Effect of Translationese on Machine Translation Performance

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Background

- Translated texts tend to be structurally different from original texts: caused partly by a systematic influence of the source language on the target language.
- Translationese features retain some characteristics like, part-of-speech, n-grams, common words or positional token frequency that pertain to the source language.
- Translation direction is an important factor, yet it is largely ignored for Machine Translation (MT) evaluations.

Related Work

- [1] showed that language models (LM) compiled from source-to-target translated texts (TL) outperform the ones compiled from original target language text (OL) in statistical machine translation (SMT).
- [2] investigated the effect of translationese on SMT tuning.
- Concurrent to our work is [3] that shows that the use of translationese as input of test sets results in higher direct assessment (DA) scores for MT systems.
- More recently, [4] demonstrated the adverse effects of translationese on MT evaluation results.

Research Questions

- What is the impact of translationese across MT architectures and languages?
- How can *translationese* features be used to improve auxiliary tasks such as MT and *vice versa*?

Data Statistics$^{\alpha}$

- Europarl bilingual corpora from L2s, i.e, *German, French, Italian, Romanian* into English.
  - FR, DE: 135k sentences parallel segments, 200k TL, 370k OL, 115k monolingual.
  - IT: 100k parallel segments, 84k TL, 370k OL, 40k monolingual.
  - RO: 95k parallel segments, 12k TL, 80k OL, 6k monolingual.

Approach

- Supervised phrase-based statistical MT (PBSMT)

  Modules: Translation model p(s|t), language model p(t)

  Training of translation model on parallel segments of data without any direction specificity.

  Training of one language model on TL, one language model on OL.
- Supervised seq2seq neural MT (NMT)

  Single-layer biLSTM encoder-decoder with attention mechanism.

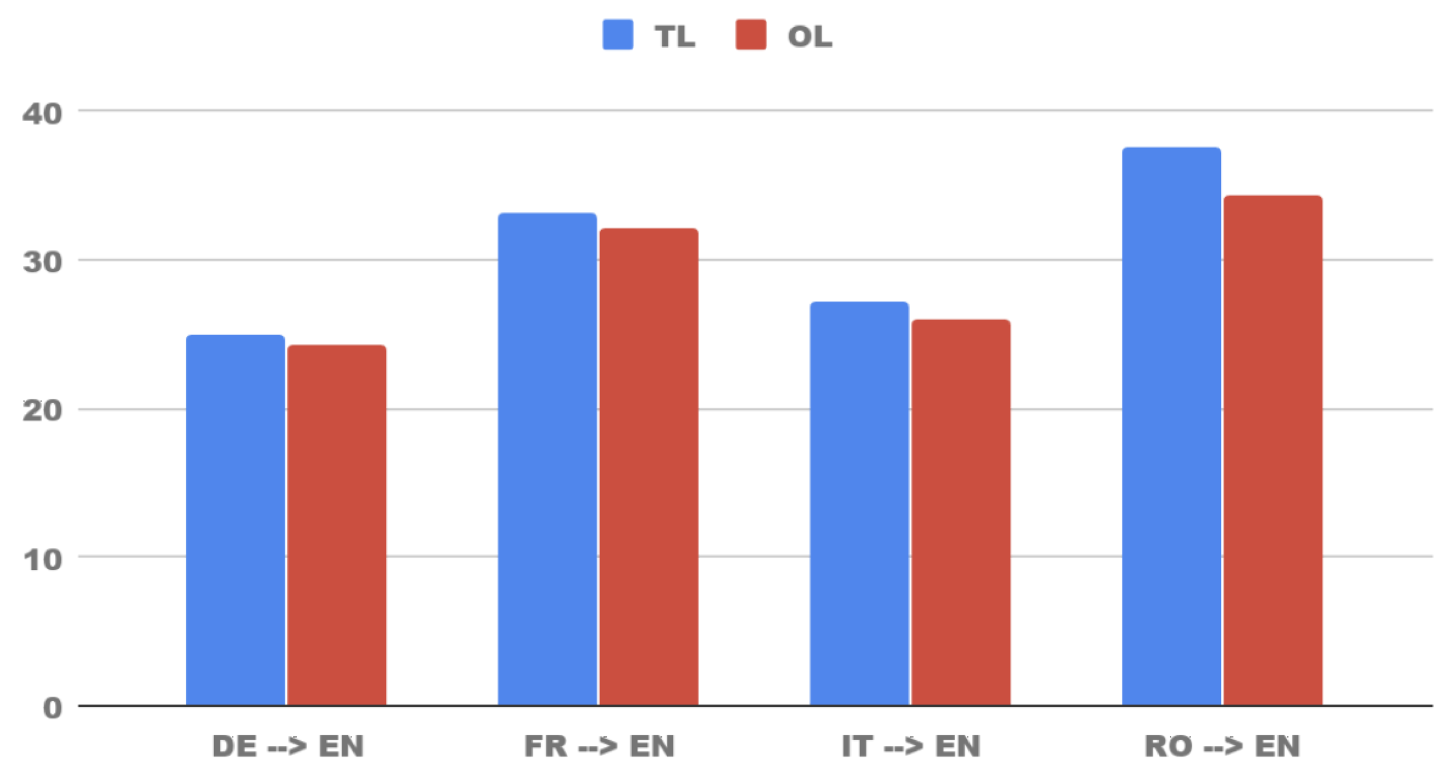
  TL model trained on a parallel corpus of original-L2 sentences and their English translations.

  OL model trained on a parallel corpus of original-English sentences and their L2 translations.
- We use BLEU scores for evaluation of final models which is performed on the test set.

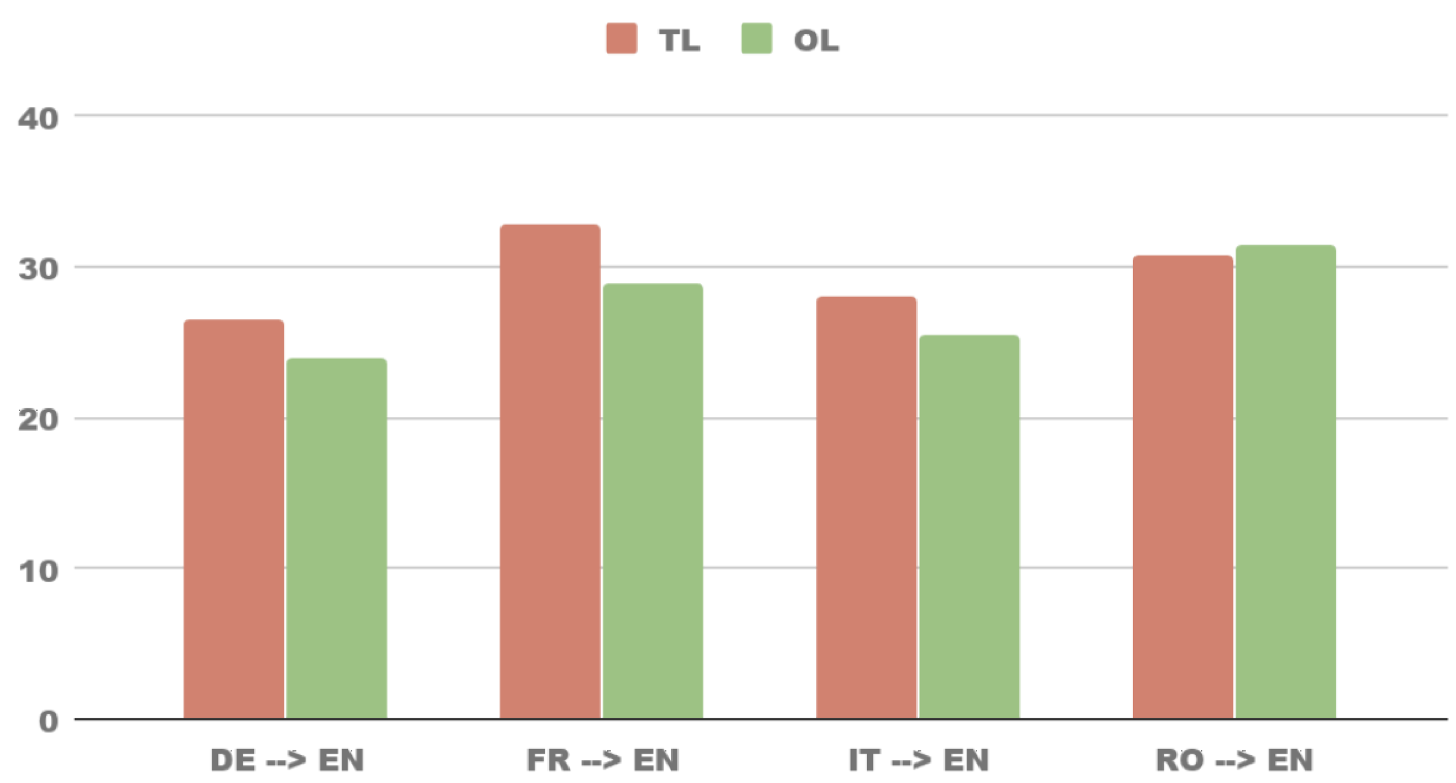
$^{\alpha}$ rounded-off sentence count.

$^{\beta}$ Similar trends in the result were observed when experimented with same amount of TL and OL data.

BLEU scores for PBSMT system



BLEU scores for NMT system



Conclusion

- Regardless of language and framework, translationese-based models outperform original-language models (with the exception of Romanian-English NMT, possibly due to corpus size effects on the neural model)
- Results$^{\beta}$ are consistent despite a significant corpus size difference between the translated and original English corpora.
- Translation directionality significantly influences translation performance.

  However, results can't be compared to existing work due to limited amount of corpora with labeled translation direction.

Future Work

- Use unsupervised PBSMT+NMT[5] to make use of monolingual corpora for low-resource scenarios.

  Based on - language modeling that act as a denoiser in the neural case, initialization from dictionaries inferred from monolingual corpora and iterative backtranslation between monolingual corpora.
- Augment corpora for low-resource language translation with translationese in closely related languages.
- Use more complex NMT architectures like Transformer[6].

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