Statistical Machine Translation: Decoding

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Outline

- What features are used in PBMT?
- How to compute the score of a translation?
- Search for the best translation: decoding.
  - Overview of the translation process.
  - Making decoding tractable: beam search.

Log-Linear Model

We know how to score a full translation hypothesis:

$$P(e, a|f) \propto \exp \sum_i \lambda_i f_i(e, a, f)$$

λ_i ... feature weights
f_i ... feature functions

Log-Linear Model: Features

Typical baseline feature set for PBMT:

- Phrase translation probability, both direct and inverse:
  - $P_{TM}(e|f)$
  - $P_{TM_{inv}}(f|e)$
- Lexical translation probability (direct and inverse):
  - $P_{lex}(e|f)$
  - $P_{lex_{inv}}(f|e)$
- Language model probability:
  - $P_{LM}(e)$
- Phrase penalty.
- Word penalty.
- Distortion penalty.

Lexical Weights (P_{lex})

The problem: many extracted phrases are rare.
(Esp. long phrases might only be seen once in the parallel corpus.)

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$$P(\text{"modrý autobus přistál na Marsu"} \mid \text{"a blue bus lands on Mars"}) = 1$$
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Is that a reliable probability estimate?

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$$P(\text{"; distortion carried - over"} | \text{"; zkreslení"}) = 1$$
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Data from the "wild" are noisy. Word alignment contains errors.
This is a real phrase pair from our best English-Czech system.
Both $P_{TM}(e|f)$ and $P_{TM_{inv}}(f|e)$ say that this is a perfect translation.

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$$P_{lex}(\mathbf{e}|\mathbf{f}, a) = \prod_{j=1}^{l_e} \frac{1}{|i|(i,j) \in a|} \sum_{\forall (i,j) \in a} w(e_j, f_i)$$

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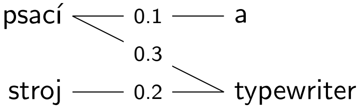

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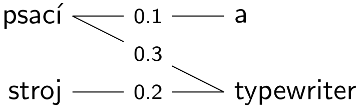

$$P_{lex}(\text{"a typewriter"}|\text{"psací stroj"}) = \left[\frac{1}{1}\cdot 0.1\right] \cdot \left[\frac{1}{2}\cdot(0.3+0.2)\right] = 0.025$$

Word Penalty

Not all languages use the same number of words on average.

```
vidím problém ||| I can see a problem
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$$\hat{e} = \arg\max_{e,a} \sum_i \lambda_i f_i(e, a, f)$$

Phrase Penalty

- Add 1 for each produced *phrase* in the translation.

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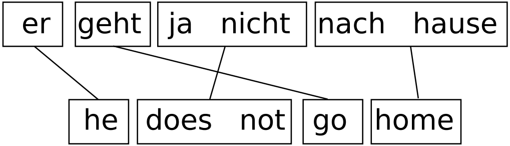
- Add 1 for each produced *phrase* in the translation.
- Varying the λ for phrase penalty can lead to more literal (word-by-word) translations (made from a lot of short phrases) or to more idiomatic outputs (use fewer, longer phrases – if available).

Distortion Penalty

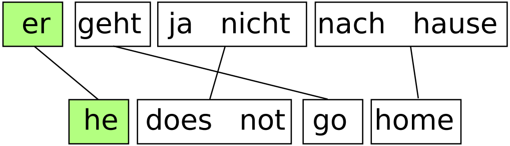
- The simplest way to capture **phrase reordering**.
- Can be sufficient for some language pairs (our English→Czech systems use it).
- Several possible definitions, e.g.:
  - Distance between the end of the previous phrase (on the source side) and the beginning of the current phrase.

How to Score a Translation?



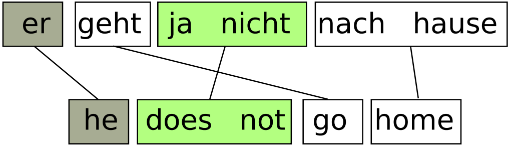
$$score(e|f) = 0$$

How to Score a Translation?



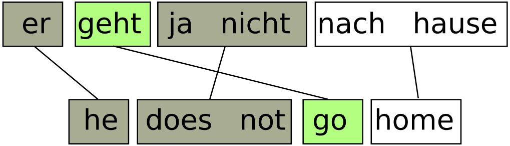
$$
\begin{aligned}
score(e|f) + = {} & \lambda_{TM} \cdot \log P_{TM}(\text{"he"}|\text{"er"}) \\
& + \lambda_{TM_{inv}} \cdot \log P_{TM_{inv}}(\text{"er"}|\text{"he"}) \\
& + \lambda_{lex} \cdot \log P_{lex}(\text{"he"}|\text{"er"}) \\
& + \lambda_{lex_{inv}} \cdot \log P_{lex_{inv}}(\text{"er"}|\text{"he"}) \\
& + \lambda_{D} \cdot 0 \\
& + \lambda_{WP} \cdot 1 \\
& + \lambda_{PP} \cdot 1 \\
& + \lambda_{LM} \cdot \log P_{LM}(\text{"he"}|\text{"}{<}\mathrm{S}{>}\text{"})
\end{aligned}
$$

How to Score a Translation?



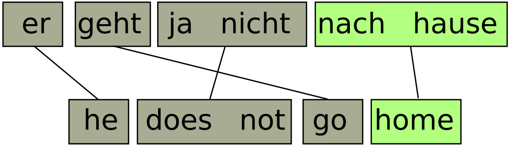
$$
\begin{aligned}
score(e|f)+ = \; & \lambda_{TM} \cdot \log P_{TM}(\text{"does not"}|\text{"ja nicht"}) \\
& + \lambda_{TM_{inv}} \cdot \log P_{TM_{inv}}(\text{"ja nicht"}|\text{"does not"}) \\
& + \lambda_{lex} \cdot \log P_{lex}(\text{"does not"}|\text{"ja nicht"}) \\
& + \lambda_{lex_{inv}} \cdot \log P_{lex_{inv}}(\text{"ja nicht"}|\text{"does not"}) \\
& + \lambda_{D} \cdot 1 \\
& + \lambda_{WP} \cdot 2 \\
& + \lambda_{PP} \cdot 1 \\
& + \lambda_{LM} \cdot \log P_{LM}(\text{"does not"}|\text{"<S>he"})
\end{aligned}
$$

How to Score a Translation?



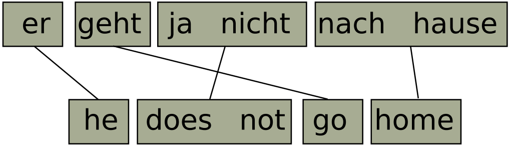
$$
\begin{aligned}
score(e|f) + &= \lambda_{TM} \cdot \log P_{TM}(\text{"go"}|\text{"geht"}) \\
&+ \lambda_{TM_{inv}} \cdot \log P_{TM_{inv}}(\text{"geht"}|\text{"go"}) \\
&+ \lambda_{lex} \cdot \log P_{lex}(\text{"go"}|\text{"geht"}) \\
&+ \lambda_{lex_{inv}} \cdot \log P_{lex_{inv}}(\text{"geht"}|\text{"go"}) \\
&+ \lambda_{D} \cdot 3 \\
&+ \lambda_{WP} \cdot 1 \\
&+ \lambda_{PP} \cdot 1 \\
&+ \lambda_{LM} \cdot \log P_{LM}(\text{"go"}|\text{"does not"})
\end{aligned}
$$

How to Score a Translation?



$$score(e|f) += \ldots$$

How to Score a Translation?



$$score(e|f) + = \ldots$$

Decoding

- We have a mathematical model for translation

$$p(\mathbf{e}|\mathbf{f})$$

- Task of decoding: find the translation $\mathbf{e}_{\text{best}}$ with highest probability

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

- Two types of error
  - the most probable translation is bad $\rightarrow$ fix the model
  - search does not find the most probably translation $\rightarrow$ fix the search

- Decoding is evaluated by search error, not quality of translations (although these are often correlated)

Translation Process

- Task: translate this sentence from German into English

er	**geht**	**ja**	**nicht**	**nach**	**hause**

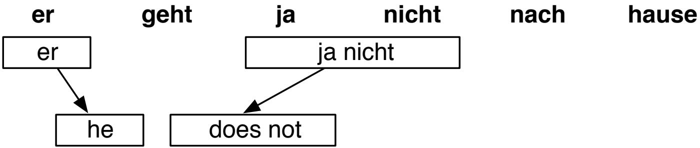
Translation Process

- Task: translate this sentence from German into English

- Pick phrase in input, translate

Translation Process

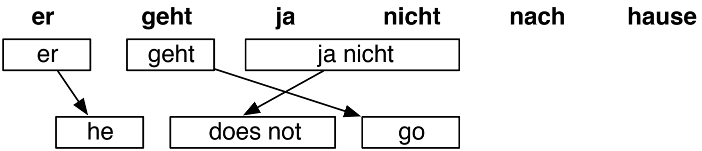
- Task: translate this sentence from German into English



- 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 Process

- Task: translate this sentence from German into English



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Translation Process

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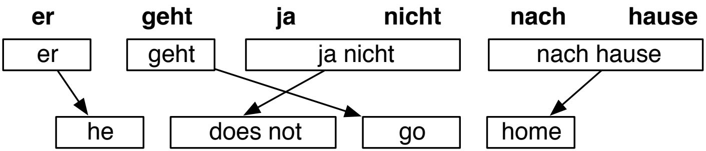

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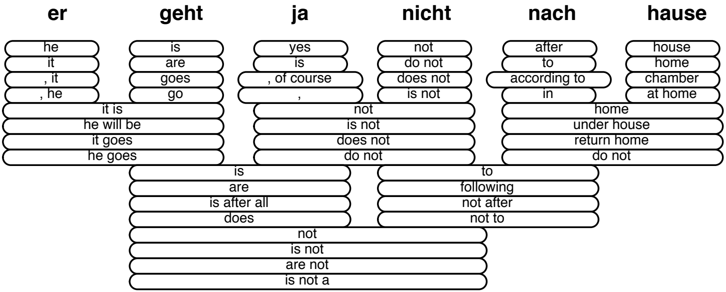
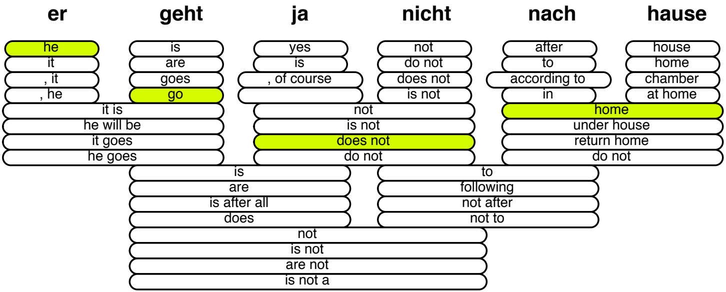
Translation Options



- 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

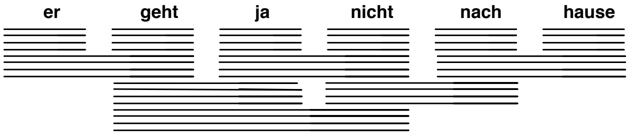
Translation Options



- The machine translation decoder does not know the right answer
  - picking the right translation options
  - arranging them in the right order

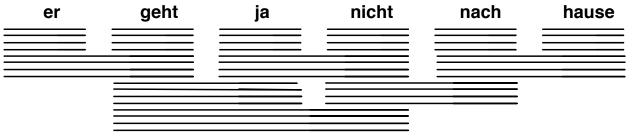
$\rightarrow$ Search problem solved by heuristic beam search

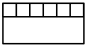
Decoding: Precompute Translation Options



consult phrase translation table for all input phrases

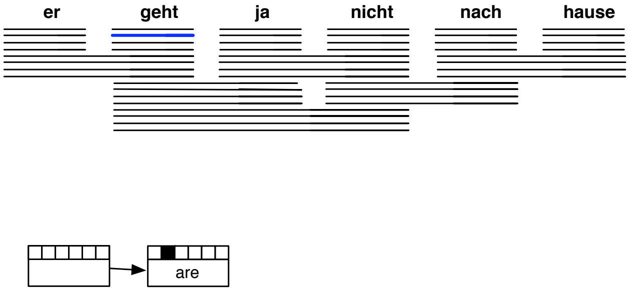
Decoding: Start with Initial Hypothesis





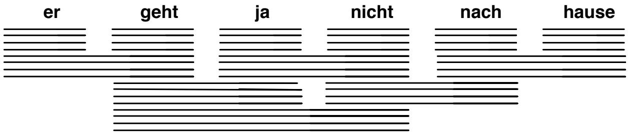
initial hypothesis: no input words covered, no output produced

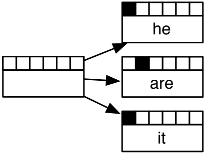
Decoding: Hypothesis Expansion



pick any translation option, create new hypothesis

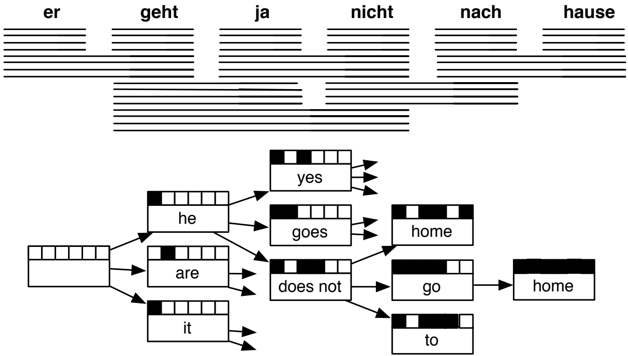
Decoding: Hypothesis Expansion





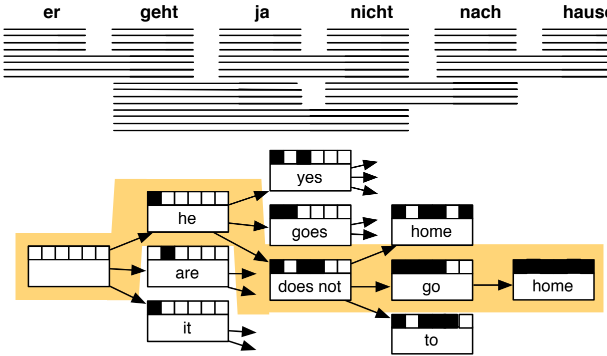
create hypotheses for all other translation options

Decoding: Hypothesis Expansion



also create hypotheses from created partial hypothesis

Decoding: Find Best Path



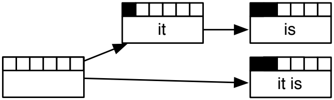
backtrack from highest scoring complete hypothesis

Computational Complexity

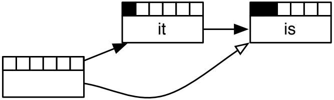
- The suggested process creates exponential number of hypothesis
- Machine translation decoding is NP-complete
- Reduction of search space:
  - recombination (risk-free)
  - pruning (risky)

Recombination

- Two hypothesis paths lead to two matching hypotheses
  - same number of foreign words translated
  - same English words in the output
  - different scores

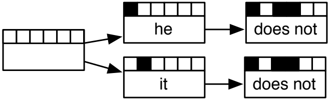


- Worse hypothesis is dropped



Recombination

- Two hypothesis paths lead to hypotheses indistinguishable in subsequent search
  - same number of foreign words translated
  - same last two English words in output (assuming trigram language model)
  - same last foreign word translated
  - different scores



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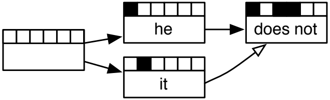


Restrictions on Recombination

- **Translation model:** Phrase translation independent from each other

  $\rightarrow$ no restriction to hypothesis recombination

- **Language model:** Last $n-1$ words used as history in n-gram language model

  $\rightarrow$ recombined hypotheses must match in their last $n-1$ words

- **Reordering model:** Distance-based reordering model based on distance to end position of previous input phrase

  $\rightarrow$ recombined hypotheses must have that same end position

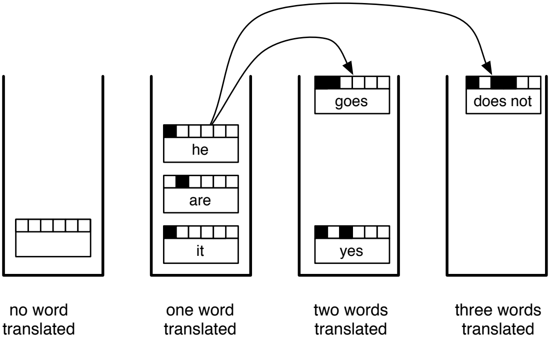
- Other feature function may introduce additional restrictions

Pruning

- Recombination reduces search space, but not enough
  (we still have a NP complete problem on our hands)

- Pruning: remove bad hypotheses early
  - put comparable hypothesis into stacks
    (hypotheses that have translated same number of input words)
  - limit number of hypotheses in each stack

Stacks



- Hypothesis expansion in a stack decoder
  - translation option is applied to hypothesis
  - new hypothesis is dropped into a stack further down

Stack Decoding Algorithm

```
place empty hypothesis into stack 0
for all stacks 0...n − 1 do
    for all hypotheses in stack do
        for all translation options do
            if applicable then
                create new hypothesis
                place in stack
                recombine with existing hypothesis if possible
                prune stack if too big
            end if
        end for
    end for
end for
```

Pruning

- Pruning strategies
  - histogram pruning: keep at most k hypotheses in each stack
  - stack pruning: keep hypothesis with score $\alpha \times$ best score ($\alpha < 1$)

- Computational time complexity of decoding with histogram pruning

$$O(\text{max stack size} \times \text{translation options} \times \text{sentence length})$$

- Number of translation options is linear with sentence length, hence:

$$O(\text{max stack size} \times \text{sentence length}^2)$$

- Quadratic complexity

Reordering Limits

- Limiting reordering to maximum reordering distance

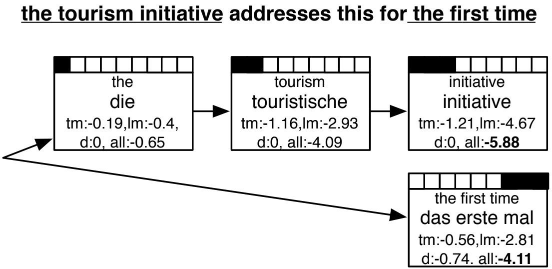
- Typical reordering distance 5–8 words
  - depending on language pair
  - larger reordering limit hurts translation quality

- Reduces complexity to linear

$$O(\text{max stack size} \times \text{sentence length})$$

- Speed / quality trade-off by setting maximum stack size

Translating the Easy Part First?

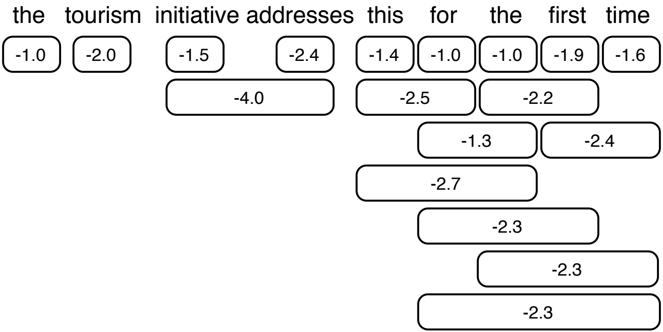


both hypotheses translate 3 words
worse hypothesis has better score

Estimating Future Cost

- Future cost estimate: how expensive is translation of rest of sentence?
- Optimistic: choose cheapest translation options
- Cost for each translation option
  - **translation model**: cost known
  - **language model:** output words known, but not context
    $\rightarrow$ estimate without context
  - **reordering model:** unknown, ignored for future cost estimation

Cost Estimates from Translation Options



cost of cheapest translation options for each input span (log-probabilities)

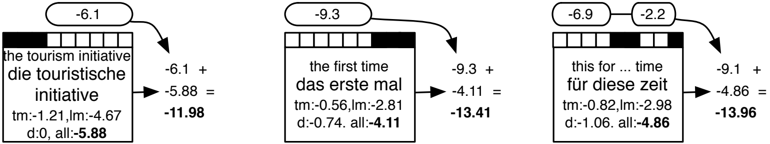
Cost Estimates for all Spans

- Compute cost estimate for all contiguous spans by combining cheapest options

first word	future cost estimate for n words (from first)								
	1	2	3	4	5	6	7	8	9
the	-1.0	-3.0	-4.5	-6.9	-8.3	-9.3	-9.6	-10.6	-10.6
tourism	-2.0	-3.5	-5.9	-7.3	-8.3	-8.6	-9.6	-9.6	
initiative	-1.5	-3.9	-5.3	-6.3	-6.6	-7.6	-7.6		
addresses	-2.4	-3.8	-4.8	-5.1	-6.1	-6.1			
this	-1.4	-2.4	-2.7	-3.7	-3.7				
for	-1.0	-1.3	-2.3	-2.3					
the	-1.0	-2.2	-2.3						
first	-1.9	-2.4							
time	-1.6								

- Function words cheaper (the: -1.0) than content words (tourism -2.0)
- Common phrases cheaper (for the first time: -2.3) than unusual ones (tourism initiative addresses: -5.9)

Combining Score and Future Cost



- Hypothesis score and future cost estimate are combined for pruning
  - left hypothesis starts with hard part: the tourism initiative
    score: -5.88, future cost: -6.1 → total cost -11.98
  - middle hypothesis starts with easiest part: the first time
    score: -4.11, future cost: -9.3 → total cost -13.41
  - right hypothesis picks easy parts: this for ... time
    score: -4.86, future cost: -9.1 → total cost -13.96

Summary

- Log-linear model: standard features in PBMT.
- Computing the score of a translation.
- Overview of the translation process.
- Beam search algorithm.
  - Hypothesis recombination.
  - Pruning.
  - Limiting distortion.
  - Future cost.