

How Contextual is Neural Machine Translation?

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Machine Translation and the Limits of Generic Knowledge

Er hat einen Krebstest entwickelt

a caricature of rule-based MT:

Machine Translation and the Limits of Generic Knowledge

Er

hat

einen

Krebstest

entwickelt

⋮

⋮

⋮

⋮

⋮

he

?

?

?

?

a caricature of rule-based MT:

- let's translate a sentence word-by-word via a bilingual dictionary 😊

Machine Translation and the Limits of Generic Knowledge

Er	hat	einen	Krebstest	entwickelt
⋮	⋮	⋮	⋮	⋮
he	have	a	?	develop

a caricature of rule-based MT:

- let's translate a sentence word-by-word via a bilingual dictionary 😊
- hm, we need a morphology tool to deal with inflected forms... 😊

Machine Translation and the Limits of Generic Knowledge

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a caricature of rule-based MT:

- let's translate a sentence word-by-word via a bilingual dictionary 😊
- hm, we need a morphology tool to deal with inflected forms... 😊
- ...and with compounds and derivational morphology 😊

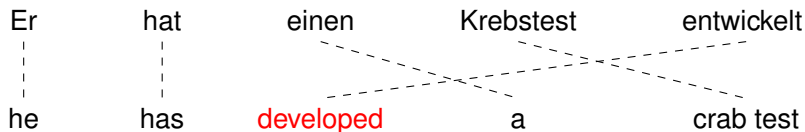
Machine Translation and the Limits of Generic Knowledge

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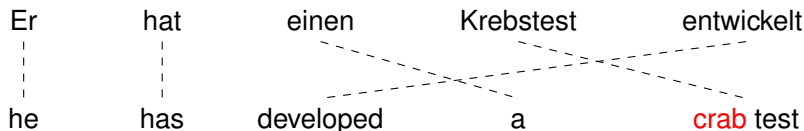
Machine Translation and the Limits of Generic Knowledge



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- oh, and we need to transfer and generate morphological features 😊
- actually, we need syntactic transfer for disambiguation and restructuring 😞

Machine Translation and the Limits of Generic Knowledge



a caricature of rule-based MT:

- let's translate a sentence word-by-word via a bilingual dictionary 😊
- hm, we need a morphology tool to deal with inflected forms... 😊
- ...and with compounds and derivational morphology 😊
- oh, and we need to transfer and generate morphological features 😊
- actually, we need syntactic transfer for disambiguation and restructuring 😊
- wait, how are we going to disambiguate “Krebs” with rules? 😞

Krebs m (genitive **Krebses**, plural **Krebse**)

1. crab
2. cancer (disease)
3. (astronomy, astrology) Cancer

How Contextual is Neural Machine Translation?

- a success story:
word sense disambiguation based on sentence context
- an open challenge:
co-reference across sentences

Word Sense Disambiguation

system	sentence
source reference	Dort wurde er von dem Schläger und einer weiteren männl. Person erneut angegriffen. There he was attacked again by his original attacker and another male.
our NMT	There he was attacked again by the racket and another male person.
Google	There he was again attacked by the bat and another male person.

Schläger

Word Sense Disambiguation

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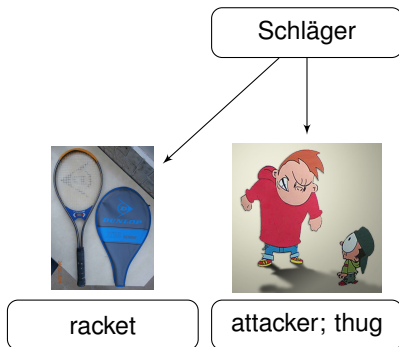
Schläger



attacker; thug

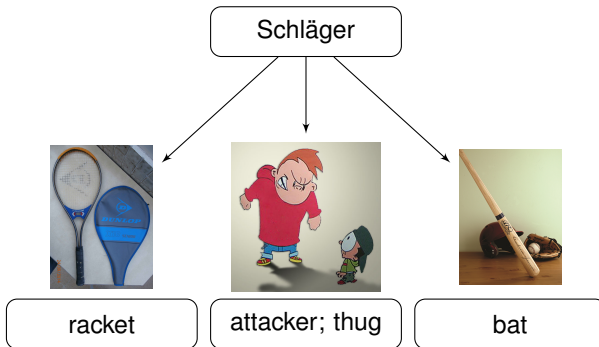
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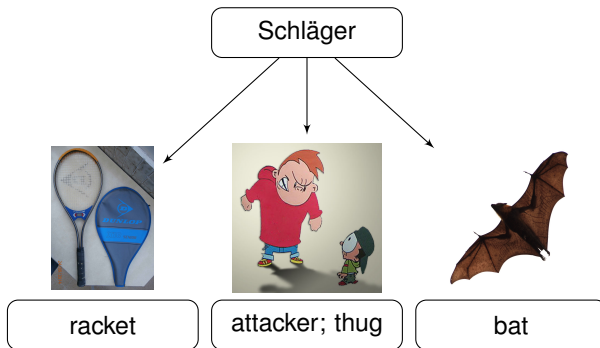
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source

*We thought a win like this might be **close**_{adj}.*

reference

*Wir dachten, dass ein solcher Sieg **nah** sein könnte.*

NMT (uedin WMT16)

Wir dachten, ein Sieg wie dieser könnte **schließen.*

Generic Knowledge and Word Sense Disambiguation

Etymology 1

From Old English *clȳsan* ("to close, shut")

Verb

close (*third-person singular simple present closes, present participle closing, simple past and past participle closed*)

1. (*physical*) To remove a gap. DE: *schließen*
2. (*social*) To finish, to terminate. DE: *beenden*

Noun

close (*plural closes*)

1. An end or conclusion. DE: *Ende*

Etymology 2

Borrowed from French *clos*, from Latin *clausum*, participle of *claudō*.

Adjective

close (*comparative closer, superlative closest*)

1. Narrow; confined. DE: *eng*
2. At a little distance; near. DE: *nah*

Noun

close (*plural closes*)

1. (*chiefly British*) A *street* that ends in a *dead end*. DE: *Sackgasse*
2. (*Scotland*) A very narrow *alley* between two buildings, often *overhung* by one of the buildings above the ground floor. DE: *Gasse*



syntactic information in embedding

$$E_1(\textit{close}) = \begin{bmatrix} 0.4 \\ 0.1 \\ 0.2 \end{bmatrix} \quad E_2(\textit{adj}) = [0.1]$$

$$E_1(\textit{close}) \parallel E_2(\textit{adj}) = \begin{bmatrix} 0.4 \\ 0.1 \\ 0.2 \\ 0.1 \end{bmatrix}$$

source

reference

NMT (uedin WMT16)

+POS, dependency,
lemma, morphology

*We thought a win like this might be **close**_{adj}.*

*Wir dachten, dass ein solcher Sieg **nah** sein könnte.*

*Wir dachten, ein Sieg wie dieser könnte **schließen**.*

*Wir dachten, ein Sieg wie dieser könnte **nah** sein.*



ContraWSD test set

- 35 ambiguous German nouns
- 2–4 senses per source noun
- ≈ 100 test instances per sense
→ ≈ 7000 test instances
- ways to evaluate:
 - is reference more probable than contrastive variant?
 - does translation contain correct sense, wrong sense, or both/neither?

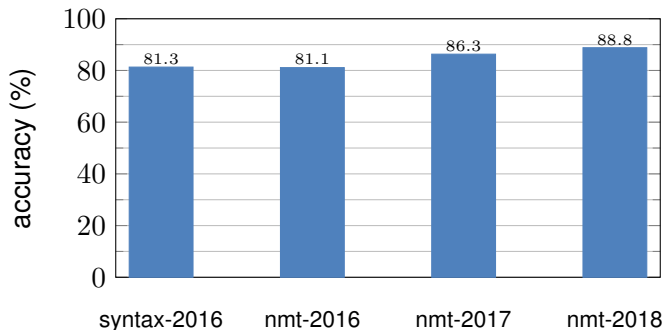
source: *Also nahm ich meinen amerikanischen Reisepass und stellte mich in die **Schlange** für Extranjeros.*

reference: *So I took my U.S. passport and got in the **line** for Extranjeros.*

contrastive: *So I took my U.S. passport and got in the **snake** for Extranjeros.*

contrastive: *So I took my U.S. passport and got in the **serpent** for Extranjeros.*

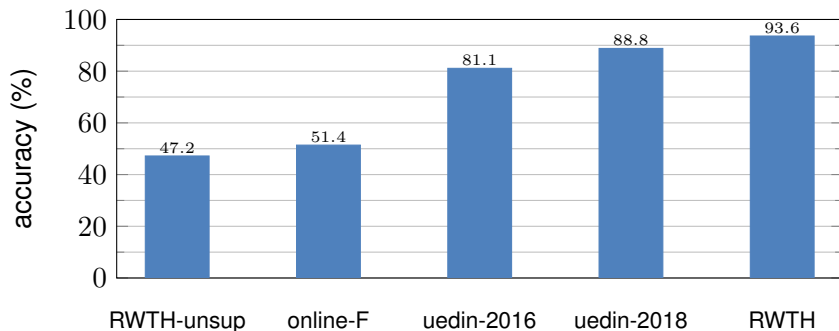
ContraWSD Results (uedin systems)



improvements to NMT systems

- 2016: shallow RNN
- 2017: deep RNN; layer norm; better ensembles; slightly more data
- 2018: Transformer; more (noisy) data

ContraWSD Results (selected systems)



- WSD is big challenge for unsupervised NMT and rule-based system
- all neural systems at WMT18 > 81%
- big reduction in WSD errors within 2 years

Google's Neural Machine Translation System: Bridging the Gap between Human and Machine Translation

Microsoft reaches a historic milestone, using AI to match human performance in translating news from Chinese to English

March 14, 2018 | [Allison Linn](#)

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

June 19, 2018, Maidenhead, UK

Coreference and Consistency

[Läubli, Sennrich, Volk, EMNLP 2018]



市民在日常出行中,发现爱车被陌生车辆阻碍了,在联系不上陌生车辆司机的情况下,可以使用“**微信挪车**”功能解决这一困扰。

8月11日起,西安交警微信服务号“西安交警”推出“**微信挪车**”服务。

这项服务推出后,日常生活中,市民如遇陌生车辆在驾驶人不在现场的情况下阻碍自己车辆行驶时,就可通过使用“**微信挪车**”功能解决此类问题。 [...]

Members of the public who find their cars obstructed by unfamiliar vehicles during their daily journeys can use the “**Twitter Move Car**” feature to address this distress when the driver of the unfamiliar vehicle cannot be reached.

On August 11, Xi'an traffic police WeChat service number “Xi'an traffic police” launched “**WeChat mobile**” service.

With the launch of the service, members of the public can tackle such problems in their daily lives by using the “**WeChat Move**” feature when an unfamiliar vehicle obstructs the movement of their vehicle while the driver is not at the scene. [...]

A citizen whose car is obstructed by vehicle and is unable to contact the owner of the obstructing vehicle can use the “**WeChat Move the Car**” function to address the issue.

The Xi'an Traffic Police WeChat official account “Xi'an Jiaojing” released the “**WeChat Move the Car**” service since August 11.

Once the service was released, a fellow citizen whose car was obstructed by another vehicle and where the driver of the vehicle was not present, the citizen could use the “**WeChat Move the Car**” function to address the issue. [...]

What We Need to Go Beyond Sentence Level

Models

make prediction conditional on context beyond the sentence

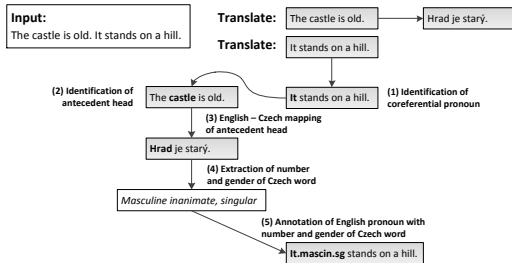
Metrics

measure improvements in consistency, and on less-frequent phenomena

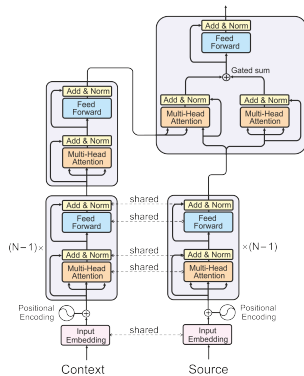
Data

provide full document pairs as training data / deal with lack thereof

Models for Context-Aware MT



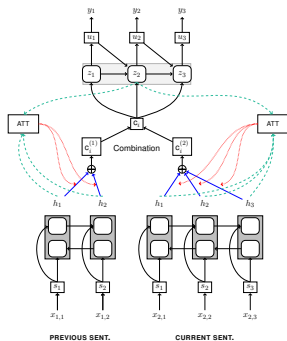
context-aware SMT architecture



context-aware NMT architecture

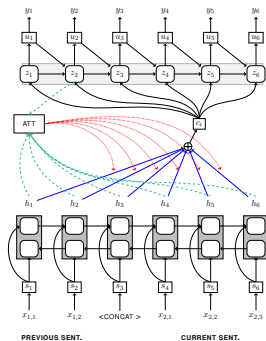
[Guillou, 2012, Volta et al., 2018]

multi-source architectures



[Jean et al., 2017, Wang et al., 2017]

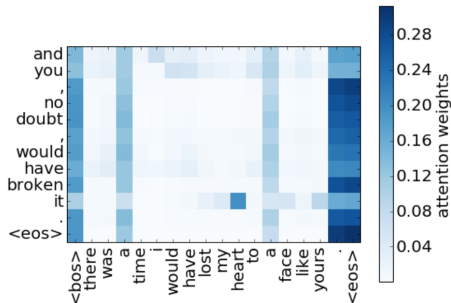
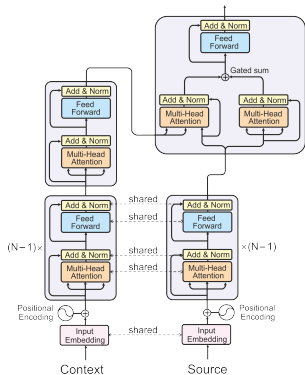
concatenation strategy



[Tiedemann and Scherrer, 2017]

Context-Aware Transformer Learns Anaphora Resolution

[Voita, Serdyukov, Sennrich, Titov, ACL 2018]



	agreement
coreNLP	77%
attention	72%
last noun	54%

Figure 1: Encoder of the discourse-aware model

Agreement with human assessment for coreference resolution of anaphoric *it*.

problems with standard metrics (BLEU etc.)

- local
- reference-based (not measuring consistency) [Guillou and Hardmeier, 2018]
- appropriate for long tail?

Repetition Rate as Cohesion Metric?

[Wong and Kit, 2012]: more cohesive translations have more repetitions

$$RC = \frac{\text{number of repeated words}}{\text{number of content words}}$$

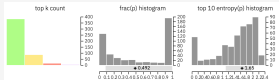
Repetition Rate as Cohesion Metric?

problem:

sentence-level MT is (accidentally) more repetitive than human translation!

an artifact of statistical language modeling?

GPT-2-produced text



In a shocking finding, scientist discovered a herd of unicorns living in a remote, previously unexamined valley, in the Andes Mountains. Even more surprising to the researchers was the fact that the unicorns spoke perfect English. The scientist named the population, after their distinctive horn, **Qvirk's Unicorn**. These four-horned, silver-white unicorns were previously unknown to science. Now, after almost two centuries, the mystery of what sparked this odd phenomenon is finally solved.

Dr. **Jorge Pádrez**, an evolutionary biologist from the University of La Paz, and several companions were exploring the Andes Mountains when they found a small valley, with no other animals or humans. Pádrez noticed that the valley had what appeared to be a natural fountain, surrounded by two peaks of rock and silver snow.

Pádrez and the others then ventured further into the valley. "By the time we reached the top of one peak, the water looked blue, with some crystals on top," said Pádrez. Pádrez and his friends were astonished to see the unicorn herd. These creatures could be seen from the air without having to move too much to see them. **AGI** they were so close they could touch their horns.

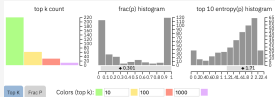
While examining these bizarre creatures the scientists discovered that the creatures also spoke some fairly regular English. Pádrez stated, "We can see, for example, that they have a common language, something like a dialect or idiosyncrasy."

Dr. Pádrez believes that the unicorns may have originated in Argentina, where the animals were believed to be descendants of a lost race of people who lived there before the arrival of humans in those parts of South America.

While their origins are still unclear, some believe that perhaps the creatures were created when a human and a unicorn met each other in a time before human civilization. According to Pádrez, "In South America, such incidents seem to be quite common."

However, Pádrez also pointed out that it is likely that the only way of knowing for sure if unicorns are indeed the descendants of a lost alien race is through DNA. "But they seem to be able to communicate in English quite well, which I believe is a sign of evolution, or at least a change in social organization," said the scientist.

human-produced text



With the ascendance of **Tori Morrison**, a literary star, it has become commonplace for critics to **de**-racialize her by saying that Morrison is not just a **50** Black woman writer, **AGI** that she has moved beyond the limiting confines of race and gender to target **AGI** universal **AGI** issues. Yet Morrison, a Nobel laureate with **six** highly acclaimed novels, bristles at having to choose between being a writer or a Black woman writer, and **willingly** accepts critical classification as the latter. To call her simply a writer **denies** the **highly** roles that Morrison's African-American roots and her Black female perspective have played in her work. For instance, many of Morrison's **AGI** characters **beat** their dreams as **AGI** are nuptissed by visitations from **dead** ancestors, **AGI** and generally experience **intimate** connections with **Beings** whose existence is **AGI** empirically verifiable. While critics might see Morrison's **AGI** use of the supernatural as purely a literary device, Morrison herself **explains**, **AGI** that **AGI** simply the way the world was for me and the Black people I knew. **AGI** Just so her work has given voice to this **highly**-marred boat of African-American culture, it has **affirmed** the unique **vergent** point of the Black woman, **AGI** really, feel the **range** of emotion and perception I have had access to as a Black person and a female person are greater than that of people who are neither. **AGI** says Morrison. **AGI** My words **did** not **shrink** because I was a Black female writer. It just got bigger. **AGI**

Hendrik Strobelt and Sebastian Gehrmann: <http://gltr.io/>

can we distinguish accidental repetition from document-level cohesion?

Contrastive Evaluation

[Bawden, Sennrich, Birch, Haddow, NAACL 2018]

[Müller, Rios, Voita, Sennrich, WMT 2018]

[Voita, Sennrich, Titov, ACL 2019]



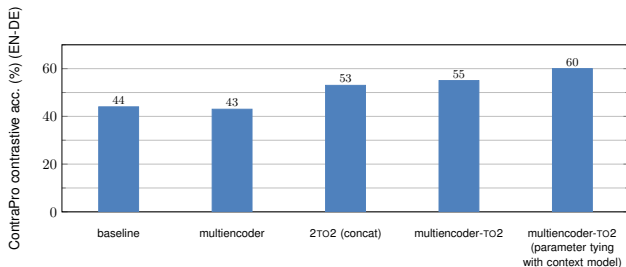
test sets targeting phenomena such as:

- anaphoric pronouns
- consistency in formality (T-V distinction)
- consistency in named entity translation
- translation of elliptical constructions

reference is paired with **contrastive variants** that introduce error

→ we count how often MT system prefers correct variant

Some Lessons From Contrastive Evaluation



[Müller et al., 2018]

- even simple concatenation models bring substantial improvements
- small design decisions matter:
learning context model from scratch suboptimal
- difficulty varies across linguistic phenomena

30 years of data collection in MT: **sentence pairs**

can we shift to document-level parallel corpora?

- requires extra work and reprocessing for some corpora
- impossible for others
(e.g. bitext mining from comparable corpora)

what can we do if **all** parallel data is sentence-level, and we only have monolingual data with wider context?

solution 1: noisy channel model [Yu et al., 2019]

$$T^* = \arg \max_T P(S|T)P(T)$$

- channel model ($P(S|T)$) operates on sentence-level.
- language model ($P(T)$) operates on document-level.

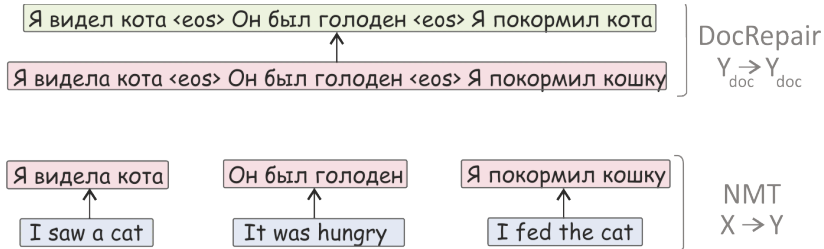
solution 2: automatic post-editing (monolingual repair)

Context-Aware Monolingual Repair

[Voita, Sennrich, Titov, EMNLP 2019]



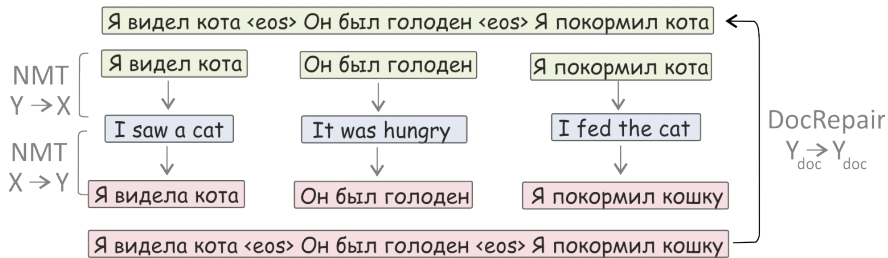
- 1 translate sentences independently
- 2 fix inconsistencies with multi-sentence monolingual repair model



Training Monolingual Repair Model

how to train monolingual repair model?

- simple sequence-to-sequence model with Transformer
- target side: original text in target language
- source side: original text, translated to source language and back with sentence-level system



Results on Consistency Test Sets [Voita et al., 2019b, Voita et al., 2019a]

system	BLEU	consistency test sets			
		deixis	lexical cohesion	ellipsis (infl.)	ellipsis (VP)
sentence-level	33.9	50.0	45.9	53.0	28.4
concatenation (4-to-4)	-	83.5	47.5	76.2	76.6
monolingual repair	34.6	91.8	80.6	86.4	75.2

- neural MT models strong at learning from context
- current challenge: going beyond the sentence level
 - better metrics for development and measuring progress
→ small design decisions have big impact on "context-awareness"!
 - document-level datasets...
...and models that work without document-level parallel data

Thank you for your attention

Resources

- ContraWSD test set for Word Sense Disambiguation:
<https://github.com/ZurichNLP/ContraWSD>
- English–French contrastive test set:
<https://diamt.limsi.fr/eval.html>
- large-scale contrastive test set of context-aware pronoun translation:
<https://github.com/ZurichNLP/ContraPro>
- code and data for English–Russian experiments:
<https://github.com/lena-voita/good-translation-wrong-in-context>

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- attacker: <https://commons.wikimedia.org/wiki/File:Wikibully.jpg>
- bat1: www.personalcreations.com / CC-BY-2.0
- bat2: Hasitha Tudugalle <https://commons.wikimedia.org/wiki/File:Flying-Fox-Bat.jpg> / CC-BY-4.0