#### **Current Challenges**

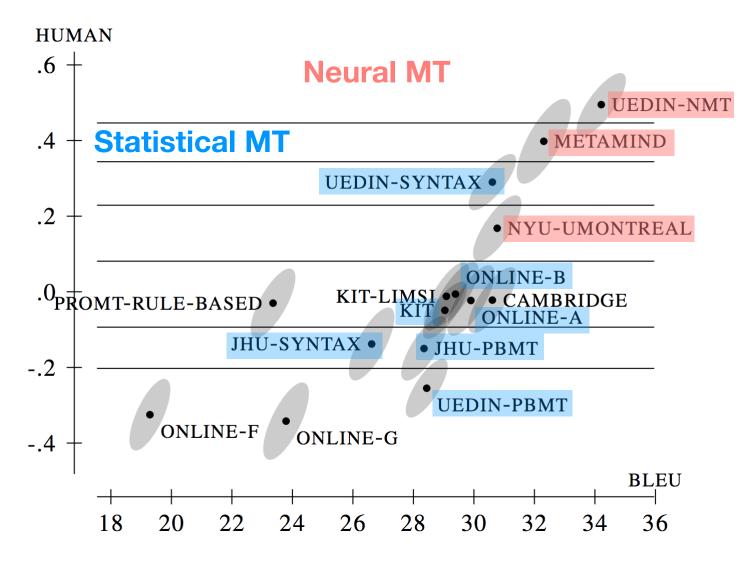
Philipp Koehn

6 November 2018



#### **WMT 2016**

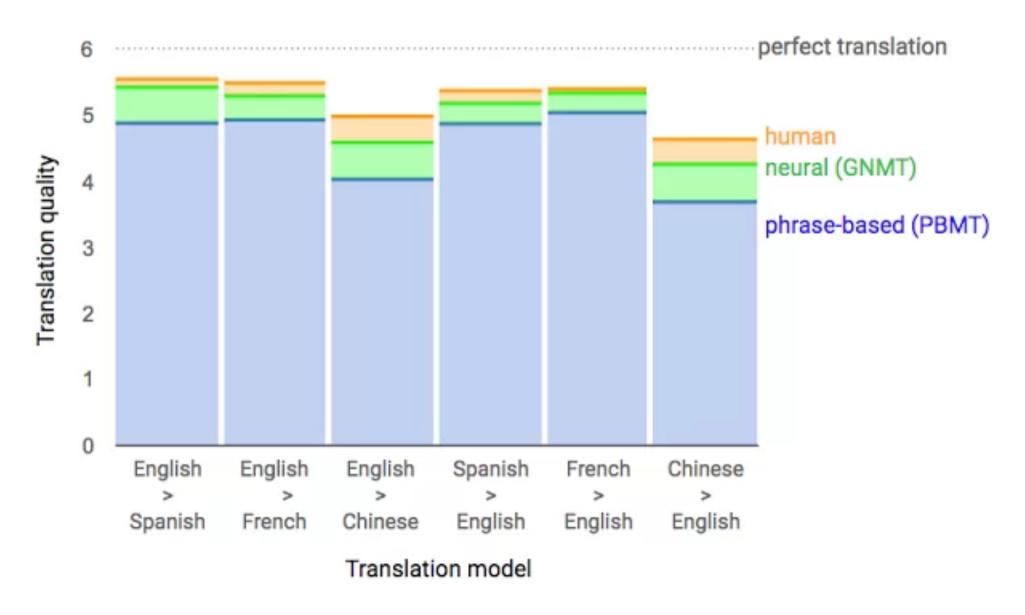




(in 2017 barely any statistical machine translation submissions)

#### 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.

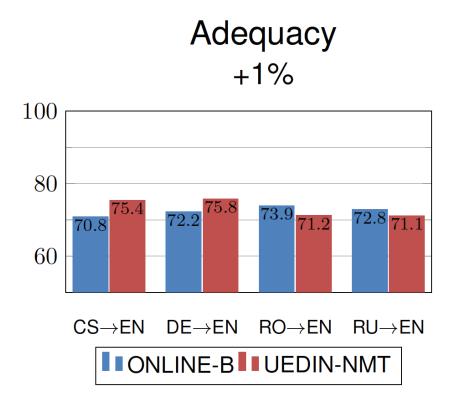
# SDL Cracks Russian to English Neural Machine Translation

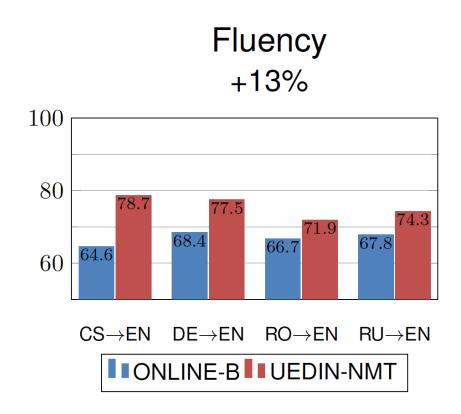
Global Enterprises to Capitalize on Near Perfect Russian to English Machine Translation as SDL Sets New Industry Standard

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

#### **Just Better Fluency?**







(from: Sennrich and Haddow, 2017)

### Challenges



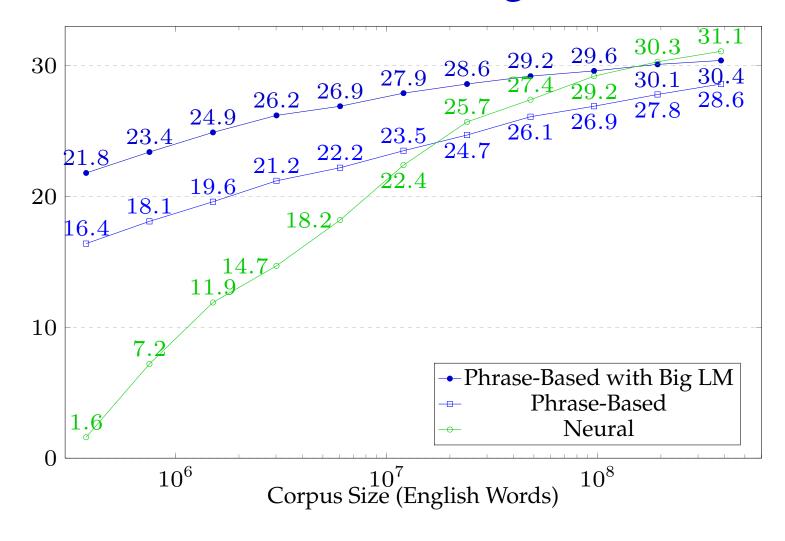
- Lack of training data
- Domain mismatch
- Rare words
- Sentence length
- Word alignment
- Beam search
- Noise



# 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	$0.4 \overline{1.8}$	$0.0\overline{2.1}$	$\overline{0.0}$ $\overline{2.3}$	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**



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



### rare words

#### **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

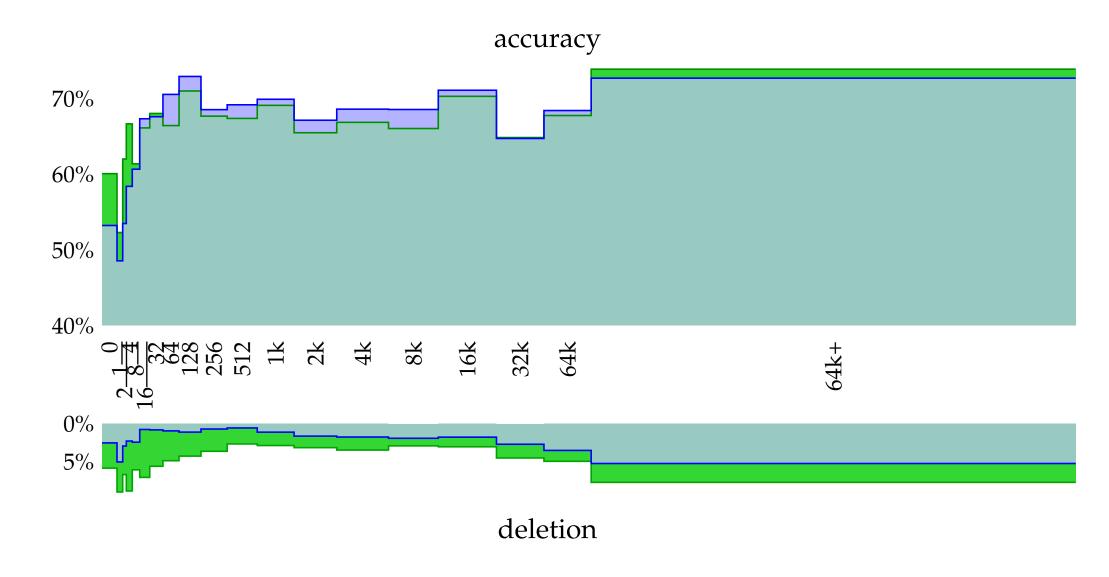
#### **Translation Accuracy for Input Words**



- 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
- 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







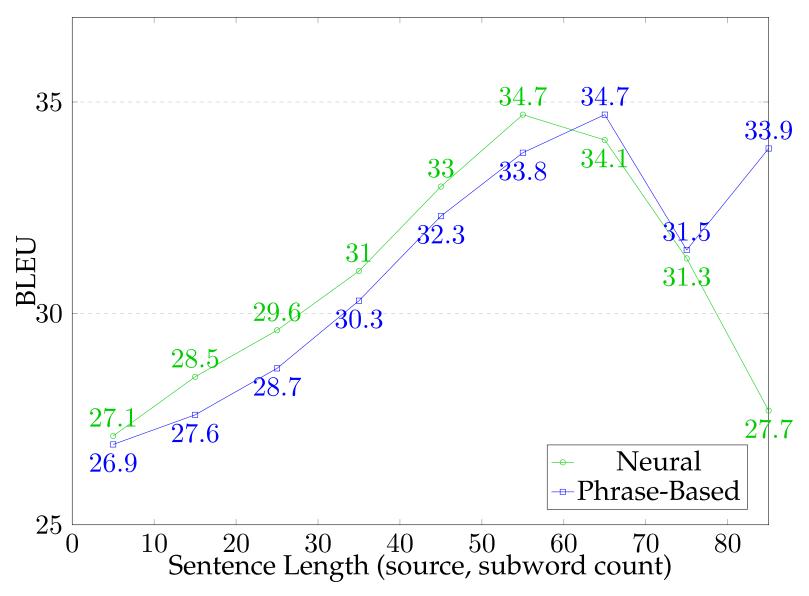
# sentence length

#### **Sentence Length**

- For longer sentences, harder to keep track of coverage
- Training sentence length limit: longer sentences not seen in training

#### **Sentence Length**



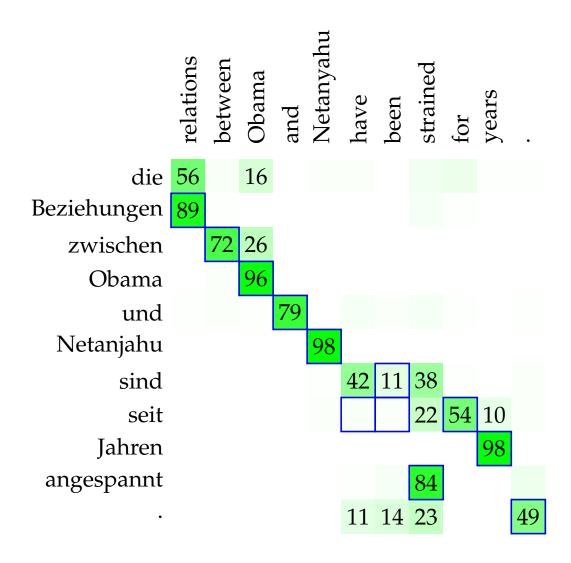




# word alignment

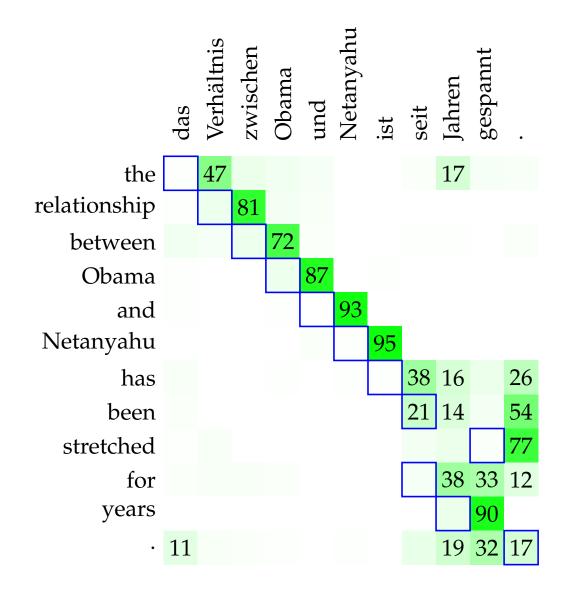
### **Word Alignment**





#### **Word Alignment?**



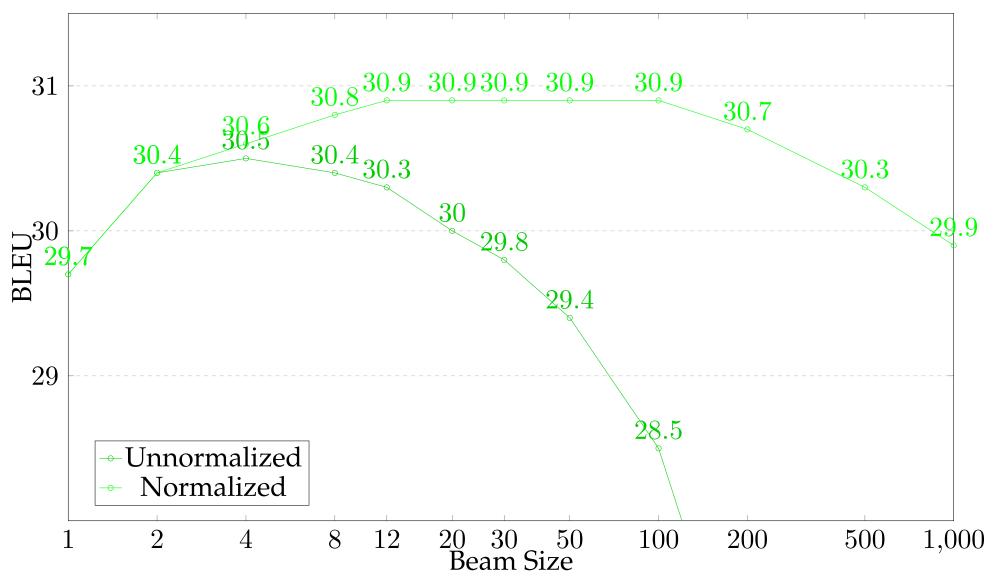




# beam search

#### **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
			-2.5		
				-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>	-0.4	<u>-0.1</u>	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%
Source	17.6 23.8 -0.2	11.2 23.9 -0.1	5.6 23.8 -0.2 -21.6	3.2 23.4 -0.6	3.2 21.1 -2.9
Target	<u>-0.0</u>	<u>-0.2</u>	<u>-0.5</u>	<u>-0.4</u>	<u>-0.3</u>

### 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	$\frac{27.1}{-0.1} \frac{24.1}{+0.1}$	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 <u>24.2</u> -0.6 +0.2

• No harm done



# questions?