02 – Machine translation

IA161 Advanced Techniques of Natural Language Processing

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October 15, 2020

Translation: English→Czech

Moses is an implementation of the statistical (or data-driven) approach to machine translation (MT). This is the dominant approach in the field at the moment, and is employed by the online translation systems deployed by the likes of Google and Microsoft.

1. Mojžíš je implementace statistické (nebo řízené daty) přístupu k strojového překladu (MT). To je převládajícím přístupem v oblasti v současné době, a je zaměstnán pro on-line překladatelských systémů nasazených likes Google a Microsoft.
2. Moses je implementace statistického (nebo daty řízeného) přístupu k strojovému překladu (MT). V současné době jde o převažující přístup v rámci strojového překladu, který je použit online překladovými systémy nasazenými Googlem a Microsoftem.
3. Mojžíš je provádění statistické (nebo aktivovaný) přístup na strojový překlad (mt). To je dominantní přístup v oblasti v tuto chvíli, a zaměstnává on - line překlad systémů uskutečněné takové, Google a Microsoft.
4. Mojžíš je implementace statistického (nebo datově řízeného) přístupu k strojovému překladu (MT). To je v současné době dominantní přístup v oboru a je využíván online překladatelskými systémy, které používají společnosti Google a Microsoft.

Statistical Machine Translation

- rule-based systems motivated by linguistics
- SMT inspired by information theory and statistics
- Google Translate (before 2016), Bing Translator, Moses
- **gisting**: the most frequent usage of MT on Internet
- in fact, MT output is always post-edited
- neural networks: boom in the last few years (state-of-the-art)

Machine translation: what is translated

- web pages
- technical manuals, how-tos
- scientific documents, papers, articles
- leaflets, flyers, catalogues
- texts from limited domains in general
- Wikipedia articles (CS–SK)

Machine translation nowadays

- intense collecting of data
- development of systems driven by evaluation metrics
- EU: 24 official languages (EuroMatrix)
- software companies focus on English as source language (i18n)
- large language pairs (En↔Sp, En↔Fr): fairly high-quality translation
- Google Translate as a gold standard
- morphologically rich languages: worse results
- En-* and *-En pairs prevail
- Moses: freely available statistical machine translation [Koehn, 2007]

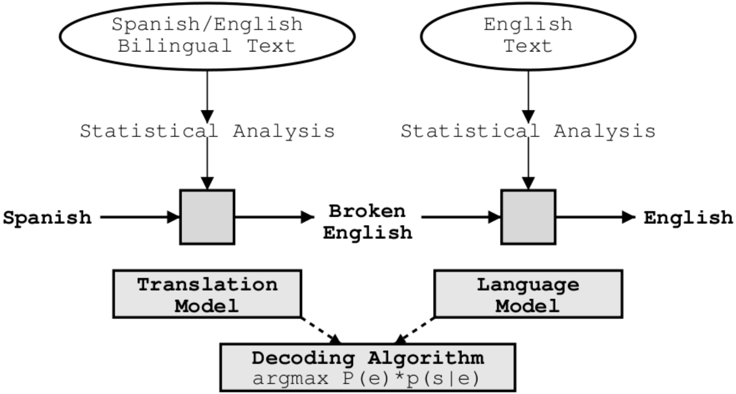
Data: parallel corpora

- Europarl: a collection of texts from the European Parliament [Koehn, 2005]
- OPUS: parallel texts of various source, one of the biggest resources [Tiedemann and Nygaard, 2004]
- Acquis Communautaire: EU laws [Steinberger et al., 2006]
- EUR-Lex: access to European Union law
- DGT translation memory [Steinberger et al., 2013], MyMemory
- freely available corpora are usually of size of 10–100 million words
- multilingual webpages (Wikipedia)
- comparable corpora: texts from the same domain

Sentence alignment

- 1:1, 1:0, 0:1, 1:2, 2:1, ... alignments
- Gale-Church (sentence lengths)
- Hunalign (with a dictionary, G-Ch is a fallback)
- BLEUalign (MT-based sentence alignment)

Schema of SMT



SMT – noisy channel

Developed by Shannon (1948) [Shannon, 1956] for self-correcting codes, for corrections of coded signals transferred through noisy channels based on information about a source message and types of errors occurring in the channels.

Another application: OCR, Optical Character Recognition. It is messy, but we can estimate what was in the source text from a language model and frequent errors: `l-1-I`, `rn-m` etc.

$$\begin{aligned} e^* &= \arg\max_e p(e|f) \\ &= \arg\max_e \frac{p(e)p(f|e)}{p(f)} \\ &= \arg\max_e p(e)p(f|e). \end{aligned}$$

We will speak about language models later.

Lexical translation

Standard translation dictionary does not contain translation probabilities for word meanings.

key → *klíč, tónina, klávesa*

How often are the individual equivalents used?

key → *klíč* (0.7), *tónina* (0.18), *klávesa* (0.08), ...

We need a lexical probability distribution p_f with the property:

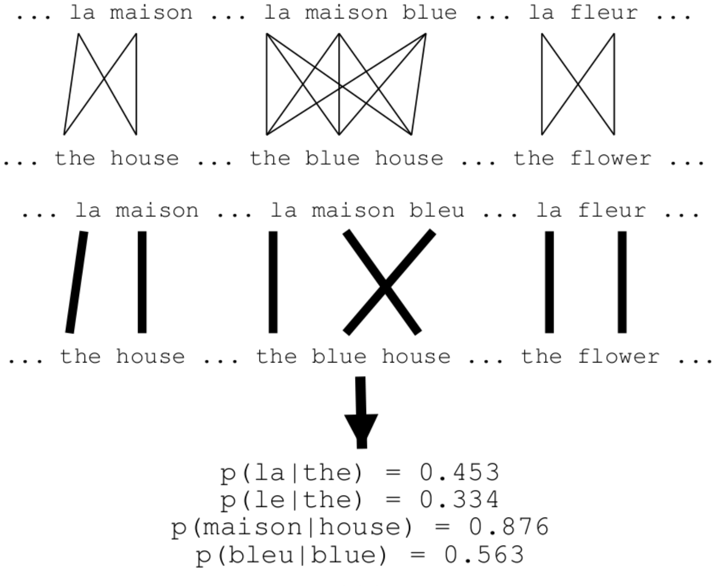
$$\sum_e p_f(e) = 1$$

$$\forall e : 0 \leq p_f(e) \leq 1$$

$$p_{\text{klíč}}(\text{key}) \ ? \ p_{\text{mrkev}}(\text{carrot})$$

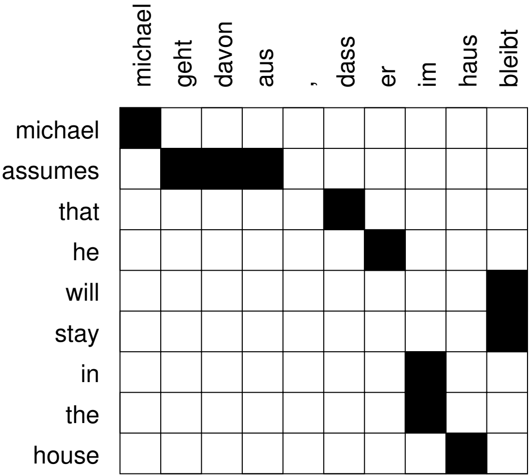
Word alignment

GIZA++ is the most widely used tool. [Och and Ney, 2003]



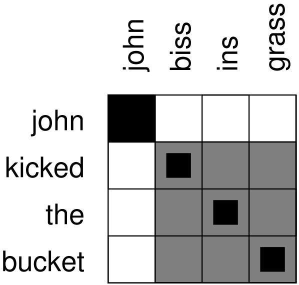
p(la|the) = 0.453
p(le|the) = 0.334
p(maison|house) = 0.876
p(bleu|blue) = 0.563
...

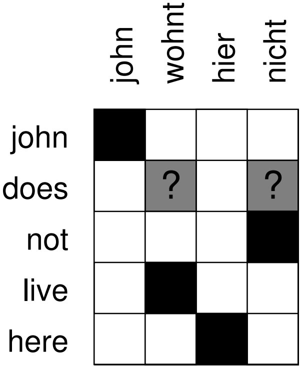
Word Alignment Matrix



	michael	geht	davon	aus	,	dass	er	im	haus	bleibt
michael	■									
assumes		■	■	■						
that						■				
he							■			
will										■
stay										■
in								■		
the								■		
house									■	

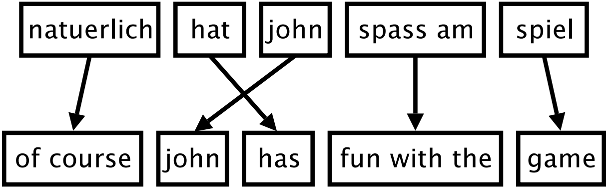
Lexical translation problems





Phrase-based translation model

State-of-the-art of SMT. Not only words, but whole phrases are translated at a time. [Koehn et al., 2003] [Chiang, 2005]

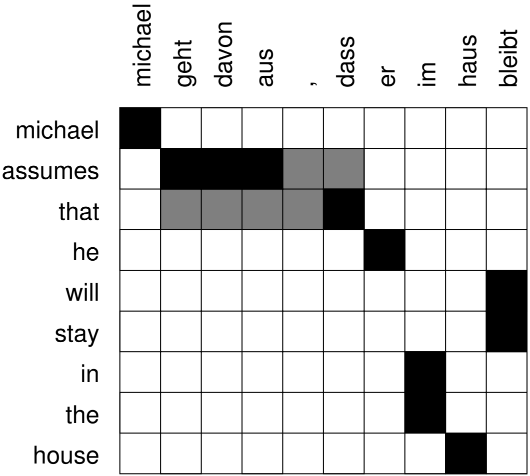


Phrases are not linguistically motivated. German *am* is usually not translated by one word *with*. Statistically significant context *spass am* helps with a proper translation. Common phrases would be segmented in a different way: *(fun (with (the game)))*.

Advantages of PBMT

- we often translate $n : m$ words, a word is unsuitable element
- the translation of groups of words helps with translation ambiguity
- and also fluency
- systems can learn longer phrases, ad infinitum, if data is available
- the model is simpler: fertility, NULL tokens are not needed

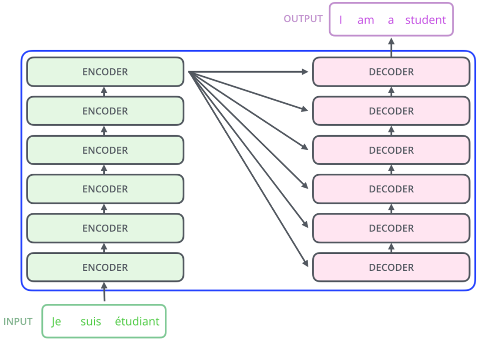
Phrase extraction



	michael	geht	davon	aus	,	dass	er	im	haus	bleibt
michael	■									
assumes		■	■	■	▨	▨				
that		▨	▨	▨	▨	■				
he							■			
will										■
stay										■
in								■		
the								■		
house									■	

Neural Machine Translation

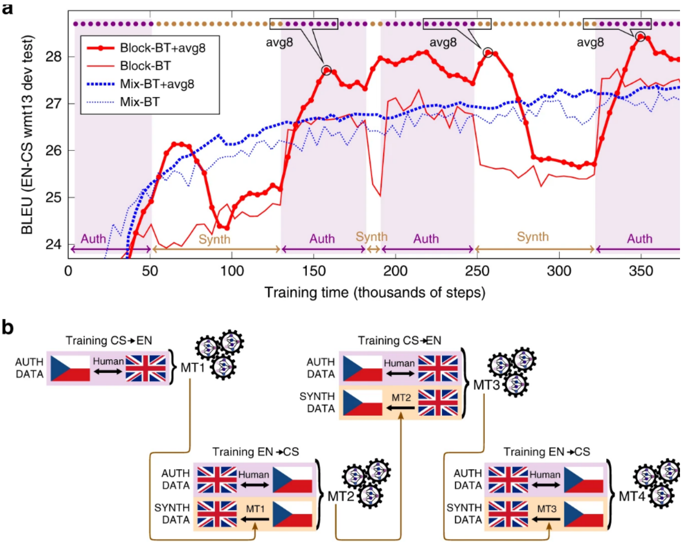
- The state of the art, Google uses it
- current trend: transformers



`http://jalammar.github.io/illustrated-transformer/`

Neural Machine Translation

- CUBBITT system for EN to CS
- better than human in adequacy in certain circumstances



Automatic evaluation of translation

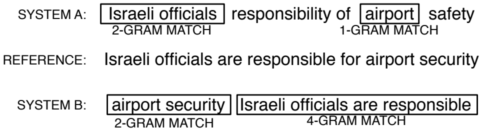
- advantages: speed, price; disadvantages: do we measure quality of translation?
- gold standard: manually prepared reference translations
- candidate c is compared with n reference translations r_i
- various approaches: n-gram agreement between c and r_i, edit distance, . . .
- BLEU: the most widely used [Papineni et al., 2002]
- METEOR: correlates best with human evaluation [Banerjee and Lavie, 2005]

BLEU

- the most popular (a standard), the most widely used, the oldest (2001)
- IBM, Papineni [Papineni et al., 2002]
- n-gram agreement between references and candidates
- precision for 1–4-grams
- brevity penalty

$$\text{BLEU} = \min\left(1, \frac{\textit{output-length}}{\textit{reference-length}}\right) \ (\prod_{i=1}^{4} \textit{precision}_i)^{\frac{1}{4}}$$

BLEU – an example



SYSTEM A: Israeli officials responsibility of airport safety

2-GRAM MATCH

1-GRAM MATCH

REFERENCE: Israeli officials are responsible for airport security

SYSTEM B: airport security Israeli officials are responsible

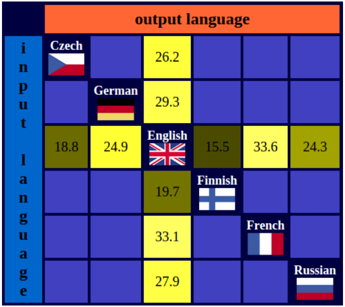
2-GRAM MATCH

4-GRAM MATCH

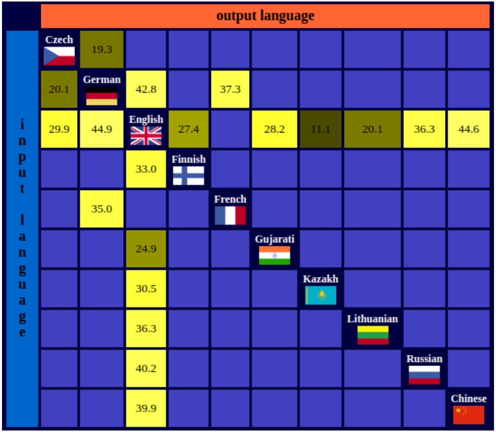
metrics	**system A**	**system B**
precision (1gram)	3/6	6/6
precision (2gram)	1/5	4/5
precision (3gram)	0/4	2/4
precision (4gram)	0/3	1/3
brevity penalty	6/7	6/7
BLEU	0 %	52 %

Translation quality according to language pairs

2015 vs 2019



	output language					
input language	**Czech**		26.2			
		German	29.3			
	18.8	24.9	**English**	15.5	33.6	24.3
			19.7	**Finnish**		
			33.1		**French**	
			27.9			**Russian**



	output language									
input language	**Czech**	19.3								
	20.1	**German**	42.8		37.3					
	29.9	44.9	**English**	27.4		28.2	11.1	20.1	36.3	44.6
			33.0	**Finnish**						
		35.0			**French**					
			24.9			**Gujarati**				
			30.5				**Kazakh**			
			36.3					**Lithuanian**		
			40.2						**Russian**	
			39.9							**Chinese**

`http://matrix.statmt.org/` [Koehn, 2007]

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