

Proposals for master theses

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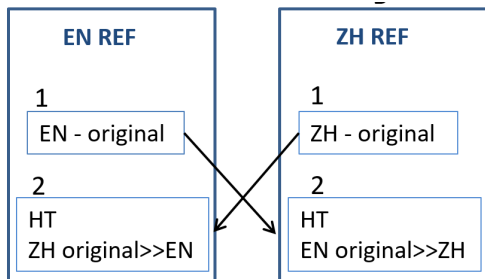
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Proposals

1. Translationese in MT Testsets
2. Posteditese
3. MT of Noisy Input

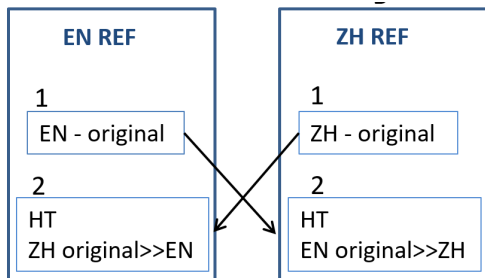
Problem

Test sets at WMT are symmetrical



Problem

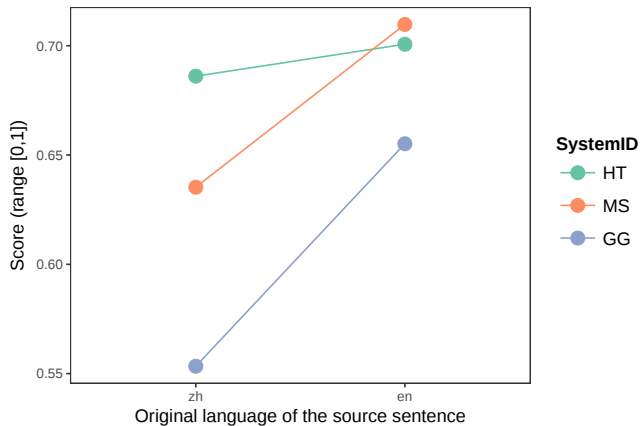
Test sets at WMT are symmetrical



Why a problem: the translationese part may be artificially easier for MT due to 3 principles of translationese: simplification, explicitation and normalisation.

Problem

EN-ZH WMT2017 testset



RQs

- ▶ RQ1. Is this issue present in other datasets or is it just an artifact of the EN-ZH 2017?
- ▶ RQ2. Would removing translationese change the system rankings?

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Czech→English			
	Ave. %	Ave. z	System
1	71.8	0.298	CUNI-TRANSFORMER
2	67.9	0.165	UEDIN
3	66.6	0.115	ONLINE-B
4	62.1	-0.023	ONLINE-A
5	57.5	-0.183	ONLINE-G

English→Czech			
	Ave. %	Ave. z	System
1	67.2	0.594	CUNI-TRANSFORMER
2	60.6	0.384	UEDIN
3	52.1	0.101	ONLINE-B
4	46.0	-0.115	ONLINE-A
5	42.0	-0.246	ONLINE-G

- ▶ RQ1. Is this issue present in other datasets or is it just an artifact of the EN–ZH 2017?
- ▶ RQ2. Would removing translationese change the system rankings?
- ▶ RQ3. Are some language pairs (e.g. more related) or some systems (e.g. SMT) more affected than others?
- ▶ RQ4. What are the characteristics of translationese? Syntax, vocabulary variety, etc.

What is there

- ▶ Testsets for WMT 2006 to 2018, at least 3 language pairs per year
- ▶ MT outputs for the testsets
- ▶ Scripts for analysing translationese in EN-ZH 2017 [Toral et al., 2018]

Plan

Translationese in MT Testsets

Posteditese

MT of Noisy Input

Problem

3 types of translations:

1. Human (from scratch)
2. Machine (automatic)
3. Machine-assisted (post-edited)

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Can they be distinguished from each other? Or: can we build an effective binary classifier?

- ▶ Yes, between 1 and 2
- ▶ Not yet, between 1 and 3

Problem: from scratch vs posteditese

In theory, posteditese should be distinguishable from translations from scratch

In practice: [Daems et al., 2017] achieved 50% accuracy

- ▶ Very small dataset: 8 articles, 160 words each (EN–NL)

Other available datasets:

- ▶ TED talks EN–FR and EN–DE. 600 sentences each
- ▶ Novel EN–CA. 330 sentences
- ▶ Industry data?

Plan

Translationese in MT Testsets

Posteditese

MT of Noisy Input

Problem

Jointly with Rob and Gertjan

[Michel and Neubig, 2018] introduces a corpus of noisy input and translations thereof. EN–{FR, JA}.

- ▶ Train: 6K to 36K sentences
- ▶ Test: 1K

Their approach

- ▶ Train on clean data
- ▶ Fine-tune on noisy input

Issue: vocabulary mismatch

Idea

Use MoNoise [van der Goot and van Noord, 2017]

- ▶ Clean the noisy data with MoNoise
- ▶ Train MT using clean and cleaned data

More advanced possibilities

- ▶ Give the n-best output of MoNoise to NMT [van der Goot and van Noord, 2018]
- ▶ Learn jointly MoNoise and NMT

References I



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Thank you!

Questions?