A Rule-Augmented Statistical Phrase-based Translation System

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Abstract

Interactive or Incremental Statistical Machine Translation (IMT) aims to provide a mechanism that allows the statistical models involved in the translation process to be incrementally updated and improved. The source of knowledge normally comes from users who either post-edit the entire translation or just provide the translations for wrongly translated domain-specific terminologies. Most of the existing work on IMT uses batch learning paradigm which does not allow translation systems to make use of the new input instantaneously. We introduce an adaptive MT framework with a Rule Definition Language (RDL) for users to amend MT results through translation rules or patterns. Experimental results show that our system acknowledges user feedback via RDL which improves the translations of the baseline system on three test sets for Vietnamese to English translation.

1 Introduction

In current Statistical Machine Translation (SMT) framework, users are often seen as passive contributors to MT performance. Even if there is a collaboration between the users and the system, it is carried out in a batch learning paradigm (Ortiz-Martinez et al., 2010), where the training of the SMT system and the collaborative process are carried out in different stages. To increase the productivity of the whole translation process, one has to incorporate human correction activities within the translation process. Barrachina et al. (2009) proposed an iterative process in which the translator activity is used by the system to compute its best (or n-best) translation suffix hypotheses to complete the prefix. Ortiz-Martinez et al. (2011) proposed an IMT framework that includes stochastic error-correction models in its statistical formalization to address the prefix coverage problems in Barrachina et al. (2009). Gonzalez-Rubio et al. (2013) proposed a similar approach with a specific error-correction model based on a statistical interpretation of the Levenshtein distance (Levenshtein, 1966). On the other hand, Ortiz-Martinez et al. (2010) presented an IMT system that is able to learn from user feedback by incrementally updating the statistical models used by the system. The key aspect of this proposed system is the use of HMM-based alignment models trained by an incremental EM algorithm.

Here, we present a system similar to Ortiz-Martinez et al. (2010). Instead of updating the translation model given a new sentence pair, we provide a framework for users to describe translation rules or patterns using a Rule Definition Language (RDL). Our RDL borrows the concept of the rule-based method that allows users to control the translation output by writing rules using their linguistic and domain knowledge. Although statistical methods pre-dominate the machine translation research currently, rule-based methods are still promising in improving the translation quality. This approach is especially useful for low resource languages where large training corpus is not always available. The advantage of rule-based methods is that they can well handle particular linguistic phenomena which are peculiar to languages and domains. For example, the TCH MT system at IWSLT 2008 (Wang et al., 2008) used dictionary and hand-crafted rules (e.g. regular expression) to process NEs. Their experiments showed that handling NE separately (e.g., person name, location name, date, time, digit) results in translation quality improvement.

In this paper, we present an adaptive and in-
interactive MT system that allows users to correct the translation and integrate the adaptation into the next translation cycle. Our experiments show that the system is specifically effective in handling translation errors related to out of vocabulary words (OOVs), language expressions, name entities (NEs), abbreviations, terminologies, idioms, etc. which cannot be easily addressed in the absence of in-domain parallel data.

2 System Overview

Figure 1 shows the translation and interactive process of our system. The system is trained with a batch of parallel texts to create a baseline model. Users improve the translation by adding RDL rules to change or correct the unsatisfactory translation. New RDL rules are tested in a working environment before uploading to the production environment where they would be used by subsequent translation requests.

In our system, RDL Management checks, validates and indexes the translation rules. The Rule-Augmented Decoder has two components: (1) the RDL Matcher to find applicable RDL rules for a given source text to create dynamic translation hypotheses; and (2) the Augmented Decoder to produce the final consensus translation using both dynamic hypotheses and static hypotheses from the baseline model.

3 Rule Definition Language (RDL)

The Rule Definition Language (RDL) comprises a RDL grammar, a RDL parser and a RDL matching algorithm.

3.1 RDL Grammar

Our RDL grammar is represented with a Backus-Naur Form (BNF) syntax. The major feature of the source pattern and target translation can be constructed using different combination of node types as described in Table 1. The rules can be further conditioned by using some pre-defined functions and the system allows users to reorder the translation of the target node. Figure 2 gives an example of a RDL rule where identifier @Num is used.

3.2 RDL Parsing and Indexing

The RDL Parser checks the syntax of the rules before indexing and storing them into the rule database. We utilize the compiler generator (WoB et al., 2003) to generate a RDL template parser and then embed all semantic parsing components into the template to form our RDL Parser.

As rule matching is performed during translation, searching of the relevant rules have to be very fast and efficient. We employed the modified version of an inverted index scheme (Zobel and Moffat, 2006) for our rule indexing. The algorithm is...
The main idea of the rule indexing algorithm is to index all string-based nodes in the source pattern of the RDL rule. Each node is represented using 3-tuple. They are ruleID, number of nodes in source pattern and all plausible positions of the node during rule matching. The indexing is carried out via a Forward Step and Backward Step. The Forward Step builds a linked item chain which traverses all possible position transitions from one node to another as illustrated in Figure 3. Note that S and E are the Start and End Node. The link indicates the order of transition from a node to another. The numbers refer to the possible positions of an item in source. The Backward Step starts at the end of the source pattern; it traverses back the link to index each node using the 3-tuple constructed in the Forward Step. This data structure allows us to retrieve, add or update RDL rules efficiently and incrementally without re-indexing.

3.3 RDL Matching Algorithm

Each word in the source string will be matched against the index table to retrieve relevant RDL rules during decoding. The aim is to retrieve all RDL rules in which the word is used as part of the context in the source pattern. We sort all the rules based on the word positions recorded during indexing, match their source patterns against the input string within the given span, check the conditions and generate the hypotheses if the rules fulfill all the constraints.
table with a default weight. Arora et al. (2008) extended the phrase table by adding new phrase translations for all source language words that do not have a single-word entry in the original phrase-table, but appear in the context of larger phrases. They adjusted the probabilities of each entry in the extended phase table.

We performed different experiments to estimate the lexical translation feature vector for each dynamic hypothesis generated by our RDL rules. We obtain the best performance by estimating the feature vector score using the baseline phrase table through context approximation. For each hypothesis generated by the RDL rule, we retrieve entries from the phrase table which have at least one similar word with the source of the generated hypothesis. We sort the entries based on the similarities between the generated and retrieved hypotheses using both source and target phrase. The medium score of the sorted list is assigned to the generated hypothesis.

5 System Features

The main features of our system are (1) the flexibilities provided to the user to create different levels of translation rules, from simple one-to-one bilingual phrases to complex generalization rules for capturing the translation of specific linguistic phenomena; and (2) the ability to validate and manage translation rules online and incrementally.

5.1 RDL Rule Management

Our system framework is language independent and has been implemented on a Vietnamese to English translation project. Figure 4 shows the RDL Management Screen where a user can add, modify or delete a translation rule using RDL. A RDL rule can be created using nodes. Each node can be defined using string or system predefined meta-identifiers with or without meta-operators as described in Table 1. Based on the node type selected by the user, the system further restricts the user to appropriate conditions and translation functions. The user can define the order of the translation output of each node and at the same time, inform the system whether to use a specific RDL exclusively during decoding, in which any phrases from the baseline phrase table overlapping with that span will be ignored\(^1\). The system also provides an editor for expert users to code the rules using the RDL controlled language. Each rule is validated by the RDL parser (discussed in section 3.2), which will display errors or warning messages when an invalid syntax is encountered.

5.2 RDL Rule Validation

Our decoder manages two types of phrase table. One is the static phrase-table obtained through the SMT training in parallel texts; the other is the dynamic table that comprises of the hypotheses generated on-the-fly during RDL rule matching. To ensure only fully tested rules are used in the production environment, the system supports two types of dynamic phrase table. The working phrase-table holds the latest updates made by the users. The users can test the translation with these latest modifications using a specific translation protocol. When users are satisfied with these modifications, they can perform an operation to upload the RDL rules to the production phrase-table, where the RDLs are used for all translation\^.

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\(^1\) Similar to Moses XML markup exclusive feature http://www.statmt.org/ Moses.\^
| Named Entity Category | Number of Rules |
|-----------------------|-----------------|
| Date-time             | 120             |
| Measurement           | 92              |
| Title                 | 13              |
| Designation           | 12              |
| Number                | 19              |
| Terminology           | 178             |
| Location              | 13              |
| Organization          | 48              |
| **Total**             | **495**         |

Table 2: Statistics of created RDL rules for Vietnamese-to-English NE Translation.

requests. Uploaded rules can be deleted, modified and tested again in the working environment before updated to the production environment. Figure 5b and Figure 5c show the differences in translation output before and after applied the RDL rule in Figure 5a.

6 A Case Study for Vietnamese–English Translation

We performed an experiment using the proposed RDL framework for a Vietnamese to English translation system. As named entity (NE) contributes to most of the OOV occurrences and impacts the system performance for out-of-domain test data in our system, we studied the NE usage in a large Vietnamese monolingual corpus comprising 50M words to extract RDL rules. We created RDL rules for 8 popular NE types including title, designation, date-time, measurement, location, organization, number and terminology. We made use of a list of anchor words for each NE category and compiled our RDL rules based on these anchor words. As a result, we compiled a total of 495 rules for 8 categories and it took about 3 months for the rule creation. Table 2 shows the coverage of our compiled rules.

6.1 Experiment & Results

Our experiments were performed on a training set of about 875K parallel sentences extracted from web news and revised by native linguists over 2 years. The corpus has 401K and 225K unique English and Vietnamese tokens. We developed 1008 and 2548 parallel sentences, each with 4 references, for development and testing, respectively. All the reference sentences are created and revised by different native linguists at different times. We also trained a very large English language model using data from Gigaword, Europarl and English web texts of Vietnamese authors to validate the impact of RDL rules on large-scale and domain-rich corpus. The experimental results show that created RDL rules improve the translation performance on all 3 test sets. Table 3 and Table 4 show respective data statistics and results of our evaluation. More specifically, the BLEU scores increase 3%, 3.6% and 1.4% on the three sets, respectively.

7 Conclusion

We have presented a system that provides a control language (Kuhn, 2013) specialized for MT for users to create translation rules. Our RDL differs from Moses’s XML mark-up in that it offers fea-
| Data Set | System     | BLEU  | NIST   | METEOR |
|----------|------------|-------|--------|--------|
| Set 1    | Baseline   | 39.21 | 9.2323 | 37.81  |
|          | + RDL (all)| 39.51 | 9.2658 | 37.98  |
| Set 2    | Baseline   | 40.25 | 9.5174 | 38.24  |
|          | + RDL (all)| 40.61 | 9.6092 | 38.84  |
| Set 3    | Baseline   | 36.77 | 8.6953 | 37.65  |
|          | + RDL (all)| 36.91 | 8.7062 | 37.69  |

Table 4: Experimental results with RDL rules.

Our experimental results show that RDL rules improve the overall performance of the Vietnamese-to-English translation system. The framework will be tested for other language pairs (e.g., Chinese-to-English, Malay-to-English) in the near future. We also plan to explore advanced methods to identify and score “good” dynamic hypotheses on-the-fly and integrate them into current SMT translation system (Simard and Foster, 2013).

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