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.
- Other decoding algorithms.
Log-Linear Model

We know how to score a full translation hypothesis:

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

\( \lambda_i \) ... 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 ($P_{\text{lex}}$)

The problem: many extracted phrases are rare.
(Esp. long phrases might only be seen once in the parallel corpus.)
Lexical Weights ($P_{\text{lex}}$)

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\[ P(\text{"modrý autobus přistál na Marsu"} | \text{"a blue bus lands on Mars"}) = 1 \]
\[ P(\text{"a blue bus lands on Mars"} | \text{"modrý autobus přistál na Marsu"}) = 1 \]

Is that a reliable probability estimate?
Lexical Weights ($P_{lex}$)

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

$$P(""; \text{distortion carried - over}""|""; \text{zkreslení}" ) = 1$$
$$P(""; \text{zkreslení}""|""; \text{distortion carried - over}" ) = 1$$

Data from the “wild” are noisy. Word alignment contains errors. “carried - over” is wrong.
This is a real phrase pair from a very good English-Czech SMT system.
Both $P_{TM}(e|f)$ and $P_{TM_{inv}}(f|e)$ say that this is a perfect translation.
Lexical Weights \( (P_{\text{lex}}) \)

Decompose the phrase pair into word pairs. Look at the word-level translation probabilities.
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Several possible definitions, e.g.:
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$$P_{\text{lex}}(e|f, a) = \prod_{j=1}^{l_e} \frac{1}{|i|(i, j) \in a} \sum_{\forall (i,j) \in a} w(e_j, f_i)$$
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<table>
<thead>
<tr>
<th>psací</th>
<th>0.1</th>
<th>a</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>0.3</td>
<td></td>
</tr>
<tr>
<td>stroj</td>
<td>0.2</td>
<td>typewriter</td>
</tr>
</tbody>
</table>
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Decompose the phrase pair into word pairs. Look at the word-level translation probabilities. Several possible definitions, e.g.:

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```
psací 0.1  a
  0.3
stroj 0.2  typewriter
```

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

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

vidím problém ||| I can see a problem
Not all languages use the same number of words on average.

vidím problém ||| I can see a problem

- We want to control how many words are generated.
Word Penalty

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▶ We want to control how many words are generated.
▶ Word penalty simply adds 1 for each produced word in the translation.
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- We want to control how many words are generated.
- Word penalty simply adds 1 for each produced word in the translation.
- Depending on the $\lambda$ for word penalty, we will either generate shorter or longer outputs.
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- We want to control how many words are generated.
- Word penalty simply adds 1 for each produced word in the translation.
- Depending on the $\lambda$ for word penalty, we will either generate shorter or longer outputs.

$$\hat{e} = \arg \max_{e,a} \sum_{i} \lambda_i f_i(e, a, f)$$
Phrase Penalty

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

- Add 1 for each produced *phrase* in the translation.
- Varying the $\lambda$ 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
- Several possible definitions!
- Definition I tend to use:
  - Distance between the end of the previous phrase (on the source side) and the beginning of the current phrase.
How to Score a Translation?

\[ \text{score}(e|f) = 0 \]
How to Score a Translation?

\[
\text{score}(e|f) = \lambda_{TM} \cdot \log P_{TM}(\text{”he”} | \text{”er”}) \\
+ \lambda_{TM_{\text{inv}}} \cdot \log P_{TM_{\text{inv}}}(\text{”er”} | \text{”he”}) \\
+ \lambda_{\text{lex}} \cdot \log P_{\text{lex}}(\text{”he”} | \text{”er”}) \\
+ \lambda_{\text{lex}_{\text{inv}}} \cdot \log P_{\text{lex}_{\text{inv}}}(\text{”er”} | \text{”he”}) \\
+ \lambda_{D} \cdot 0 \\
+ \lambda_{WP} \cdot 1 \\
+ \lambda_{PP} \cdot 1 \\
+ \lambda_{LM} \cdot \log P_{LM}(\text{”he”} | \text{”<S>”})
\]
How to Score a Translation?

\[
\text{score}(e|f) + = \lambda_{TM} \cdot \log P_{TM}(”does not”|”ja nicht”) \\
+ \lambda_{TM_{inv}} \cdot \log P_{TM_{inv}}(”ja nicht”|”does not”) \\
+ \lambda_{lex} \cdot \log P_{lex}(”does not”|”ja nicht”) \\
+ \lambda_{lex_{inv}} \cdot \log P_{lex_{inv}}(”ja nicht”|”does not”) \\
+ \lambda_{D} \cdot 1 \\
+ \lambda_{WP} \cdot 2 \\
+ \lambda_{PP} \cdot 1 \\
+ \lambda_{LM} \cdot \log P_{LM}(”does not”|”<S>he”) 
\]
How to Score a Translation?

\[
score(e|f) + = \lambda_{TM} \cdot \log P_{TM}("go"|"geht") + \lambda_{TM_{inv}} \cdot \log P_{TM_{inv}}("geht"|"go") + \lambda_{lex} \cdot \log P_{lex}("go"|"geht") + \lambda_{lex_{inv}} \cdot \log P_{lex_{inv}}("geht"|"go") + \lambda_{D} \cdot 3 + \lambda_{WP} \cdot 1 + \lambda_{PP} \cdot 1 + \lambda_{LM} \cdot \log P_{LM}("go"|"does not")
\]
How to Score a Translation?

score(e|f) + = ...
How to Score a Translation?

\[
\text{score}(e|f) + = \ldots
\]
Decoding

• We have a mathematical model for translation

\[ p(e|f) \]

• Task of decoding: find the translation \( e_{\text{best}} \) with highest probability

\[ e_{\text{best}} = \operatorname{argmax}_e p(e|f) \]

• 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

er geht ja nicht nach hause

• Pick phrase in input, translate

Slide by Philipp Koehn (Statistical Machine Translation, Chapter 6)
Translation Process

- Task: translate this sentence from German into English

er geht ja nicht nach hause

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

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Translation Process

- Task: translate this sentence from German into English

er geht ja nicht nach hause
he does not go

- Pick phrase in input, translate

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Translation Process

- Task: translate this sentence from German into English

```
er geht ja nicht nach hause
```

- Pick phrase in input, translate

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

→ Search problem solved by heuristic beam search
Decoding: Precompute Translation Options

consult phrase translation table for all input phrases

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Decoding: Start with Initial Hypothesis

initial hypothesis: no input words covered, no output produced

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Decoding: Hypothesis Expansion

pick any translation option, create new hypothesis
Decoding: Hypothesis Expansion

he
goes
ja
nicht
not
nach
at
hause
home

create hypotheses for all other translation options
Decoding: Hypothesis Expansion

er geht ja nicht nach hause
are it he goes does not go to home home
also create hypotheses from created partial hypothesis

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Decoding: Find Best Path

Backtrack from highest scoring complete hypothesis

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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

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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

- Worse hypothesis is dropped

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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

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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

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

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Stack Decoding Algorithm

1: place empty hypothesis into stack 0
2: for all stacks 0...n − 1 do
3: for all hypotheses in stack do
4: for all translation options do
5: if applicable then
6: create new hypothesis
7: place in stack
8: recombine with existing hypothesis if possible
9: prune stack if too big
10: end if
11: end for
12: end for
13: end for

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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

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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?

the tourism initiative addresses this for the first time

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
    → estimate without context
  - **reordering model**: unknown, ignored for future cost estimation
**Cost Estimates from Translation Options**

<table>
<thead>
<tr>
<th>the</th>
<th>tourism</th>
<th>initiative</th>
<th>addresses</th>
<th>this</th>
<th>for</th>
<th>the</th>
<th>first</th>
<th>time</th>
</tr>
</thead>
<tbody>
<tr>
<td>-1.0</td>
<td>-2.0</td>
<td>-1.5</td>
<td>-2.4</td>
<td>-1.4</td>
<td>-1.0</td>
<td>-1.0</td>
<td>-1.9</td>
<td>-1.6</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
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<td>-4.0</td>
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<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>-2.5</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>-2.2</td>
<td></td>
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<td></td>
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<tr>
<td></td>
<td></td>
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<td>-1.3</td>
<td></td>
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<td></td>
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<td></td>
<td></td>
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<td>-2.4</td>
<td></td>
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<td></td>
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<td></td>
<td></td>
<td></td>
<td></td>
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<td>-2.7</td>
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<td>-2.3</td>
<td></td>
<td></td>
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<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>-2.3</td>
<td></td>
</tr>
</tbody>
</table>

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

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## Cost Estimates for all Spans

- Compute cost estimate for all contiguous spans by combining cheapest options first future cost estimate for \( n \) words (from first)

<table>
<thead>
<tr>
<th>first word</th>
<th>future cost estimate for ( n ) words (from first)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>1</td>
</tr>
<tr>
<td>the</td>
<td>-1.0</td>
</tr>
<tr>
<td>tourism</td>
<td>-2.0</td>
</tr>
<tr>
<td>initiative</td>
<td>-1.5</td>
</tr>
<tr>
<td>addresses</td>
<td>-2.4</td>
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<tr>
<td>this</td>
<td>-1.4</td>
</tr>
<tr>
<td>for</td>
<td>-1.0</td>
</tr>
<tr>
<td>the</td>
<td>-1.0</td>
</tr>
<tr>
<td>first</td>
<td>-1.9</td>
</tr>
<tr>
<td>time</td>
<td>-1.6</td>
</tr>
</tbody>
</table>

- 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)

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Combining Score and Future Cost

<table>
<thead>
<tr>
<th>Hypothesis</th>
<th>Score</th>
<th>Future Cost</th>
<th>Total Cost</th>
</tr>
</thead>
<tbody>
<tr>
<td>the tourism initiative</td>
<td>-5.88</td>
<td>-6.1</td>
<td>-11.98</td>
</tr>
<tr>
<td>das erste mal</td>
<td>-0.56</td>
<td>-2.81</td>
<td>-3.37</td>
</tr>
<tr>
<td>this for ... time</td>
<td>-0.82</td>
<td>-2.98</td>
<td>-3.80</td>
</tr>
</tbody>
</table>

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

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Other Decoding Algorithms

- A* search
- Greedy hill-climbing
- Using finite state transducers (standard toolkits)
A* Search

- Uses *admissible* future cost heuristic: never overestimates cost
- Translation agenda: create hypothesis with lowest score + heuristic cost
- Done, when complete hypothesis created

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Greedy Hill-Climbing

• Create one complete hypothesis with depth-first search (or other means)

• Search for better hypotheses by applying change operators
  – change the translation of a word or phrase
  – combine the translation of two words into a phrase
  – split up the translation of a phrase into two smaller phrase translations
  – move parts of the output into a different position
  – swap parts of the output with the output at a different part of the sentence

• Terminates if no operator application produces a better translation
Finite-state transducers

- It is also possible to output a pruned search graph to an external finite-state transducer package.
- This then carries out the search, but I will omit the details of this.
- Allows efficient search of this (pruned) graph
- Can be useful for rescoring the hypotheses using models that are difficult to implement directly in, e.g., Moses.
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.
- Other decoding algorithms.
Questions?
Thank you for your attention.