Detecting over/under-translation errors for determining adequacy in human translations

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Abstract

We present a novel approach to detecting over and under translations (OT/UT) as part of adequacy error checks in translation evaluation. We do not restrict ourselves to machine translation (MT) outputs and specifically target applications with human generated translation pipeline. The goal of our system is to identify OT/UT errors from human translated video subtitles with high error recall. We achieve this without reference translations by learning a model on synthesized training data. We compare various classification networks that we trained on embeddings from pre-trained language model with our best hybrid network of GRU + CNN achieving 89.3% accuracy on high-quality human-annotated evaluation data in 8 languages.

1 Introduction

Quality evaluation (QE) in machine translation (MT) focuses on evaluating translation quality without reference text (Blatz et al., 2004; Specia et al., 2009). Translation quality captures both the fluency of the translation and its adequacy relative to the source. Given a source sentence \( s \) and corresponding MT output \( t \), QE system is a mapping \( f : (s, t) \rightarrow r \) quantifying translation quality. Human-mediated Translation Edit Rate (HTER) (Snover et al., 2006) is often used for \( r \) to quantify the human post-edit burden to arrive at good translations.¹ Recent advancements in QE modelling have attempted with limited corpora that surfaced numerous undesirable artefacts. For example, (Kepler et al., 2019) and (Gupta and Nelakanti, 2020) model QE as a classification problem that grades the semantic match between original source and the machine translated target. They provide a binary verdict of the translation as good/bad with very low miss-rate leaving the final judgements to translators. It is unclear if a monolith binary classifier can learn to detect multiple errors of very different nature with varying syntactic and semantic language patterns. Due to issues like sampling bias and lexical homogeneity in data, pre-trained models could game the tasks without actually learning to evaluate quality (Sun et al., 2020). Further, considering usability, a good/bad label is less helpful to post-editors than fine-grained errors that mark a pair as, say, over-translation likely due to these tokens in target.

While human translations (HT) are synonymous to gold standard for purposes of MT system evaluations, numerous operational pipelines that employ humans for translating often return output with much lower than acceptable quality. Relaxing the scope of QE to include HT can help assisting humans translators like various applications do for spell checkers and English grammar. Digital entertainment industry, for example, makes extensive use of professional human translators for translating video subtitles to increase content viewership. Translated subtitles often require human quality checks that are as expensive as acquiring translations (Poirier, 2014). To reduce post-editing quality checks costs, we could flag errors as the translations are typed in with the QE serving as a guardrail.

However, is such broadening of scope for QE to identify error patterns in any generic translation possible? In this work, we work towards this direction addressing specifically over-/under-translations (OT/UT) that constitute one subset of adequacy errors. We propose to learn classification models that directly evaluate fluency and adequacy without resorting to HTER estimates as an intermediate step. In addition to evaluating quality, this approach offers editing cues to human post-editors by flagging specific errors. Each translation pair \((s, t)\) is labelled as either OT or UT or otherwise.

¹Note that one needs reference translation to compute HTER while most QE systems attempt to estimate them in the absence of references.

Both had equal contribution
as good class with no error (NE). OT (or UT) captures the asymmetry with source containing less (or more) information than the target \(t\). We use pre-trained language models (LM) to synthesize training data and train a binary classifier using synthetic data. We experimented with various choices for classifier heads that are compared in the results section. Evaluation uses human annotators to validate model predictions across different languages.

This problem becomes much more difficult for video subtitles because it is possible for a translation to be linguistically incomplete and be acceptable during post-edits. This is due to the fact subtitles are required to follow a set of technical constraints limiting the choice and number of words in translation. For example, an English subtitle: "There is a green tree in the park" can be translated to "Green tree in park" and still be considered acceptable because it is successfully conveying the context to the viewer.

Considering this idiosyncratic behaviour of video subtitles, we present novel approaches to generate synthetic training data that capture errors frequently encountered in human translations. Our focus is on improving operational efficiency of pipelines involving human translators and we specifically focus on subtitling on which we evaluate our methods. We show the effectiveness of our model in detecting OT and UT in human translations without any access to reference translations. The goal is to operate at high error recall to ensure poor subtitles are not pushed into the final data to be viewed by numerous customers. Finally, we compare the performances from four of our networks with the hybrid GRU and CNN model performing best on our high-quality evaluation data acquired from multiple human translators.

2 Related Work

There is considerable work on QE for MT \(^2\). Fitting discriminative models to hand-crafted linguistic features trained to estimate HTER was common until pre-trained neural models with regression heads came along with better metrics. MT output with reference translations are necessary to train these models which will then estimate the likely HTER for any given \((s, t)\) translation pair. Correspondingly, error patterns are restricted to those from MT systems used for generating the data.

In expanding error patterns beyond MT, we will need alternate approaches for generating training data that capture various plausible adequacy errors. Also, gathering reference texts is a blocker in scaling the approach across both, error patterns and languages. Synthesizing errors to generate negatives for the model to learn from is a suitable alternative where feasible. \((\text{Popović and Ney}, 2011)\), for example, use linguistic features to synthesize errors for MT output analysis. This approach is common in learning grammatical error checkers that uses syntactic structure to generate errors for model training \((\text{see (Omelianchuk et al., 2020; Kaneko et al., 2020; Lichtarge et al., 2020)})\).

We follow a similar approach to synthesize errors to train our models. The closest to our work is that of \text{Tu et al. (2016)} that describes a coverage mechanism for detecting OT and UT errors in neural MT outputs. It has two drawbacks; they require reference text to generate the coverage matrix and their definition of OT/UT errors is also limited to source-side errors ignoring target-side additions and omissions. \(\text{(Yang et al., 2018)}\) attempts to improve the BLEU scoring metric \((\text{Papineni et al., 2002})\) by handling OT/UT errors but again they rely on reference translations for their evaluations.

We give details of the methods we employ to generate subtle and gross errors for OT and UT across languages using a pre-trained LM followed by a discussion of our evaluation data, model architectures, experiments and their results.

3 Data generation

We began with a set of fairly clean subtitle files appearing on movies and TV shows from a subscription video-on-demand provider. We restricted the source language to English and target to be in one of 28 languages listed below. All sentences in our set were between 5 and 60 tokens long and the sentence-pair cosine similarity score was \(> 0.8\) when computed using LASER embeddings \((\text{Artetxe and Schwenk}, 2019)\). This ensured that the seed set of 20MM subtitle translations we began with were a fairy-clean sample with good translation pairs.

Synthesizing OT/UT errors requires adding and omitting words to create information asymmetry between \(s\) and \(t\). We modify only English language source sentence \(s\) for both OT/UT errors by omitting/adding words and rely on pre-trained
Table 1: English-French subtle negatives for UT

| Original Source Subtitle | New Source Subtitle | Target Subtitle |
|-------------------------|---------------------|-----------------|
| it is my duty to remind you of what you’ve got there. | it still is my duty to remind you fully of what you’ve already got done there recently. | il est de mon devoir de te rappeler ce que tu as. |
| put that book away for a while to make money. | put that book away for a good while to make money. | mettre ton livre de côté pour gagner un peu d’argent, |
| I didn’t know if you’d have your luggage with you. I have no luggage. | I didn’t know if even you’d always have your luggage with you. I have no luggage. | J’ignorais si vous aviez des bagages. Je n’ai pas de bagage. |

Table 2: English-French subtle negatives for OT

| Original Source Subtitle | New Source Subtitle | Target Subtitle |
|-------------------------|---------------------|-----------------|
| Please take care of Espada until this war is over. | Please care of until this war is over. | Prenez soin d’Espada en attendant que la guerre soit finie. |
| We were gonna stop at the Elephant Cafe. | We were at the Elephant. | Je veux dire, on allait s’arrêter à l’Elephant Cafe. |

multi-lingual models to handle cross-lingual patterns (Wu and Dredze, 2019). This is so that we could leverage various openly available English language tools for sentence edits.

**UT subtle negatives.** For UT subtle negatives, we inserted tokens in source sentence $s$ chosen by probing a pre-trained English BERT LM (Devlin et al., 2019) with mask at a randomly chosen index. We filter out token suggestions with subwords, punctuation, stop words, special symbols, previous/next word repetitions and numerals. We insert up to five tokens incrementally rather than filling multiple tokens at once as that could yield meaningless candidates. To filter out edits with minimal changes we compute a similarity score of source $s$ and candidate $s'$ using cosine of averaged Glove word embeddings (Pennington et al., 2014). Top $40^{th}$ percentile constituting the most similar candidates sorted by this similarity score are filtered out and negatives are sampled at random from the remaining candidates. Table 1 shows some examples of UT subtle negatives for en-fr.

**OT subtle negatives.** We did not get meaningful insertion candidates using multilingual BERT LM for insertion into target to generate OT errors. Hence, we randomly omitted up to five tokens incrementally from the source. $40\%$ of the candidates are filtered out similar to the UT above using similarity scores derived from Glove embeddings and actual OT subtle negatives are sampled at random from the rest. Table 2 shows some examples of $(s, s', t)$ for en-fr.

**Gross negatives.** Subtle negatives are errors with a few independent tokens added or omitted. However, some errors are off by complete phrases or sentences. These errors are synthesized by removing or adding complete sentences to the source. Some gross examples are given in Table 3 for en-fr.

We generated a total of over 6.1 million subtitle pairs covering 28 target languages, namely, Arabic, Bengali, Chinese (Simplified), Chinese (Traditional), Czech, Danish, Dutch, Finnish, French, German, Greek, Hebrew, Hindi, Indonesian, Italian, Korean, Marathi, Norwegian, Polish, Portuguese, Romanian, Russian, Spanish, Swedish, Tamil, Telugu, Thai, Turkish. Subtle errors constitute 83% of all errors and 17% are gross errors. 30% of all samples are OT errors, another 30% are UT errors and remaining 40% have no errors. Dataset was split 80-20 into train-validation sets.

**Evaluation data.** We created a high-quality human annotated dataset for evaluation. A random sample of 5,000 subtitle pairs each for English as source language and 8 target languages (Chinese (Traditional), French, Hindi, Italian, Portuguese, Russian, Spanish, Turkish). We carefully chose our target language set to include as many different scripts as possible. We asked three professional subtitle translators to mark if each pair had OT error or UT error along with the error-cause. They were asked to not mark anything if there was any confusion. We collated the results and selected sentences where there was an unanimous agreement of either it having error or not having error.
Out of 40,000 pairs, there was an unanimous agreement on 30,942 pairs; with 30,003 marked NE, 307 marked OT and 632 marked UT. Table 5 shows language-wise distribution of this dataset.

4 Model Training and Results

We trained models that classify each sample to one of the three classes; NE (No-Error), OT (Over-Translation) and UT (Under-Translation). A single model is trained for all language pairs with Adam optimizer (Kingma and Ba, 2015) and a multilingual cased BERT model (Devlin et al., 2019) to generate token embeddings. We experimented with four model architectures (1) Weighted GRU which was a GRU network with re-scaled weights. (2) (M1) GRU + CNN which had three CNN layers on one GRU encoder. (3) (M2) CNN with four CNN layers. (4) Hybrid M1 + M2 was a combined architecture of M1 and M2. We gave the input BERT embeddings to a GRU + CNN network and a vanilla CNN network; concatenated the embeddings of both parallel networks into common linear layer, followed by a softmax. Table 4 tabulates their performances. M1 was performing better in classifying UT class while M2 was better classifying NE class; therefore we combined both the architectures to train the best performing model.

Table 5 shows language-wise results on evaluation data. The error recall captures the percentage of OT/UT errors that are flagged by the system for further manual processing. Depending on the language, the model can capture only about 15-35% of the errors by learning solely from synthesized errors. This stresses on the need to improve methods for synthesizing errors closer to the actual distribution. However, this is very tricky since there is subjectivity involved in judging adequacy due to the complexities of paraphrasing as shown by the large disagreement (on about 25% of the samples) among the three voters in human annotation.

5 Conclusion

We presented a novel approach of detecting over-translation (OT) and under-translation (UT) in human translated subtitle data using BERT. We pursue this as an alternative direction to HTER predicting QE methods popular for MT output analysis. As an advantage this extends to any translations, not necessarily MT, while explicitly modelling fluency and adequacy that helps translators. Even though our training dataset mostly comprised of synthetically introduced errors, it performs well on high-quality human annotated data. We wish to improve upon this in two directions; (1) by improving error patterns through tighter coupling with human translators following methods similar to (Kaushik et al., 2020) and (Gardner et al., 2020) and (2) by focusing on localizing errors down to tokens within the sentences rather than merely flagging the whole sentence. For OT, we could identify the sequence.
of tokens in target subtitle that cause the issue and similarly in source subtitle for UT.

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