn, 2003: Europarl]

- **Log-scale improvements** on BLEU:
  Doubling the training data gives constant improvement *(+1 %BLEU)*

Moses: Open Source Toolkit

- **Open source** statistical machine translation system (developed from scratch 2006)
  - state-of-the-art *phrase-based* approach
  - novel methods: *factored translation models*, *confusion network decoding*
  - support for *very large models* through *memory-efficient* data structures

- Documentation, source code, binaries **available** at `http://www.statmt.org/moses/`
- Development also **supported by**
  - EC-funded *TC-STAR*, *EuroMatrix* project
  - *US* funding agencies DARPA, NSF
  - universities (Edinburgh, Maryland, MIT, ITC-irst, RWTH Aachen, ...)

Competitions

- Progress driven by **MT Competitions**
  - **NIST/DARPA**: Yearly campaigns for Arabic-English, Chinese-English, newstexts, since 2001
  - **IWSLT**: Yearly competitions for Asian languages and Arabic into English, speech travel domain, since 2003
  - **WPT/WMT**: Yearly competitions for European languages, European Parliament proceedings, since 2005
- Increasing number of statistical MT groups participate
- Competitions won by statistical systems

Rule-based vs. Statistical in WMT08

Language Pair	In Domain Europarl	Out of Domain News
Czech-English	SMT*	SMT**
English-Czech	SMT*	RBMT
French-English	SMT	SMT
English-French	SMT	RBMT
German-English	SMT	RBMT
English-German	RBMT	RBMT
Hungarian-English	-	RBMT
Spanish-English	SMT	RBMT
English-Spanish	SMT	RBMT

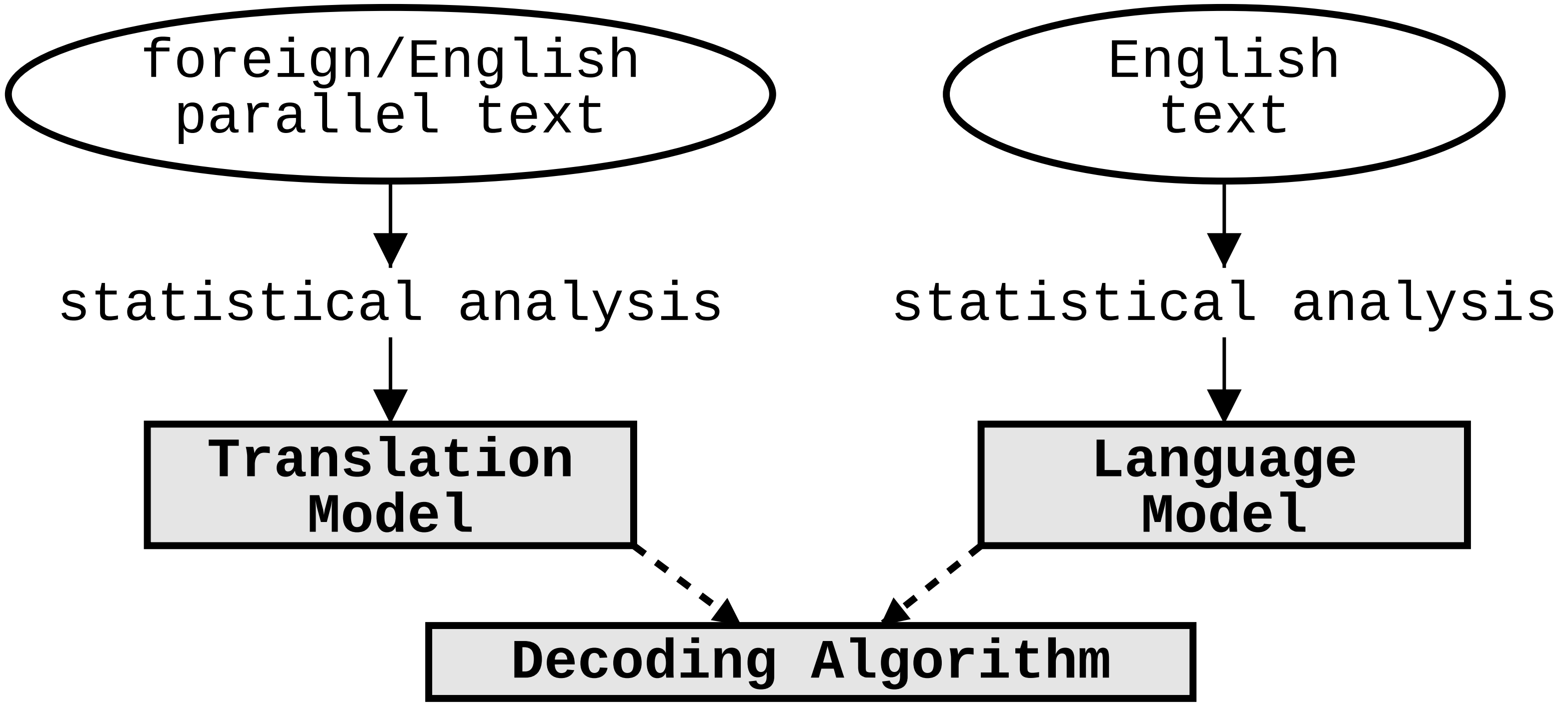
* News Commentary

** no RBMT system in competition

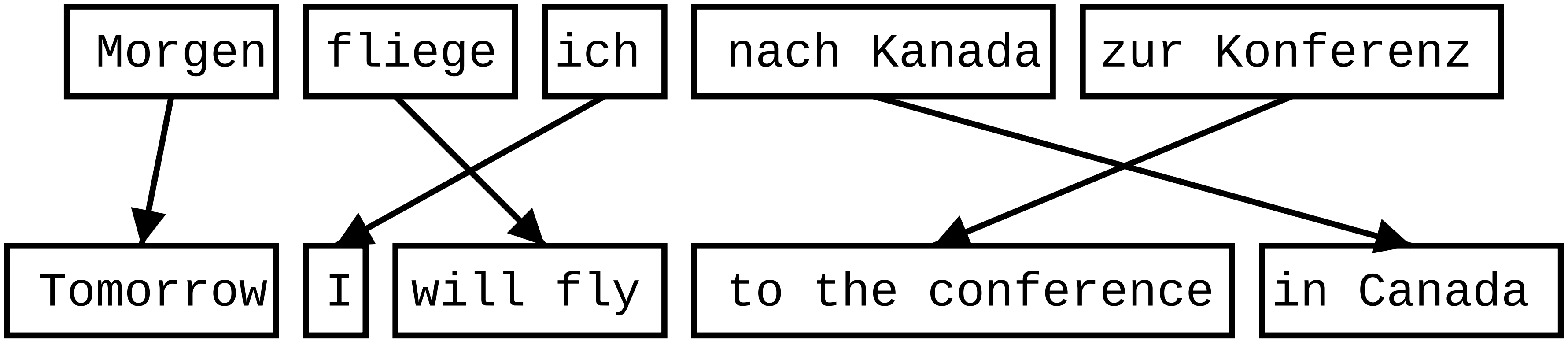
Phrase-Based Models: Decoding

Statistical Machine Translation

- Components: Translation model, language model, decoder



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

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	...	...

Decoding Process

Maria	no	dio	una	bofetada	a	la	bruja	verde

- Build translation left to right
  - *select foreign* words to be translated

Decoding Process

- Build translation *left to right*
  - select foreign words to be translated
  - *find English* phrase translation
  - *add English* phrase to end of partial translation

Decoding Process

Maria	no	dio	una	bofetada	a	la	bruja	verde

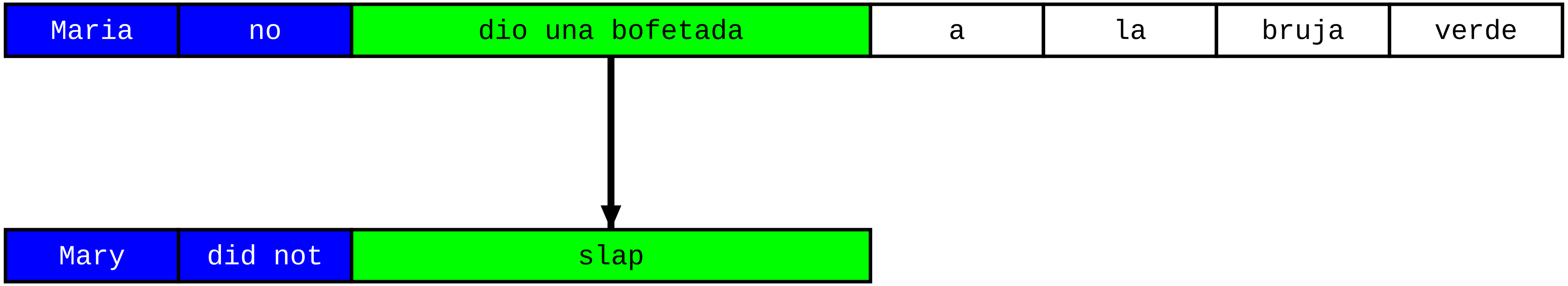
Mary

- Build translation left to right
  - select foreign words to be translated
  - find English phrase translation
  - add English phrase to end of partial translation
  - *mark foreign* words as translated

Decoding Process

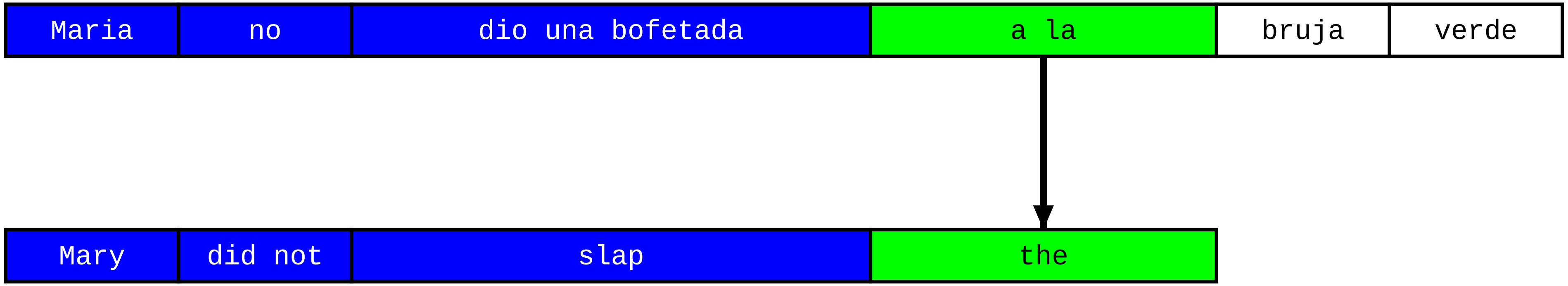
- *One to many* translation

Decoding Process



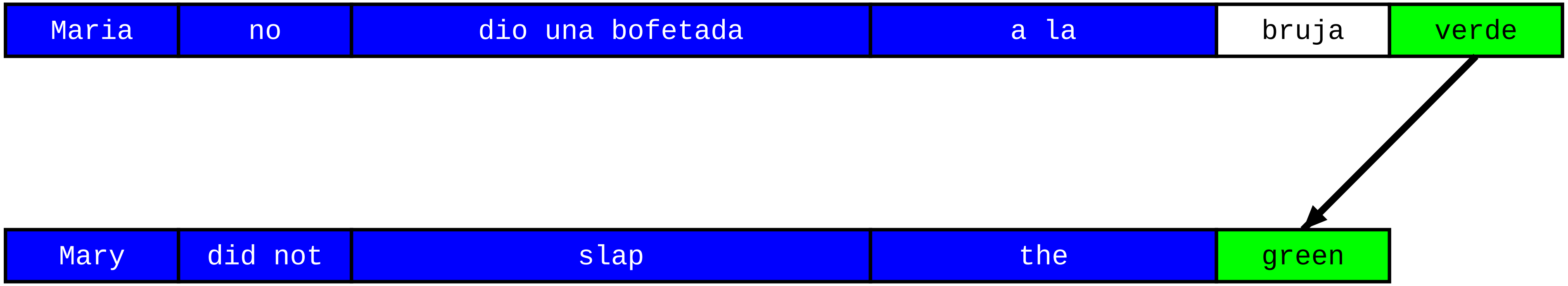
- Many to one translation

Decoding Process



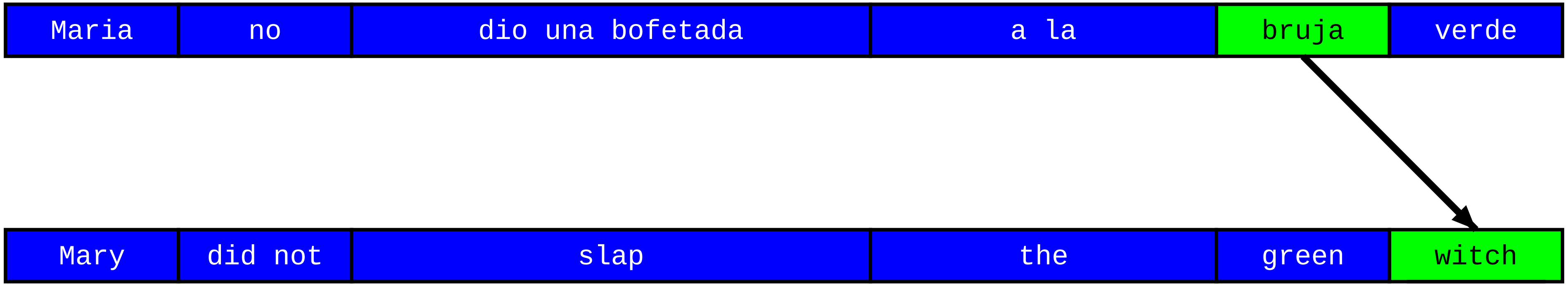
- *Many to one* translation

Decoding Process



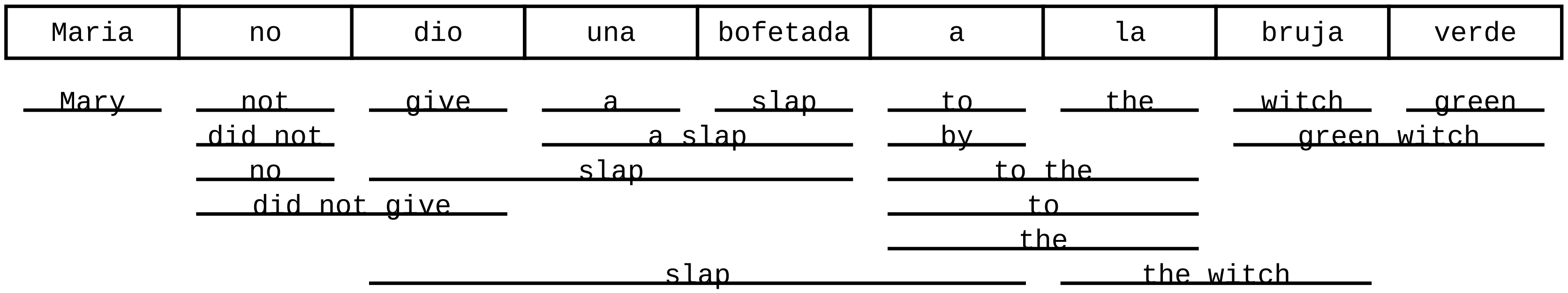
- *Reordering*

Decoding Process



- Translation *finished*

Translation Options



- Look up *possible phrase translations*
  - many different ways to *segment* words into phrases
  - many different ways to *translate* each phrase

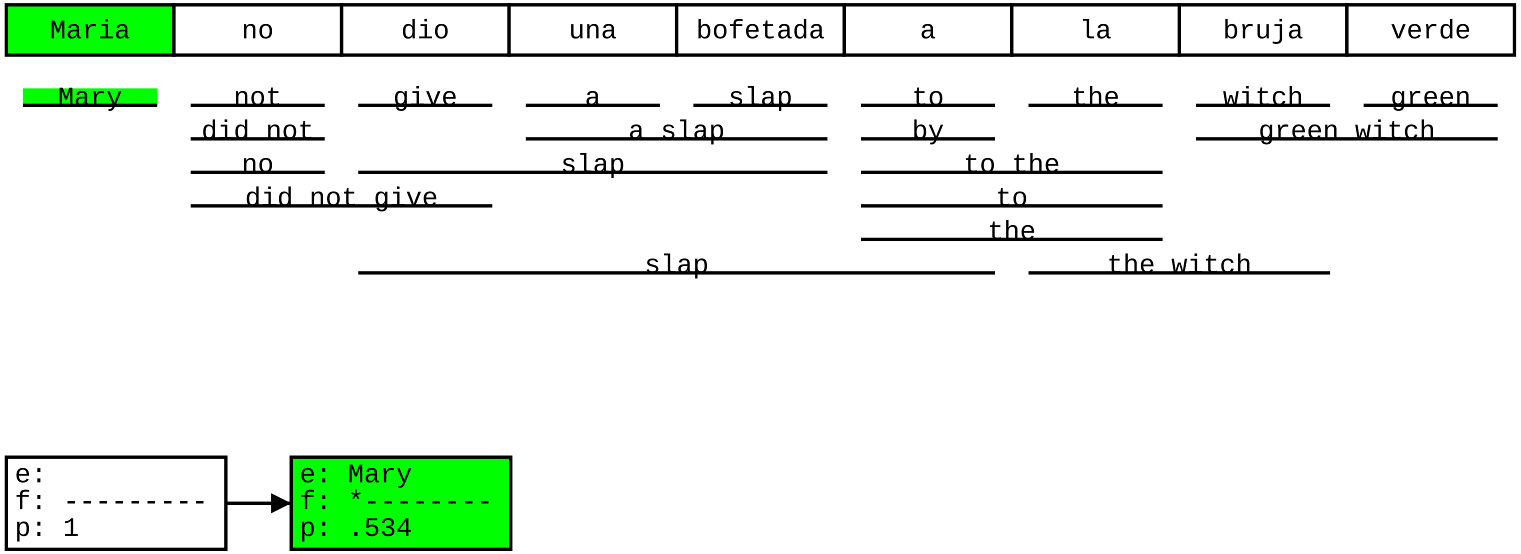
Hypothesis Expansion

Maria	no	dio	una	bofetada	a	la	bruja	verde
Mary	not	give	a	slap	to	the	witch	green
	did not		a slap		by		green witch	
	no	slap			to the			
	did not give				to			
					the			
		slap				the witch		

```
e:
f: ---------
p: 1
```

- Start with **empty hypothesis**
  - e: no English words
  - f: no foreign words covered
  - p: probability 1

Hypothesis Expansion

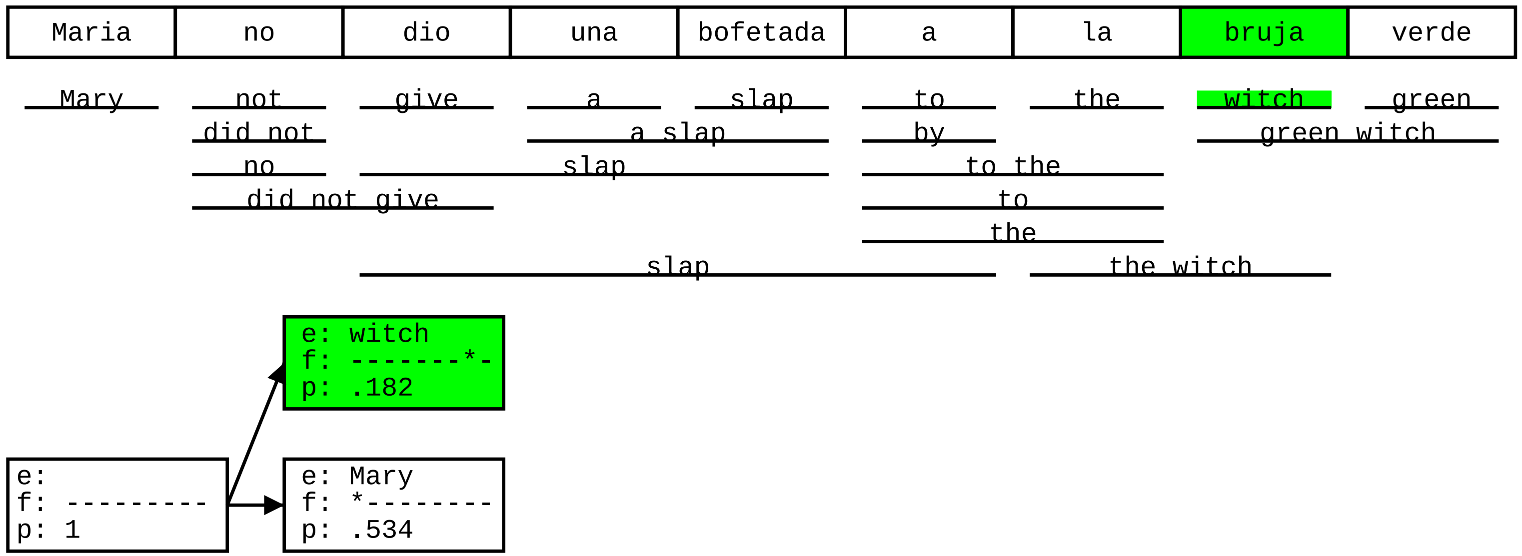


- Pick *translation option*
- Create *hypothesis*
  - e: add English phrase `Mary`
  - f: first foreign word covered
  - p: probability 0.534

A Quick Word on Probabilities

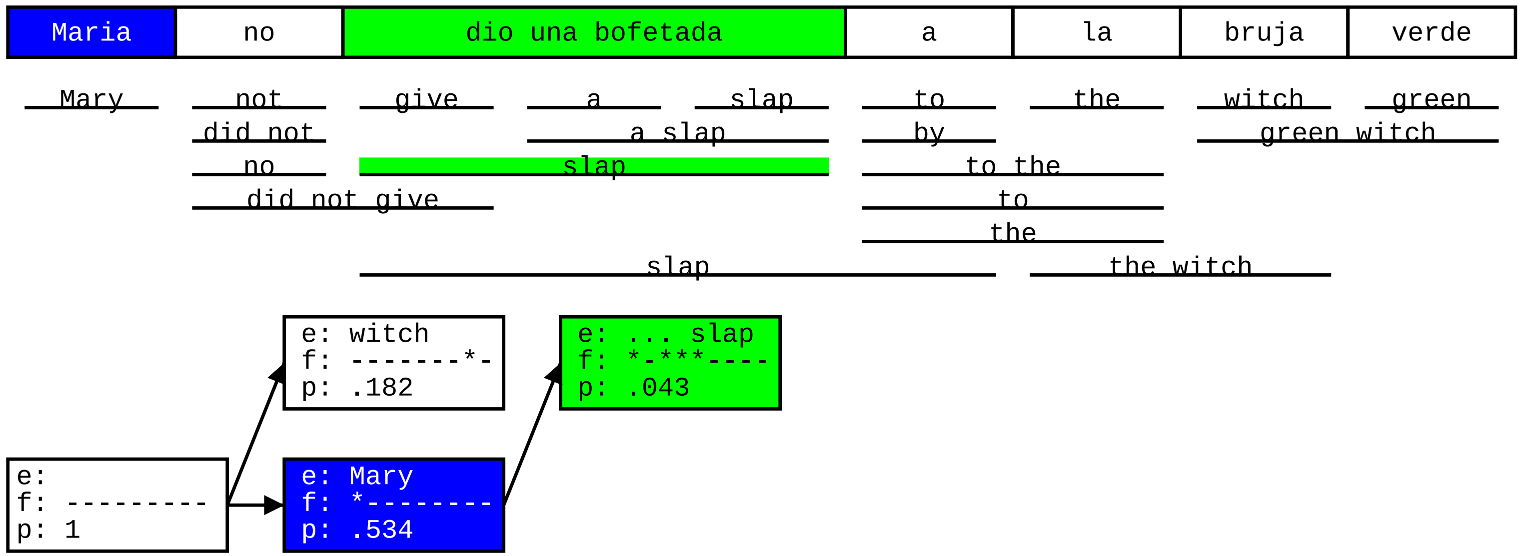
- Not going into detail here, but...
- *Translation Model*
  - phrase translation probability p(Mary|Maria)
  - reordering costs
  - phrase/word count costs
  - ...
- *Language Model*
  - uses trigrams:
  - p(Mary did not) $=$
    p(Mary|START) $\times p$(did|Mary,START) $\times$ p(not|Mary did)

Hypothesis Expansion



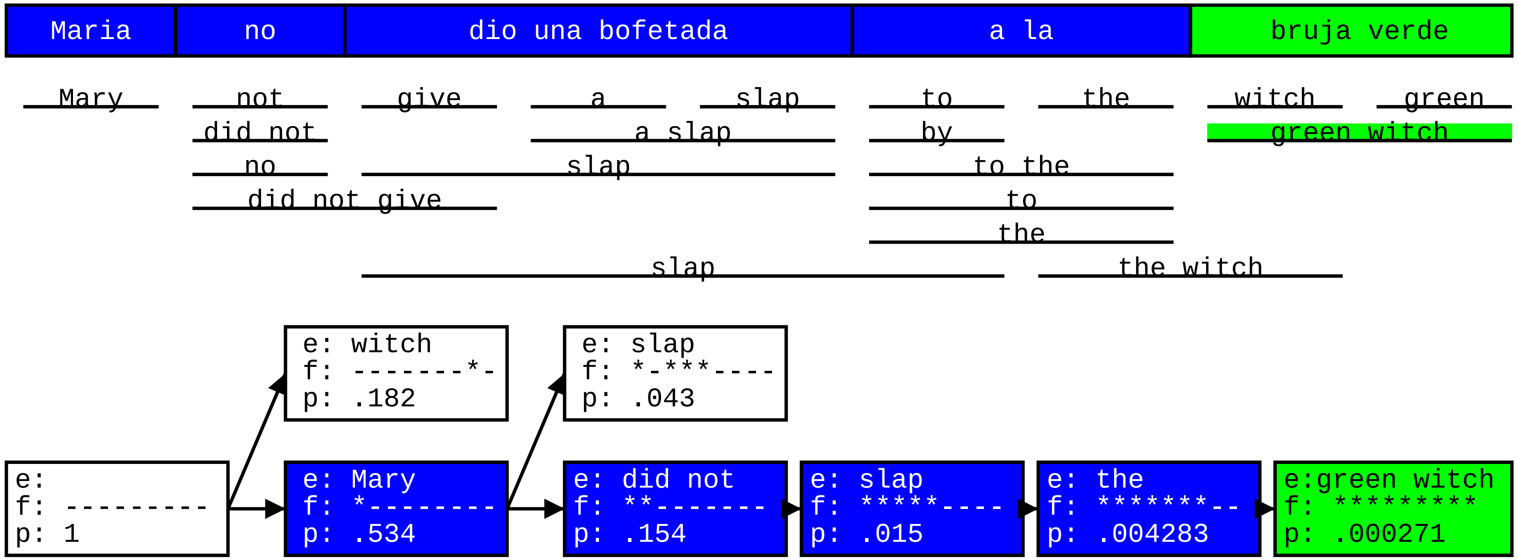
- Add another *hypothesis*

Hypothesis Expansion



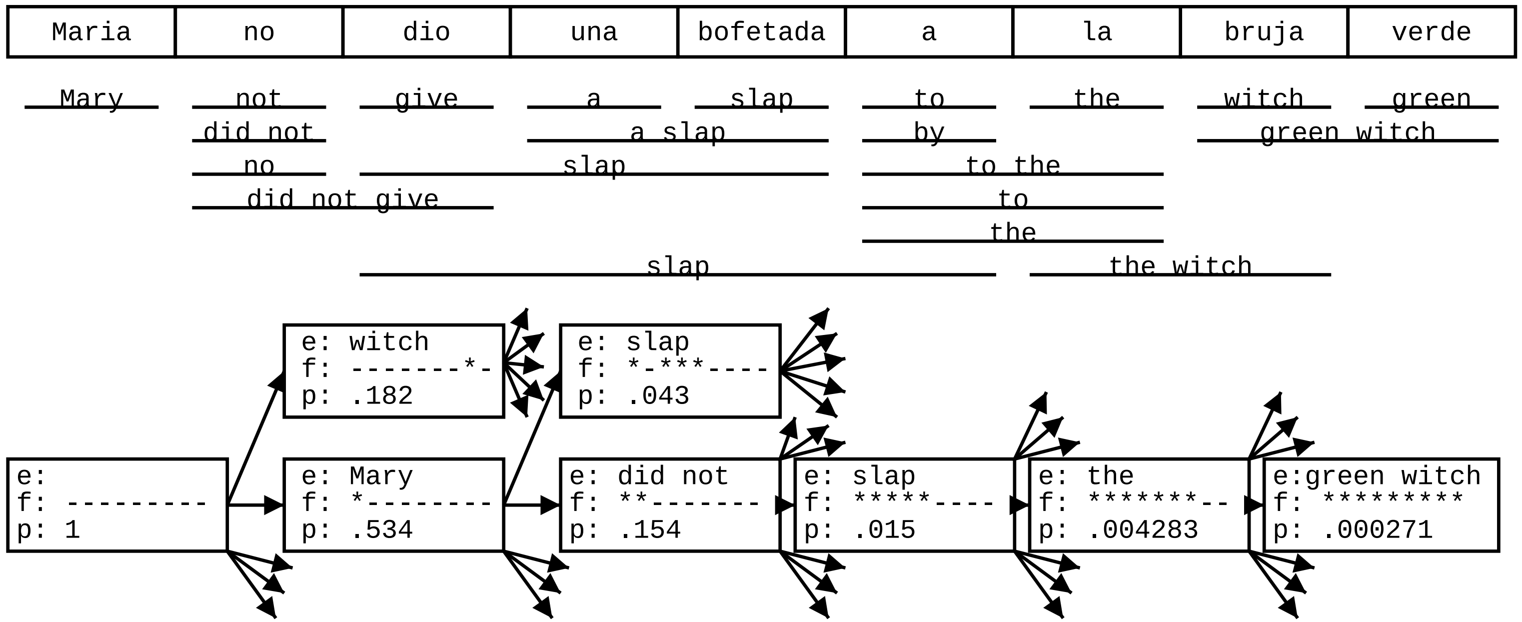
- Further *hypothesis expansion*

Hypothesis Expansion



- ... until all foreign words *covered*
  - find *best hypothesis* that covers all foreign words
  - *backtrack* to read off translation

Hypothesis Expansion



- Adding more hypothesis

⇒ *Explosion* of search space

Explosion of Search Space

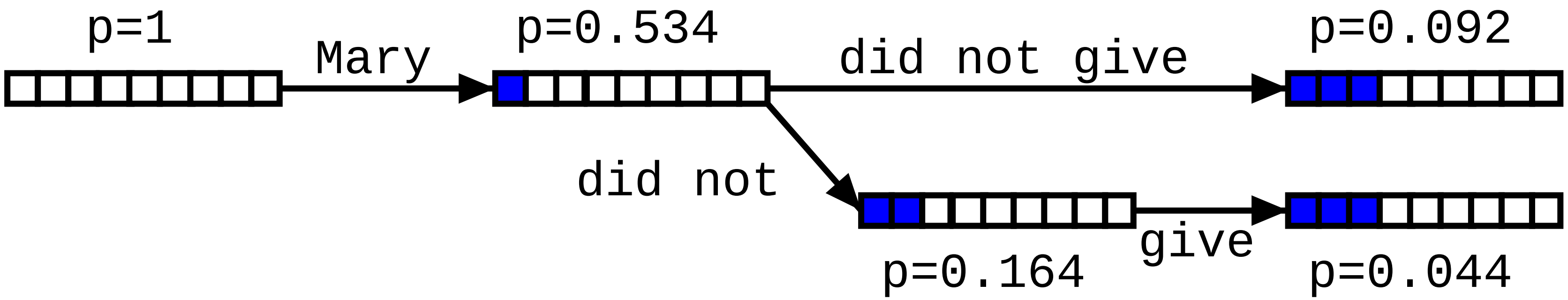
- Number of hypotheses is *exponential* with respect to sentence length

⇒ Decoding is NP-complete [Knight, 1999]

⇒ Need to *reduce search space*

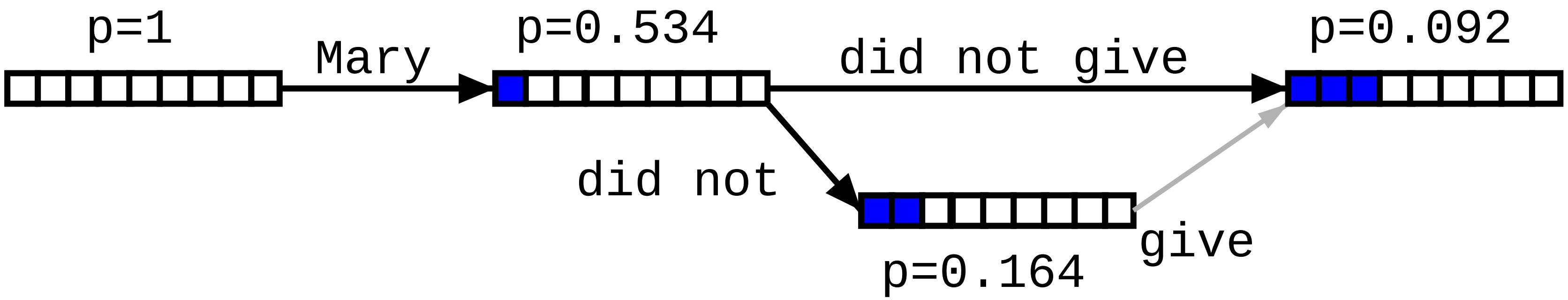
  – risk free: hypothesis **recombination**
  – risky: **histogram/threshold pruning**

Hypothesis Recombination



- Different paths to the *same* partial translation

Hypothesis Recombination

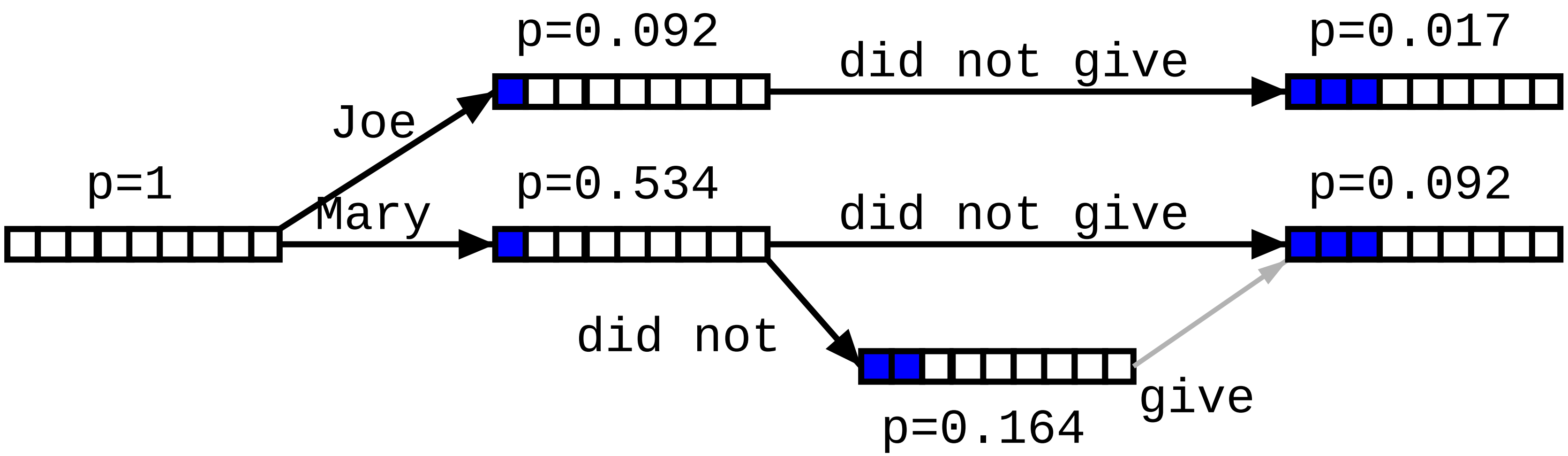


- Different paths to the same partial translation

⇒ *Combine paths*

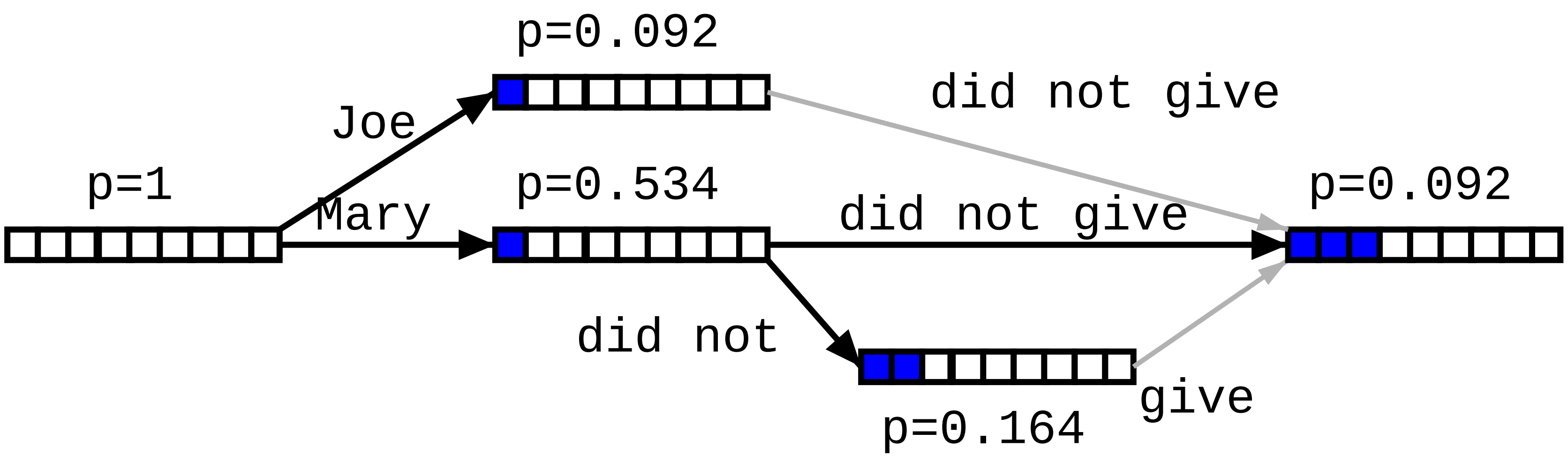
- – *drop weaker* path
- – keep pointer from weaker path (for lattice generation)

Hypothesis Recombination



- Recombined hypotheses do *not* have to *match completely*
- No matter what is added, weaker path can be dropped, if:
  - *last two English words* match (matters for language model)
  - *foreign word coverage* vectors match (effects future path)

Hypothesis Recombination



- Recombined hypotheses do not have to match completely
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  - last two English words match (matters for language model)
  - foreign word coverage vectors match (effects future path)

⇒ *Combine paths*

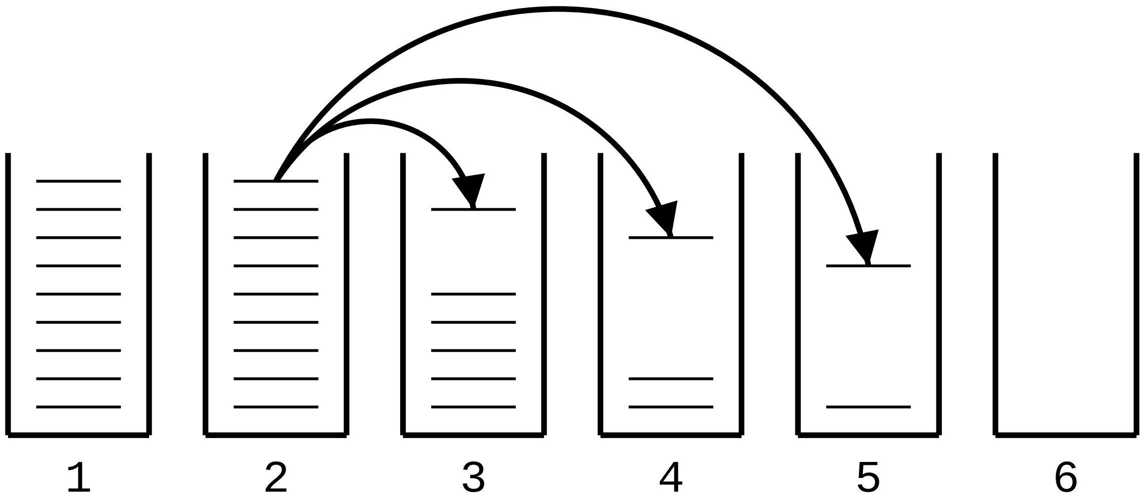
Pruning

- Hypothesis recombination is *not sufficient*

⇒ Heuristically *discard* weak hypotheses early

- Organize Hypothesis in **stacks**, e.g. by
  - *same* foreign words covered
  - *same number* of foreign words covered
- Compare hypotheses in stacks, discard bad ones
  - **histogram pruning**: keep top n hypotheses in each stack (e.g., n=100)
  - **threshold pruning**: keep hypotheses that are at most α times the cost of best hypothesis in stack (e.g., $\alpha = 0.001$)

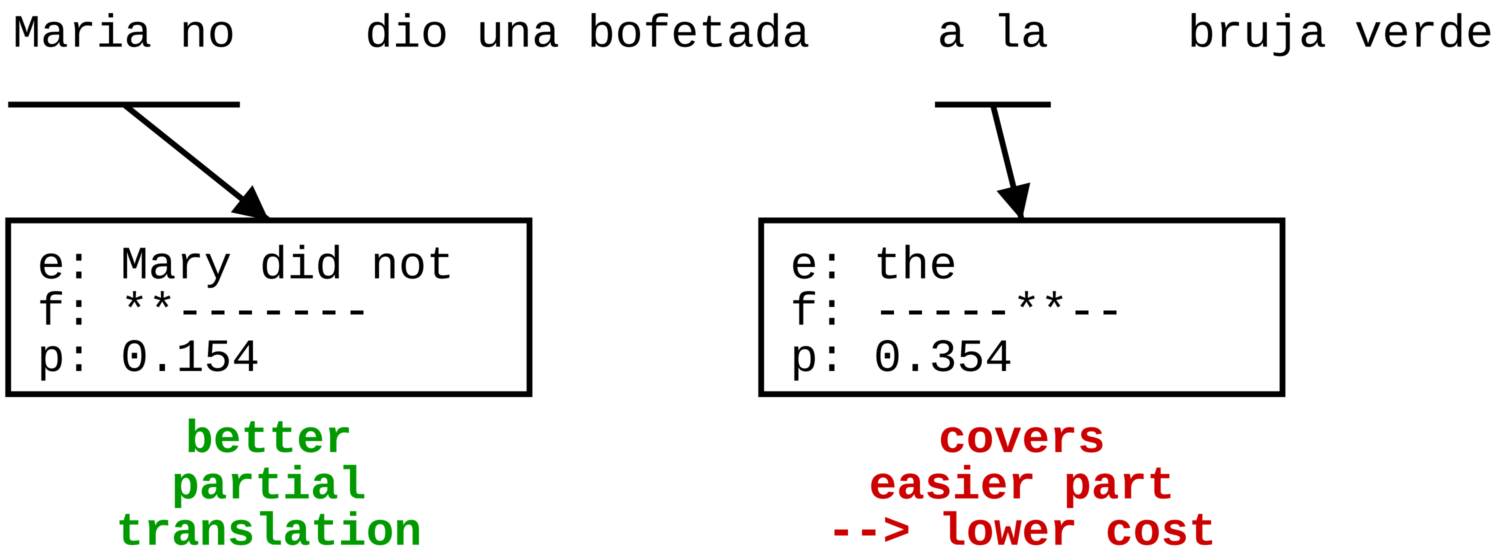
Hypothesis Stacks



- Organization of hypothesis into stacks
  - here: based on *number of foreign words* translated
  - during translation all hypotheses from one stack are expanded
  - expanded Hypotheses are placed into stacks

Comparing Hypotheses

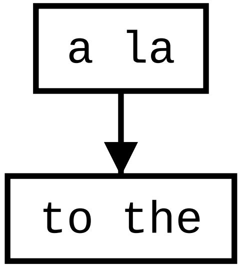
- Comparing hypotheses with *same number of foreign words* covered



- Hypothesis that covers *easy part* of sentence is preferred

⇒ Need to consider **future cost** of uncovered parts

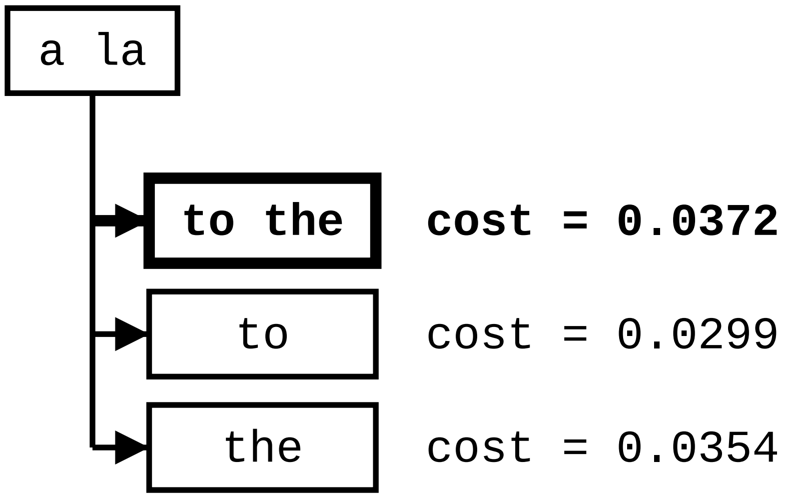
Future Cost Estimation



- *Estimate cost* to translate remaining part of input
- Step 1: estimate future cost for each *translation option*
  - look up translation model cost
  - estimate language model cost (no prior context)
  - ignore reordering model cost

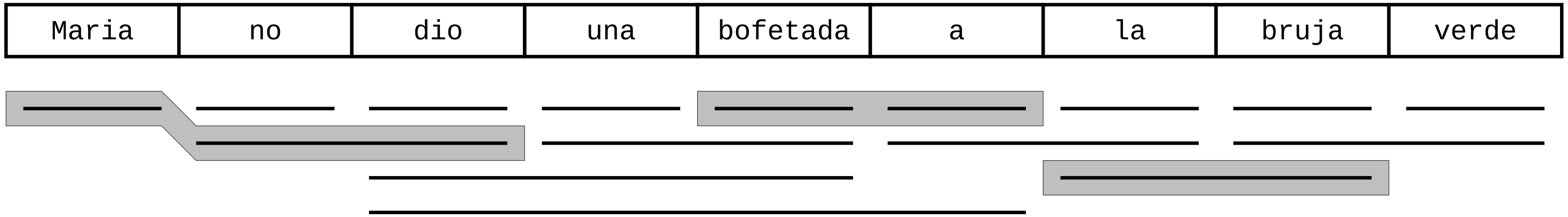
  $\rightarrow$ LM * TM = p(to) * p(the|to) * p(to the|a la)

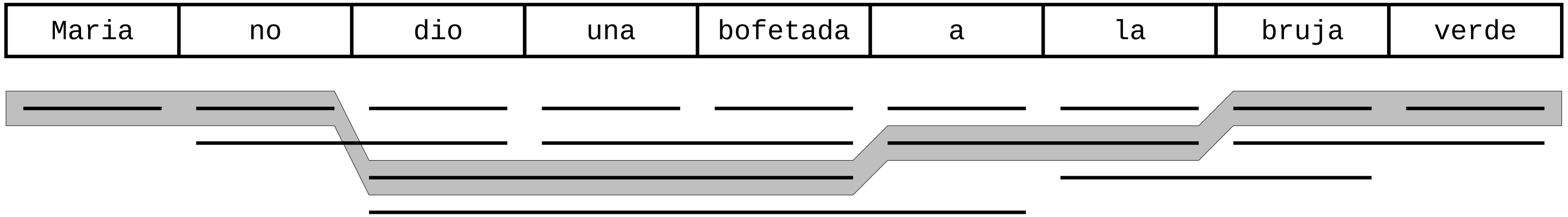
Future Cost Estimation: Step 2



- Step 2: find *cheapest cost* among translation options

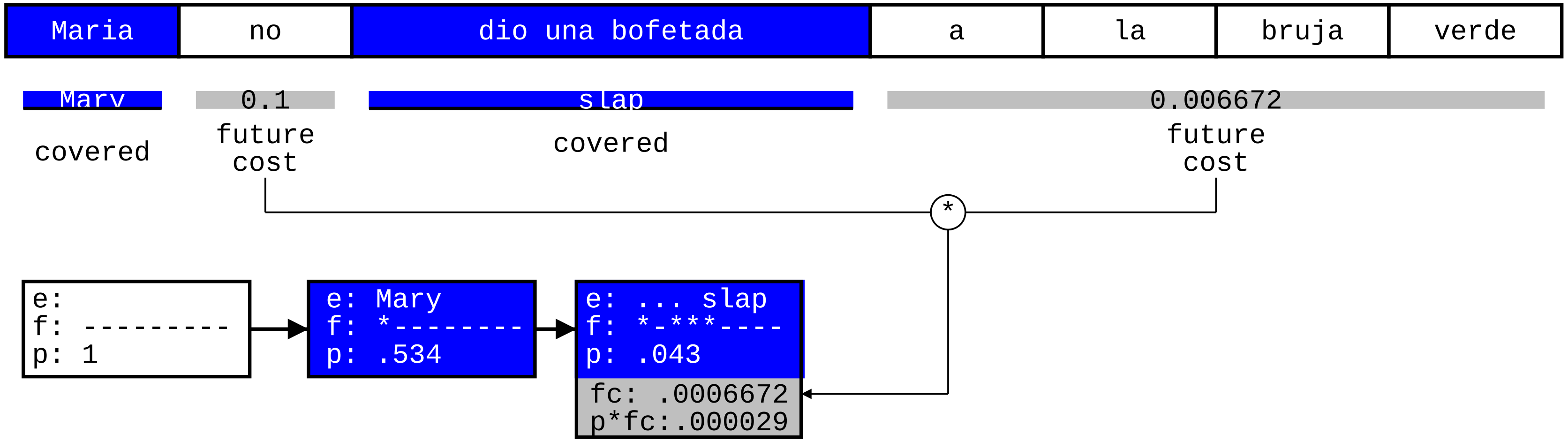
Future Cost Estimation: Step 3





- Step 3: find *cheapest future cost path* for each span
  - can be done *efficiently* by dynamic programming
  - future cost for every span can be *pre-computed*

Future Cost Estimation: Application



- Use future cost estimates when *pruning* hypotheses
- For each *uncovered contiguous span*:
  - look up *future costs* for each maximal contiguous uncovered span
  - *add* to actually accumulated cost for translation option for pruning

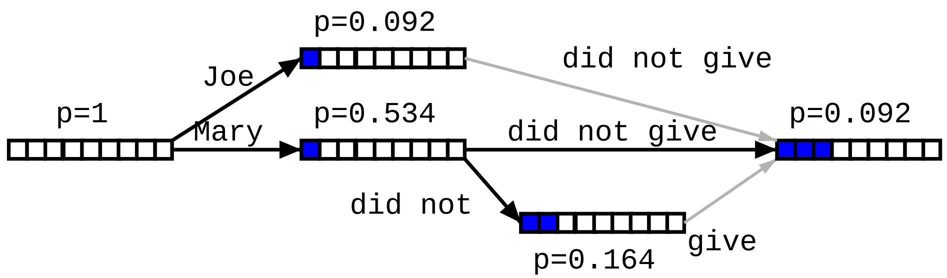
A* search

- Pruning might drop hypothesis that lead to the best path (**search error**)
- **A* search**: safe pruning
  - future cost estimates have to be accurate or underestimates
  - **lower bound** for probability is established early by **depth first search**: compute cost for one complete translation
  - if cost-so-far and future cost are worse than *lower bound*, hypothesis can be safely discarded
- Not commonly done, since not aggressive enough

Limits on Reordering

- Reordering may be **limited**
  - **Monotone** Translation: No reordering at all
  - Only phrase movements of at most n words
- Reordering limits *speed* up search (polynomial instead of exponential)
- Current reordering models are weak, so limits *improve* translation quality

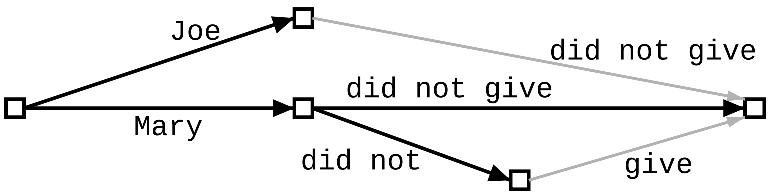
Word Lattice Generation



- **Search graph** can be easily converted into a **word lattice**
  - can be further mined for **n-best lists**

$\rightarrow$ enables **reranking** approaches

$\rightarrow$ enables **discriminative training**



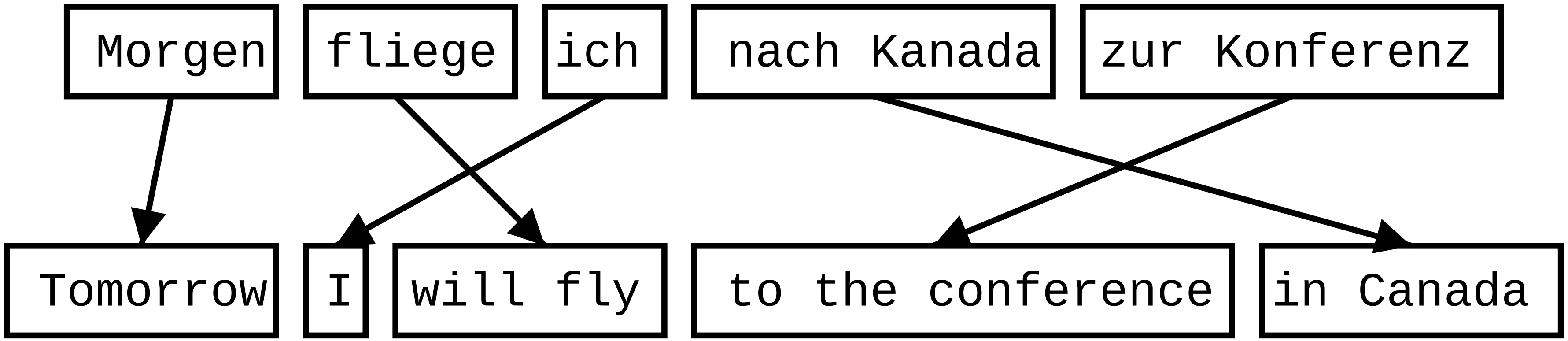
Sample N-Best List

- Simple **N-best list**:

```
Translation ||| Reordering LM TM WordPenalty ||| Score
this is a small house ||| 0 -27.0908 -1.83258 -5 ||| -28.9234
this is a little house ||| 0 -28.1791 -1.83258 -5 ||| -30.0117
it is a small house ||| 0 -27.108 -3.21888 -5 ||| -30.3268
it is a little house ||| 0 -28.1963 -3.21888 -5 ||| -31.4152
this is an small house ||| 0 -31.7294 -1.83258 -5 ||| -33.562
it is an small house ||| 0 -32.3094 -3.21888 -5 ||| -35.5283
this is an little house ||| 0 -33.7639 -1.83258 -5 ||| -35.5965
this is a house small ||| -3 -31.4851 -1.83258 -5 ||| -36.3176
this is a house little ||| -3 -31.5689 -1.83258 -5 ||| -36.4015
it is an little house ||| 0 -34.3439 -3.21888 -5 ||| -37.5628
it is a house small ||| -3 -31.5022 -3.21888 -5 ||| -37.7211
this is an house small ||| -3 -32.8999 -1.83258 -5 ||| -37.7325
it is a house little ||| -3 -31.586 -3.21888 -5 ||| -37.8049
this is an house little ||| -3 -32.9837 -1.83258 -5 ||| -37.8163
the house is a little ||| -7 -28.5107 -2.52573 -5 ||| -38.0364
the is a small house ||| 0 -35.6899 -2.52573 -5 ||| -38.2156
is it a little house ||| -4 -30.3603 -3.91202 -5 ||| -38.2723
the house is a small ||| -7 -28.7683 -2.52573 -5 ||| -38.294
it 's a small house ||| 0 -34.8557 -3.91202 -5 ||| -38.7677
this house is a little ||| -7 -28.0443 -3.91202 -5 ||| -38.9563
it 's a little house ||| 0 -35.1446 -3.91202 -5 ||| -39.0566
this house is a small ||| -7 -28.3018 -3.91202 -5 ||| -39.2139
```

Phrase-based models: Training

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

Phrase-based translation model

- Major components of phrase-based model
  - **phrase translation model** $\phi(\mathbf{f}|\mathbf{e})$
  - **reordering model** $\omega^{d(\mathsf{start}_i - \mathsf{end}_{i-1} - 1)}$
  - **language model** $p_{\text{LM}}(\mathbf{e})$
- Bayes rule

$$\begin{aligned} \text{argmax}_{\mathbf{e}} p(\mathbf{e}|\mathbf{f}) &= \text{argmax}_{\mathbf{e}} p(\mathbf{f}|\mathbf{e}) p(\mathbf{e}) \\ &= \text{argmax}_{\mathbf{e}} \phi(\mathbf{f}|\mathbf{e})\ p_{\text{LM}}(\mathbf{e})\ \omega^{d(\mathsf{start}_i - \mathsf{end}_{i-1} - 1)} \end{aligned}$$

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

$$\phi(\bar{f}_1^I|\bar{e}_1^I) = \prod_{i=1}^{I} \phi(\bar{f}_i|\bar{e}_i)\ \omega^{d(\mathsf{start}_i - \mathsf{end}_{i-1} - 1)})$$

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

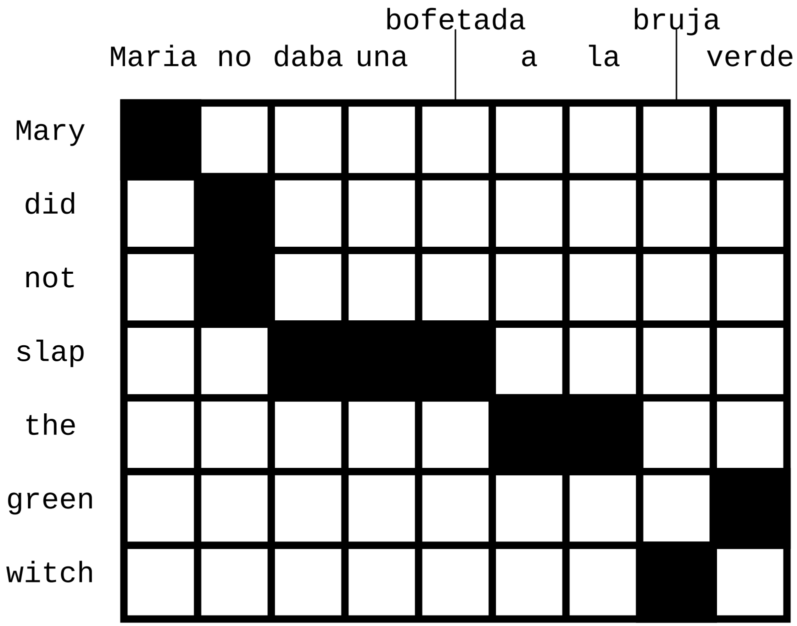
Phrase translation table

- 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	...	...

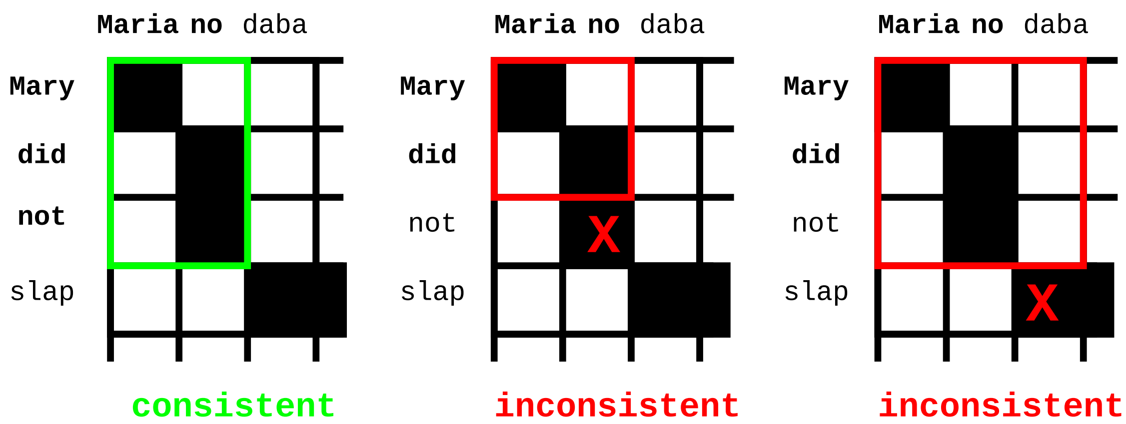
How to learn the phrase translation table?

- Start with the *word alignment*:



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

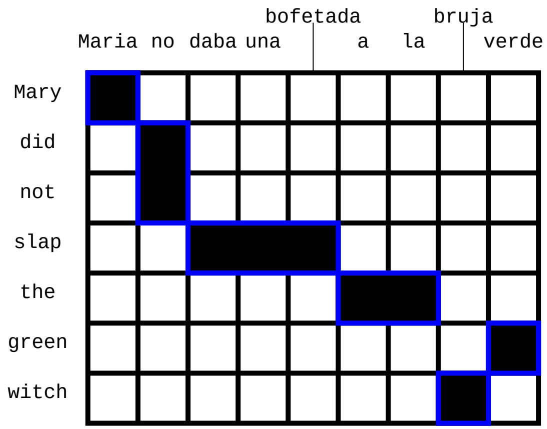
Consistent with word alignment



- **Consistent with the word alignment** :=
  phrase alignment has to *contain all alignment points* for all covered words

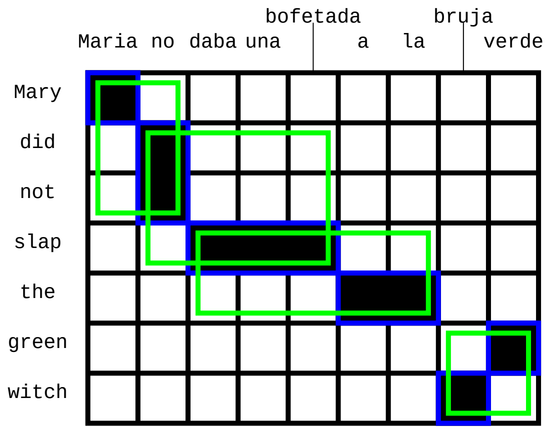
$$
\begin{aligned}
(\bar{e}, \bar{f}) \in BP \Leftrightarrow \quad & \forall e_i \in \bar{e} : (e_i, f_j) \in A \rightarrow f_j \in \bar{f} \\
\text{AND} \quad & \forall f_j \in \bar{f} : (e_i, f_j) \in A \rightarrow e_i \in \bar{e}
\end{aligned}
$$

Word alignment induced phrases



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

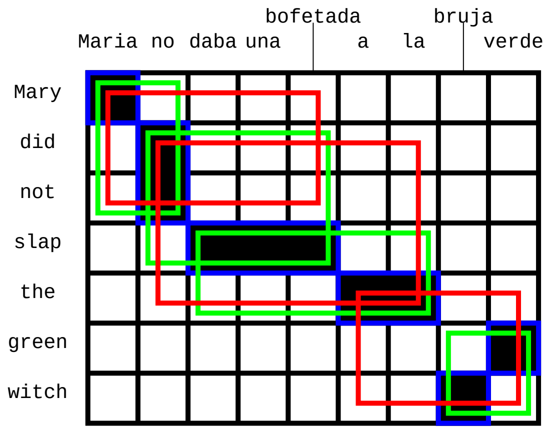
Word alignment induced phrases



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

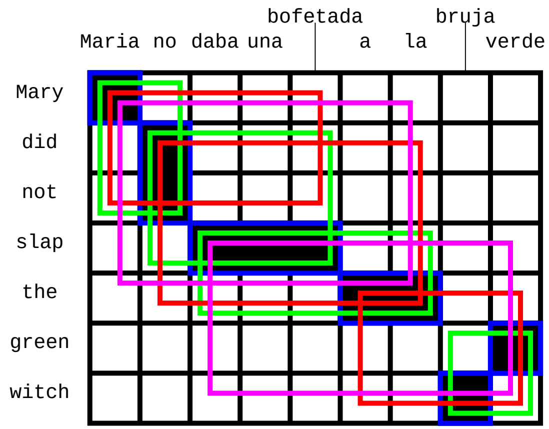
(Maria no, Mary did not), (no daba una bofetada, did not slap), (daba una bofetada a la, slap the), (bruja verde, green witch)

Word alignment induced phrases



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

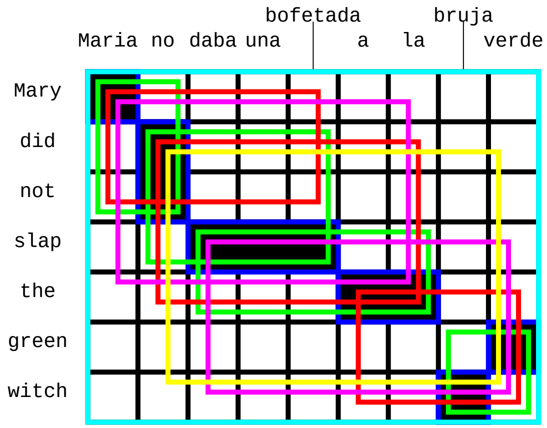
Word alignment induced phrases



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

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

Word alignment induced phrases (5)



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

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

Probability distribution of phrase pairs

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

⇒ Possible *choices*

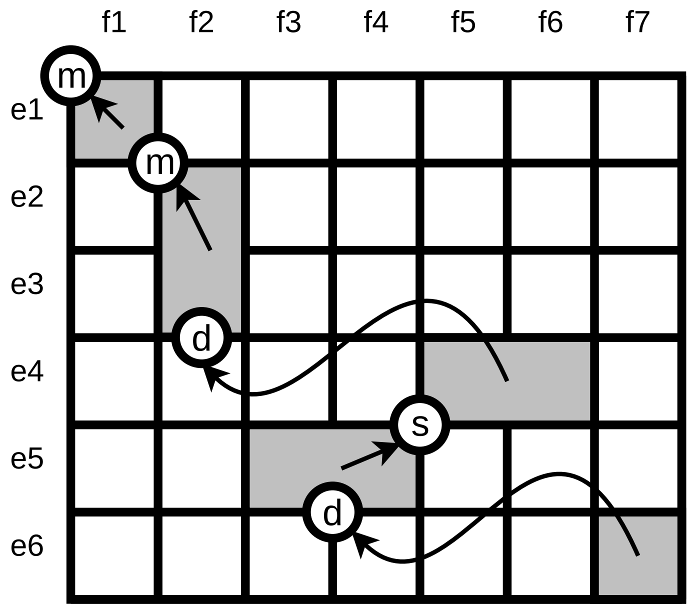
- *relative frequency* of collected phrases: $\phi(\bar{f}|\bar{e}) = \frac{\text{count}(\bar{f},\bar{e})}{\sum_{\bar{f}} \text{count}(\bar{f},\bar{e})}$
- or, conversely $\phi(\bar{e}|\bar{f})$
- use *lexical translation probabilities*

Reordering

- *Monotone* translation
  - do not allow any reordering

  $\longrightarrow$ worse translations
- *Limiting* reordering (to movement over max. number of words) helps
- *Distance-based* reordering cost
  - moving a foreign phrase over n words: cost ω^n
- *Lexicalized* reordering model

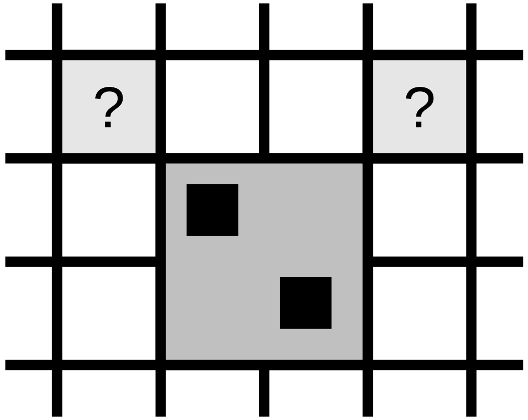
Lexicalized reordering models



[from Koehn et al., 2005, IWSLT]

- Three **orientation** types: **monotone**, **swap**, **discontinuous**
- Probability $p(swap|e, f)$ depends on foreign (and English) *phrase* involved

Learning lexicalized reordering models



[from Koehn et al., 2005, IWSLT]

- Orientation type is *learned during phrase extractions*
- *Alignment point* to the *top left* (monotone) or *top right* (swap)?
- For more, see [Tillmann, 2003] or [Koehn et al., 2005]

Factored Translation Models

Factored Translation Models

- **Motivation**
- Example
- Model and Training
- Decoding
- Experiments
- Planned Work

Statistical machine translation today

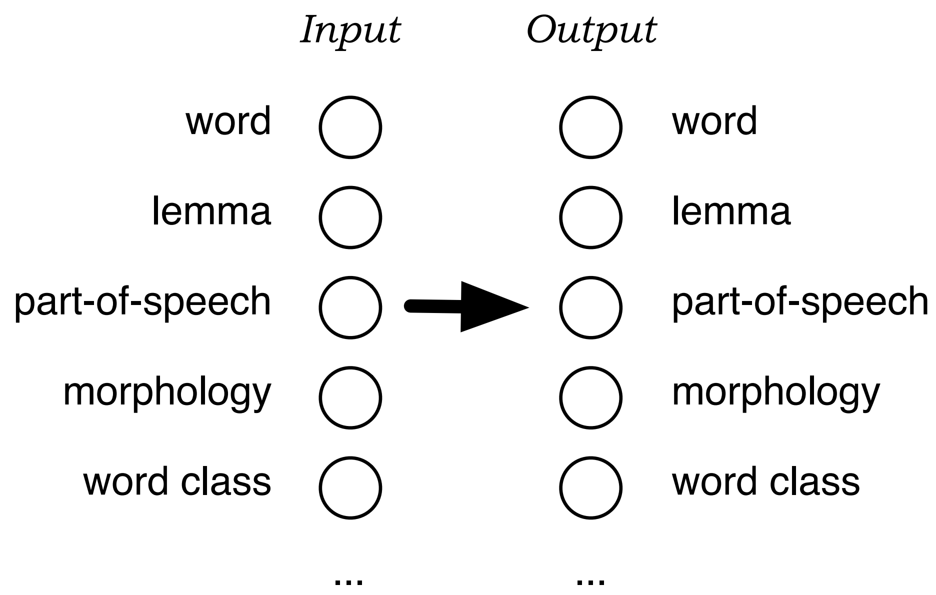
- Best performing methods based on **phrases**
  - short sequences of words
  - no use of explicit syntactic information
  - no use of morphological information
  - currently best performing method
- Progress in **syntax-based** translation
  - tree transfer models using syntactic annotation
  - still shallow representation of words and non-terminals
  - active research, improving performance

One motivation: morphology

- Models treat *car* and *cars* as completely different words
  - training occurrences of *car* have no effect on learning translation of *cars*
  - if we only see *car*, we do not know how to translate *cars*
  - rich morphology (German, Arabic, Finnish, Czech, ...) → many word forms
- Better approach
  - analyze surface word forms into **lemma** and **morphology**, e.g.: *car +plural*
  - translate lemma and morphology separately
  - generate target surface form

Factored translation models

- **Factored represention** of words



- Goals
  - **Generalization**, e.g. by translating lemmas, not surface forms
  - **Richer model**, e.g. using syntax for reordering, language modeling)

Related work

- **Back off** to representations with richer statistics (lemma, etc.)
  [Nießen and Ney, 2001, Yang and Kirchhoff 2006, Talbot and Osborne 2006]
- Use of additional annotation in **pre-processing** (POS, syntax trees, etc.)
  [Collins et al., 2005, Crego et al, 2006]
- Use of additional annotation in **re-ranking** (morphological features, POS, syntax trees, etc.)
  [Och et al. 2004, Koehn and Knight, 2005]

→ we pursue an *integrated approach*

- Use of syntactic **tree structure**
  [Wu 1997, Alshawi et al. 1998, Yamada and Knight 2001, Melamed 2004, Menezes and Quirk 2005, Chiang 2005, Galley et al. 2006]

→ may be *combined* with our approach

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Decomposing translation: example

- **Translate** lemma and syntactic information **separately**

$$\begin{bmatrix} \text{lemma} \end{bmatrix} \Rightarrow \begin{bmatrix} \text{lemma} \end{bmatrix}$$

$$\begin{bmatrix} \text{part-of-speech} \\ \text{morphology} \end{bmatrix} \Rightarrow \begin{bmatrix} \text{part-of-speech} \\ \text{morphology} \end{bmatrix}$$

Decomposing translation: example

- **Generate surface** form on target side

$$\begin{bmatrix}\text{surface}\end{bmatrix}$$

$$\Uparrow$$

$$\begin{bmatrix}\text{lemma}\\ \text{part-of-speech}\\ \text{morphology}\end{bmatrix}$$

Translation process: example

Input: *(Autos, Auto, NNS)*

1. Translation step: lemma ⇒ lemma
   (?, car, ?), (?, auto, ?)
2. Generation step: lemma ⇒ part-of-speech
   (?, car, NN), (?, car, NNS), (?, auto, NN), (?, auto, NNS)
3. Translation step: part-of-speech ⇒ part-of-speech
   (?, car, NN), (?, car, NNS), (?, auto, NNP), (?, auto, NNS)
4. Generation step: lemma,part-of-speech ⇒ surface
   (car, car, NN), (cars, car, NNS), (auto, auto, NN), (autos, auto, NNS)

Factored Translation Models

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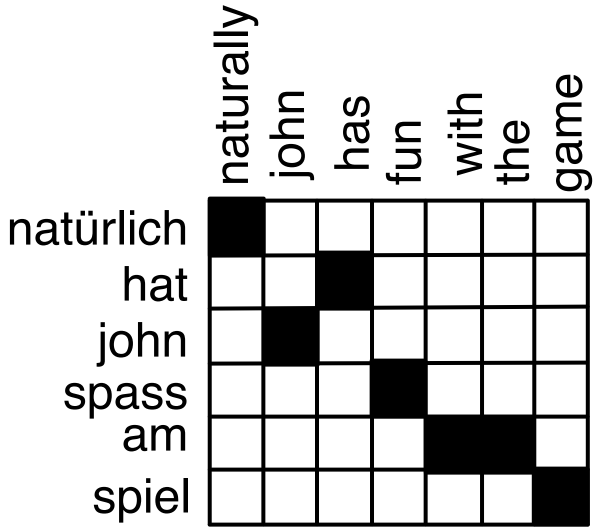
Model

- Extension of *phrase model*
- Mapping of foreign words into English words broken up into steps
  - **translation step**: maps foreign factors into English factors (on the phrasal level)
  - **generation step**: maps English factors into English factors (for each word)
- Each step is modeled by one or more *feature functions*
  - fits nicely into log-linear model
  - weight set by discriminative training method
- Order of mapping steps is chosen to optimize search

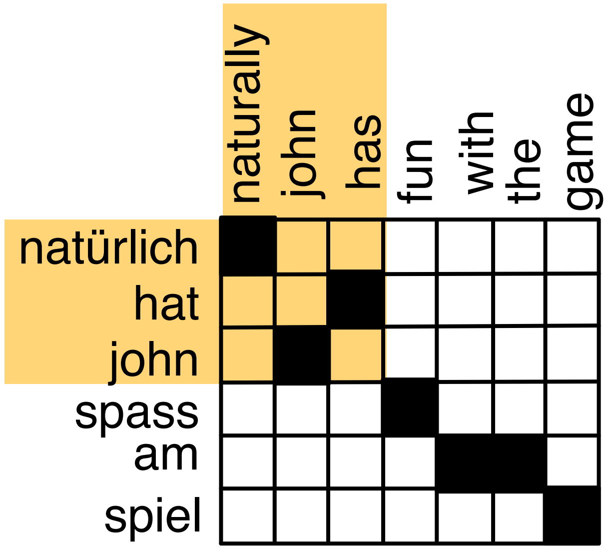
Phrase-based training

- Establish word alignment (GIZA++ and symmetrization)



Phrase-based training

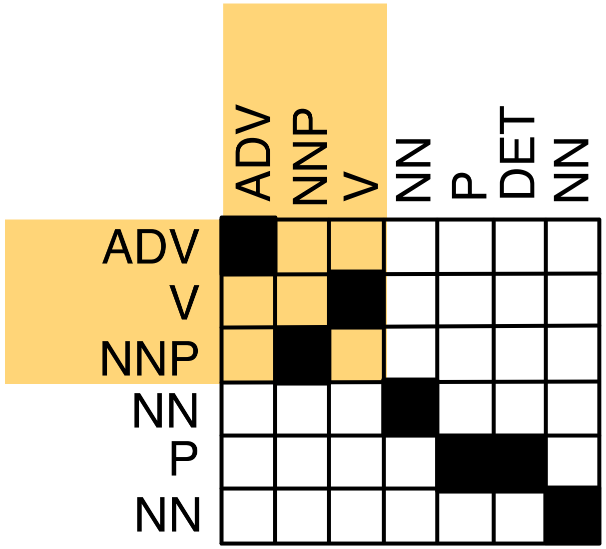
- Extract phrase



⇒ *natürlich hat john* — *naturally john has*

Factored training

- Annotate training with factors, extract phrase



$\Rightarrow$ *ADV V NNP — ADV NNP V*

Training of generation steps

- Generation steps map target factors to target factors
  - typically trained on target side of parallel corpus
  - may be trained on additional monolingual data
- Example: *The*/DET *man*/NN *sleeps*/VBZ
  - count collection
    - count(*the*,DET)++
    - count(*man*,NN)++
    - count(*sleeps*,VBZ)++
  - evidence for probability distributions (max. likelihood estimation)
    - p(DET|*the*), p(*the*|DET)
    - p(NN|*man*), p(*man*|NN)
    - p(VBZ|*sleeps*), p(*sleeps*|VBZ)

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Phrase-based translation

- Task: *translate this sentence* from German into English

er geht ja nicht nach hause

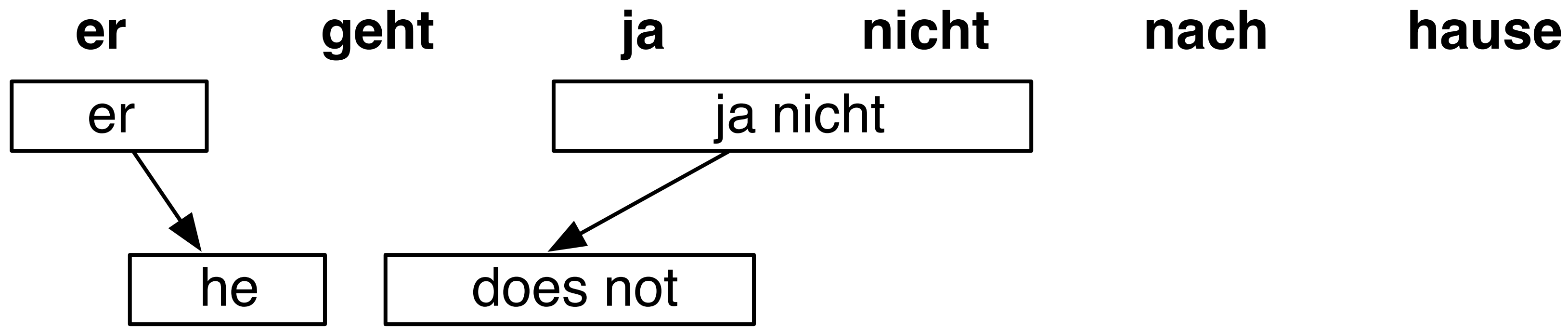
Translation step 1

- Task: translate this sentence from German into English

- *Pick* phrase in input, *translate*

Translation step 2

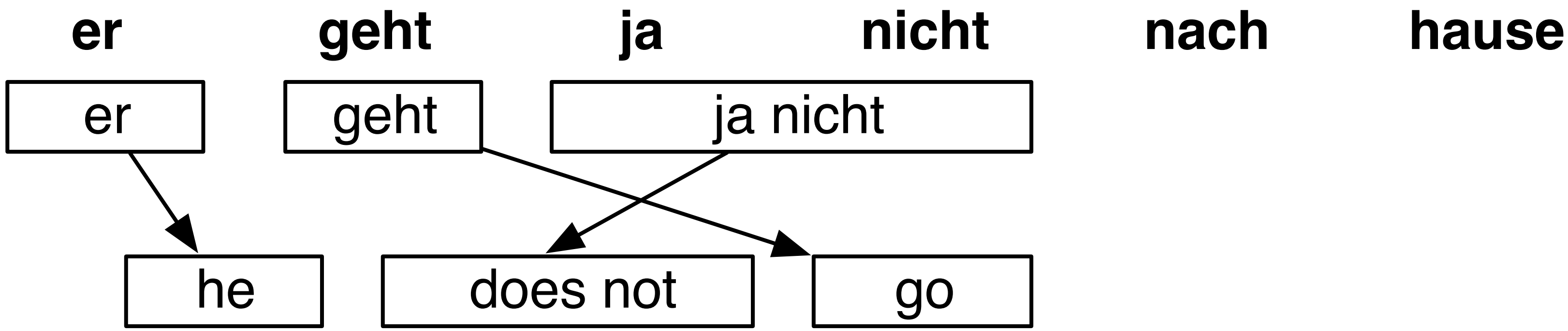
- Task: translate this sentence from German into English



- Pick phrase in input, translate
  - it is allowed to pick words *out of sequence* (**reordering**)
  - phrases may have multiple words: *many-to-many* translation

Translation step 3

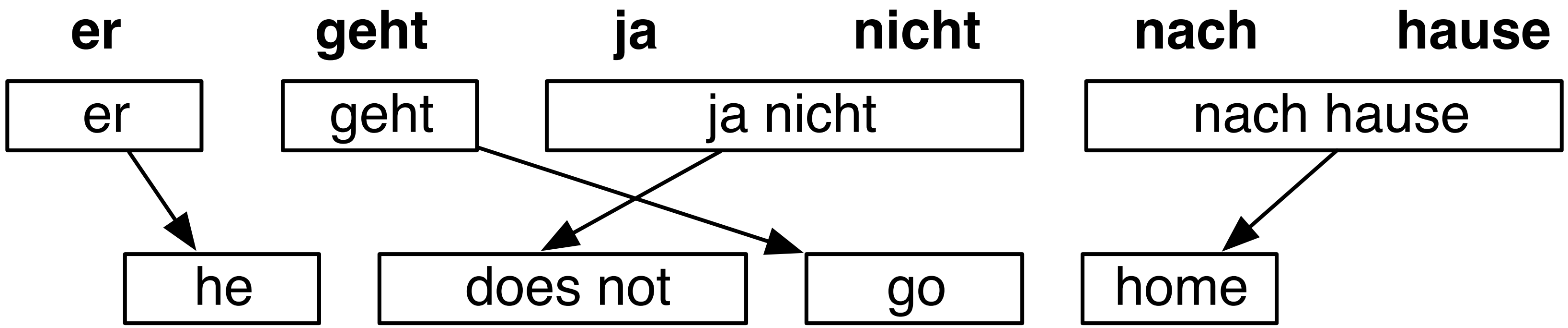
- Task: translate this sentence from German into English



- Pick phrase in input, translate

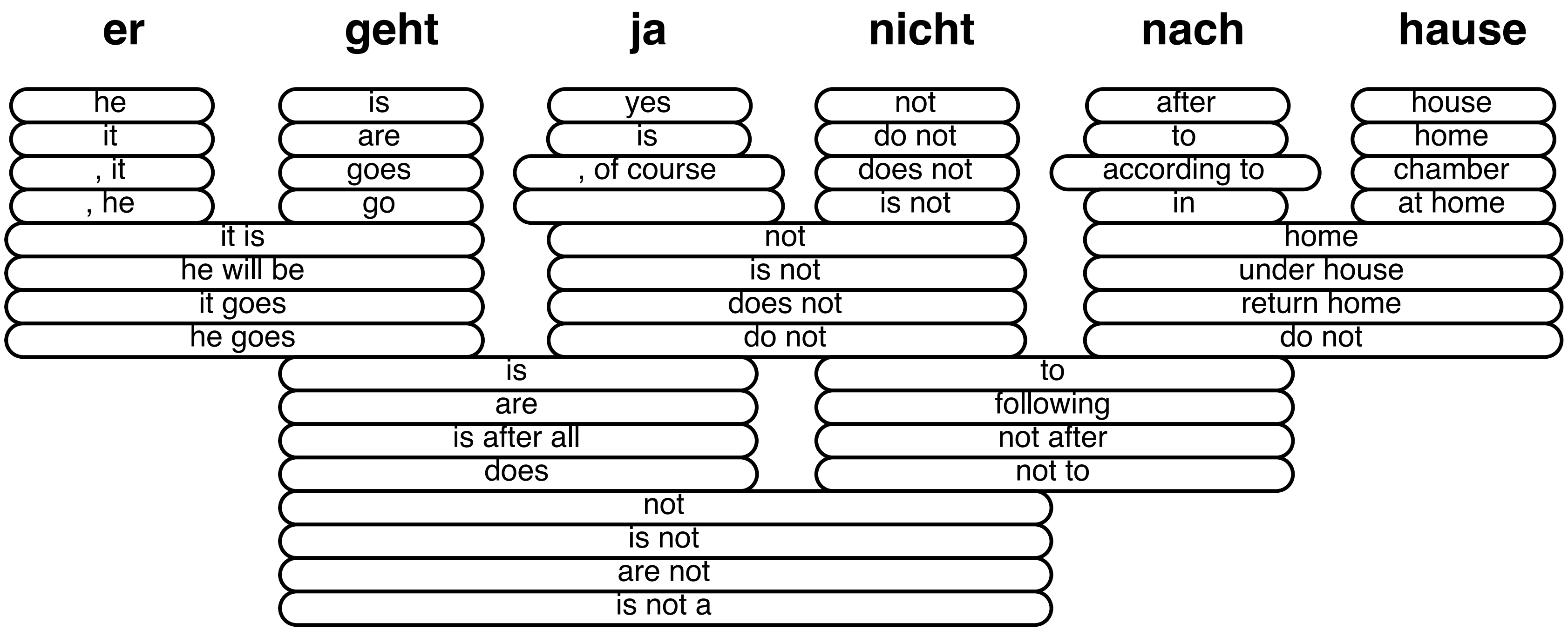
Translation step 4

- Task: translate this sentence from German into English



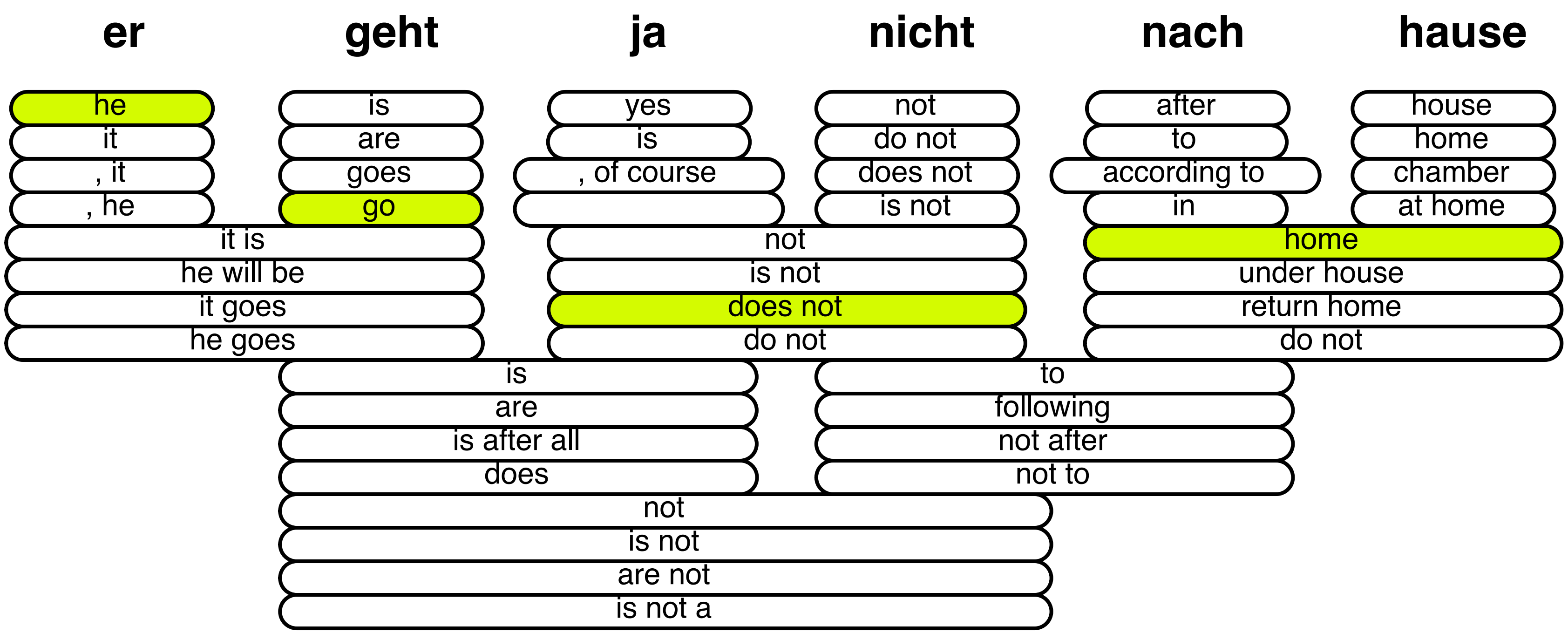
- Pick phrase in input, translate

Translation options



- *Many translation options* to choose from
  - in Europarl phrase table: *2727 matching phrase pairs* for this sentence
  - by pruning to the top 20 per phrase, *202 translation options* remain

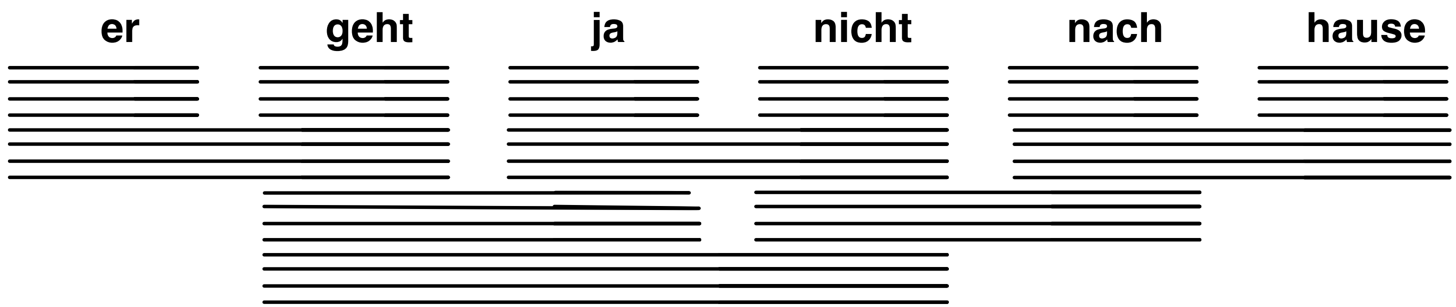
Translation options



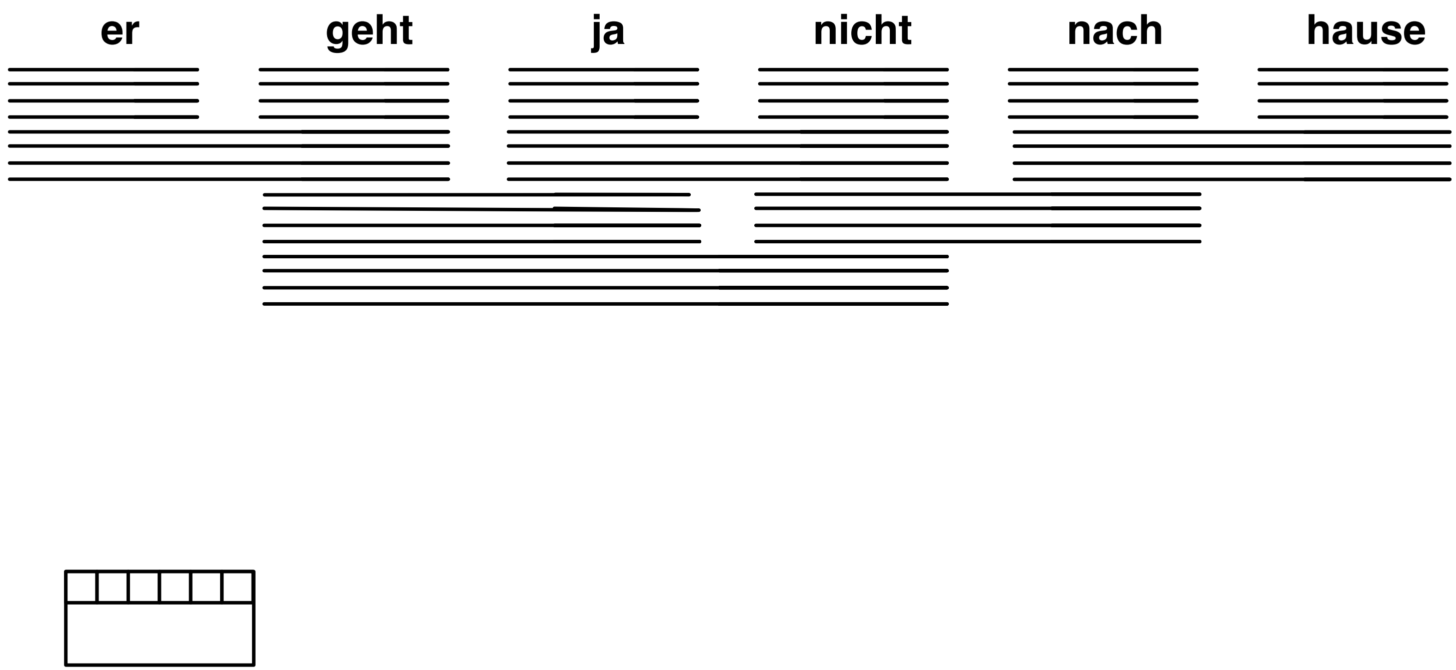
- The machine translation decoder does not know the right answer

→ *Search problem* solved by heuristic beam search

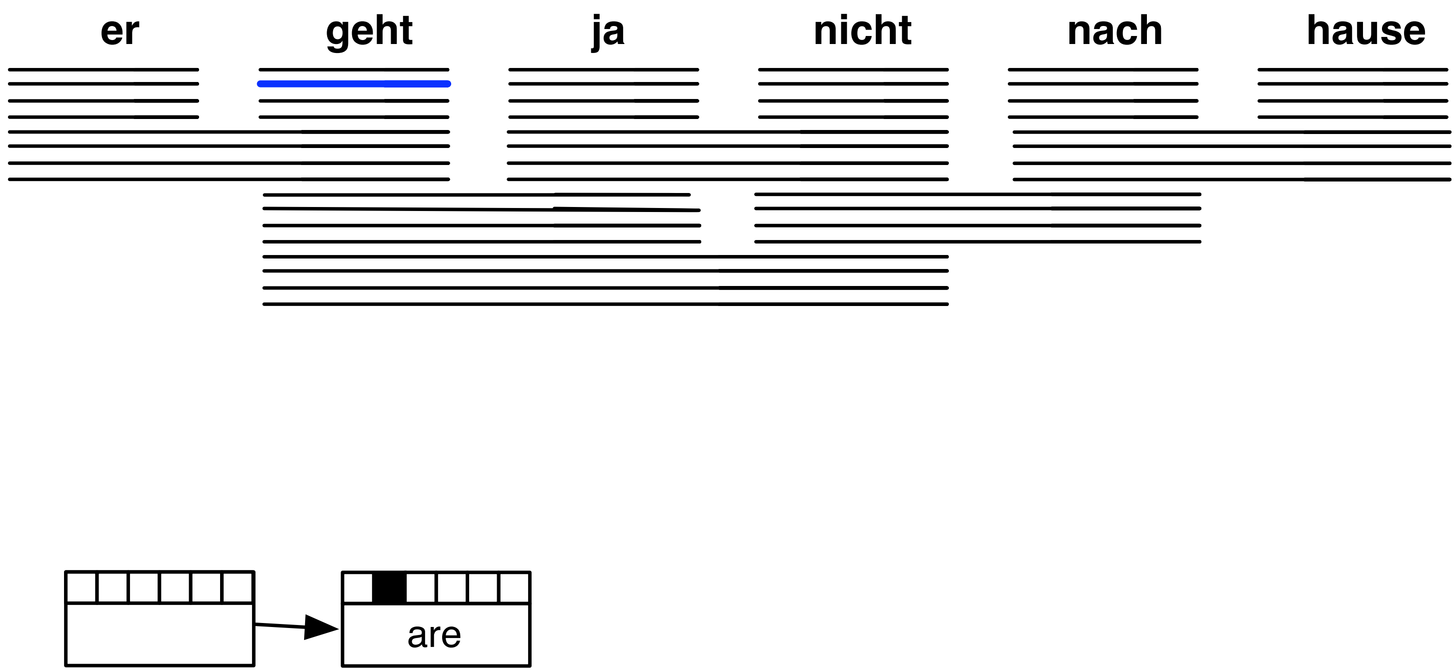
Decoding process: precompute translation options



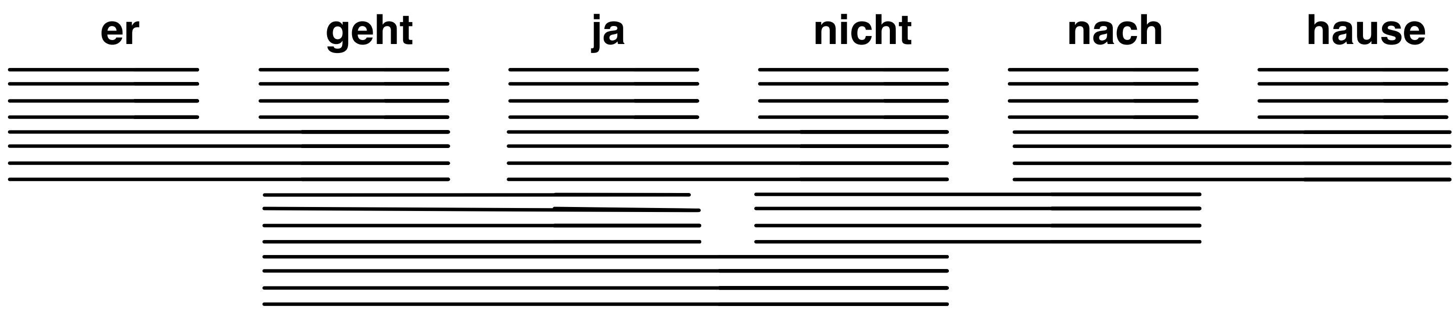
Decoding process: start with initial hypothesis

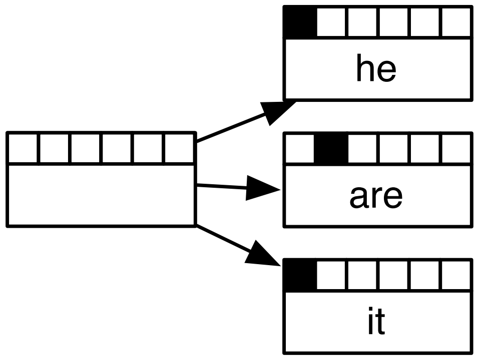


Decoding process: hypothesis expansion

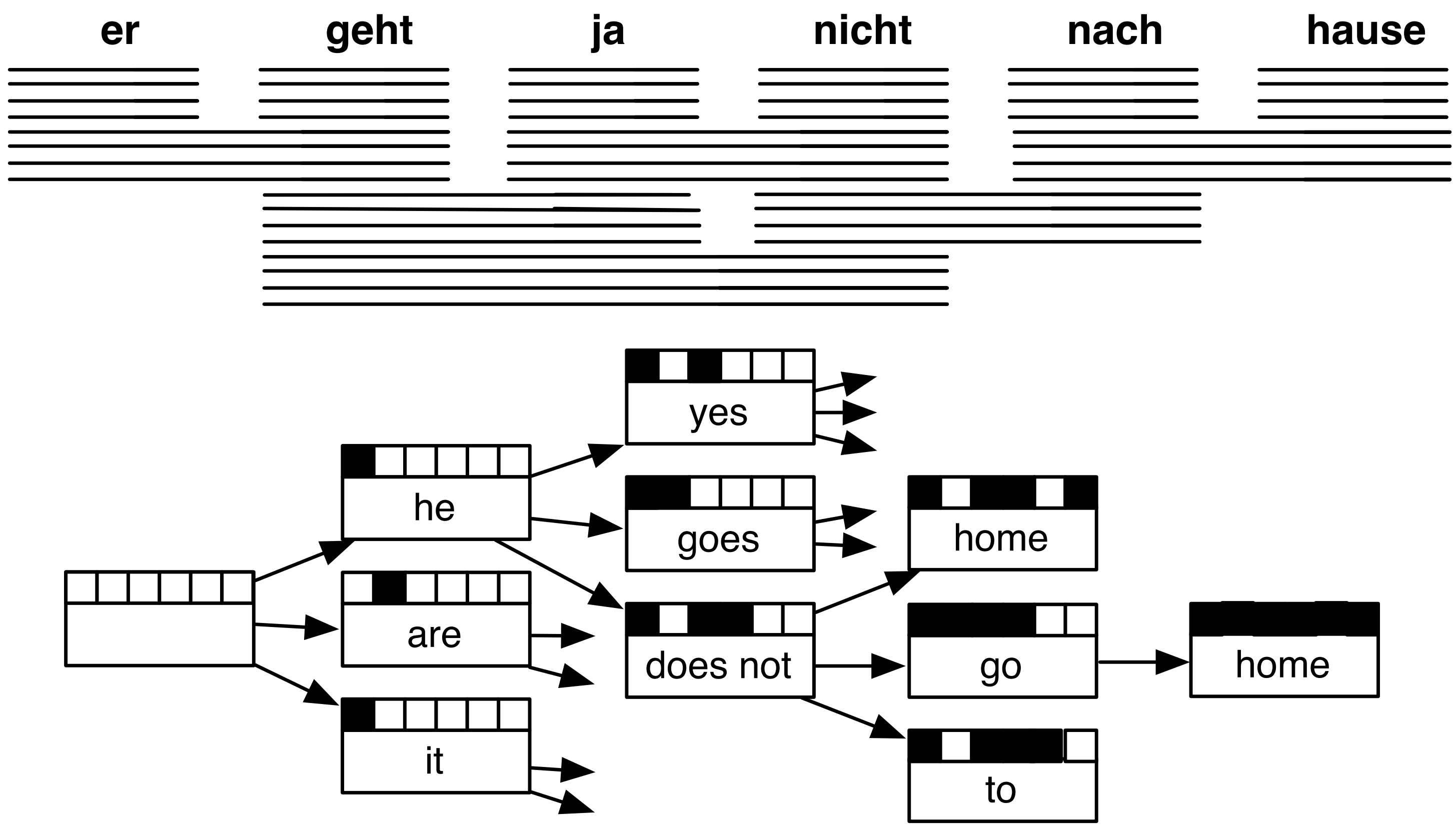


Decoding process: hypothesis expansion

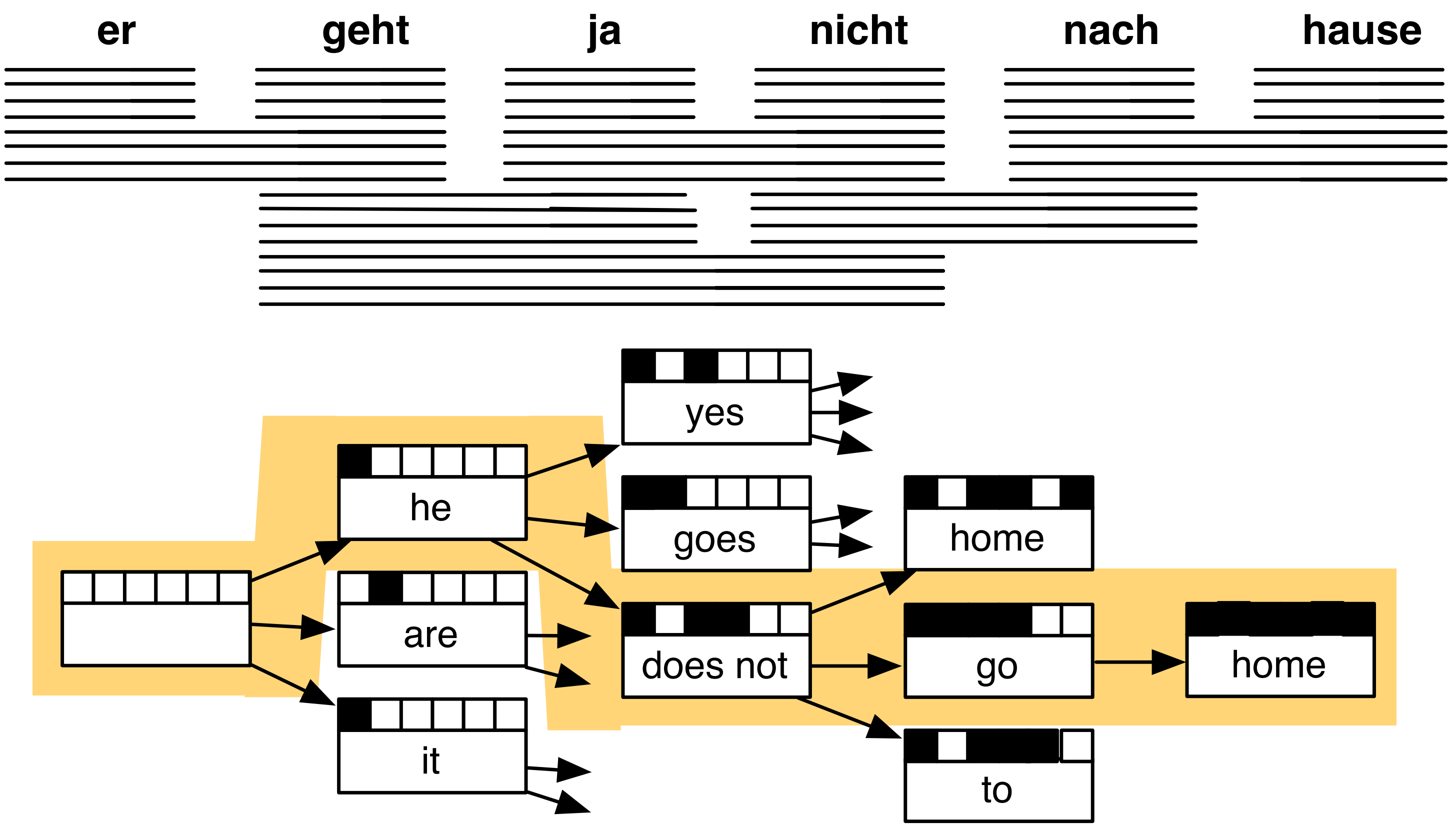




Decoding process: hypothesis expansion



Decoding process: find best path

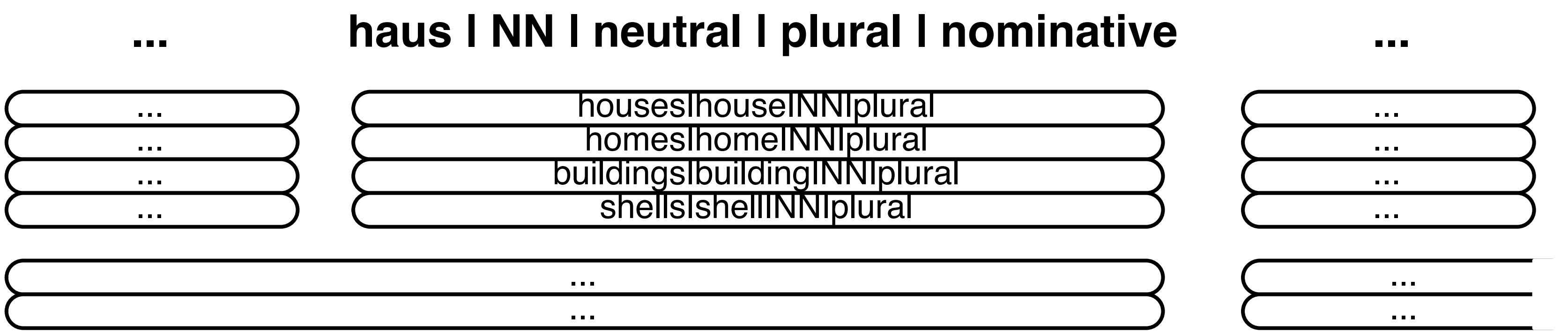


Factored model decoding

- Factored model decoding introduces *additional complexity*
- Hypothesis expansion not any more according to simple translation table, but by *executing a number of mapping steps*, e.g.:
  1. translating of *lemma* → *lemma*
  2. translating of *part-of-speech, morphology* → *part-of-speech, morphology*
  3. generation of *surface form*
- Example: *haus|NN|neutral|plural|nominative*
  → { *houses|house|NN|plural, homes|home|NN|plural, buildings|building|NN|plural, shells|shell|NN|plural* }
- Each time, a hypothesis is expanded, these mapping steps have to applied

Efficient factored model decoding

- Key insight: executing of mapping steps can be *pre-computed* and stored as translation options
  - apply mapping steps to all input phrases
  - store results as *translation options*
  - → decoding algorithm *unchanged*



Efficient factored model decoding

- Problem: *Explosion* of translation options
  - originally limited to 20 per input phrase
  - even with simple model, now 1000s of mapping expansions possible
- Solution: *Additional pruning* of translation options
  - *keep only the best* expanded translation options
  - current default 50 per input phrase
  - decoding only about 2-3 times slower than with surface model

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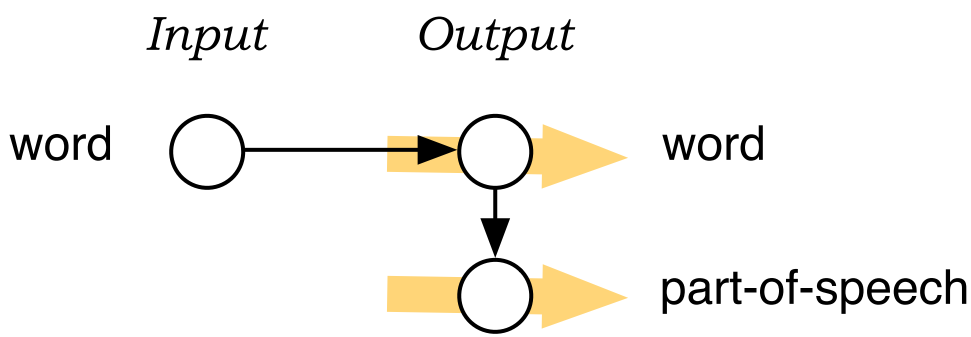
- **Experiments**
- Outlook

Adding linguistic markup to output



- Generation of POS tags on the target side
- Use of high order language models over POS (7-gram, 9-gram)
- Motivation: syntactic tags should enforce syntactic sentence structure model not strong enough to support major restructuring

Some experiments

- English–German, Europarl, 30 million word, test2006

Model	BLEU
best published result	18.15
baseline (surface)	18.04
surface + POS	18.15

- German–English, News Commentary data (WMT 2007), 1 million word

Model	BLEU
Baseline	18.19
With POS LM	19.05

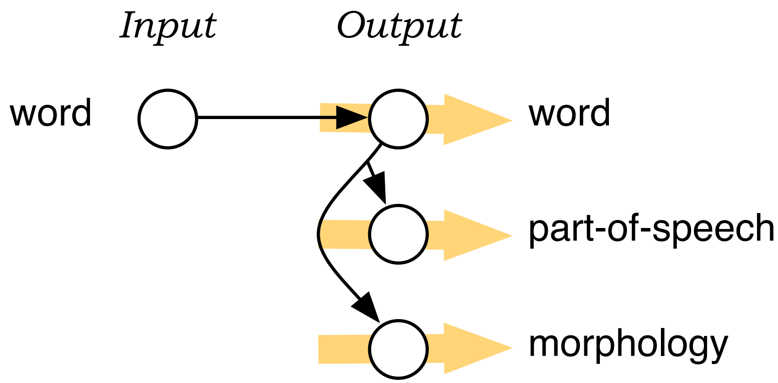
- Improvements under sparse data conditions
- Similar results with CCG supertags [Birch et al., 2007]

Sequence models over morphological tags

die	**hellen**	**Sterne**	**erleuchten**	**das**	**schwarze**	**Himmel**
(the)	*(bright)*	*(stars)*	*(illuminate)*	*(the)*	*(black)*	*(sky)*
fem	*fem*	*fem*	*-*	*neutral*	*neutral*	*male*
plural	*plural*	*plural*	*plural*	*sgl.*	*sgl.*	*sgl*
nom.	*nom.*	*nom.*	*-*	*acc.*	*acc.*	*acc.*

- Violation of noun phrase agreement in gender
  - *das schwarze* and *schwarze Himmel* are perfectly fine bigrams
  - but: *das schwarze Himmel* is not
- If relevant n-grams does not occur in the corpus, a lexical n-gram model would *fail to detect* this mistake
- Morphological sequence model: $p(\text{N-male}|\text{J-male}) > p(\text{N-male}|\text{J-neutral})$

Local agreement (esp. within noun phrases)



- High order language models over POS and morphology
- Motivation
  - *DET-sgl NOUN-sgl* good sequence
  - *DET-sgl NOUN-plural* bad sequence

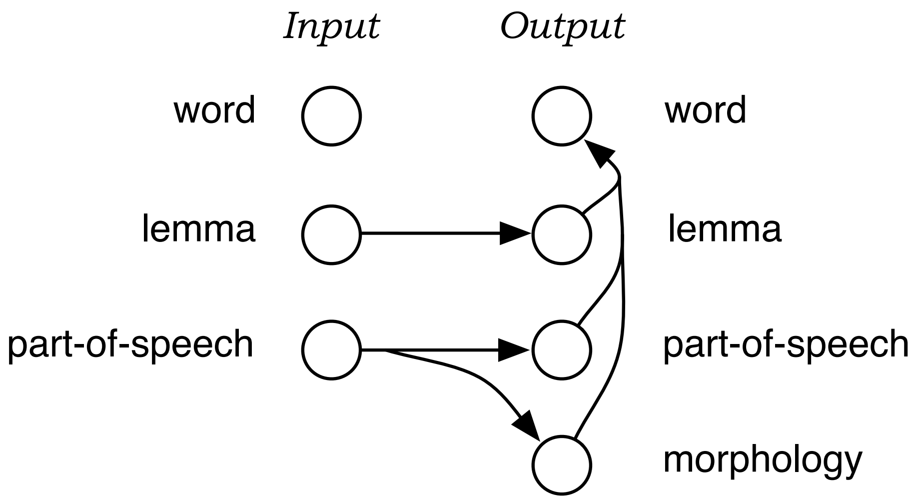
Agreement within noun phrases

- Experiment: 7-gram POS, morph LM in addition to 3-gram word LM
- Results

Method	Agreement errors in NP	devtest	test
baseline	15% in NP $\geq$ 3 words	18.22 BLEU	18.04 BLEU
factored model	4% in NP $\geq$ 3 words	18.25 BLEU	18.22 BLEU

- Example
  - baseline: *... zur zwischenstaatlichen methoden ...*
  - factored model: *... zu zwischenstaatlichen methoden ...*
- Example
  - baseline: *... das zweite wichtige änderung ...*
  - factored model: *... die zweite wichtige änderung ...*

Morphological generation model



- Our motivating example
- Translating lemma and morphological information more robust

Initial results

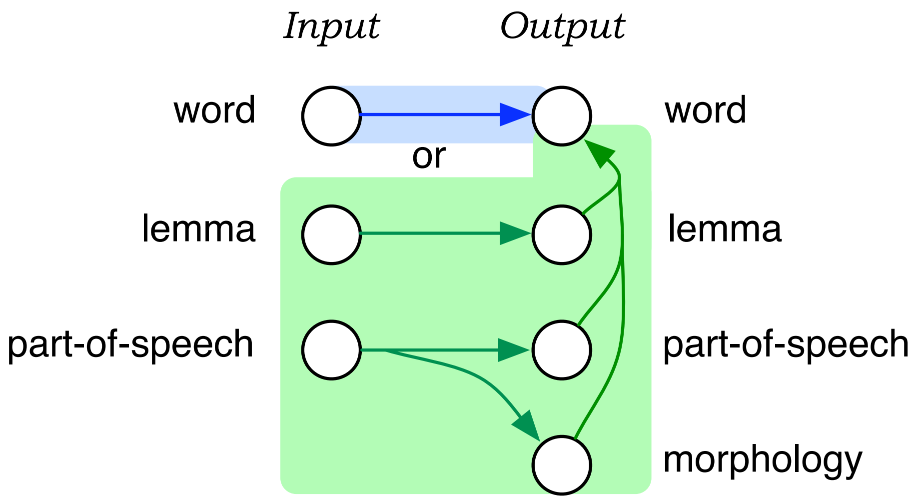
- Results on 1 million word News Commentary corpus (German–English)

System	In-doman	Out-of-domain
Baseline	18.19	15.01
With POS LM	19.05	15.03
Morphgen model	14.38	11.65

- What went wrong?
  - why back-off to lemma, when we know how to translate surface forms?

$\rightarrow$ loss of information

Solution: alternative decoding paths



- Allow both surface form translation and morphgen model
  - prefer surface model for known words
  - morphgen model acts as back-off

Results

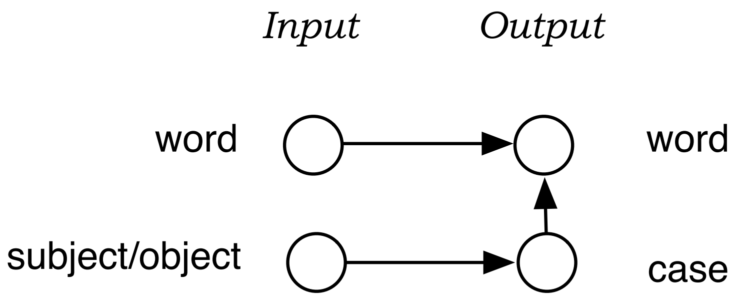
- Model now beats the baseline:

System	In-doman	Out-of-domain
Baseline	**18.19**	**15.01**
With POS LM	19.05	15.03
Morphgen model	14.38	11.65
Both model paths	**19.47**	**15.23**

Adding annotation to the source

- Source words may **lack sufficient information** to map phrases
  - English-German: what case for noun phrases?
  - Chinese-English: plural or singular
  - pronoun translation: what do they refer to?
- Idea: **add additional information** to the source that makes the required information available locally (where it is needed)
- see [Avramidis and Koehn, ACL 2008] for details

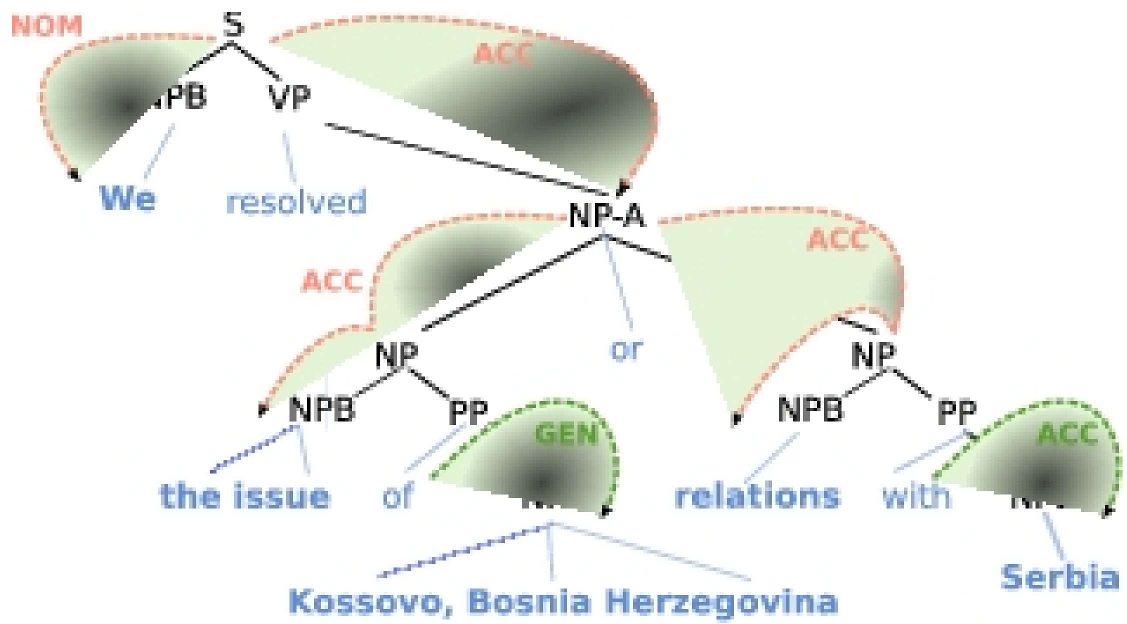
Case Information for English–Greek



- Detect in English, if noun phrase is subject/object (using parse tree)
- Map information into case morphology of Greek
- Use case morphology to generate correct word form

Obtaining Case Information

- Use syntactic parse of English input
  (method similar to semantic role labeling)



Results English-Greek

- Automatic BLEU scores

System	devtest	test07
baseline	18.13	18.05
enriched	18.21	18.20

- Improvement in verb inflection

System	Verb count	Errors	Missing
baseline	311	19.0%	7.4%
enriched	294	5.4%	2.7%

- Improvement in noun phrase inflection

System	NPs	Errors	Missing
baseline	247	8.1%	3.2%
enriched	239	5.0%	5.0%

- Also successfully applied to English-Czech

Factored Translation Models

- Motivation
- Example
- Model and Training
- Decoding
- Experiments
- **Planned Work**

Using POS in reordering

- **Reordering** is often due to syntactic reasons
  - French-English: *NN ADJ* → *ADJ NN*
  - Chinese-English: *NN1 F NN2* → *NN1 NN2*
  - Arabic-English: *VB NN* → *NN VB*
- Extension of lexicalized reordering model
  - already have model that learns *p(monotone|bleue)*
  - can be extended to *p(monotone|ADJ)*
- Gains in preliminary experiments

Shallow syntactic features

the	**paintings**	**of**	**the**	**old**	**man**	**are**	**beautiful**
-	*plural*	*-*	*-*	*-*	*singular*	*plural*	*-*
B-NP	*I-NP*	*B-PP*	*I-PP*	*I-PP*	*I-PP*	*V*	*B-ADJ*
SBJ	*SBJ*	*OBJ*	*OBJ*	*OBJ*	*OBJ*	*V*	*ADJ*

- Shallow syntactic tasks have been formulated as sequence labeling tasks
  - base noun phrase chunking
  - syntactic role labeling

Long range reordering

- **Long range** reordering
  - movement often not limited to local changes
  - German-English: *SBJ AUX OBJ V* $\rightarrow$ *SBJ AUX V OBJ*
- **Asynchronous** models
  - some factor mappings (POS, syntactic chunks) may have longer scope than others (words)
  - larger mappings form template for shorter mappings
  - computational problems with this

Discriminative Training

Overview

- Evolution from generative to discriminative models
  - IBM Models: purely generative
  - MERT: discriminative training of generative components
  - More features $\rightarrow$ better discriminative training needed
- Perceptron algorithm
- Problem: overfitting
- Problem: matching reference translation

The birth of SMT: generative models

- The definition of translation probability follows a **mathematical derivation**

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

- Occasionally, some **independence assumptions** are thrown in
  for instance IBM Model 1: word translations are independent of each other

$$p(\mathbf{e}|\mathbf{f}, a) = \frac{1}{Z} \prod_i p(e_i|f_{a(i)})$$

- Generative story leads to **straight-forward estimation**
  - maximum likelihood estimation of component probability distribution
  - **EM algorithm** for discovering hidden variables (alignment)

Log-linear models

- IBM Models provided mathematical justification for factoring **components** together

$$p_{LM} \times p_{TM} \times p_D$$

- These may be **weighted**

$$p_{LM}^{\lambda_{LM}} \times p_{TM}^{\lambda_{TM}} \times p_D^{\lambda_D}$$

- **Many components** p_i with weights λ_i

$$\prod_i p_i^{\lambda_i} = exp(\sum_i \lambda_i log(p_i))$$

$$log \prod_i p_i^{\lambda_i} = \sum_i \lambda_i log(p_i)$$

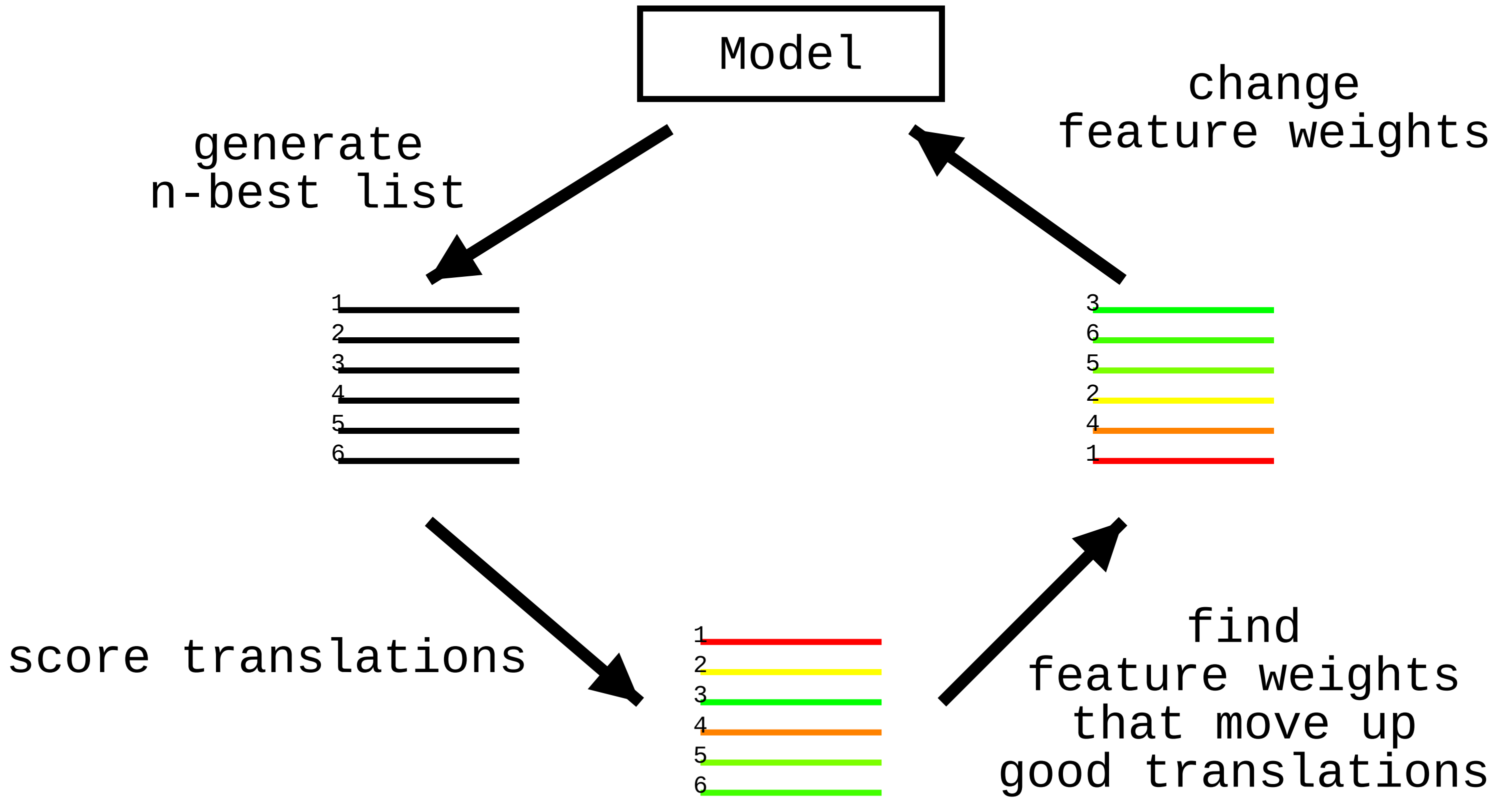
Knowledge sources

- Many different **knowledge sources** useful
  - language model
  - reordering (distortion) model
  - phrase translation model
  - word translation model
  - word count
  - phrase count
  - drop word feature
  - phrase pair frequency
  - additional language models
  - additional features

Set feature weights

- Contribution of components p_i determined by weight λ_i
- Methods
  - *manual setting* of weights: try a few, take best
  - *automate* this process
- Learn weights
  - set aside a **development corpus**
  - set the weights, so that **optimal translation performance** on this development corpus is achieved
  - requires *automatic scoring* method (e.g., BLEU)

Discriminative training



Discriminative vs. generative models

- Generative models
  - translation process is broken down to *steps*
  - each step is modeled by a *probability distribution*
  - each probability distribution is estimated from the data by *maximum likelihood*
- Discriminative models
  - model consist of a number of *features* (e.g. the language model score)
  - each feature has a *weight*, measuring its value for judging a translation as correct
  - feature weights are *optimized on development data*, so that the system output matches correct translations as close as possible

Discriminative training

- Training set (*development set*)
  - different from original training set
  - small (maybe 1000 sentences)
  - must be different from test set
- Current model *translates* this development set
  - *n-best list* of translations (n=100, 10000)
  - translations in n-best list can be *scored*
- Feature weights are *adjusted*
- N-Best list generation and feature weight adjustment repeated for a number of iterations

Learning task

- Task: *find weights*, so that feature vector of the correct translations *ranked first*

rank	translation	LM	TM	WP	SER
1	Mary not give slap witch green .	-17.2	-5.2	-7	1
2	Mary not slap the witch green .	-16.3	-5.7	-7	1
3	Mary not give slap of the green witch .	-18.1	-4.9	-9	1
4	Mary not give of green witch .	-16.5	-5.1	-8	1
5	Mary did not slap the witch green .	-20.1	-4.7	-8	1
6	Mary did not slap green witch .	-15.5	-3.2	-7	1
7	Mary not slap of the witch green .	-19.2	-5.3	-8	1
8	Mary did not give slap of witch green .	-23.2	-5.0	-9	1
9	Mary did not give slap of the green witch .	-21.8	-4.4	-10	1
10	Mary did slap the witch green .	-15.5	-6.9	-7	1
11	**Mary did not slap the green witch .**	**-17.4**	**-5.3**	**-8**	**0**
12	Mary did slap witch green .	-16.9	-6.9	-6	1
13	Mary did slap the green witch .	-14.3	-7.1	-7	1
14	Mary did not slap the of green witch .	-24.2	-5.3	-9	1
15	Mary did not give slap the witch green .	-25.2	-5.5	-9	1

feature vector

Och's minimum error rate training (MERT)

- **Line search** for best feature weights

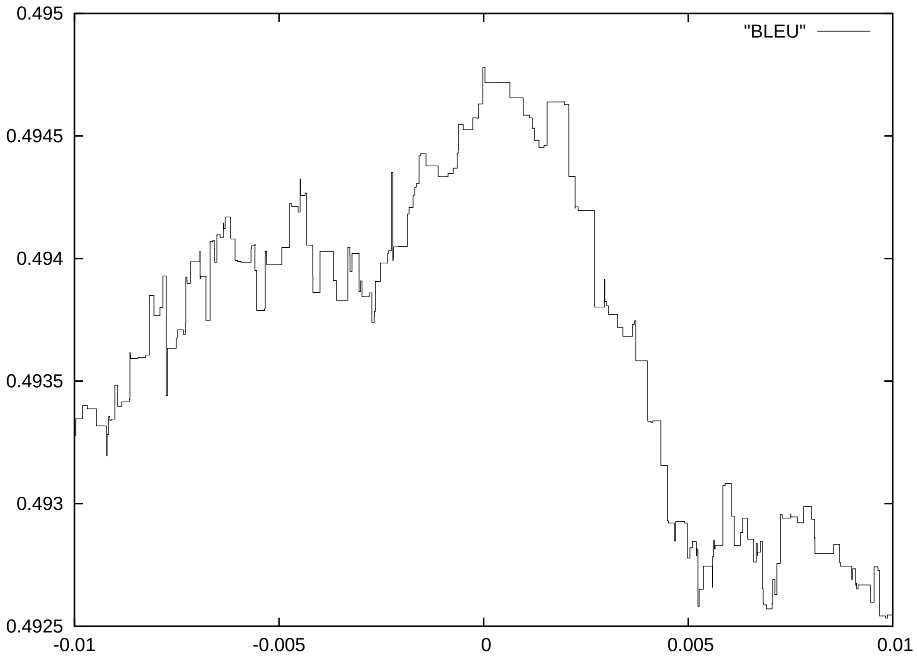
```
given:  sentences with n-best list of
translations
iterate n times
    randomize starting feature weights
        iterate until convergences
            for each feature
                find best feature weight
                update if different from current
return best feature weights found in any
iteration
```

Methods to adjust feature weights

- **Maximum entropy** [Och and Ney, ACL2002]
  - match *expectation* of feature values of model and data
- **Minimum error rate** training [Och, ACL2003]
  - try to *rank best translations first* in n-best list
  - can be adapted for various error metrics, even BLEU
- **Ordinal regression** [Shen et al., NAACL2004]
  - *separate* k worst from the k best translations

BLEU error surface

- Varying one parameter: a rugged line with many local optima



Unstable outcomes: weights vary

component	run 1	run 2	run 3	run 4	run 5	run 6
distance	0.059531	0.071025	0.069061	0.120828	0.120828	0.072891
lexdist 1	0.093565	0.044724	0.097312	0.108922	0.108922	0.062848
lexdist 2	0.021165	0.008882	0.008607	0.013950	0.013950	0.030890
lexdist 3	0.083298	0.049741	0.024822	-0.000598	-0.000598	0.023018
lexdist 4	0.051842	0.108107	0.090298	0.111243	0.111243	0.047508
lexdist 5	0.043290	0.047801	0.020211	0.028672	0.028672	0.050748
lexdist 6	0.083848	0.056161	0.103767	0.032869	0.032869	0.050240
lm 1	0.042750	0.056124	0.052090	0.049561	0.049561	0.059518
lm 2	0.019881	0.012075	0.022896	0.035769	0.035769	0.026414
lm 3	0.059497	0.054580	0.044363	0.048321	0.048321	0.056282
ttable 1	0.052111	0.045096	0.046655	0.054519	0.054519	0.046538
ttable 1	0.052888	0.036831	0.040820	0.058003	0.058003	0.066308
ttable 1	0.042151	0.066256	0.043265	0.047271	0.047271	0.052853
ttable 1	0.034067	0.031048	0.050794	0.037589	0.037589	0.031939
phrase-pen.	0.059151	0.062019	-0.037950	0.023414	0.023414	-0.069425
word-pen	-0.200963	-0.249531	-0.247089	-0.228469	-0.228469	-0.252579

Unstable outcomes: scores vary

- Even different scores with different runs (varying 0.40 on dev, 0.89 on test)

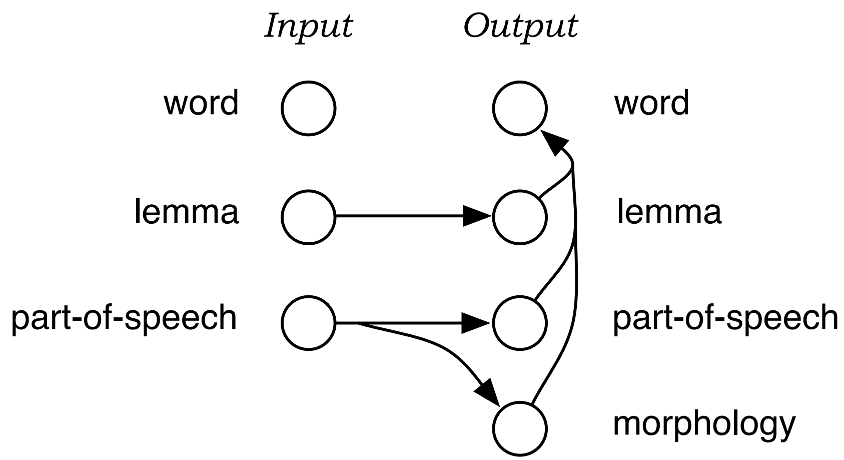
run	iterations	dev score	test score
1	8	50.16	51.99
2	9	50.26	51.78
3	8	50.13	51.59
4	12	50.10	51.20
5	10	50.16	51.43
6	11	50.02	51.66
7	10	50.25	51.10
8	11	50.21	51.32
9	10	50.42	51.79

More features: more components

- We would like to add **more components** to our model
  - multiple language models
  - domain adaptation features
  - various special handling features
  - using linguistic information

→ MERT becomes even **less reliable**
  - runs many more iterations
  - fails more frequently

More features: factored models



- Factored translation models break up phrase mapping into smaller steps
  - multiple translation tables
  - multiple generation tables
  - multiple language models and sequence models on factors

→ **Many more features**

Millions of features

- Why **mix** of discriminative training and generative models?
- Discriminative training of all components
  - phrase table [Liang et al., 2006]
  - language model [Roark et al, 2004]
  - additional features
- **Large-scale** discriminative training
  - millions of features
  - training of full training set, not just a small development corpus

Perceptron algorithm

- Translate each sentence
- If no match with reference translation: update features

```
set all lambda = 0
do until convergence
    for all foreign sentences f
        set e-best to best translation according to model
        set e-ref to reference translation
        if e-best != e-ref
            for all features feature-i
                lambda-i += feature-i(f,e-ref)
                          - feature-i(f,e-best)
```

Problem: overfitting

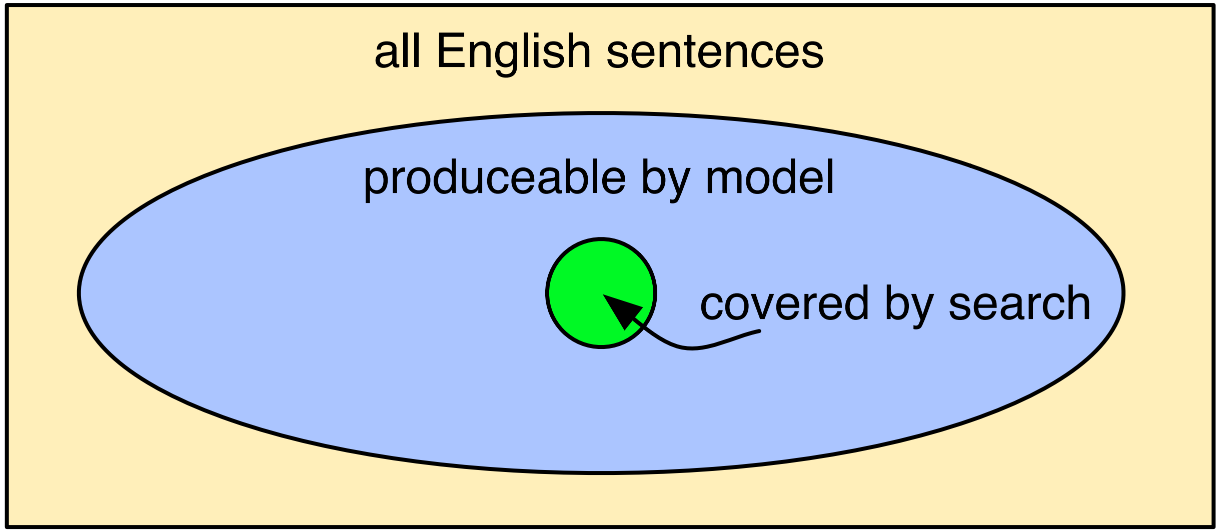
- Fundamental problem in machine learning
  - what works best for training data, may not work well in general
  - **rare, unrepresentative features** may get too much weight
- **Especially severe problem** in phrase-based models
  - **long phrase pairs** explain well *individual sentences*
  - ... but are less general, *suspect to noise*
  - EM training of phrase models [Marcu and Wong, 2002] has same problem

Solutions

- **Restrict to short phrases**, e.g., maximum 3 words (current approach)
  - limits the power of phrase-based models
  - ... but not very much [Koehn et al, 2003]
- **Jackknife**
  - collect phrase pairs from one part of corpus
  - optimize their feature weights on another part
- IBM direct model: **only one-to-many** phrases [Ittycheriah and Salim Roukos, 2007]

Problem: reference translation

- Reference translation may be anywhere in this box



- If produceable by model → we can compute feature scores
- If not → we can not

Some solutions

- **Skip sentences**, for which reference can not be produced
  - invalidates large amounts of training data
  - biases model to shorter sentences
- Declare candidate translations closest to reference as **surrogate**
  - closeness measured for instance by smoothed BLEU score
  - may be not a very good translation: odd feature values, training is severely distorted

Experiment

- Skipping sentences with unproduceable reference **hurts**

Handling of reference	BLEU
with skipping	25.81
w/o skipping	29.61

- When including all sentences: surrogate reference picked from 1000-best list using maximum *smoothed BLEU score* with respect to reference translation
- Czech-English task, **only binary features**
  - phrase table features
  - lexicalized reordering features
  - source and target phrase bigram
- See also [Liang et al., 2006] for similar approach

Better solution: early updating?

- At some point the reference translation **falls out** of the search space
  - for instance, due to *unknown words*:

Reference: `The group attended the meeting in Najaf ...`

System: `The group meeting was attended in UNKNOWN ...`

only update features involved in this part

- Early updating [Collins et al., 2005]:
  - stop search, when reference translation is not covered by model
  - only update **features involved in partial** reference / system output

Conclusions

- Proof-of-concept implementations
- Future work: Overcome various technical challenges
  - reference translation may not be produceable
  - overfitting
  - mix of binary and real-valued features
  - scaling up
- More and more features are unavoidable, let's deal with them