

Phrase-Based MT

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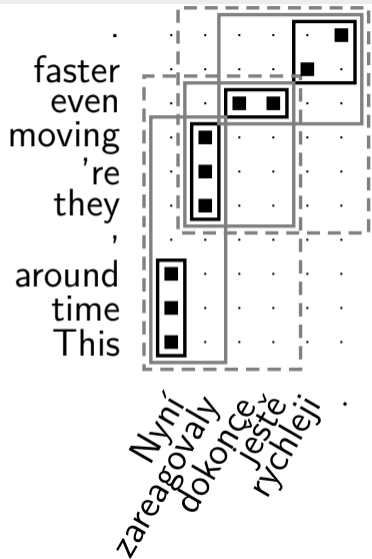


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Outline

- PBMT Overview.
- Reminder: Log-linear model.
- PBMT Model.
 - Features Used.
- Traditional MT “Pipeline”
- Translating with PBMT (Decoding)
 - Translation Options and Stack-Based Beam Search
 - MT is NP-Hard.
 - Pruning, Future Cost Estimation.
 - Local and Non-Local Features.
- Minimum Error-Rate Training.
- Moses as the implementation.

Reminder: Phrase-Based MT



This time around = Nyní
they 're moving = zareagovaly
even = dokonce ještě

... = ...

This time around, they 're moving = Nyní zareagovaly
even faster = dokonce ještě rychleji

... = ...

Phrase-based MT: choose such segmentation of input string and such phrase “replacements” to make the output sequence “coherent” (3-grams most probable).

Reminder: Log-Linear Model

- $p(e_1^I | f_1^J)$ is modelled as a weighted combination of models, called “feature functions”: $h_1(\cdot, \cdot) \dots h_M(\cdot, \cdot)$

$$p(e_1^I | f_1^J) = \frac{\exp(\sum_{m=1}^M \lambda_m h_m(e_1^I, f_1^J))}{\sum_{e_1^{I'}} \exp(\sum_{m=1}^M \lambda_m h_m(e_1^{I'}, f_1^J))} \quad (1)$$

- The constant denominator not needed in maximization:

$$\begin{aligned} \hat{e}_1^I &= \operatorname{argmax}_{I, e_1^I} \frac{\exp(\sum_{m=1}^M \lambda_m h_m(e_1^I, f_1^J))}{\sum_{e_1^{I'}} \exp(\sum_{m=1}^M \lambda_m h_m(e_1^{I'}, f_1^J))} \\ &= \operatorname{argmax}_{I, e_1^I} \exp(\sum_{m=1}^M \lambda_m h_m(e_1^I, f_1^J)) \end{aligned} \quad (2)$$

Phrase-Based Translation Model

- Captures the basic assumption of phrase-based MT:
 1. Segment source sentence f_1^J into K phrases $\tilde{f}_1 \dots \tilde{f}_K$.
 2. Translate each phrase independently: $\tilde{f}_k \rightarrow \tilde{e}_k$.
 3. Concatenate translated phrases (with possible reordering R):
 $\tilde{e}_{R(1)} \dots \tilde{e}_{R(K)}$
- In theory, the segmentation s_1^K is a hidden variable in the maximization, we should be summing over all segmentations: (Note the three args in $h_m(\cdot, \cdot, \cdot)$ now.)

$$\hat{e}_1^I = \operatorname{argmax}_{I, e_1^I} \sum_{s_1^K} \exp(\sum_{m=1}^M \lambda_m h_m(e_1^I, f_1^J, s_1^K)) \quad (3)$$

- In practice, the sum is approximated with a max (the biggest element only):

$$\hat{e}_1^I = \operatorname{argmax}_{I, e_1^I} \max_{s_1^K} \exp(\sum_{m=1}^M \lambda_m h_m(e_1^I, f_1^J, s_1^K)) \quad (4)$$

Estimating P-B Translation Model

The most important feature: phrase-to-phrase translation:

$$h_{\text{Phr}}(f_1^J, e_1^I, s_1^K) = \log \prod_{k=1}^K p(\tilde{f}_k | \tilde{e}_k) \quad (5)$$

The conditional probability of phrase \tilde{f}_k given phrase \tilde{e}_k is estimated from relative frequencies:

$$p(\tilde{f}_k | \tilde{e}_k) = \frac{\text{count}(\tilde{f}, \tilde{e})}{\text{count}(\tilde{e})} \quad (6)$$

- $\text{count}(\tilde{f}, \tilde{e})$ is the number of co-occurrences of a phrase pair (\tilde{f}, \tilde{e}) that are consistent with the word alignment
- $\text{count}(\tilde{e})$ is the number of occurrences of the target phrase \tilde{e} in the training corpus.
- h_{Phr} usually used twice, in both directions: $p(\tilde{f}_k | \tilde{e}_k)$ and $p(\tilde{e}_k | \tilde{f}_k)$

Common Features of PBMT

- Phrase translation probability:

$$h_{\text{Phr}}(f_1^J, e_1^I, s_1^K) = \log \prod_{k=1}^K p(\tilde{f}_k | \tilde{e}_k) \text{ where } p(\tilde{f}_k | \tilde{e}_k) = \frac{\text{count}(\tilde{f}, \tilde{e})}{\text{count}(\tilde{e})}$$

⇒ Are all used units $\tilde{f} \leftrightarrow \tilde{e}$ likely translations?

- Word count/penalty: $h_{\text{wp}}(e_1^I, \cdot, \cdot) = I$

⇒ Do we prefer longer or shorter output?

- Phrase count/penalty: $h_{\text{pp}}(\cdot, \cdot, s_1^K) = K$

⇒ Do we prefer translation in more or fewer less-dependent bits?

- Reordering model: different basic strategies (Lopez, 2009)

⇒ Which source spans can provide continuation at a moment?

- n -gram LM: $h_{\text{LM}}(\cdot, e_1^I, \cdot) = \log \prod_{i=1}^I p(e_i | e_{i-n+1}^{i-1})$

⇒ Is output n -gram-wise coherent?

Traditional MT “Pipeline”

“Training the Translation Model”

1. Find relevant parallel texts.
2. Align at the level of sentences.
3. Align at the level of words.
4. Extract translation units, with scores (co-oc. stats.).
(Language Model similar, “simple” words co-oc. stats, no alignment.)

“**Tuning**” (“MERT”) = Actual training in the ML sense

5. Identify TM/LM/other model component weights.

Translation:

6. Decompose input into known units.
7. Search for best combinations of units.

Translation with PBMT

Translation with phrase-based model has two main stages:

1. Translation Options Preparation.
 - Search the phrase table for all phrases applicable to the input sentence.
2. Decoding (Main Search).
 - Gradual hypothesis expansion.
 - Output produced left-to-right.
 - Input consumed in any order.

Stage 1: Translation Options

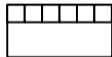
er	geht	ja	nicht	nach	hause
he	is	yes	not	after	house
it	are	is	do not	to	home
, it	goes	, of course	does not	according to	chamber
, he	go		is not	in	at home
it is		not		home	
he will be		is not		under house	
it goes		does not		return home	
he goes		do not		do not	
	is			to	
	are			following	
	is after all			not after	
	does			not to	
	not				
	is not				
	are not				
	is not a				

Stage 2: Decoding (Beam Search)



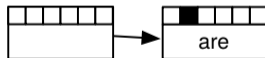
consult phrase translation table for all input phrases

Stage 2: Decoding (Beam Search)



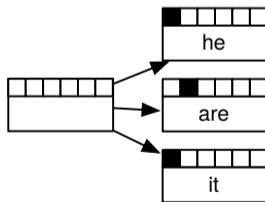
initial hypothesis: no input words covered, no output produced

Stage 2: Decoding (Beam Search)



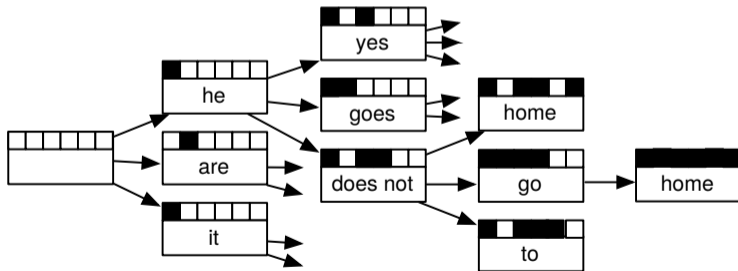
pick any translation option, create new hypothesis

Stage 2: Decoding (Beam Search)



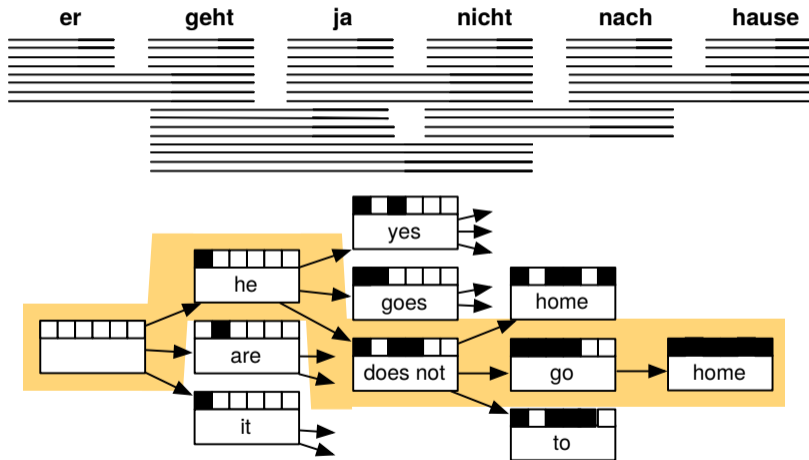
create hypotheses for all other translation options

Stage 2: Decoding (Beam Search)



also create hypotheses from created partial hypothesis

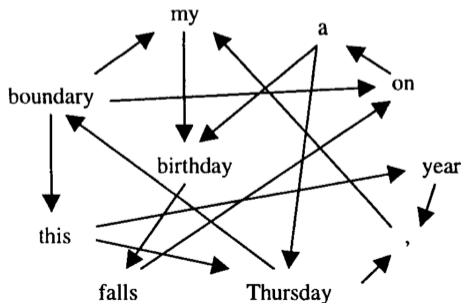
Stage 2: Decoding (Beam Search)



backtrack from highest scoring complete hypothesis

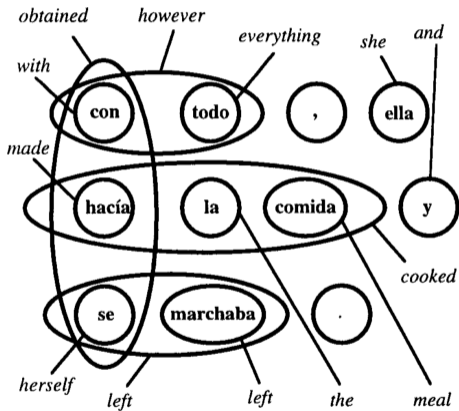
Interlude: MT is NP-Hard (1/2)

- Translation options lead to exponentially many hypotheses.
- Indeed, MT is NP-hard for at least two reasons:
 - Finding the best word ordering.
 - Covering with multi-word units.
- Remember the NP-hardness proof strategy:
 - Use MT as a black box to solve an NP-complete task.



With a 2-gram language model, finding the best word ordering solves the Hamilton Circuit or Travelling Salesman Problem. (Knight, 1999)

Interlude: MT is NP-Hard (2/2)



Selecting a set of multi-word translations to cover the whole sentence solves Minimum Set Cover Problem. (Knight, 1999) (However, she cooked and left.)

Fighting the Complexity

See slides 17–32 by Barry Haddow.

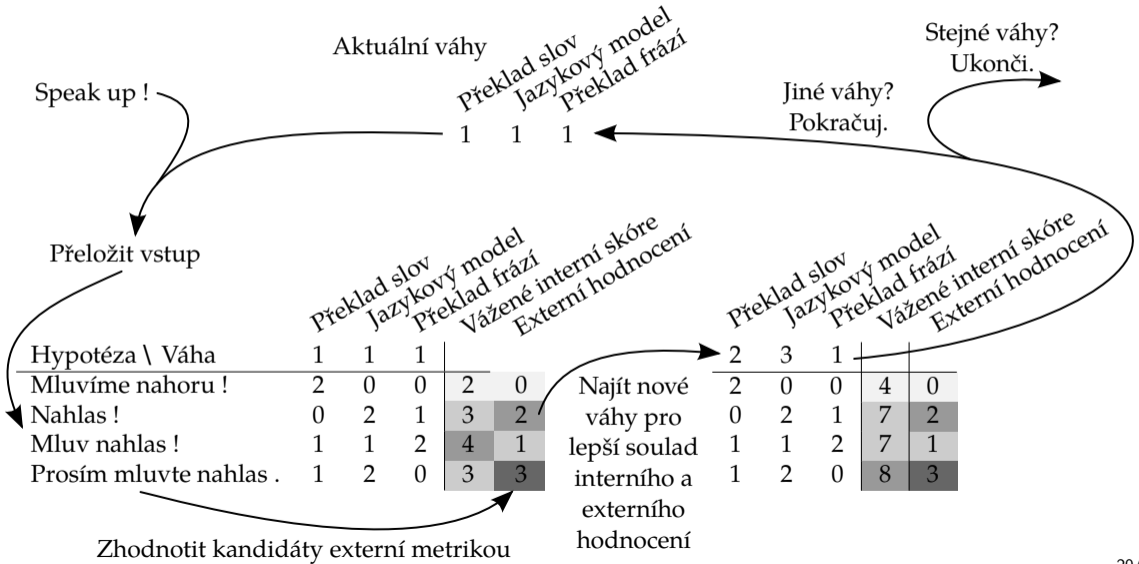
- Hypothesis Recombination.
- Stack-based Pruning.
- Future Cost Estimation.

Local and Non-Local Features

		Total	Weight	Weighted
Phrase log. prob.	0,0 -0,69 -1,39	-2,08	2,0	-4,16
Phrase penalty	1,0 1,0 1,0	3,0	-1,0	-3,0
Word penalty	1,0 2,0 1,0	4,0	-0,5	-2,0
	Peter left for home .			
	▷ Petr odešel domů . ◁			
Bigram log. prob.	-4,02 -2,50 -3,61 -0,39 -0,08	-10,59	1,0	-10,59
			Total	-19,75

- Local features decompose along hypothesis construction.
 - Phrase- and word-based features.
- Non-local features span the boundaries (e.g. LM).

Weight Optimization: MERT Loop



Effects of Weights



- Higher phrase penalty chops sentence into more segments.
- Too strong LM weight leads to words dropped.
- Negative LM weight leads to obscure wordings.

Moses Decoder

- <http://www.statmt.org/moses>
- Moses Installation Tutorial.

Phrase-Based MT Summary

Phrase-based MT:

- is a log-linear model
- decomposes sentence into contiguous phrases (=MTU)
- assumes phrases relatively independent of each other
- search has two parts:
 - lookup of all relevant translation options
 - stack-based beam search, gradually expanding hypotheses

To train a PBMT system:

1. Align words.
2. Extract (and score) phrases consistent with word alignment.
3. Optimize weights (MERT).

Best implementation: Moses Decoder.

References

- Kevin Knight. 1999. Decoding complexity in word-replacement translation models. Comput. Linguist., 25(4):607–615.
- Adam Lopez. 2009. Translation as weighted deduction. In Proceedings of the 12th Conference of the European Chapter of the ACL (EACL 2009), pages 532–540, Athens, Greece, March. Association for Computational Linguistics.
- Franz Josef Och. 2003. Minimum Error Rate Training in Statistical Machine Translation. In Proc. of the Association for Computational Linguistics, Sapporo, Japan, July 6–7.