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 ($P_{lex}$)

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

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

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

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

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. This is a real phrase pair from our best English-Czech system. Both $P_{TM}(e|f)$ and $P_{TM_{\text{inv}}}(f|e)$ 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.

Several possible definitions, e.g.:

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

\[
\begin{align*}
    \text{psací} & \quad 0.1 \quad \text{a} \\
    \text{stroj} & \quad 0.3 \quad \text{typewriter}
\end{align*}
\]

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

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

vidím problém ||| I can see a problem

- 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.

- 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 (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?

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

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

\[
score(e|f)^+ = \ldots
\]
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

\[ e_{\text{best}} = \arg\max_e p(e|f) \]

- 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

> he does not

• 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

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
he does not go home

• Pick phrase in input, translate

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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

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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

er geht ja nicht nach hause

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
Decoding: Hypothesis Expansion

pick any translation option, create new hypothesis

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Decoding: Hypothesis Expansion

create hypotheses for all other translation options

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Decoding: Hypothesis Expansion

also create hypotheses from created partial hypothesis

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Decoding: Find Best Path

er geht ja nicht nach hause

are it he goes does not go to home home

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
• 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: \textbf{for all} stacks 0\ldots n-1 \textbf{do}
3: \textbf{for all} hypotheses in stack \textbf{do}
4: \textbf{for all} translation options \textbf{do}
5: \textbf{if} applicable \textbf{then}
6: create new hypothesis
7: place in stack
8: recombine with existing hypothesis \textbf{if} possible
9: prune stack \textbf{if} too big
10: \textbf{end if}
11: \textbf{end for}
12: \textbf{end for}
13: \textbf{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?

The tourism initiative addresses this for the first time.

Both hypotheses translate 3 words. The worse hypothesis has a better score.

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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

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Cost Estimates from Translation Options

-1.0 -2.0 -1.5 -2.4 -1.4 -1.0 -1.0 -1.9 -1.6

-4.0

-2.5

-2.2

-2.7

-2.3

-2.3

-2.3

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

<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>
</tr>
<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

- 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
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.