CS378: Natural Language Processing
Lecture 19: Machine Translation

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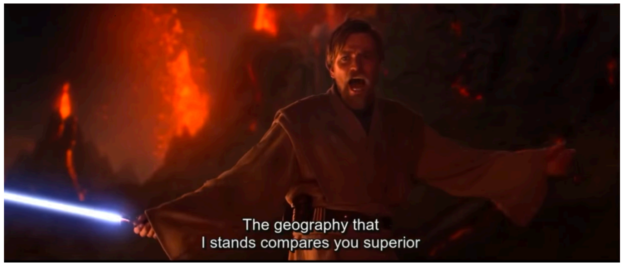


Star Wars The Third Gathers: The Backstroke of the West
(subtitles machine translated from Chinese)

Administrivia

- P3 back
- FP presentations start in 3 weeks

Today's Lecture

- MT basics
- Phrase-based MT, word alignment
- Phrase-based decoding
- MT frontiers

MT Basics

MT in Practice

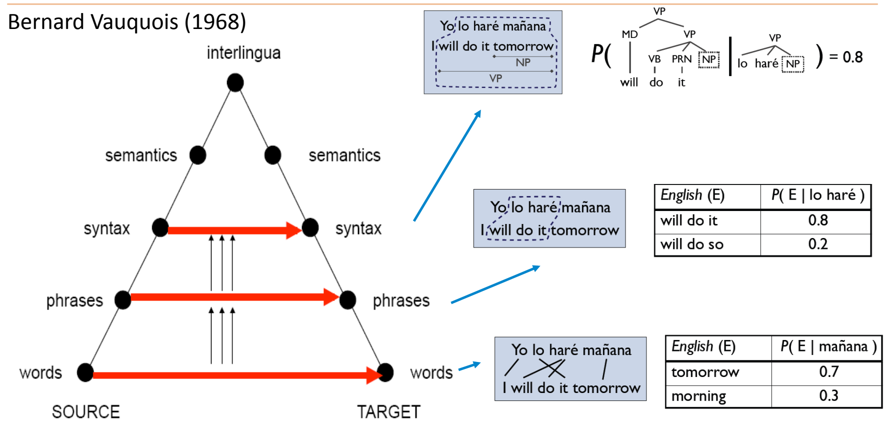
- Bitext: this is what we learn translation systems from. What can you learn?

Je fais un bureau	I'm making a desk
Je fais une soupe	I'm making soup
Je fais un bureau	I make a desk
Qu'est-ce que tu fais?	What are you doing?

- What makes this hard? Not word-to-word translation
  Multiple translations of a single source (ambiguous)

Levels of Transfer: Vauquois Triangle

Bernard Vauquois (1968)



- Classic systems were mostly phrase-based

Slide credit: Dan Klein

Evaluating MT

- What should our evaluation goals be?

Evaluating MT

- Fluency: does it sound good in the target language?
- Fidelity/adequacy: does it capture the meaning of the original?
- Classic autuomatic metric: BLEU score: geometric mean of 1-, 2-, 3-, and 4-gram *precision* vs. a reference, multiplied by brevity penalty (penalizes short translations)

$$\text{BLEU} = \text{BP} \cdot \exp\left(\sum_{n=1}^{N} w_n \log p_n\right)$$

Typically n = 4, w_i = 1/4

$$\text{BP} = \begin{cases} 1 & \text{if } c > r \\ e^{(1-r/c)} & \text{if } c \leq r \end{cases}$$

r = length of reference
c = length of prediction

- Which of these criteria does it capture?

Phrase-based MT, Word Alignment

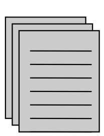
Phrase-Based MT

- Key idea: translation works better the bigger chunks you use
- Remember phrases from training data, translate piece-by-piece and stitch those pieces together to translate
  - How to identify phrases? Word alignment over source-target bitext
  - How to stitch together? Language model over target language
  - Decoder takes phrases and a language model and searches over possible translations
- NOT like standard discriminative models (take a bunch of translation pairs, learn a ton of parameters in an end-to-end way)

Phrase-Based MT

cat ||| chat ||| 0.9
the cat ||| le chat ||| 0.8
dog ||| chien ||| 0.8
house ||| maison ||| 0.6
my house ||| ma maison ||| 0.9
language ||| langue ||| 0.9
...

Phrase table P(f|e)



Language model P(e)

Unlabeled English data

- Where does the phrase table come from? First need **word alignment**

$$P(e|f) \propto P(f|e)P(e)$$

Noisy channel model: combine scores from translation model + language model to translate foreign to English

"Translate faithfully but make fluent English"

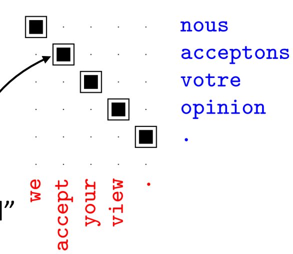
Word Alignment

- Input: a bitext, pairs of translated sentences

  nous acceptons votre opinion . ||| we accept your view

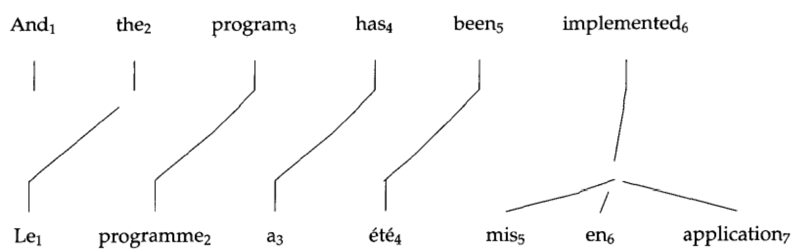
  nous allons changer d'avis ||| we are going to change our minds

- Output: alignments between words in each sentence
  - We will see how to turn these into phrases



"accept and acceptons are aligned"

1-to-Many Alignments



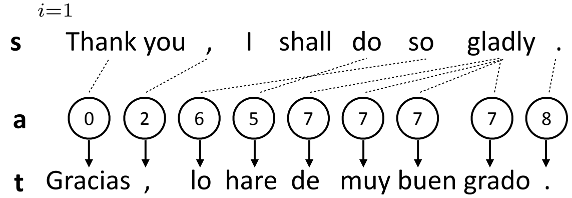
Word Alignment

- Models P(**t**|**s**): probability of "target" sentence being generated from "source" sentence according to a model
- Latent variable model: $P(\mathbf{t}|\mathbf{s}) = \sum_{\mathbf{a}} P(\mathbf{t}|\mathbf{a},\mathbf{s})P(\mathbf{a})$
- Correct alignments should lead to higher-likelihood generations, so by optimizing this objective we will learn correct alignments

IBM Model 1

- Each target word is aligned to *at most* one source word

$$P(\mathbf{t},\mathbf{a} \mid \mathbf{s}) = \prod_{i=1}^{n} P(t_i \mid s_{a_i})P(a_i)$$



- Set P(a) uniformly (no prior over good alignments)
- $P(t_i \mid s_{a_i})$: word translation probability table. Learn with EM

Brown et al. (1993)

IBM Model 1: Example

$$P(\mathbf{t},\mathbf{a} \mid \mathbf{s}) = \prod_{i=1}^{n} P(t_i \mid s_{a_i})P(a_i)$$

	I	like	eat
Je	0.8	0.1	0.1
J'	0.8	0.1	0.1
mange	0	0	1.0
aime	0	1.0	0
NULL	0.4	0.3	0.3

s = Je NULL

t = I

What is P(**t**, **a** | **s**)?

What is P(**a** | **t**, **s**)?

Brown et al. (1993)

IBM Model 1: Example 2

$$P(\mathbf{t}, \mathbf{a} \mid \mathbf{s}) = \prod_{i=1}^{n} P(t_i \mid s_{a_i}) P(a_i)$$

	I	like	eat
Je	0.8	0.1	0.1
J’	0.8	0.1	0.1
mange	0	0	1.0
aime	0	1.0	0
NULL	0.4	0.3	0.3

s = J’ aime NULL

t = I like

What is P(a_1 | **t**, **s**)?

Brown et al. (1993)

Learning with EM

- E-step: estimate P(**a** | **t**, **s**)
- M-step: treat P(**a** | **t**, **s**) as “pseudo-labels” for the data. Read off counts + normalize
- How does this work?

Je I

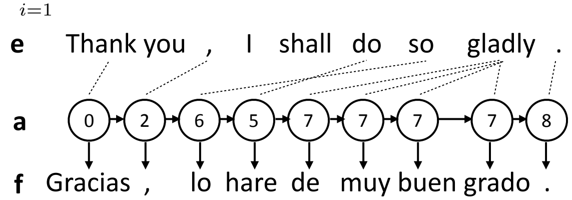
Je fais I do

Brown et al. (1993)

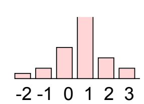
HMM for Alignment

- Sequential dependence between a’s to capture monotonicity

$$P(\mathbf{t}, \mathbf{a} \mid \mathbf{s}) = \prod_{i=1}^{n} P(t_i \mid s_{a_i}) P(a_i \mid a_{i-1})$$



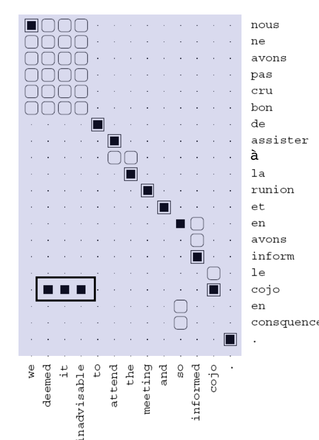
- Alignment dist parameterized by jump size: $P(a_j - a_{j-1})$



Vogel et al. (1996)

HMM Model

- Alignments are generally monotonic (along diagonal)
- Some mistakes, especially when you have rare words (*garbage collection*)



Phrase Extraction

- Find contiguous sets of aligned words in the two languages that don't have alignments to other words

d'assister à la reunion et ||| to attend the meeting and

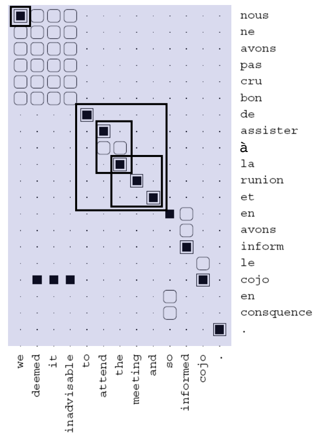
assister à la reunion ||| attend the meeting

la reunion and ||| the meeting and

nous ||| we

…

- Lots of phrases possible, count across all sentences and score by frequency



Phrase-Based Decoding

Recall: *n*-gram Language Models

$$P(\mathbf{w}) = P(w_1)P(w_2|w_1)P(w_3|w_1, w_2)\dots$$

- *n*-gram models: distribution of next word is a multinomial conditioned on previous *n*-1 words $P(w_i|w_1, \dots, w_{i-1}) = P(w_i|w_{i-n+1}, \dots, w_{i-1})$

I visited San ______ put a distribution over the next word

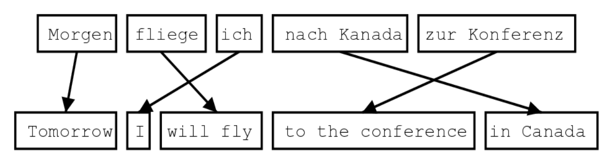
$$P(w|\text{visited San}) = \frac{\text{count}(\text{visited San}, w)}{\text{count}(\text{visited San})}$$

Maximum likelihood estimate of this 3-gram probability from a corpus

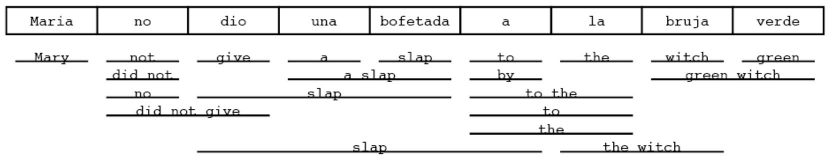
- Typically use ~5-gram language models for translation

Phrase-Based Decoding

- Inputs:
  - n-gram language model: $P(e_i|e_1, \dots, e_{i-1}) \approx P(e_i|e_{i-n-1}, \dots, e_{i-1})$
  - Phrase table: set of phrase pairs (**e**, **f**) with probabilities P(**f**|**e**)
- What we want to find: **e** produced by a series of phrase-by-phrase translations from an input **f**, possibly with reordering:



Monotonic Translation

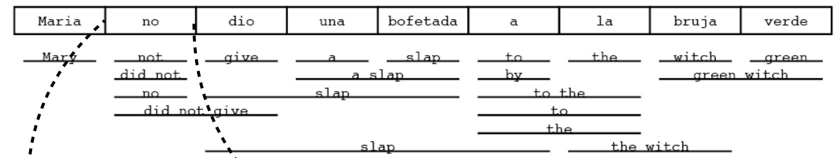


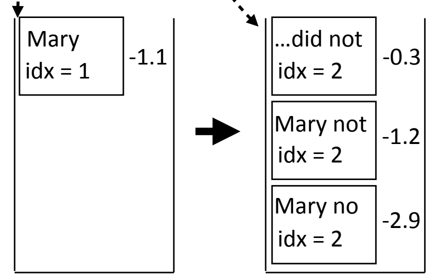
- If we translate with beam search, what state do we need to keep in the beam?
  - What have we translated so far?
  - What words have we produced so far? (need to remember the last 2 words for a 3-gram LM)

$$\arg\max_{\mathbf{e}} \left[\prod_{\langle \bar{e}, \bar{f} \rangle} P(\bar{f}|\bar{e}) \cdot \prod_{i=1}^{|\mathbf{e}|} P(e_i|e_{i-1}, e_{i-2}) \right]$$

Koehn (2004)

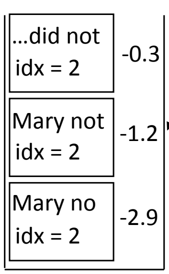
Monotonic Translation





- Beam state: where we're at, what the current translation so far is, and score of that translation
- Advancing state consists of trying each possible translation that could get us to this timestep

Monotonic Translation



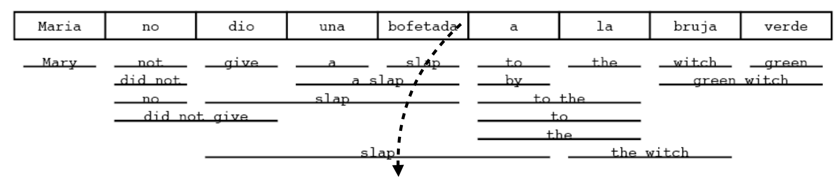
score = log [$\underbrace{\text{P(Mary) P(not | Mary)}}_{\text{LM}}$ $\underbrace{\text{P(Maria | Mary) P(no | not)}}_{\text{TM}}$]

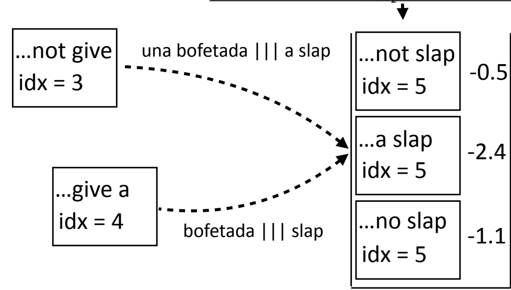
In reality: score = α log P(LM) + β log P(TM)

...and TM is broken down into several features

Koehn (2004)

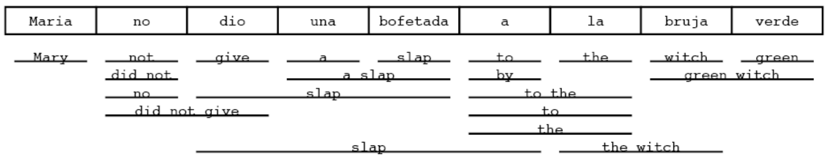
Monotonic Translation



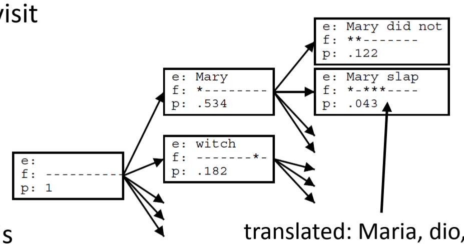


- Several paths can get us to this state, max over them (like Viterbi)
- Variable-length translation pieces = semi-HMM

Non-Monotonic Translation



- Non-monotonic translation: can visit source sentence "out of order"
- State needs to describe which words have been translated and which haven't
- Big enough phrases already capture lots of reorderings, so this isn't as important as you think



translated: Maria, dio, una, bofetada

Moses

- Toolkit for machine translation due to Philipp Koehn + Hieu Hoang
  - Pharaoh (Koehn, 2004) is the decoder from Koehn's thesis
- Moses implements word alignment, language models, and this decoder, plus training regimes and more
  - Highly optimized and heavily engineered, could more or less build SOTA translation systems with this from 2007-2015
- Next time: results on these and comparisons to neural methods

Transformer MT + Frontiers

Transformers

Model	BLEU	
	EN-DE	EN-FR
ByteNet [18]	23.75	
Deep-Att + PosUnk [39]		39.2
GNMT + RL [38]	24.6	39.92
ConvS2S [9]	25.16	40.46
MoE [32]	26.03	40.56
Deep-Att + PosUnk Ensemble [39]		40.4
GNMT + RL Ensemble [38]	26.30	41.16
ConvS2S Ensemble [9]	26.36	**41.29**
Transformer (base model)	27.3	38.1
Transformer (big)	**28.4**	**41.8**

- Big = 6 layers, 1000 dim for each token, 16 heads, base = 6 layers + other params halved

Vaswani et al. (2017)

Frontiers in MT: Small Data

ID	system	BLEU 100k	BLEU 3.2M
1	phrase-based SMT	15.87 ± 0.19	26.60 ± 0.00
2	NMT baseline	0.00 ± 0.00	25.70 ± 0.33
3	2 + "mainstream improvements" (dropout, tied embeddings, layer normalization, bideep RNN, label smoothing)	7.20 ± 0.62	31.93 ± 0.05
4	3 + reduce BPE vocabulary (14k → 2k symbols)	12.10 ± 0.16	-
5	4 + reduce batch size (4k → 1k tokens)	12.40 ± 0.08	31.97 ± 0.26
6	5 + lexical model	13.03 ± 0.49	31.80 ± 0.22
7	5 + aggressive (word) dropout	15.87 ± 0.09	**33.60** ± 0.14
8	7 + other hyperparameter tuning (learning rate, model depth, label smoothing rate)	**16.57** ± 0.26	32.80 ± 0.08
9	8 + lexical model	16.10 ± 0.29	33.30 ± 0.08

- Synthetic small data setting: German -> English

Sennrich and Zhang (2019)

Frontiers in MT: Low-Resource

- Particular interest in deploying MT systems for languages with little or no parallel data
- BPE allows us to transfer models even without training on a specific language
- Pre-trained models can help further

Burmese, Indonesian, Turkish

Transfer	BLEU My→En	BLEU Id→En	BLEU Tr→En
baseline (no transfer)	4.0	20.6	19.0
transfer, train	17.8	27.4	20.3
transfer, train, reset emb, train	13.3	25.0	20.0
transfer, train, reset inner, train	3.6	18.0	19.1

Table 3: Investigating the model's capability to restore its quality if we reset the parameters. We use En→De as the parent.

Aji et al. (2020)

Frontiers in MT: Low-Resource

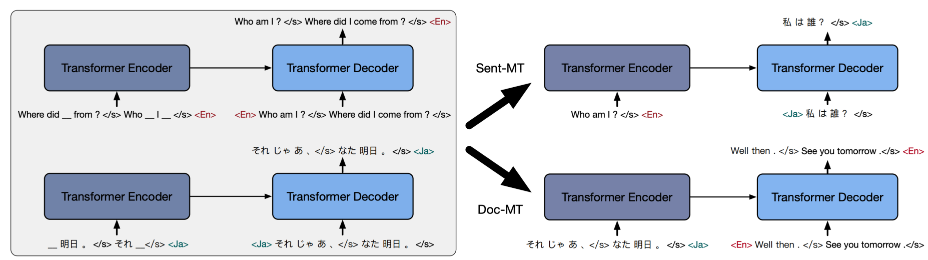
Transferring Emb.	Transferring Inner	De→En parent My→En	De→En parent Id→En	De→En parent Tr→En	En→De parent My→En	En→De parent Id→En	En→De parent Tr→En	avg.
Y	Y	17.8	27.4	20.3	17.5	27.5	20.2	21.7
N	Y	13.6	25.3	19.4	10.8	24.9	19.3	18.3
Y	N	3.0	18.2	19.1	3.4	18.8	18.9	13.7
N	N	4.0	20.6	19.0	4.0	20.6	19.0	14.5

Table 2: Transfer learning performance by only transferring parts of the network. Inner layers are the non-embedding layers. N = not-transferred. Y = transferred.

- Very important to transfer the basic Transformer "skills", but re-learning the embeddings seems fine in many cases

Aji et al. (2020)

Frontiers in MT: Multilingual Models



Multilingual Denoising Pre-Training (mBART)

Fine-tuning on Machine Translation

Yinhan Liu et al. (2020)

Frontiers in MT: Multilingual Models

Languages	En-Gu		En-Kk		En-Vi		En-Tr		En-Ja		En-Ko	
Data Source	WMT19		WMT19		IWSLT15		WMT17		IWSLT17		IWSLT17	
Size	10K		91K		133K		207K		223K		230K	
Direction	←	→	←	→	←	→	←	→	←	→	←	→
Random	0.0	0.0	0.8	0.2	23.6	24.8	12.2	9.5	10.4	12.3	15.3	16.3
mBART25	**0.3**	**0.1**	**7.4**	**2.5**	**36.1**	**35.4**	**22.5**	**17.8**	**19.1**	**19.4**	**24.6**	**22.6**

Languages	En-Nl		En-Ar		En-It		En-My		En-Ne		En-Ro	
Data Source	IWSLT17		IWSLT17		IWSLT17		WAT19		FLoRes		WMT16	
Size	237K		250K		250K		259K		564K		608K	
Direction	←	→	←	→	←	→	←	→	←	→	←	→
Random	34.6	29.3	27.5	16.9	31.7	28.0	23.3	34.9	7.6	4.3	34.0	34.3
mBART25	**43.3**	**34.8**	**37.6**	**21.6**	**39.8**	**34.0**	**28.3**	**36.9**	**14.5**	**7.4**	**37.8**	**37.7**

- Random = random initialization

Yinhan Liu et al. (2020)

Frontiers in MT: Multilingual Models

SOURCE Zh	针对政府的沉默态度,初级医生委员会执行委员会已于今日正式要求英国医学协会理事会召开特别会议批准旨在从九月初开始升级劳工行动的一项长期计划。
TARGET En	In response to the government's silence, JDC exec has today made a formal request for a special meeting of BMA Council to authorise a rolling programme of escalated industrial action beginning in early September.
mBART25 Ja-En	In response to the government's silence, the Council of Chief Medical Officers has formally requested today the Royal College of Physicians to hold a special meeting to approve a long-term workforce action that starts in September.
mBART25 Ko-En	In response to the government's silence, the Chief Medical Officers' Council is calling today for a special session at the Council of the British Medical Association, which is a long-term initiative to upgrade labor from September.
mBART25 Zh-En	In response to the government's silence, the Board of Primary Doctors has today formally asked the British Medical Association to hold a special meeting to approve a long-term plan that starts in the beginning of September.

Yinhan Liu et al. (2020)

Frontiers in MT: ChatGPT

Table 3: Comparison of different prompts for ChatGPT to perform Chinese-to-English (Zh⇒En) translation.

System	BLEU↑	ChrF++↑	TER↓
Google	31.66	57.09	56.21
DeepL	31.22	56.74	57.84
Tencent	29.69	56.24	57.16
ChatGPT w/ TP1	23.25	53.07	66.03
ChatGPT w/ TP2	24.54	53.05	63.79
ChatGPT w/ TP3	**24.73**	**53.71**	**62.84**

- Works okay for Chinese-English, but less good at generating into low-resource languages (English -> Romanian doesn't work well)

Table 5: Performance of ChatGPT with pivot prompting. New results are obtained from the updated ChatGPT version on 2023.01.31. LR: length ratio.

System	De⇒Zh		Ro⇒Zh	
	BLEU	LR	BLEU	LR
Google	38.71	0.94	39.05	0.95
DeepL	40.46	0.98	38.95	0.99
ChatGPT (Direct)	34.46	0.97	30.84	0.91
ChatGPT (Direct_{new})	30.76	0.92	27.51	0.93
ChatGPT (Pivot_{new})	34.68	0.95	34.19	0.98

- Better with "pivoting"

"Is ChatGPT A Good Translator? Yes With GPT-4 As The Engine" Jia et al. (2023)

Frontiers: Evaluation with LLMs

```
Score the following translation from {source_lang} to {target_lang} with respect
to the human reference on a continuous scale from 0 to 100, where score of zero means
"no meaning preserved" and score of one hundred means "perfect meaning and grammar".

{source_lang} source: "{source_seg}"
{target_lang} human reference: {reference_seg}
{target_lang} translation: "{target_seg}"
Score:
```

Figure 1: The best-performing prompt based on Direct Assessment expecting a score between 0–100. Template **portions in bold face** are used only when a human reference translation is available.

- Outperforms many learned MT metrics (Transformers trained over (source, target, reference) triples to reproduce human judgments of quality)

Kocmi et al. (2023)

Takeaways

- Word alignment is a way to learn unsupervised correspondences between words and build phrase tables
- Phrase-based MT was SOTA for a long time (and until the past couple of years was still best for low-resource settings)
- Transformers are state-of-the-art for machine translation
- They work really well on languages where we have a ton of data. When they don't: pre-training can help