AUTOMATIC DETECTION OF DIFFERENT TYPES OF TRANSLATION

BASED ON TRANSLATIONESE FEATURES

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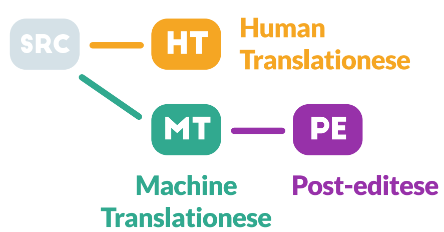
INTRODUCTION

Machine translation (MT) with human post-edits (PE) has become common for publication due to its high productivity. On the other hand, studies have shown readers still prefer human translation (HT) even though the translations are produced by state-of-the-art machines. (Toral et al., 2018) What traits set human translation and the machine-based translation apart must be clarified and resolved if MT development strives for achieving human performance. This comparative study of different types of translation in terms of translationese offers another qualitative view of MT performance and evaluation. To empirically examine the phenomena, we employ machine learning classifiers to determine which characteristics of translationese are the most significant indicators for human-translated texts and machine-based translation.

Human vs. Machine Translationese



Translationese & Post-editese

Translated texts have proved to be syntactically and lexically different from original non-translated texts. This phenomenon is termed as translationese. Translationese does not necessarily mean inferior translation quality; instead, it is empirical linguistic phenomena exhibited only in the translated texts. Such distinct features are universal: the translated texts have shown these specific feature distribution regardless of the source languages. These translation universals are further grouped into four categories: simplification, normalization, explicitation (Baker et al., 1993) and interference. (Toury, 1995)
Post-editese, a variant of translationese, represents the distinct characteristics that PE texts exhibit when compared with HT. (Daems et al., 2017) Although human accessors do not seem to distinguish between PE and HT; PE texts show empirical evidence of 'exacerbated translationese' in terms of simplification, normalization, and interference. (Toral, 2019)

RESEARCH QUESTIONS

RQ1. Can human translation be distinguished from machine-based translation according to translationese features?

RQ2. If the answer to RQ 1 is yes, then which characteristics of translationese are valuable to distinguish human and machine-based translation?

RQ3. If the answer to RQ1 is yes, then MT and PE are both distinguishable from human translation. However, between these two machine-based translations, what are the most useful characteristics to distinguish the two?

DATA

WMT: News Task (HT ⇌ MT)

We plan to conduct experiments on seven languages translated into English: German, Finnish, Gujarati, Kazakh, Lithuanian, Russian, Chinese. Three languages translated from English: German, Russian and Gujarati.

MS human parity (HT ⇌ PE)

It contains one language pair, Chinese-English. There are 2,001 pairs of (HT, PE), however, we will only use 1,000 pairs, which are translated from the texts originally written in Chinese to avoid translationese.

WMT: APE (MT ⇌ PE)

We use the publicly available data from one of the WMT shared tasks: Automatic Post-Editing (APE). The datasets contain two language directions, English-German and English-Russian. The training and development sets are made of triplets of (source, MT outputs, human post-edit)

SYSTEMS

SVM We use Support-vector machines (SVMs) algorithm with balanced class weights and linear kernel.

BERT We would also like to employ deep learning model, BERT, a language model uses an attention mechanism and learns contextual relations between words in a text.

PROPOSED FEATURES

Inspired by Volansky et al. (2013), features are grouped into four categories:

Simplification

Translation uses simpler lexical and syntactic structures

$$\text{Lexical Density} = \frac{\text{number of content words}}{\text{number of total words}}$$

$$\text{Lexical Richness (TTR)} = \frac{\text{number of types}}{\text{number of tokens}}$$

Perplexity = inverse of the likelihood of the given sequence

$$\text{Mean Dependency Distance (MDD)} = \frac{1}{n-1}\sum_{i=1}^{n}|DDi|$$

Remaining features: average word length, average word rank, parse tree depth, mean/max out-degree

Explicitation

The implicity in the source texts is addressed explicitly in the translation

$$\text{Explicit Naming} = \frac{\text{number of personal pronouns}}{\text{number of proper nouns}}$$

$$\text{Ave. Function Words} = \frac{\text{number of function words}}{\text{number of total words}}$$

Normalization

It refers to grammatically standardized translation

$$\text{Repetition Ratio} = \frac{\text{content words occurring} > 1}{\text{number of total words}}$$

Interference

It points out the fingerprints of source language usage in the translation.

Perplexity diff = PP (T, LMsource) - PP(T,LMtarget)

Remaining features: Character n-grams, POS n-grams

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