Current Challenges

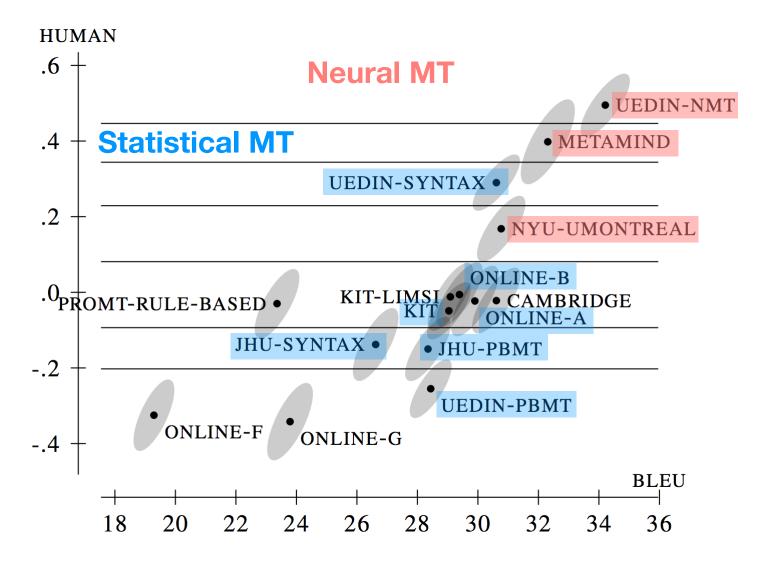
Philipp Koehn

3 November 2022



WMT 2016

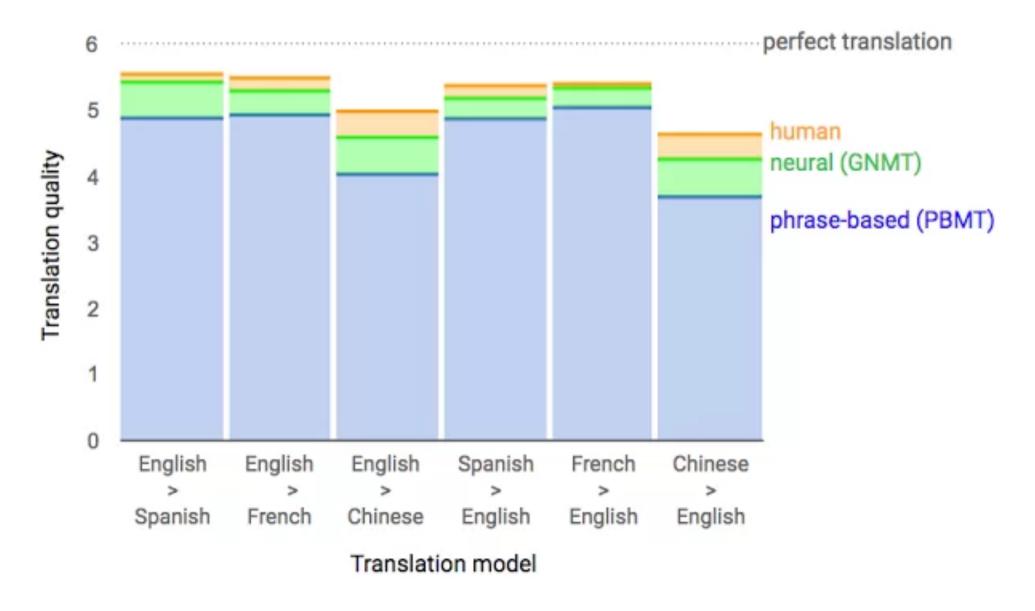




(in 2017 barely any statistical machine translation submissions)

2017: Google: "Near Human Quality"





2018: More Hype



Microsoft Research Achieves Human Parity For Chinese English Translation

Written by Sue Gee

Wednesday, 21 March 2018

Researchers in Microsoft's labs in Beijing and in Redmond and Washington have developed an Al machine translation system that can translate with the same accuracy as a human from Chinese to English.

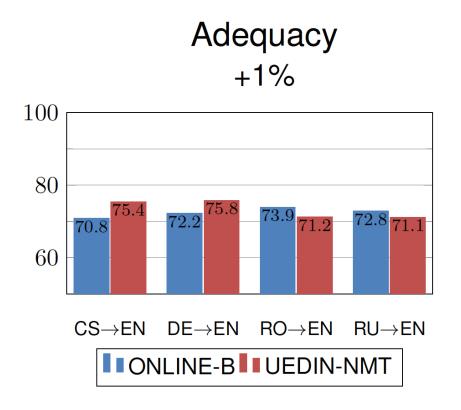
SDL Cracks Russian to English Neural Machine Translation

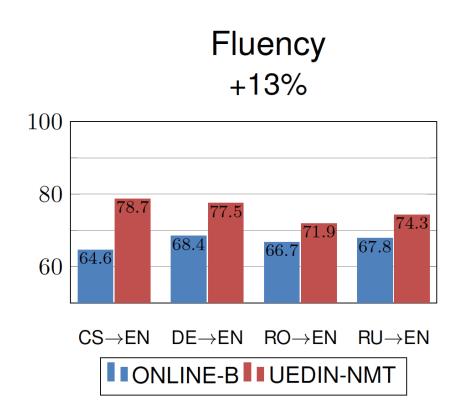
Global Enterprises to Capitalize on Near Perfect Russian to English Machine Translation as SDL Sets New Industry Standard

"90% of the system's output labelled as perfect by professional Russian-English translators"

Just Better Fluency?







(from: Sennrich and Haddow, 2017)

Challenges



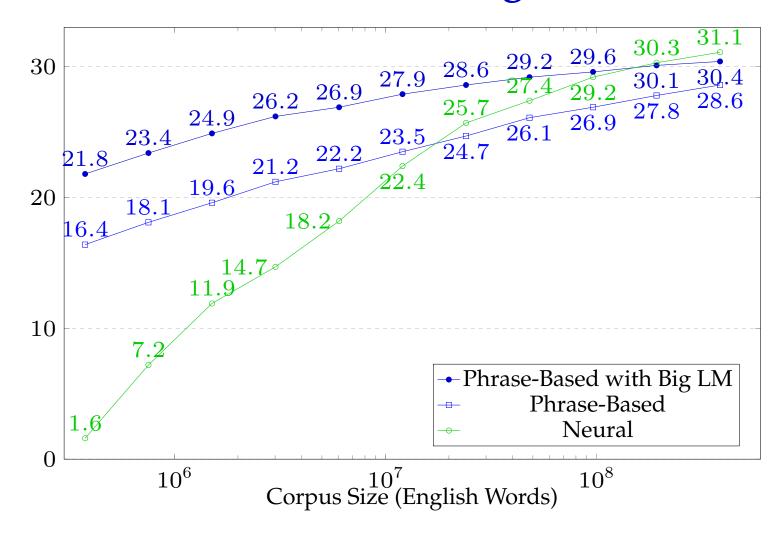
- Lack of training data
- Domain mismatch
- Rare words
- Word alignment
- Beam search
- Noise
- Control over output
- Interpretability



lack of training data

Amount of Training Data





English-Spanish systems trained on 0.4 million to 385.7 million words

Translation Examples



Source	A Republican strategy to counter the re-election of Obama
$\frac{1}{1024}$	Un órgano de coordinación para el anuncio de libre determinación
$\frac{1}{512}$	Lista de una estrategia para luchar contra la elección de hojas de Ohio
$\frac{1}{256}$	Explosión realiza una estrategia divisiva de luchar contra las
	elecciones de autor
$\frac{1}{128}$	Una estrategia republicana para la eliminación de la reelección de
	Obama
$\frac{1}{64}$	Estrategia siria para contrarrestar la reelección del Obama .
$\frac{1}{32}+$	Una estrategia republicana para contrarrestar la reelección de Obama



domain mismatch

Domain Mismatch



System ↓	Law	Medical	IT	Koran	Subtitles
All Data	30.532.8	45.142.2	35.344.7	17.917.9	26.420.8
Law	31.134.4	12.118.2	3.5 6.9	1.3 2.2	2.8 6.0
Medical	3.9 10.2	39.443.5	2.0 8.5	$0.6 \ 2.0$	1.4 5.8
IT	1.9 3.7	6.5 5.3	42.139.8	1.8 1.6	3.9 4.7
Koran	$0.4 \overline{1.8}$	$0.0 \overline{2.1}$	$0.0\ \overline{2.3}$	15.918.8	1.0 5.5
Subtitles	7.0 9.9	9.3 17.8	9.213.6	9.0 8.4	25.922.1

Translation Examples



Schaue um dich herum.
Look around you.
NMT: Look around you.
SMT: Look around you.
NMT: Sughum gravecorn.
SMT: In order to implement dich Schaue.
NMT: EMEA / MB / 049 / 01-EN-Final Work progamme for 2002
SMT: Schaue by dich around.
NMT: Switches to paused.
SMT: To Schaue by itself . \t
NMT: Take heed of your own souls.
SMT: And you see.
NMT: Look around you.
SMT: Look around you .



rare words

Rare Words



- ullet More frequent in training \to more likely to get right in test
- Let's measure this

Rare Words



- More frequent in training → more likely to get right in test
- Let's measure this
- One problem
 - frequency measured for input words
 - translation correctness measured for output words

Translation Accuracy for Input Words



- Generate word alignment between input and output words
- Look up count of input word in training
- Link to output word via word alignment
- Check if it is also in the reference translation

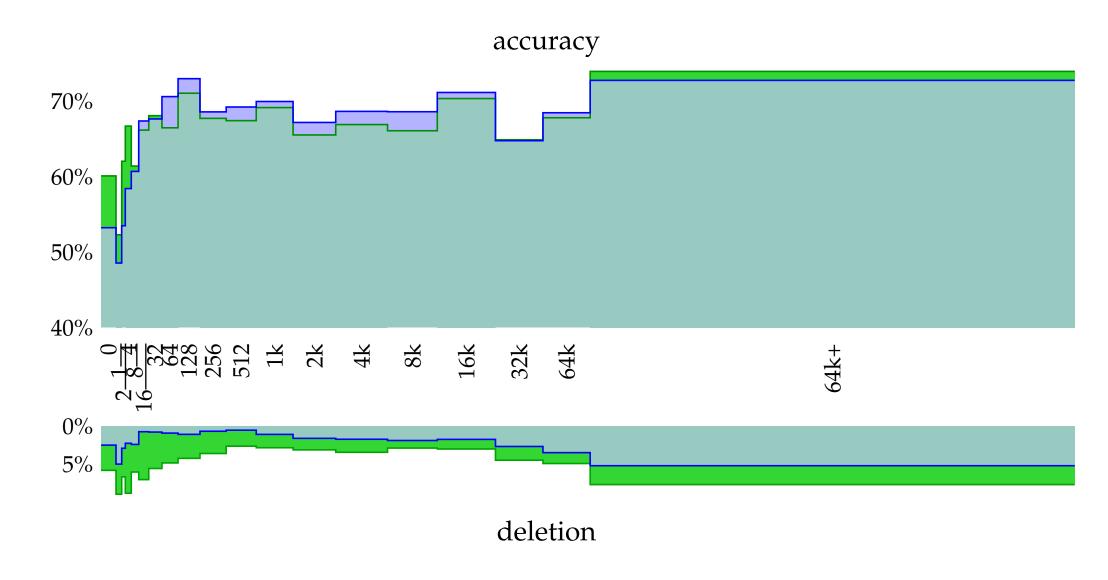
Translation Accuracy for Input Words



- Generate word alignment between input and output words
- Look up count of input word in training
- Link to output word via word alignment
- Check if it is also in the reference translation
- A lot of tedious special cases
 - one-to-many alignment, only some output words in reference
 - input word not aligned to any target word
 - many-to-one alignment
 - output word occurs multiple time in output or reference sentence

Count vs. Accuracy



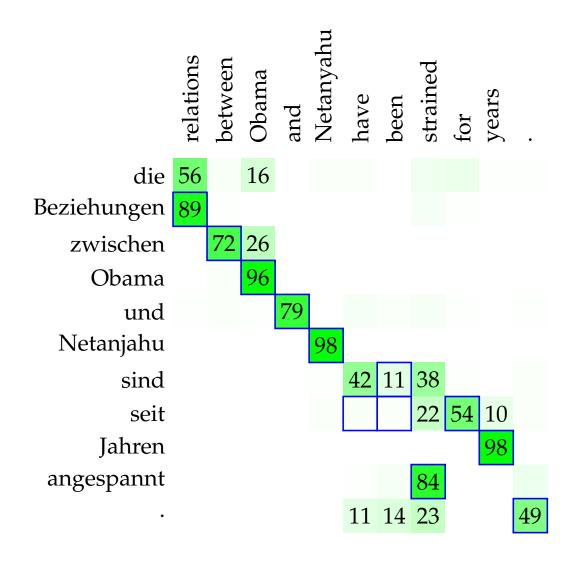




word alignment

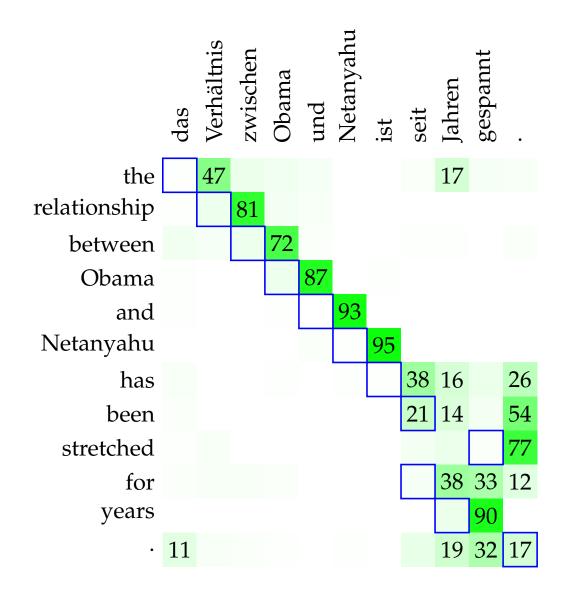
Word Alignment





Word Alignment?



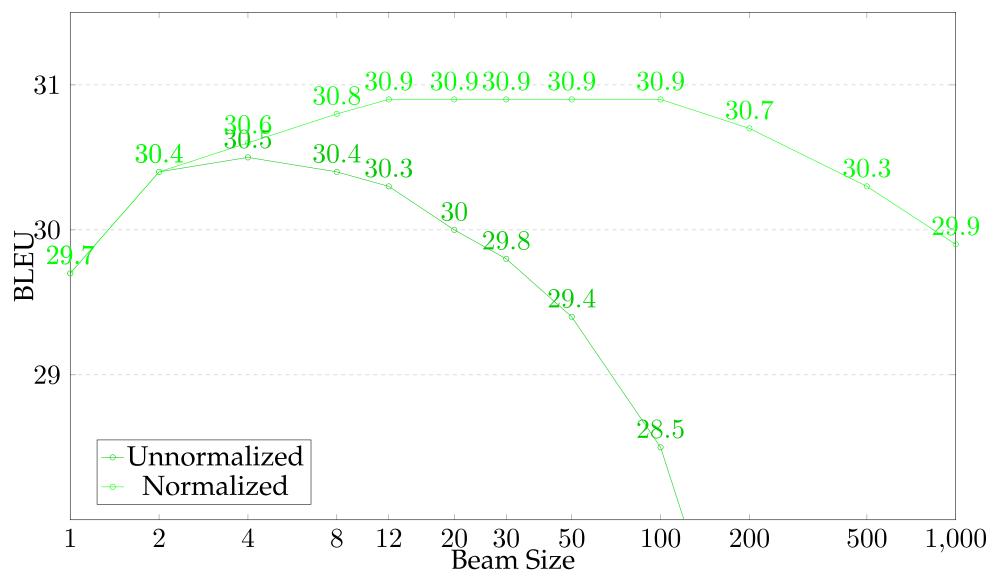




beam search

Beam Search







noisy data

Noise in Training Data



• Crawled parallel data from the web (very noisy)

	SMT	NMT
WMT17	24.0	27.2
+ Paracrawl	25.2 (+1.2)	17.3 (-9.9)

(German-English, 90m words each of WMT17 and Crawl data)

	5%	10%	20%	50%	100%
Raw crawl data	27.4 24.2	26.6 24.2	24.7 24.4	20.9 24.8	17.3 25.2
	+0.2 +0.2	-0.9 +0.2	+0.4	+0.8	+1.2
				-6.3	
					_Q Q

• Corpus cleaning methods [Xu and Koehn, EMNLP 2017] give improvements

Types of Noise



- Misaligned sentences
- Disfluent language (from MT, bad translations)
- Wrong language data (e.g., French in German–English corpus)
- Untranslated sentences
- Short segments (e.g., dictionaries)
- Mismatched domain

Mismatched Sentences



- Artificial created by randomly shuffling sentence order
- Added to existing parallel corpus in different amounts

5%	10%	20%	50%	100%
24.0	24.0	23.9	26.1 23.9	25.3 23.4
-0.0	-0.0	-0.1	-1.1 -0.1	-1.9 -0.6

• Bigger impact on NMT (green, left) than SMT (blue, right)

Misordered Words



• Artificial created by randomly shuffling words in each sentence

	5%	10%	20%	50%	100%
Source	<u>-0.0</u>	23.6 -0.4	-0.1	26.6 23.6 -0.6 -0.4	25.5 23.7 -1.7 -0.3
Target	<u>-0.0</u>	<u>-0.0</u>	-0.6	26.7 23.2 -0.5 -0.8	26.1 22.9 -1.1 -1.1

• Similar impact on NMT than SMT, worse for source reshuffle

Untranslated Sentences



	5%	10%	20%	50%	100%
	17.6 23.8	11.2 23.9	5.6 23.8	3.2 23.4	3.2 21.1
	-0.2	-0.1	-0.2	-0.6	
					-2.9
_	-9.8				
Source	-9.0				
		-16.0			
			01.6		
			-21.6	-24.0	-24.0
		 .			
Target	27.2	27.0	26.7	26.8	26.9
9 - •	-0.0	-0.2	-0.5	-0.4	-0.3

Wrong Language



	5%	10%	20%	50%	100%
fr source	26.9 <u>24.0</u>	26.8 23.9	26.8 23.9	26.8 23.9	26.8 23.8
	-0.3 -0.0	-0.4 -0.1	-0.4 -0.1	-0.4 -0.1	-0.4 -0.2
fr target	26.7 <u>24.0</u>	26.6 <u>23.9</u>	26.7 23.8	26.2 23.5	25.0 23.4
	-0.5 -0.0	-0.6 -0.1	-0.5 -0.2	-1.0 -0.5	-2.2 -0.6

• Surprisingly robust, maybe due to domain mismatch of French data

Short Sentences



	5%	10%	20%	50%
1-2 words	27.1 <u>24.1</u> -0.1 +0.1	26.5 <u>23.9</u> -0.7 -0.1	26.7 23.8 -0.5 -0.2	
1-5 words	27.8 24.2 +0.6 +0.2	27.6 24.5 +0.4 +0.5	28.0 24.5 +0.8 +0.5	26.6 24.2 -0.6 +0.2

• No harm done



control over output

Specifying Decoding Constraints



- Overriding the decisions of the decoder
- Why?
 - ⇒ translations have followed strict terminology
 - \Rightarrow rule-based translation of dates, quantities, etc.

XML Schema



```
The <x translation="Router"> router </x> is <wall/> a model <zone> Psy X500 Pro </zone> .
```

- The XML tags specify to the decoder that
 - the word router to be translated as Router
 - The router is, to be translated before the rest (<wall/>)
 - brand name Psy X500 Pro to be translated as a unit (<zone>, </zone>)

Formal Constraints



Subtitles

- translation has to fit into space on screen (may have to be shortened)
- input and output broken up into lines

Formal Constraints



Subtitles

- translation has to fit into space on screen (may have to be shortened)
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• Speech translation

- input often not well-formed
- real time translation: start while sentence is spoken
- subtitles: have be readable in limited time
- dubbing: sync up with video of speaker's mouth movement

Formal Constraints



Subtitles

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Poetry

- meter
- rhyme



catastrophic errors

Catastrophic Errors



News | Science and Technology

Facebook apologises for rude mistranslation of Xi Jinping's name

Company blames technical glitch that 'caused incorrect translations' of Chinese leader's name from Burmese to English.

Facebook's auto translation Al fail leads to a nightmare for a Palestinian man

The Al feature had "Good morning" in Arabic wrongly translated as "attack them" in Hebrew.

By Gianluca Mezzofiore on October 24, 2017







Industry News • By Marion Marking On 3 Aug 2020

Thai Mistranslation Shows Risk of Auto-Translating Social Media Content



After a machine translation of a post from English into Thai about the King's birthday proved offensive to the Thai monarchy, Facebook Thailand said it was deactivating auto-translate on Facebook and Instagram, revamping machine translation (MT) quality, and offering the Thai people its "profound apology."

What are Catastrophic Errors?



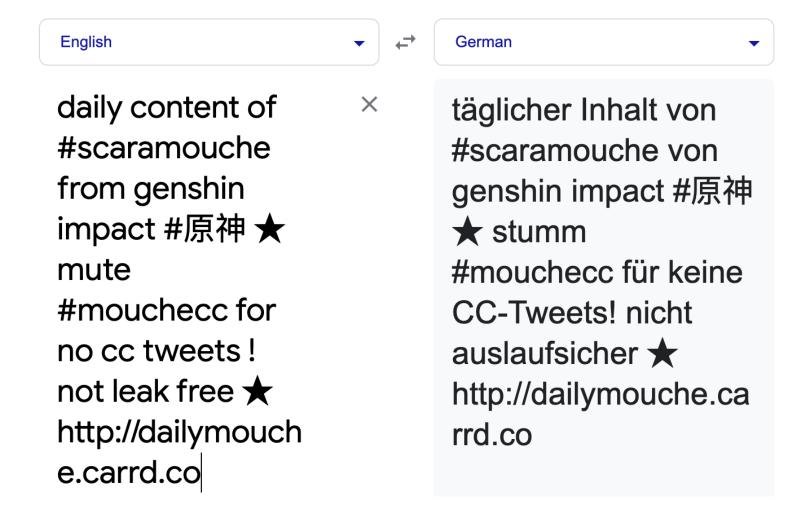
- Generation of profanity
 - first step: maintain list of offensive words for each language
 - only eliminate these words, if the input did not include such words
 - but: offensive language is not limited to specific words
- Generation of violent / inciting content
- Opposite meaning
- Mistranslation of names
- \Rightarrow All this is hard to detect



robustness

Robustness to User Generated Content





Challenges



- Jargon and acronyms
- Misspellings (sometimes intended for effect)
- Mangled grammar
- Special symbols (emojis, etc.)
- Hashtags, URLs, ...
- Use of dialectical languages
- Use of non-standard writing systems (e.g., Latin script due to lack of keyboard)

Some Methods



- Special handling of non-words like emojis, hashtags, URLs
- Creating synthetic noisy training data
- Adversarial training
- Resources
 - Machine translation of noisy text data set (MTNT)
 - WMT 2020 Shared Task on Machine Translation Robustness



bias

Gender Bias

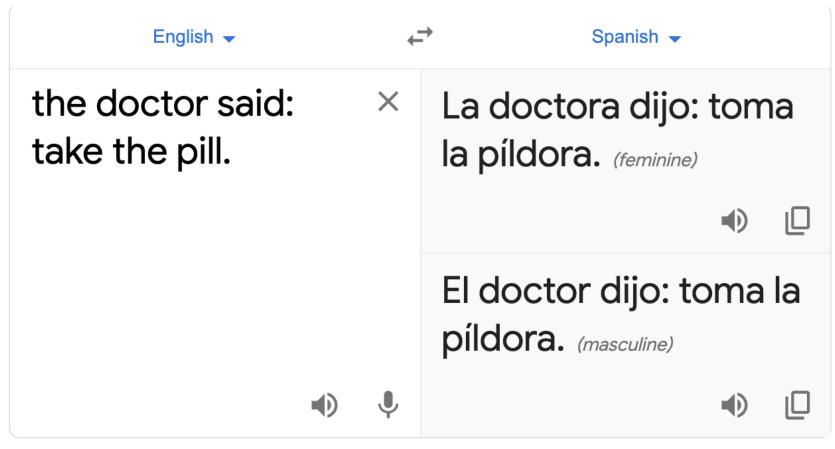


The doctor asked the nurse to help her in the procedure

El doctor le pidio a la enfermera que le ayudara con el procedimiento

Gender Bias





Open in Google Translate Feedback

Robustness to Style



"You Sound Just Like Your Father" Commercial Machine Translation Systems Include Stylistic Biases

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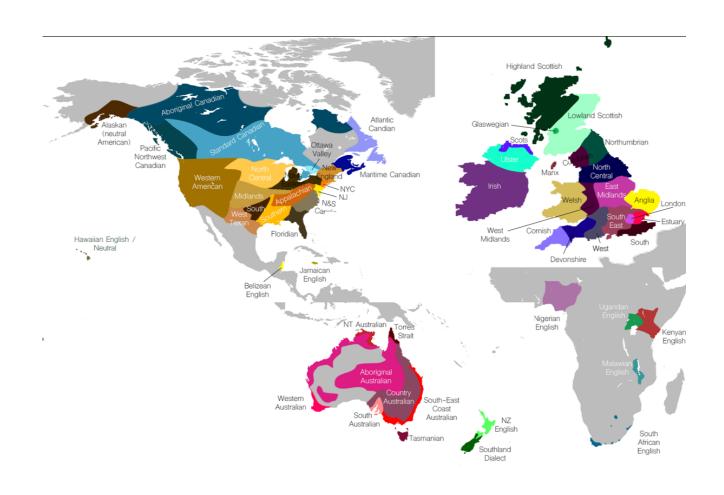




Dialect Bias



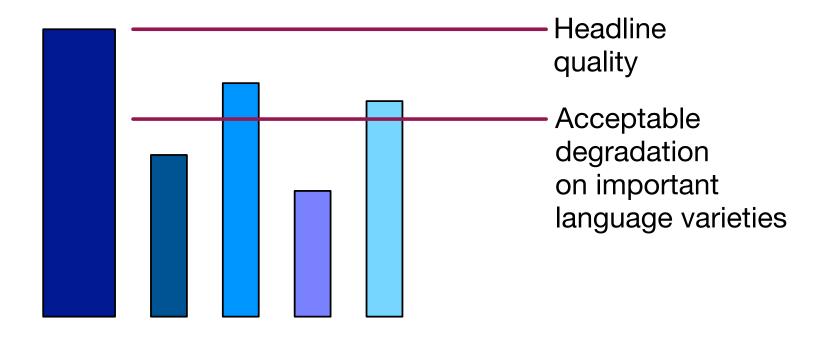
- Models often trained only on standard languages (British, American)
- Work less well on other dialects
- Bigger problem for automatic speech recognition



Evaluate Across Language Varieties



- BLEU score on standard language is not enough
- Also need test sets for each language variety





document-level translation



- Machine translation translates one sentence at a time
- But: surrounding context may help



- Machine translation translates one sentence at a time
- But: surrounding context may help
 - translation of pronouns may require co-reference



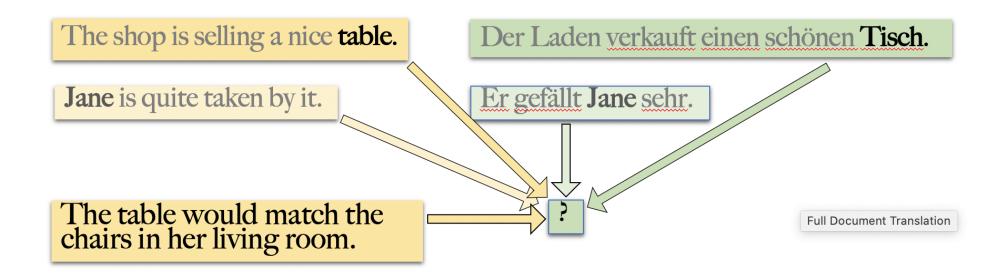
- Machine translation translates one sentence at a time
- But: surrounding context may help
 - translation of pronouns may require co-reference
 - ambiguous words may be informed by broader context



- Machine translation translates one sentence at a time
- But: surrounding context may help
 - translation of pronouns may require co-reference
 - ambiguous words may be informed by broader context
 - consistent translation of repeated words

Conditioning on Broader Context





- Hierarchical attention
 - compute which previous sentences matter most
 - compute which words in these sentences matter most

Conditioning on Broader Context



The shop is selling a nice table. <s> Jane is quite taken by it. <s> The table would match the chairs in her living room.

Der Laden verkauft einen schönen Tisch. <s> Er gefällt Jane sehr. <s> ...

- Concatenate all sentences together
 - document = very long sentence
 - special treatment for sentence boundaries
 - requires scaling of neural decoding implementation



questions?