Learning to Detect Unacceptable Machine Translations for Downstream Tasks

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Abstract

The field of machine translation has progressed tremendously in recent years. Even though the translation quality has improved significantly, current systems are still unable to produce uniformly acceptable machine translations for the variety of possible use cases. In this work, we put machine translation in a cross-lingual pipeline and introduce downstream tasks to define task-specific acceptability of machine translations. This allows us to leverage parallel data to automatically generate acceptability annotations on a large scale, which in turn help to learn acceptability detectors for the downstream tasks. We conduct experiments to demonstrate the effectiveness of our framework for a range of downstream tasks and translation models.

1 Introduction

The past few years have witnessed strong performance gains for machine translation (MT), especially since the rise of neural machine translation (Sutskever et al., 2014; Bahdanau et al., 2015). Some recent research reports that the neural machine translation results are comparable to those by human translators in certain domains (Wu et al., 2016; Hassan et al., 2018).

However, such success comes with several conditions, most notably a large parallel corpus for training and a close domain for testing. Even with plentiful resources, state-of-the-art systems like Google Translate may still produce erroneous translations that baffle users (Zheng et al., 2018). In a word, a general-purpose machine translation system that consistently produces human-level translations in open domains is still yet to come. Therefore, in many real-world applications, it would be desirable to predict whether the MT output fits the purpose.

As an attempt to address the above issue, researchers propose the machine translation quality estimation (QE) task (Specia et al., 2009), aiming to predict the quality of the translated text without access to the reference text. The typical sentence-level QE task is framed as supervised regression towards HTER (Snover et al., 2006), a quality score between 0 and 1 defined with respect to the human post-edited text. However, such a problem formulation brings several limitations:

- Gathering data labeled with HTER requires human post-editing effort, which is costly to collect.
- By definition, HTER is only informative for the scenario where MT is used for post-editing.
- HTER, as a single real-value score, is difficult for users to interpret its exact meaning for the quality of machine translation (Turchi et al., 2014).
A key motivation in this work is that MT can be used in various scenarios, and their quality needs may differ. For example, fields like law or patent have high quality standards that go beyond adequacy and fluency towards style, while for purposes like gisting, loss of unimportant information in the source text or small grammatical errors in the target text can be tolerated.

We focus our attention on the usage scenarios where MT systems supply output to downstream tasks that can be executed without human involvement, and form an automatic cross-lingual pipeline (Figure 2). This pipeline system is useful when the downstream task of interest has automatic tools in the target language, but not in the source language (Klementiev et al., 2012; Zhou et al., 2016; Araujo et al., 2016). However, its usability clearly depends on the quality of MT, and our goal is to build an automatic quality control system for MT to enhance this pipeline.

In our setting, the downstream systems specify the MT quality standards for their corresponding own tasks, so we introduce a new notion for task-specific MT quality called acceptability (Section 2). Since we can run the downstream systems automatically, it allows us to leverage the large-scale parallel data and generate the labels of acceptability (Section 3), which are used to supervise the learning of our acceptability detection models (Section 4). As the quality labels are produced specifically for each downstream task, the same type of learning model can automatically adapt to the need of the corresponding tasks during training. The trained acceptability detector can then be integrated into the cross-lingual pipeline to perform quality control for MT. Figure 1 provides an illustration for the process.

Our experiments demonstrate the advantages of our framework: the adaptability to different downstream tasks, the benefit of automatic generation of large-scale quality labels, and the applicability to different translation models.

## 2 Acceptability: Binary Task-Specific Machine Translation Quality

As introduced in Figure 2, we consider the cross-language processing problem where we are interested in performing a task on the source language text, for example sentiment classification on Chinese, but the NLP system for this task is only available in the target language (e.g., English). A simple and general solution to cross the language barrier is to make use of a machine translation system to translate the source language text into the target language, and then perform the task with the NLP system in the target language. The solution is general in the sense that the MT system is agnostic to the downstream task and is supposed to accommodate every possible need. In particular, it should preserve all information of the source language sentence (so that the downstream system can extract the relevant information), and render the information in a fluent target language sentence (because the downstream system is only trained in such condition). Downstream tasks are many, with common ones including sentiment analysis, spam detection, intent classification, and named entity recognition. Naturally, the tasks may vary dramatically in nature, while a one-size-fits-all MT is expected to meet the quality needs for all of them.

Therefore, we alleviate the burden of the MT system by relaxing the quality expectation. With the involvement of downstream system, we propose that a machine translated text meets the quality need as long as it suffices to make the downstream system function properly. Thereby, we introduce a new notion of machine translation quality specific to the downstream task, which we call acceptability and define it as follows.

**Definition (acceptability):** A machine translated text is acceptable for a given downstream task if and only if the information required for the downstream task is correctly transferred from the source text.

For instance, given sentiment analysis as the downstream task, the translation is acceptable provided that the translated text has the same polarity as the source text.

More formally, let $s$ be a source sentence, $t = MT(s)$ be its machine translation. A program that executes the downstream task and returns the result of interest is denoted as a function $f$, with $f^S$ and $f^T$ acting on the source and target language, respectively. Then the definition of acceptability can be written as

\[
\text{acceptability}_f(s, t) = \text{true} \iff f^S(s) = f^T(t).
\] (1)

Note the dependence of the acceptability on $f$, which reflects the task-specific nature of the translation quality. This means a piece of translation...
Figure 2: The cross-lingual pipeline that first translates the source sentence and then feeds the translation into a downstream system in the target language. An illustrative instance is given below the boxes for Chinese-English cross-lingual sentiment classification.

Figure 3: The process of using a parallel sentence pair and a downstream system to automatically annotate acceptability to obtain a labeled instance.

unacceptable for one task may be well acceptable for another, and vice versa.

Also note that, conceptually, an ideal semantic extraction function $f$ would define what humans perceive as “acceptable translation”. However, for practical purpose, we restrict our attention to functions implemented by automatic downstream systems. This means acceptability defined with respect to such functions does not necessarily agree with human perception of translation quality.

In our problem setting, $f^S$ is unavailable, which is the reason we introduce MT at first place. To make the definition workable, we introduce the reference translation $r$ of the source sentence $s$, giving

$$\text{acceptability}_f (s, t) = \text{true} \iff f^T (t) = f^T (r).$$

In practice, the actual acceptability may be compromised by several factors. For example, the reference translation may be noisy, or introduce cultural difference across languages (Mohammad et al., 2016), or obfuscate certain source text traits like author’s gender (Mirkin et al., 2015; Rabinovich et al., 2017), so we need to make the assumption that the reference translation preserves the information needed by the downstream task. For another, automatic downstream systems that implement $f^T$ are almost always imperfect. In this regard, we assume that the downstream systems are reliable enough, otherwise it would be inconceivable to achieve desired results with the cross-lingual pipeline.

In the next section, we show how to automatically collect the annotations of acceptability for machine translation.

3 Automatic Acceptability Annotation

To obtain training instances for the acceptability detection system, instead of annotating acceptability manually, we can automate the process with existing parallel sentence pairs by virtue of the machine executability of $f^T$. This process is illustrated in Figure 3.

The MT system in Figure 3 is the one used in the cross-lingual pipeline, and its quality is what we care about. First we use the MT system to translate every source sentence $s$ in the parallel corpus. Then the translated sentence $t$ is paired with its reference $r$ and fed into the downstream system $f^T$ to obtain their respective outputs. Finally the outputs of each pair are compared to generate the acceptability annotation, which is denoted as $y$. When the process is complete, we gather tuples of $(s, t, y)$ as the training instances of the acceptability detection system.

The acceptability detector is trained to pre-
dict acceptability $y$ given $(s, t)$ as input. Once trained, it can be incorporated into the cross-lingual pipeline as a new component, as shown in the lower part of Figure 1. The handler module that takes unacceptable MT sentences may perform actions specific to each task, and the most general way of handling is probably presenting the case to human. However, if the downstream task is binary classification, we can still feed the unacceptable MT sentence into the downstream system and then flip the predicted label.

We elaborate the learning of the acceptability detection models in the next section.

4 Acceptability Detection Models

After we have gathered instances of $((s, t), y)$, we are ready to build the acceptability detector: $y = A_f (s, t; \theta)$. From the machine learning point of view, the difference between acceptability detection and quality estimation is the type of the target variable $y$, which leads to the learning problem of acceptability detector being framed as binary classification. This connection hints that models developed in the quality estimation literature may also be effective for acceptability detection. Therefore, we draw inspiration from the existing quality estimation methods and propose to approach acceptability detection with two different models, called BiQuEst and BiRNN respectively.

4.1 BiQuEst

QuEst (Specia et al., 2013) is a traditional method for quality estimation, serving as the official baseline of the quality estimation shared task since 2012 (Callison-Burch et al., 2012). It works by extracting various human-designed features of $(s, t)$ that could be indicative of its quality. We hope these features are also helpful for our acceptability detection purpose, and use them to represent instances of $(s, t)$. In our experiments, we use the default 17 blackbox features\textsuperscript{1} extracted by the QuEst++ toolkit (Specia et al., 2015). We then extend it to learn from binary labels (hence the name BiQuEst) by using the support vector machine.

4.2 BiRNN

One difference between acceptability detection and quality estimation is that the same $(s, t)$ pair may receive different acceptability labels depending on the downstream task. However, the features extracted by QuEst for the same $(s, t)$ are fixed, and the different labels can only be reflected by the weights of the model. This limitation can be overcome by an end-to-end neural network model that performs feature extraction and classification as a whole.

We propose BiRNN as illustrated in Figure 4. This model is adapted from (Ive et al., 2018). The source and MT sentences $s$ and $t$ are represented as sequences of vectors by separate word embedding layers, bidirectional GRU (Bahdanau et al., 2014) layers, and non-linear layers:

$$x_i^S = W_s^S s_i, \quad i \in [1, L],$$

$$g_i^S = \text{BiGRU}^S (x_i^S), \quad i \in [1, L],$$

$$h_i^S = \text{ReLU} (W_g^S g_i^S + b_g^S), \quad i \in [1, L].$$

The target language part shares similar equations. The two sentence vectors $\{h_i^S\}_{i=1}^L$ and $\{h_i^T\}_{i=1}^{2L}$ are concatenated together as a sequence of length $2L$, denoted as $\{h_i\}_{i=1}^{2L}$. They are then combined into a single vector with the word attention mechanism:

$$\alpha_i = \frac{\exp (h_i^T w)}{\sum_{j=1}^{2L} \exp (h_j^T w)}, \quad i \in [1, 2L],$$

$$u = \sum_{i=1}^{2L} \alpha_i h_i.$$

Finally, this vector is passed through a non-linear layer before it is used to compute the probability of the acceptability:

$$v = \text{ReLU} (W_v u + b_v),$$

$$p = \text{sigmoid} (W_v v + b_v).$$

The cross-entropy loss is used for learning.

5 Experimental Setup

A direct way to demonstrate the efficacy of the acceptability detector would be evaluating the performance gain from plugging it into the cross-lingual pipeline. However, the task-specific handler module that generally involves human complicates the creation of a uniform test set. Even for binary classification downstream tasks, a suitable cross-lingual data set is difficult to obtain. Therefore, we decide to use the parallel data with automatic acceptability annotations to create the experiment suite.

\textsuperscript{1}https://www.quest.dcs.shef.ac.uk/quest\_files/ features\_blackbox\_baseline\_17
We take Chinese as the source language and English as the target, and use parallel data from WMT18 (Bojar et al., 2018). After generating acceptability annotations, we reserve 10k instances as the development set and another 10k instances as the test set. In addition to acceptability detection models BiQuEst and BiRNN, we also report the performance of a baseline that takes every translation as acceptable, which corresponds to the original cross-lingual pipeline in Figure 2.

We lowercase the English side of all parallel corpora. The MT training corpus includes LDC2002E18, LDC2003E07, LDC2003E14, Hansards portion of LDC2004T07, LDC2004T08, and LDC2005T06. For training both Transformer and Moses translation models, we apply byte pair encoding (Sennrich et al., 2016) with 32,000 operations. Note that when we use the 0.1m LDC subset, the coding scheme differs accordingly. When we generate acceptability annotation using the WMT18 corpus, only the source sentences with 50 subwords or fewer are retained. The BiRNN model takes input at the subword level with maximum sequence length $L = 64$, so no source sentence is truncated.

All existing toolkits follow default settings. The Moses uses a 3-order language model trained on the target side of the parallel corpus, which is correspondingly smaller when the 0.1m LDC subset is used. The Stanford NER distinguishes three types: person, location, and organization.

The model hyperparameters are set as follows. For BiQuEst, 3-order language models are trained on the 1.25m LDC parallel corpus for each language to be used for feature extraction. For SVM learning, we use the RBF kernel as it shows slightly better performance on the development set than the linear kernel, although the training time is much longer. The other hyperparameters are left as default. For BiRNN, the vocabulary sizes for each language are truncated at 30,000. The embedding size and RNN hidden size are set to 256. The non-linear layers are of sizes 512 and 1,024 respectively (i.e. $b_S^g, b_T^g \in \mathbb{R}^{512}$ and $b_u \in \mathbb{R}^{1024}$). Dropout probability 0.1 is applied to word embeddings. The mini-batch size is 128. The optimizer is Adam with learning rate $5 \times 10^{-4}$, and early stopping is employed based on accuracy on the development set.

5.1 Evaluation Metric
We report acceptability detection accuracy on the test set as our evaluation metric. Note that, true positives (TP) and true negatives (TN) are both important for our purpose because failing to catch unacceptable translations or presenting acceptable cases to human (thereby increasing the cost) are both undesirable. Therefore, F score is less suitable here than e.g. information retrieval where true negatives are innumerable. Besides, if the downstream task is binary classification, we also present a formula to estimate the cross-lingual accuracy with downstream system accuracy and acceptability detection accuracy.

Let $p_f \triangleq P(c = 1|s)$ be the probability of predicting the correct final label given the source sentence $s$. Introducing a binary random variable $y$ with $y = 1$ representing the MT sentence is ac-
ceptable, we have

\[
P(c = 1|s) = \sum_{y} P(c = 1|y, s) P(y|s) = P(c = 1|y = 1, s) P(y = 1|s) + P(c = 1|y = 0, s) P(y = 0|s).
\]

(10)

Because the downstream task is binary classification, we have

\[
P(c = 1|y = 1, s) = 1 - P(c = 1|y = 0, s).
\]

Defining \( p_t \equiv P(c = 1|y = 1, s) \) and \( p_d \equiv P(y = 1|s) \) gives

\[
p_f = p_tp_d + (1 - p_t)(1 - p_d).
\]

(11)

The probabilities \( p_f, p_t, p_d \) can be estimated by cross-lingual accuracy, downstream system accuracy, and acceptability detection accuracy, respectively. This formula reflects the dependence of cross-lingual accuracy on both MT and downstream system performance. In our setting, the downstream system is fixed, while an improvement of acceptability detection accuracy \( \Delta p_d \) will bring an overall improvement

\[
\Delta p_f = (2p_t - 1) \Delta p_d.
\]

(12)

Because \( p_t > 0.5 \) for binary classification, improving acceptability detection accuracy will always positively affect the cross-lingual pipeline.

Finally, it is worth noting that acceptability detection accuracy of the baseline reflects the proportion of acceptable instances on test sets.

5.2 Downstream Tasks and Systems

We experiment with three downstream tasks: subjectivity classification, sentiment classification, and named entity recognition. These tasks are framed as binary classification, three-way classification (positive, negative, neutral), and structured prediction, respectively. Unlike classification tasks that return a single label, named entity recognition tags the input sentence with named entities. The exact definition of acceptability in Equation (2) can be designed for specific needs. In our experiments, we take acceptability to represent whether the multisets of named entities in the reference sentence and the MT sentence are the same.

We use off-the-shelf toolkits to perform downstream tasks: Datumbox\(^2\) for subjectivity and sentiment classification, and Stanford NER\(^3\) for named entity recognition.

5.3 Machine Translation Models

Our acceptability detection framework can be applied to any translation system as long as we can use it to perform decoding. To facilitate experiment, we build machine translation systems of our own. We investigate neural machine translation and phrase-based statistical machine translation, which are the Transformer implemented in THUMT (Zhang et al., 2017) and the Moses toolkit (Koehn et al., 2007), respectively. The parallel corpus for training comes from LDC with 1.25m sentence pairs. In order to vary the translation performance and represent different training conditions, we also train with a subset of 0.1m sentence pairs. This results in four translation models. In the following section, we will report acceptability detection accuracy for each of them.

6 Experimental Results

6.1 Performance of Acceptability Detection

We can see from the accuracy scores of acceptability detection in Table 1 that both BiQuEst and BiRNN are able to improve over the baseline, and BiRNN performs much better than BiQuEst. The same thing can be said for different downstream tasks, but the degree of improvement for named entity recognition is much larger than the other two tasks, with an absolute improvement of 25% for the best-performing BiRNN model. This indicates that named entity translation issues are well captured by our models.

We also report detailed evaluation of the BiRNN-1m acceptability detection model for Transformer-0.1m in Table 2, taking positive to mean acceptable. For unacceptable translations

\[\text{accuracy (%)}\]

\[\text{training data size (in million)}\]

Figure 5: Training BiRNN on different data sizes impacts acceptability detection accuracy. The setting is sentiment acceptability detection for Transformer trained on 0.1m parallel sentence pairs.
| MT      | BLEU detection model | training data size | subjectivity | sentiment | named entity |
|---------|----------------------|--------------------|--------------|-----------|--------------|
| T-0.1m  | -                    | 0.1m               | 65.79 (+ 0.08) | 74.82 (+0.52) | 72.56 (+ 3.66) |
|         | BiQuEst              | 0.2m               | 65.89 (+ 0.10) | 74.94 (+0.64) | 72.62 (+ 5.72) |
|         | BiQuEst              | 0.5m               | 66.01 (+ 0.22) | 75.05 (+0.75) | 72.80 (+ 5.90) |
|         | BiQuEst              | 1m                 | 65.96 (+ 0.17) | 75.17 (+0.87) | 72.90 (+ 6.00) |
| T-1.25m | -                    | 0.1m               | 70.53 (+ 4.47) | 78.96 (+4.66) | 86.79 (+19.89) |
|         | BiQuEst              | 0.2m               | 72.77 (+ 6.98) | 80.82 (+6.52) | 89.20 (+22.30) |
|         | BiQuEst              | 0.5m               | 75.52 (+ 9.73) | 82.04 (+7.74) | 90.68 (+23.78) |
|         | BiQuEst              | 1m                 | 75.93 (+10.14) | 83.29 (+8.99) | 91.86 (+24.96) |
| M-0.1m  | -                    | 0.1m               | 73.08 (+0.07)  | 78.18 (+0.43) | 75.76 (+ 3.54) |
|         | BiQuEst              | 0.2m               | 73.07 (+0.06)  | 78.31 (+0.56) | 75.85 (+ 3.63) |
|         | BiQuEst              | 0.5m               | 73.08 (+0.07)  | 78.25 (+0.50) | 75.96 (+ 3.74) |
|         | BiQuEst              | 1m                 | 73.13 (+0.12)  | 78.24 (+0.49) | 76.09 (+ 3.87) |
|         | BiQuEst              | 0.1m               | 73.43 (+0.42)  | 79.81 (+2.06) | 86.03 (+13.81) |
| M-1.25m | -                    | 0.2m               | 74.35 (+1.34)  | 81.07 (+3.12) | 87.24 (+15.02) |
|         | BiQuEst              | 0.5m               | 76.02 (+3.01)  | 82.32 (+4.57) | 89.41 (+17.19) |
|         | BiQuEst              | 1m                 | 77.52 (+4.51)  | 83.19 (+5.44) | 90.35 (+18.13) |
| M-1.25m | -                    | 0.1m               | 68.88 (+0.50)  | 76.59 (+0.37) | 73.50 (+ 3.44) |
|         | BiQuEst              | 0.2m               | 68.92 (+0.54)  | 76.80 (+0.58) | 73.55 (+ 3.49) |
|         | BiQuEst              | 0.5m               | 69.03 (+0.65)  | 76.87 (+0.65) | 73.85 (+ 3.79) |
|         | BiQuEst              | 1m                 | 69.18 (+0.80)  | 76.94 (+0.72) | 73.81 (+ 3.75) |
|         | BiQuEst              | 0.1m               | 71.30 (+2.92)  | 79.46 (+3.24) | 86.57 (+16.51) |
|         | BiQuEst              | 0.2m               | 73.19 (+4.81)  | 80.62 (+4.40) | 88.12 (+18.06) |
|         | BiQuEst              | 0.5m               | 75.75 (+7.37)  | 81.73 (+5.51) | 90.08 (+20.02) |
|         | BiQuEst              | 1m                 | 76.82 (+8.44)  | 82.90 (+6.68) | 90.49 (+20.43) |

Table 1: Acceptability detection accuracy (%) for different downstream tasks and MT systems (T stands for Transformer and M stands for Moses). The BLEU scores are case-insensitive BLEU-4 calculated on NIST 2008. Absolute improvements over the baseline are shown in parentheses.

| MT      | subjectivity sentiment named entity |
|---------|-------------------------------------|
| TP      | 5,676                               |
| FP      | 1,504                               |
| TN      | 1,917                               |
| FN      | 903                                 |

Table 2: Detailed evaluation of BiRNN trained with 1m data for Transformer trained on 0.1m parallel sentence pairs.

that will be processed by the handler module, we note that TN > FN. This means the majority of detected-as-unacceptable translations are truly unacceptable (i.e. the labels they receive from the downstream system would be different than their references). Therefore, when the downstream task is binary classification (subjectivity classification), flipping their labels is a better strategy than passing them untouched as in the original cross-lingual pipeline.
6.2 Effect of the Acceptability Training Data Size

One advantage of our framework is the automatic generation of acceptability annotation data from large-scale parallel corpora. It is expected that more acceptability annotation data can result in better acceptability detection models. This is confirmed by the accuracy scores in Table 1: For Transformer-0.1m, BiRNN trained on 1m data improves on its 0.1m version by around 5 points, and the improvements are similarly large for other MT systems. For BiQuEst, however, the gain from large training set is marginal, likely due to underfitting with the small feature set.

We further explored even more data for sentiment acceptability detection of Transformer-0.1m, and generated up to 10m training instances. BiRNN was also trained on subsets of 2m and 5m. The results are summarized along with smaller-scale experiments in Figure 5. Increasing the training data size can bring further improvement, but the return gradually diminishes. We also tried doubling the embedding size and hidden size to train on 10m data, but no gain was observed from this larger network. This may indicate that data at the 10m scale expose little extra information for the learning of acceptability detection task in the current experiments.

6.3 Behavior of Different Translation Models

Enlarging parallel corpus for the training of the translation model will improve its translation quality; we thus obtain a Transformer model trained on the full 1.25m parallel corpus and detect acceptability for it, with results given in the Transformer-1.25m row of Table 1. We first notice that the baseline accuracy gets higher for every downstream task. This means a translation model with higher quality (as measured by BLEU (Papineni et al., 2002)) also produces more acceptable translations for downstream tasks. As for the acceptability detection models, their accuracy scores remain at similar levels, although their improvements on the baseline appear smaller.

Similar observations can be made for Moses translation models in Table 1. In line with received wisdom, Moses can outperform Transformer when parallel data is limited, but is superseded when the corpus is sufficiently large. This is not only reflected in BLEU scores, but also in the relative levels of the baseline accuracy for acceptability detection. BiRNN models again show consistently high performance, which indicates they are general for working with different types of translation models.

As the baseline acceptability detection accuracies show the label distributions of test sets, which are similar for training sets in our experiments, it is clear that stronger MT systems will result in more unbalanced label distributions that might hinder the learning of acceptability detectors. However, our experiments for balancing strategies did not yield improvement, which indicates that the current unbalance levels are tolerable. Nevertheless, we anticipate that highly strong MT systems diminish the need for acceptability detection, and our approach is more beneficial for weak MT systems by helping to close their gap with strong MT systems for downstream tasks, as the acceptability detection accuracy improvements over the baseline (shown in parentheses in Table 1) are consistently larger for weaker MT systems.

7 Discussion

Our experiments demonstrate the utility of the acceptability detection framework for three downstream tasks. We have seen that the named entity recognition task is somewhat special due to its structured output, which calls for specific decision for what exactly constitutes $f^T(t) = f^T(r)$ in Equation (2). This also means other variations are possible, for example taking $f^T$ to be the number of named entities, thereby excusing named entity translation error as long as they are not over or under translated, if this is actually needed by the translation quality specification. The flexibility in interpreting Equation (2) also allows combining several downstream tasks by taking $f^T$ to perform multiple tasks together and return a tuple of task outputs; this can also be equivalently seen as a single downstream task composed of several subtasks.

Despite the flexibility, our framework is not without limitation, as not every downstream task can fit into it. If the input to the downstream task is more than one sentence, for example semantic textual similarity that takes a pair of sentences, or document classification that operates on documents, then our framework is less useful because parallel data in those forms are rare. If the output of the downstream task is even more complex than named entity recognition that we have dealt
with, for example summarization that outputs a sentence, then the definition in Equation (2) would not be easily settled. This can be attributed to the root cause that NLP tasks with unstructured output are difficult to evaluate, even if references are provided.

Although NLP tasks with complex output are unsuitable for downstream tasks, they open up opportunities for extending our framework to define and detect acceptability for them. Like machine translation, their output may also be further processed by downstream tasks. This is especially true for automatic speech recognition and semantic parsing, which also attract research on quality estimation for them (Zamani et al., 2015; Dong et al., 2018). Our framework can also build acceptability detectors for these systems as long as abundant parallel data (parallel in the sense specific for each complex-output task) are available.

8 Related Work

Machine translation quality is difficult to measure, even if we involve human experts. The idea of introducing downstream tasks has been explored earlier (White and Taylor, 1998; Jones et al., 2007) by asking humans to perform downstream tasks like reading comprehension based on machine translated text, and the machine translation quality is measured by human performance of those tasks. The involvement of human means this approach cannot scale up, and is purely for the purpose of evaluation.

Quality estimation shares similar purpose with our work. As we mention in Section 1, the usual formulation of sentence-level quality estimation outputs scores in the [0, 1] interval, leaving users to interpret the implications. Researchers are aware that binary labels are the most intuitive for users. A straightforward idea is to threshold real-valued scores to obtain binary-labeled data (Blatz et al., 2004; Quirk, 2004; Specia et al., 2010). One work more related to ours (Turchi et al., 2014) proposes an automatic method to obtain binary-labeled data that discriminate whether the translation is useful for manual post-editing. Like usual QE, that work is also targeted at the scenario of machine translation for post-editing. This also means data collection is difficult due to the high cost of human post-editing, and thus only small-scale experiments were conducted.

Our work can also be viewed as estimating specific aspects of machine translation quality designated by downstream tasks. In neural machine translation, under translation and over translation are often observed as quality issues. Focusing on these certain types of translation failures allows researchers to design targeted detection algorithms (Zheng et al., 2018).

Besides detecting aspects of quality issues for machine translation, researchers also attempt to make machine translation models more robust and reduce the production of certain errors (Cheng et al., 2018). There are also endeavors to build MT systems that maintain particular aspects of the source text like sentiment (Lohar et al., 2017, 2018).

9 Conclusion and Future Work

In this work, we investigate machine translation quality by proposing a new definition called acceptability. It is binary, thus easy to interpret. It considers downstream usage of machine translation, thus adaptable to different quality needs. It enables large-scale annotation by exploiting parallel data and automatic downstream systems, thus allowing the creation of useful acceptability detectors for downstream tasks with machine learning.

Our framework is general and encompasses various downstream tasks, leaving much room for extension. We are also interested in exploring more powerful detection models given the large amount of labeled data. Finally, it may be possible to propagate labeled information to translation models to make them aware of downstream needs.

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