CS388: Natural Language Processing
Lecture 19: Machine Translation

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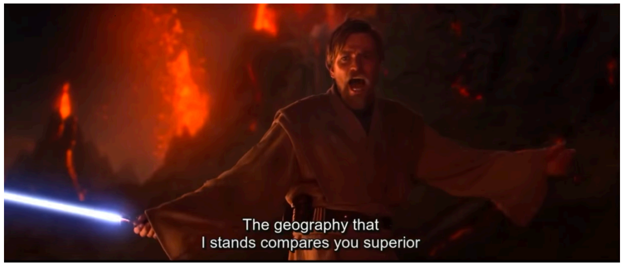


Star Wars The Third Gathers: The Backstroke of the West
(subtitles machine translated from Chinese)

Administrivia

- P3 back this weekend
- Check-ins due April 4

Today's Lecture

- MT basics
- Phrase-based MT, word alignment
- Multilingual models
- Transformer-based MT, pre-trained models, frontiers

MT Basics

MT in Practice

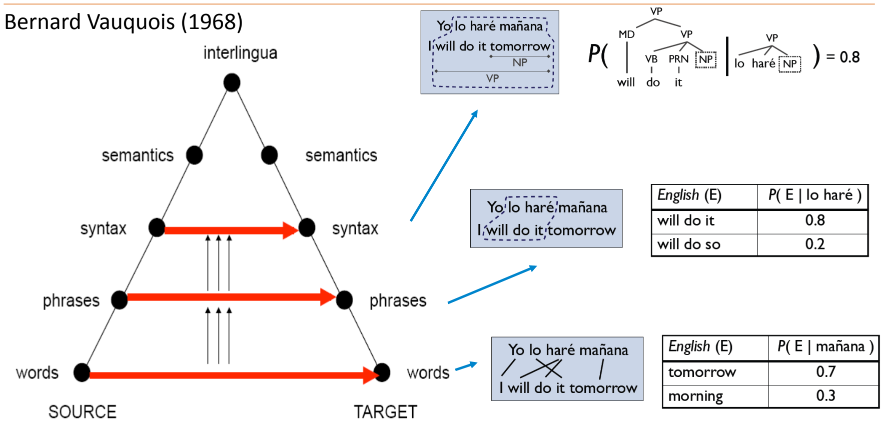
- Bitext: this is what we learn translation systems from. What can you learn?

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"

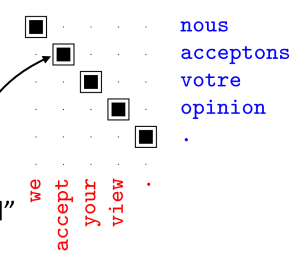
Word Alignment

- Input: a bitext, pairs of translated sentences

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

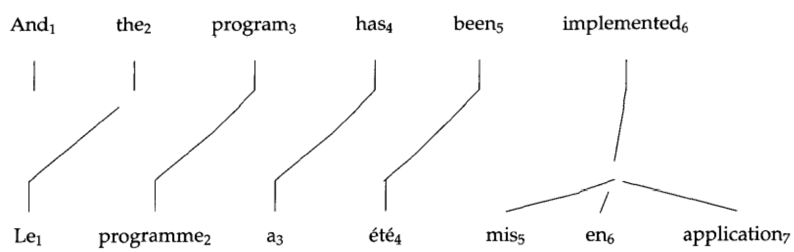
  nous allons changer d'avis ||| we are going to change our minds

- 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



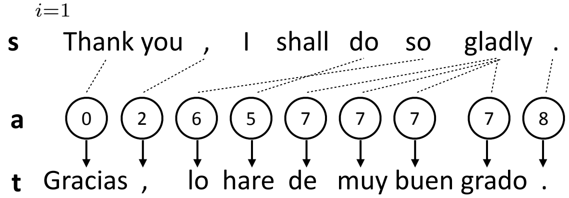
Word Alignment

- 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 $P(a_1 \mid \mathbf{t}, \mathbf{s})$?

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

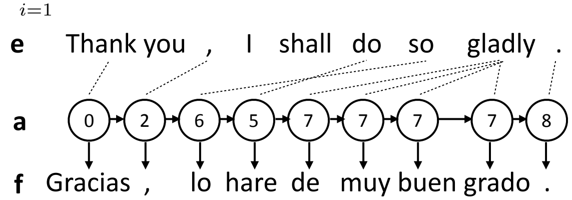
Je fais I do

Brown et al. (1993)

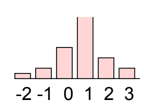
HMM for Alignment

- Sequential dependence between a's to capture monotonicity

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



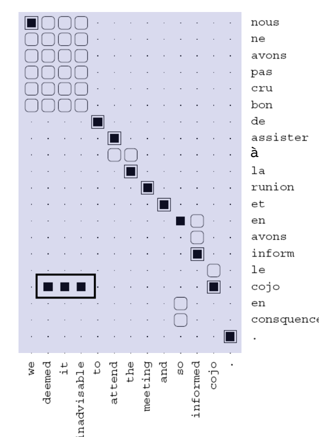
- Alignment dist parameterized by jump size: $P(a_j - a_{j-1})$



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

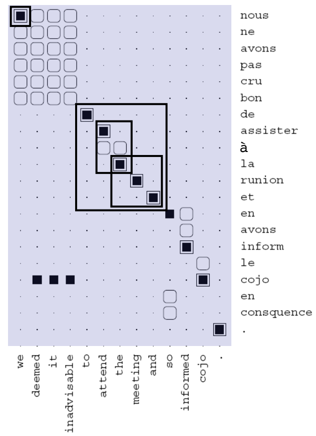
assister à la reunion ||| attend the meeting

la reunion and ||| the meeting and

nous ||| we

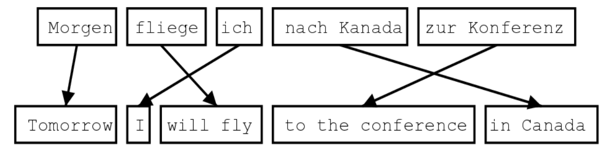
...

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



Phrase-Based Decoding

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



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

Cross-Lingual, Multilingual Word Representations

Multilingual Embeddings

- MT involves directly mapping between strings in different languages
- Potentially easier task: learn model that can do the same task in multiple languages? E.g., do POs tagging in both English and French, do a QA in 10 languages, etc.
- We'll see some neural techniques that can do this, then come back to translation

Multilingual Embeddings

- Input: corpora in many languages. Output: embeddings where similar words *in different languages* have similar embeddings

I have an apple
47 24 18 427

J' ai des oranges
47 24 89 1981

ID: 24
ai have

ID: 47
I Je J'

- multiCluster: use bilingual dictionaries to form clusters of words that are translations of one another, replace corpora with cluster IDs, train "monolingual" embeddings over all these corpora
- Works okay but not all that well

Ammar et al. (2016)

Multilingual BERT

- Take top 104 Wikipedias, train BERT on all of them simultaneously
- What does this look like?

Beethoven may have proposed unsuccessfully to Therese Malfatti, the supposed dedicatee of "Für Elise"; his status as a commoner may again have interfered with those plans.

当人们在马尔法蒂身后发现这部小曲的手稿时，便误认为上面写的是"Für Elise"（即《给爱丽丝》）[51]。

Кита́й (официально — Кита́йская Наро́дная Респу́блика, сокращённо — КНР; кит. трад. 中華人民共和國, упр. 中华人民共和国, пиньинь: Zhōnghuá Rénmín Gònghéguó, палл.: Чжунхуа Жэньминь Гунхэго) — государство в Восточной Аз

Devlin et al. (2019)

Multilingual BERT: Results

Fine-tuning \ Eval	EN	DE	ES	IT
EN	**96.82**	89.40	85.91	91.60
DE	83.99	**93.99**	86.32	88.39
ES	81.64	88.87	**96.71**	93.71
IT	86.79	87.82	91.28	**98.11**

Table 2: POS accuracy on a subset of UD languages.

- Can transfer BERT directly across languages with some success
- ...but this evaluation is on languages that all share an alphabet

Pires et al. (2019)

Multilingual BERT: Results

	HI	UR
HI	**97.1**	85.9
UR	91.1	**93.8**

	EN	BG	JA
EN	**96.8**	87.1	49.4
BG	82.2	**98.9**	51.6
JA	57.4	67.2	**96.5**

Table 4: POS accuracy on the UD test set for languages with different scripts. Row=fine-tuning, column=eval.

- Urdu (Arabic/Nastaliq script) => Hindi (Devanagari). Transfers well despite different alphabets!
- Japanese => English: different script and very different syntax

Pires et al. (2019)

Scaling Up: XLM-R

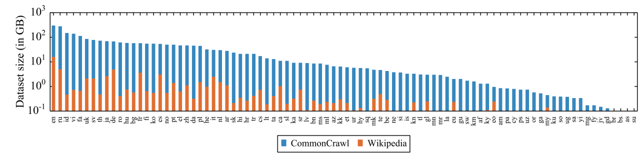


Figure 1: Amount of data in GiB (log-scale) for the 88 languages that appear in both the Wiki-100 corpus used for mBERT and XLM-100, and the CC-100 used for XLM-R. CC-100 increases the amount of data by several orders of magnitude, in particular for low-resource languages.

- Larger "Common Crawl" dataset, better performance than mBERT
- Low-resource languages benefit from training on other languages
- High-resource languages see a small performance hit, but not much

Conneau et al. (2019)

Scaling Up: Benchmarks

Task	Corpus	|Train|	|Dev|	|Test|	Test sets	|Lang.|	Task
Classification	XNLI	392,702	2,490	5,010	translations	15	NLI
	PAWS-X	49,401	2,000	2,000	translations	7	Paraphrase
Struct. pred.	POS	21,253	3,974	47-20,436	ind. annot.	33 (90)	POS
	NER	20,000	10,000	1,000-10,000	ind. annot.	40 (176)	NER
QA	XQuAD	87,599	34,726	1,190	translations	11	Span extraction
	MLQA			4,517–11,590	translations	7	Span extraction
	TyDiQA-GoldP	3,696	634	323–2,719	ind. annot.	9	Span extraction
Retrieval	BUCC	-	-	1,896–14,330	-	5	Sent. retrieval
	Tatoeba	-	-	1,000	-	33 (122)	Sent. retrieval

- Many of these datasets are translations of base datasets, not originally annotated in those languages
- Exceptions: POS, NER, TyDiQA

Hu et al. (2021)

TyDiQA

- Typologically-diverse QA dataset
- Annotators write questions based on very short snippets of articles; answers may or may not exist, fetched from elsewhere in Wikipedia

Q: Как далеко Уран от
how far Uranus-SG.NOM from
Земл-и?
Earth-SG.GEN?
How far is Uranus from Earth?

A: Расстояние между Уран-ом
distance between Uranus-SG.INSTR
и Земл-ёй меняется от 2,6
and Earth-SG.INSTR varies from 2,6
до 3,15 млрд км...
to 3,15 bln km...
The distance between Uranus and Earth fluctuates from 2.6 to 3.15 bln km...

Clark et al. (2021)

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	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	Id→En	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

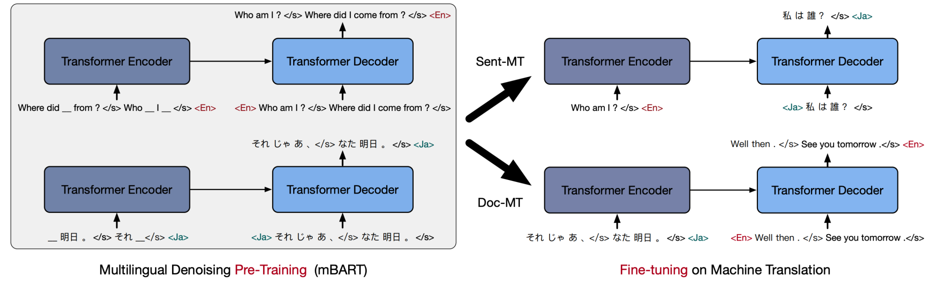
Transferring		BLEU						
		De→En parent			En→De parent			
Emb.	Inner	My→En	Id→En	Tr→En	My→En	Id→En	Tr→En	avg.
Y	Y	17.8	27.4	20.3	17.5	27.5	20.2	21.7
N	Y	13.6	25.3	19.4	10.8	24.9	19.3	18.3
Y	N	3.0	18.2	19.1	3.4	18.8	18.9	13.7
N	N	4.0	20.6	19.0	4.0	20.6	19.0	14.5

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 ($\text{Direct}_{\text{new}}$)	30.76	0.92	27.51	0.93
ChatGPT ($\text{Pivot}_{\text{new}}$)	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