A Machine Learning Method to Distinguish Machine Translation from Human Translation

Yitong Li¹, Rui Wang¹,², Hai Zhai¹,²
¹Center for Brain-Like Computing and Machine Intelligence, Department of Computer Science and Engineering, Shanghai Jiao Tong University, Shanghai, 200240, China
²Key Laboratory of Shanghai Education Commission for Intelligent Interaction and Cognitive Engineering, Shanghai Jiao Tong University, Shanghai, 200240, China
lrank@sjtu.edu.cn, wangrui.nlp@gmail.com, zhaohai@cs.sjtu.edu.cn

Abstract

This paper introduces a machine learning approach to distinguish machine translation texts from human texts in the sentence level automatically. Instead of traditional methods, we extract some linguistic features only from the target language side to train the prediction model and these features are independent of the source language. Our prediction model presents an indicator to measure how much a sentence generated by a machine translation system looks like a real human translation. Furthermore, the indicator can directly and effectively enhance statistical machine translation systems, which can be proved as BLEU score improvements.

1 Introduction

The translation performance of Statistical Machine Translation (SMT) systems has been improved significantly within this decade. However, it is still incomparable to the human translation (Feng et al., 2012; Li et al., 2012). Most translation text generated by SMT systems can be understood in some degree but still not good enough. However, a significant proportion of text that exists serious mistakes and even does not make sense, and these text can be easily recognized by human.

It is not difficult to understand the reason why SMT systems generate ill-formed or non-sense sentences. SMT systems combine probability models in a log-linear framework (Och and Ney, 2003), where the systems always attempt to find a sentence with the highest probability from the candidates. However, Language Model (LM), such as n-gram LM, and reordering model only have limited capacity to represent context, where sentences with local optimum could often be output. Meanwhile, it can be a very different thing for the entire translation sentence due to complicated semantic and pragmatic issues.

Therefore, to improve SMT performance, if poorly translated sentences can be distinguished automatically, it is possible for us to refine these sentences by some extra efforts. In this paper, to order to define the quality of the sentence generated by SMT systems, we borrow the idea from the evaluation of machine translation task, that the more like human translation text, the better the machine translation output is. Considering that the poorly translated sentences show great difference from human text, we compare text generated by SMT systems with human translations. This comparison motivates us to design a predictor to tell whether a sentence is machine generated or human generated. Above all, such a predictor can be treated as a binary classification problem.

In this paper, we use Support Vector Machines (SVMs) (Hearst et al., 1998) to solve such a problem. The benefits of SVMs for text categorization have been identified since it learns well with many
relevant features (Joachims, 1998). In order to find those poorly SMT-translated sentences, we train an SVM-classifier on a feature space. Most features are linguistically motivated only from the target language side. As only target language is concerned, our model will be facilitated of some direct applications.

Among all features, a major part is related to the syntactic parser. The parsing structure of the output sentence is very sensible to the quality of SMT outputs. We therefore especially select these features related to the branching properties of the parse tree. One of the reason is that it had become apparent from failure analysis in (Corston-Oliver et al., 2001) that SMT system output tended to favor right-branching structures over noun compounding.

The remainder of this paper is organized as follows: In Section 2, we will give a quick review on SMT and relevant classification tasks. The SVM approaches and all the features used in our method will be presented in Section 3. Section 4 will give a description on the experiments and an analysis of corresponding results. Last, we will conclude our work in Section 5.

2 Related Work

In the classification task part, as our goal is to distinguish sentences with different quality, we are actually working on confidence estimation or automatic evaluation of SMT systems (Doddington, 2002; Papineni et al., 2002; Zhang et al., 2014).

Early work on automatic evaluation of machine translation text estimates the quality at the word level (Gandrabur and Foster, 2003; Ueffing and Ney, 2005). Namely, \( n \)-gram features played an important role in translation quality differentiation. However, this paper considers deep level of linguistic features such as those derived from parsing tree instead of \( n \)-gram features.

Liu and Gildea (2005) also used features related to the syntactic parser. Compared with our work, they cared more about detailed syntax properties of the sentences on the parse trees. In this paper, we use less properties but more syntactic structure features.

Corston-Oliver et al. (2001) adopted parse tree related features to evaluating MT. Their work shows a high accuracy in the classification task. However, the generation of their training and test data should limit to the same SMT system. In this paper, we devote to developing a model that is capable of distinguishing texts generated by multiple sourced SMT systems from human texts. To achieve such an aim, we will introduce quite different types of features such as emotion agreement inside a sentence.

In the statistical machine translation systems part, the performance is depended on the LM and translation model. Traditional Back-off \( n \)-gram LMs (BNLMs) (Chen and Goodman, 1996; Chen and Goodman, 1999; Stolcke, 2002) have been widely used for probability estimation and BNLMs also show up in many other NLP tasks (Jia and Zhao, 2014; Zhang et al., 2012; Xu and Zhao, 2012). Recently, a better probability estimation method, Continuous-Space Language Models (CSLMs), especially Neural Network Language Models (NNLMs) (Bengio et al., 2003; Schwenk et al., 2006; Schwenk, 2007; Le et al., 2011) are being used in SMT tasks (Son et al., 2010; Son et al., 2012; Wang et al., 2013; Wang et al., 2015; Wang et al., 2014). Also, Neural Network Translation Models (NNTMs) show a success in SMT (Kalchbrenner and Blunsom, 2013; Blunsom et al., 2014). However, the high cost of CSLMs makes it difficult to decoding directly. This leads to a \( n \)-best reranking method which is available for our paper (Schwenk et al., 2006; Son et al., 2012).

3 The Proposed Approach

In this Section, we present a machine learning method to distinguish poor translated sentences from good ones.

3.1 Support Vector Machine

For text classification tasks, Many approaches have been proposed (Sebastiani, 2002). Among these approaches, SVM has shown widely applications (Joachims, 1998; Joachims, 1999; Joachims, 2002; Tong and Koller, 2002). And in following subsection we will introduces how to formalize the proposed task.

The training corpus for the classifier includes \( l \) human translation sentences as positive samples and \( l \) corresponding SMT outputs as negative samples. For a sentence \( S \), it can be represented by an
$N$-dimensional feature vector $V \{v_1, v_2, \cdots, v_N\}$, where $N$ is total number of all the features, and in most cases, $v_i$ is a real number feature normalized by the length $L_S$ of sentence $S$.

With the above training corpus, we will train an SVM classifier with linear kernel. The SVM prediction function is defined as the following:

$$\text{predict}(S) = \begin{cases} +1, & h(S) \geq 0 \\ -1, & h(S) < 0 \end{cases}$$

where

$$h(S) = w_1 v_1 + w_2 v_2 + \cdots + w_N v_N$$

In this paper, Liblinear (Fan et al., 2008) is adopted as our SVM implementation and the parameter soft margin width is optimized over a small development set.

### 3.2 Features

In this subsection, we will present our feature collections.

Considering that only the properties of target language are involved in our expectation, we decide to use specific types of linguistic features to present the quality of the sentence.

A very important type of linguistic features is directly linked to syntactic structure of sentence. When getting the parse tree of a sentence, we can exploit a number of available properties, such as sentence structure and the densities of constituent types, to design as our features.

For parser implementation, we use Stanford Lexicalized Parser version 3.3.1. (De Marneffe et al., 2006). Figure 1 gives an example of a parse tree.

The features related to the parse tree are as the following\(^1\):

- number of right-branching nodes for all constituent types and for NPs.
- number of pre-modifiers, adjectives before nouns, for all constituent types and for NPs.
- number of post-modifiers, adjectives after nouns, for all constituent types and for NPs.
- branching index, the number of right-branching nodes minus number of left-branching nodes, for all constituent types and for NPs.
- branching weight index, number of tokens covered by right-branching nodes minus number of tokens covered by left-branching nodes, for all constituent types and for NPs.
- modification index, the number of pre-modifiers minus the number of post-modifiers, for all constituent types and for NPs.
- modification weight index, length in tokens of all pre-modifiers minus length in tokens of all post-modifiers, for all constituent types and for NPs.
- modification index, length in tokens of all pre-modifiers minus length in tokens of all post-modifiers, for all constituent types and for NPs.

\(^1\)In default, all the following counting numbers for feature score computation are normalized by the length of the sentence.

We also consider density of function words as well as the pronouns, where SMT systems make mistakes frequently. All densities are computed by counting the words with sentence length normalization:

- overall function word density
- density of determiners
- density of quantifiers
- density of pronouns
- density of prepositions
- density of punctuation marks
- density of auxiliary verbs
- density of conjunctions
- density of different pronoun: Wh-, 1st, 2nd, and 3rd person pronouns
The presence of out of vocabulary (OOV) word usually make situations more complicated. Also, problem like subject-verb disagreement are easy to be detected. Therefore, we give a group of lexical-level features:

- number of OOV words
- types of the immediate children of the root
- subject-verb disagreement

In additional, we score emotion agreement inside a sentence as features. This is motivated by the observation that a reasonable sentence should have a consistent emotion strength among different words. To evaluate such agreement, we build a dictionary $D_{emotion}$ especially for emotion words in advance, in which each word $s_i$ can be scored from $-3$ to $+3$. We score all the words into these categories with a linear model to describe the strength of emotion. To a sentence, the average scoring and standard deviation will be considered:

- $\mu_{emotion}(S)$
- $\sigma_{emotion}(S)$

where $S$ is a sentence with length $len$.

Finally, sizes of the following constituents are measured:

- sentence length
- parse tree depth
- maximal and average NP length
- maximal and average Adjective Phrase (ADJP) length
- maximal and average Prepositional Phrase (PP) length
- maximal and average Adverb Phrase (ADVP) length

## 4 Experiment

### 4.1 Classification

In this subsection, we will give experiment details of the prediction model.

In all of our experiments, the default settings\(^2\) of Moses (Koehn et al., 2007) and GIZA++ (Och and Ney, 2003) are used for system building. For each SMT system, a 5-gram LM (Chen and Goodman, 1996) is trained on the target side of training set using IRST LM Toolkit.

We use four language pairs from version 7 of the Europarl corpus\(^3\) (Koehn, 2005) as our experiment data and train four SMT systems, respec-
tively: French-English, German-English, Italian-
English and Danish-English.

Considering the consistency of system and con-
venience of analysis, all these four systems use En-
GLISH as target language. We use these four systems
to generate translation text.

We randomly pick 5K sentences from the French
corpus, noted as \(F_1(5K)\), and translated into En-
GLISH sentences \(E_1(5K)\) as our negative samples, by
SMT system. The corresponding English part \(E_1'\)
of \(F_1\) is used as the positive samples. \(\{E_1, E_1'\}\)
forms the required training set. Then, we randomly
pick 10K sentences from each of French \(F_2(10K)\),
German \(G_2(10K)\), Italian \(I_2(10K)\) and Danish
\(D_2(10K)\) corpora and translate them into English
text \(E_2(40K)\). Another 40K sentences are extracted
from English \(E_2'(40K)\). \(\{E_2, E_2'\}\) forms a multi-
model-translated-text test set. \(F_2\) has no cover with
\(F_1\).

The prediction results are shown in Table 1:

| Data Set   | Accuracy |
|------------|----------|
| Training set | 92.3%    |
| Test set    | 74.2%    |

Table 1: Classification Accuracy

4.2 Feedback to SMT system

One direct application of our prediction model is to
provide feedback to SMT systems.

We select the French-English SMT system that
we built above as our baseline. For the sake of mod-
ifying the system as little as possible, we consider
an \(n\)-best list and reranking method on the output
candidates of the baseline.

We make a slight change on the prediction model
so that it can give a confidence score between 0 and
1 on each sentence. The nearer with 1 its score is,
the better the sentence will be. For each SMT output
sentence, we choose a 1000-candidate\(^4\) list sorted by
the baseline, and score them by our prediction mod-
el. We check each candidate by the original sort,
and find out the first candidate whose score is greater
than a threshold \(H\) as our new output.\(^5\) In case that
no candidates satisfy the condition, we simply give
the origin output.

In our experiment, we set \(H\) empirically. Table 2
shows the 1.6 BLEU score refined by our method.

| MT System | BLEU Score |
|-----------|------------|
| Baseline  | 23.5       |
| Refined \(H = 0.6\) | 24.7       |
| Refined \(H = 0.7\) | 25.1       |
| Refined \(H = 0.8\) | 23.9       |

Table 2: BLEU scores

4.3 Discussion

We will discuss how our method works by examples.
Table 3 shows a translation and refined example.

\(S\) Quelle que soit la bonne réponse, la ques-
tion est que la détermination des mesures
to prendre concernant la race représente
un problème dominant dans la politique
américaine.

\(T\) Whatever the answer, the question is the
determination of the action on the race is
a dominant issue in American politics.

\(R\) Whatever the answer, the question is that
determining what to do about race is a
dominant issue in American politics.

\(Ref\) Regardless of the correct answer, the point
is that determining what to do about race is
a dominant issue in US politics.

Table 3: A Translation Example. \(S\): Source, \(T\): Target, \(R\):
Refined, and \(Ref\): Reference

According to the analysis, the parse tree structure
of output \(T\) is seriously right-deviated, while sen-
tence \(R\) has a more balance tree structure. Our pre-
diction model will consider \(R\) as a good translation
but \(T\) as a bad one. When reordering candidates, our
algorithm successfully selects \(R\) as output instead of
\(T\). In addition, compared with reference sentence,
we see that \(R\) is an even better translation.

5 Conclusion

In this paper, we present an indicator that using lin-
guistic features to train an SVM classifier to distin-
guish poor SMT sentences from good ones. We use

\(^4\)This is an empirical value.

\(^5\)We considered directly adding SVM score as a new feature
into SMT system, however our current method shown in this
paper gets better results. Also, this method is more efficient.
single-MT-model-generated text as training data and multi-MT-model-generated text as test data to show the stability of our method. With the help of a series of features derived from parse tree, emotion agreement and lexical features, our classifier gives acceptable accuracy. In addition, we show that such a predicator can effectively enhance the corresponding SMT task.

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