A Structured Language Model for Incremental Tree-to-String Translation

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Abstract

Tree-to-string systems have gained significant popularity thanks to their simplicity and efficiency by exploring the source syntax information, but they lack in the target syntax to guarantee the grammaticality of the output. Instead of using complex tree-to-tree models, we integrate a structured language model, a left-to-right shift-reduce parser in specific, into an incremental tree-to-string model, and introduce an efficient grouping and pruning mechanism for this integration. Large-scale experiments on various Chinese-English test sets show that with a reasonable speed, our method gains an average improvement of 0.7 points in terms of (TER-BLEU)/2 than a state-of-the-art tree-to-string system.

1 Introduction

Tree-to-string models (Liu et al., 2006; Huang et al., 2006) have made promising progress and gained significant popularity in recent years, as they run faster than string-to-tree counterparts (e.g. (Galley et al., 2006)), and do not need binarized grammars. Especially, Huang and Mi (2010) make it much faster by proposing an incremental tree-to-string model, which generates the target translation exactly in a left-to-right manner. Although, tree-to-string models have made those progresses, they can not utilize the target syntax information to guarantee the grammaticality of the output, as they only generate strings on the target side.

One direct approach to handle this problem is to extend tree-to-string models into complex tree-to-tree models (e.g. (Quirk et al., 2005; Liu et al., 2009; Mi and Liu, 2010)). However, tree-to-tree approaches still significantly underperform than tree-to-string systems due to the poor rule coverage (Liu et al., 2009) and bi-parsing failures (Liu et al., 2009; Mi and Liu, 2010).

Another potential solution is to use structured language models (SLM) (Chelba and Jelinek, 2000; Charniak et al., 2003; Post and Gildea, 2008; Post and Gildea, 2009), as the monolingual SLM has achieved better perplexity than the traditional n-gram word sequence model. More importantly, the SLM is independent of any translation model. Thus, integrating a SLM into a tree-to-string model will not face the problems that tree-to-tree models have. However, integration is not easy, as the following two questions arise. First, the search space grows significantly, as a partial translation has a lot of syntax structures. Second, hypotheses in the same bin may not be comparable, since their syntactic structures may not be comparable, and the future costs are hard to estimate. Hassan et al. (2009) skip those problems by only keeping the best parsing structure for each hypothesis.

In this paper, we integrate a shift-reduce parser into an incremental tree-to-string model, and introduce an efficient grouping and pruning method to handle the growing search space and incomparable hypotheses problems. Large-scale experiments on various Chinese-English test sets show that with a reasonable speed, our method gains an average improvement of 0.7 points in terms of (TER-BLEU)/2 than a state-of-the-art tree-to-string system.
### 2 Linear-time Shift-reduce Parsing

A shift-reduce parser performs a left-to-right scan of the input sentence, and at each parsing step, chooses one of two parsing actions: either shift (sh) the current word onto the stack, or reduce (re) the top two (or more) items at the end of the stack (Aho and Ullman, 1972). In the dependency parsing scenario, the reduce action is further divided into two cases: left-reduce (re\( \prec \)) and right-reduce (re\( \succ \)), depending on which one of the two items becomes the head after reduction. Each parsing derivation can be represented by a sequence of parsing actions.

#### 2.1 Shift-reduce Dependency Parsing

We will use the following sentence as the running example:

> Bush held a meeting with Sharon

<table>
<thead>
<tr>
<th>action</th>
<th>signature</th>
<th>dependency structure</th>
</tr>
</thead>
<tbody>
<tr>
<td>sh</td>
<td>s1</td>
<td>Bush S0</td>
</tr>
<tr>
<td>sh</td>
<td>held Bush</td>
<td>S1: Bush</td>
</tr>
<tr>
<td>re( \prec )</td>
<td>held Bush meeting</td>
<td>S3: Bush held</td>
</tr>
<tr>
<td>sh</td>
<td>held meeting with</td>
<td>S5: Bush held meeting</td>
</tr>
<tr>
<td>re( \prec )</td>
<td>held Bush meeting a</td>
<td>S6: Bush held a meeting</td>
</tr>
<tr>
<td>re( \prec )</td>
<td>held Bush meeting</td>
<td>S7: Bush held a meeting</td>
</tr>
<tr>
<td>sh</td>
<td>held meeting Sharon</td>
<td>S8: Bush held a meeting with Sharon</td>
</tr>
<tr>
<td>sh</td>
<td>with Sharon</td>
<td>S9: Bush held a meeting with Sharon</td>
</tr>
<tr>
<td>re( \prec )</td>
<td>held Bush meeting Sharon</td>
<td>S10: Bush held a meeting with Sharon</td>
</tr>
<tr>
<td>re( \prec )</td>
<td>held Bush meeting</td>
<td>S11: Bush held a meeting with Sharon</td>
</tr>
</tbody>
</table>

![Figure 1: Linear-time left-to-right dependency parsing.](image-url)
Bush held a meeting with Sharon

Given an input sentence $e$, where $e_i$ is the $i$th token, $e_i...e_j$ is the substring of $e$ from $i$ to $j$, a shift-reduce parser searches for a dependency tree with a sequence of shift-reduce moves (see Figure 1). Starting from an initial structure $S_0$, we first shift (sh) a word $e_1$, “Bush”, onto the parsing stack $s_0$, and form a structure $S_1$ with a singleton tree. Then $e_2$, “held”, is shifted, and if there are two or more structures in the parsing stack, we can use $\text{re}_\leftarrow$ or $\text{re}_\rightarrow$ step to combine the top two trees on the stack, replace them with dependency structure $e_1 \leftarrow e_0$ or $e_1 \rightarrow e_0$ (shown as $S_3$), and add one more dependency edge between $e_0$ and $e_1$.

Note that the shade nodes are exposed heads on which $\text{re}_\leftarrow$ or $\text{re}_\rightarrow$ parsing actions can be performed. The middle columns in Figure 1 are the parsing signatures: $q_0$ (parsing queue), $s_0$ and $s_1$ (parsing stack), where $s_0$ and $s_1$ only have one level dependency. Take the line of $S_{11}$ for example, “a” is not in the signature. As each action results in an update of cost, we can pick the best one (or few, with beam) after each action. Costs are accumulated in each step by extracting contextual features from the structure and the action. As the sentence gets longer, the number of partial structures generated at each steps grows exponentially, which makes it impossible to search all of the hypothesis. In practice, we usually use beam search instead.

(a) atomic features

<table>
<thead>
<tr>
<th></th>
<th>$s_0$.w</th>
<th>$s_0$.t</th>
<th>$s_1$.w</th>
<th>$s_1$.t</th>
<th>$s_{0,\text{lc}}$.t</th>
<th>$s_{0,\text{rc}}$.t</th>
<th>$q_0$.w</th>
<th>$q_0$.t</th>
</tr>
</thead>
</table>

(b) feature templates

<table>
<thead>
<tr>
<th></th>
<th>$s_0$.w</th>
<th>$s_0$.t</th>
<th>$s_1$.w</th>
<th>$s_1$.t</th>
<th>$q_0$.w</th>
<th>$q_0$.t</th>
</tr>
</thead>
<tbody>
<tr>
<td>unigram</td>
<td>$s_0$.w</td>
<td>$s_0$.t</td>
<td>$s_0$.w</td>
<td>$s_0$.t</td>
<td>$s_1$.w</td>
<td>$s_1$.t</td>
</tr>
<tr>
<td></td>
<td>$s_1$.w</td>
<td>$s_1$.t</td>
<td>$s_1$.w</td>
<td>$s_1$.t</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>$q_0$.w</td>
<td>$q_0$.t</td>
<td>$q_0$.w</td>
<td>$q_0$.t</td>
<td></td>
<td></td>
</tr>
<tr>
<td>bigram</td>
<td>$s_0$.w</td>
<td>$s_1$.w</td>
<td>$s_0$.w</td>
<td>$s_0$.t</td>
<td>$s_0$.w</td>
<td>$s_0$.t</td>
</tr>
<tr>
<td></td>
<td>$s_0$.t</td>
<td>$q_0$.t</td>
<td>$s_0$.w</td>
<td>$s_0$.t</td>
<td>$s_0$.w</td>
<td>$s_0$.t</td>
</tr>
<tr>
<td></td>
<td>$s_0$.w</td>
<td>$s_0$.t</td>
<td>$s_0$.w</td>
<td>$s_0$.t</td>
<td>$s_0$.w</td>
<td>$s_0$.t</td>
</tr>
<tr>
<td>trigram</td>
<td>$s_0$.t</td>
<td>$s_0$.t</td>
<td>$s_0$.t</td>
<td>$s_0$.t</td>
<td>$s_0$.t</td>
<td>$s_0$.t</td>
</tr>
<tr>
<td></td>
<td>$s_1$.t</td>
<td>$s_1$.t</td>
<td>$s_1$.t</td>
<td>$s_1$.t</td>
<td>$s_1$.t</td>
<td>$s_1$.t</td>
</tr>
</tbody>
</table>

(c) ← parsing stack | parsing queue →

Table 1: (a) atomic features, used for parsing signatures. (b): parsing feature templates, adapted from Huang and Sagae (2010). $x$.w and $x$.t denotes the root word and POS tag of the partial dependency tree, $x$.lc and $x$.rc denote $x$’s leftmost and rightmost child respectively. (c) the feature window.

2.2 Features

We view features as “abstractions” or (partial) observations of the current structure. Feature templates $f$ are functions that draw information from the feature window, consisting of current partial tree and first word to be processed. All Feature functions are listed in Table 1(b), which is a conjunction of atomic features in Table 1(a). To decide which action is the best of the current structure, we perform a three-way classification based on $f$, and conjoin these feature instances with each action:

$$[f \circ \text{action=sh/re}_\leftarrow/re\rightarrow]$$
We extract all the feature templates from training data, and use the average perceptron algorithm and early-update strategy (Collins and Roark, 2004; Huang et al., 2012) to train the model.

3 Incremental Tree-to-string Translation with SLM

The incremental tree-to-string decoding (Huang and Mi, 2010) performs translation in two separate steps: parsing and decoding. A parser first parses the source language input into a 1-best tree in Figure 2, and the linear incremental decoder then searches for the best derivation that generates a target-language string in strictly left-to-right manner. Figure 3 works out the full running example, and we describe it in the following section.

3.1 Decoding with SLM

Since the incremental tree-to-string model generates translation in strictly left-to-right fashion, and the shift-reduce dependency parser also processes an input sentence in left-to-right order, it is intuitive to combine them together. The last two columns in Figure 3 show the dependency structures for the corresponding hypotheses. Start at the root translation stack with a dot, before the root node IP:

\[ [. \text{IP}] \]

we first predict (pr) with rule $r_1$,

\[(r_1) \quad \text{IP} (x_1;\text{NP} \ x_2;\text{VP}) \rightarrow x_1 \ x_2,\]

and push its English-side to the translation stack, with variables replaced by matched tree nodes, here $x_1$ for NP and $x_2$ for VP. Since this translation action does not generate any translation string, we don’t perform any dependency parsing actions. So we have the following translation stack

\[ [. \text{IP}] [. \text{NP VP}],\]

where the dot . indicates the next symbol to process in the English word-order. Since node NP is the next symbol, we then predict with rule $r_2$,

\[(r_2) \quad \text{NP}(\text{Bushi}) \rightarrow \text{Bush},\]

and add it to the translation stack:

\[ [. \text{IP}] [. \text{NP VP}] [. \text{Bush}]\]

Since the symbol right after the dot in the top rule is a word, we scan (sc) it, and append it to the current translation, which results in the new translation stack

\[ [. \text{IP}] [. \text{NP VP}] [\text{Bush .}]\]

Immediately after each sc translation action, our shift-reduce parser is triggered. Here, our parser applies the parsing action $sh$, and shift “Bush” into a partial dependency structure $S_1$ as a root “Bush” (shaded
### Table: Simulation of the Integration of an SLM into an Incremental Tree-to-String Decoding

<table>
<thead>
<tr>
<th>Stack</th>
<th>String</th>
<th>Dependency Structure</th>
<th>SLM</th>
</tr>
</thead>
<tbody>
<tr>
<td>[. IP ]</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1 pr [. IP ] [. NP VP]</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2 pr [. IP ] [. NP VP ] [. Bush ]</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>3 sc [. IP ] [. NP VP] [Bush . ]</td>
<td>Bush</td>
<td>S₄: Bush held</td>
<td>P(Bush</td>
</tr>
<tr>
<td>4 co [. IP ] [NP . VP]</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>5 pr [. IP ] [NP . VP] [. held NP with NP]</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>6 sc [. IP ] [NP . VP] [held . NP with NP] held</td>
<td></td>
<td>S₅: Bush held</td>
<td>P(held</td>
</tr>
<tr>
<td>7 pr [. IP ] [NP, VP] [held, NP with NP] [. a meeting]</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>8 sc [. IP] [NP, VP] [held . NP with NP] [. a meeting ] [. a meeting]</td>
<td></td>
<td>S₇: Bush held a meeting</td>
<td>P(a meeting</td>
</tr>
<tr>
<td>9 co [. IP ] [NP, VP] [held NP . with NP]</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>10 sc [. IP] [NP, VP] [held NP with . NP] with</td>
<td></td>
<td>S₆: Bush held a meeting with</td>
<td>P(with</td>
</tr>
<tr>
<td>11 pr [. IP] [NP, VP] [held NP with . NP] [. Sharon]</td>
<td></td>
<td>S₈: Bush held a meeting with Sharon</td>
<td>P(Sharon</td>
</tr>
<tr>
<td>12 sc [. IP] [NP . VP] [held NP with . NP] [Sharon .] Sharon</td>
<td></td>
<td>S₁₁: Bush held a meeting with Sharon</td>
<td>P(Sharon</td>
</tr>
<tr>
<td>13 co [. IP] [NP . VP] [held NP with NP, ]</td>
<td></td>
<td>S₁₁: Bush held a meeting with Sharon</td>
<td>P'(Sharon</td>
</tr>
<tr>
<td>14 co [. IP ] [NP VP . ]</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>15 co [. IP .]</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

**Figure 3:** Simulation of the integration of an SLM into an incremental tree-to-string decoding. The first column is the line number. The second column shows the translation actions: predict (pr), scan (sc), and complete (co). $S_i$ denotes a dependency parsing structure. The shaded nodes are exposed roots of $S_i$.

Node (in Figure 3) Now the top rule on the translation stack has finished (dot is at the end), so we complete (co) it, pop the top rule and advance the dot in the second-to-top rule, denoting that NP is completed:

```
[. IP ] [NP . VP].
```

Following this procedure, we have a dependency structure $S₃$ after we scan (sc) the word “held” and take a shift (sh) and a left reduce (reₗ) parsing actions. The shaded node “held” means exposed roots, that the shift-reduce parser takes actions on.

Following Huang and Mi (2010), the hypotheses with same translation step\(^1\) fall into the same bin. Thus, only the prediction (pr) actions actually make a jump from a bin to another. Here line 2 to 4 fall into one bin (translation step = 4, as there are 4 nodes, IP, NP, VP and Bûshî, in the source tree are covered). Similarly, lines 7 to 10 fall into another bin (translation step = 15).

Noted that as we number the bins by the translation step, only pr actions make progress, the sc and co actions are treated as ”closure” operators in practice. Thus we always do as many sc/co actions as

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\(^1\)The step number is defined by the number of tree nodes covered in the source tree, and it is not equal to the number of translation actions taken so far.
possible immediately after a pr step until the symbol after the dot is another non-terminal. The total number of bins is equal to the size of the parse tree, and each hypothesis has a constant number of outgoing hyper-edges to predict, so the time complexity is linear in the sentence length.

After adding our SLM to this translation, an interesting branch occurs after we scan the word “with”, we have two different partial dependency structures $S_8$ and $S'_8$ for the same translation. If we denote $N(S_i)$ as the number of re actions that $S_i$ takes, $N(S_8)$ is 3, while $N(S'_8)$ is 4. Here $N(S_i)$ does not take into account the number of $\&$h parsing actions, since all partial structures with same translations should shift the same number of translations. Thus, $N(S_i)$ determines the score of dependency structures, and only the hypotheses with same $N(S_i)$ are comparable to each other. In this case, we should distinguish $S_8$ with $S'_8$, and if we make a prediction over the hypothesis of $S_8$, we can reach the correct parsing state $S_{11}$ (shown in the red dashed line in Figure 3).

So the key problem of our integration is that, after each translation step, we will apply different sequences of parsing actions, which result in different and incomparable dependency structures with the same translation. In the following two Sections, we introduce three ways for this integration.

### 3.2 Na"ive: Adding Parsing Signatures into Translation Signatures

One straightforward approach is to add the parsing signatures (in Figure 1) of each dependency structure (in Figure 1 and Figure 3) to translation signatures. Here, we only take into account of the $s_0$ and $s_1$ in the parsing stack, as the $q_0$ is the future word that is not available in translation strings. For example, the dependency structure $S_8$ has parsing signatures:

```
held
```
```
Bush meeting
```

We add those information to its translation signature, and only the hypothesis that have same translation and parsing signatures can be recombined.

So, in each translation bin, different dependency structures with same translation strings are treated as different hypothesis, and all the hypothesis are sorted and ranked in the same way. For example, $S_8$ and $S'_8$ are compared in the bin, and we only keep top $b$ (the beam size) hypothesis for each bin.

Obviously, this simple approach suffers from the incomparable problem for those hypothesis that have different number of parsing actions (e.g. $S_8$ and $S'_8$). Moreover, it may result in very low translation variance in each beam.

### 3.3 Best-parse: Keeping the Best Dependency Structure for Each Translation

Following Hassan et al. (2009), we only keep the best parsing tree for each translation. That means after a consecutive translation $\&$c actions, our shift-reduce parser applies all the possible parsing actions, and generates a set of new partial dependency structures. Then we only choose the best one with the highest SLM score, and only use this dependency structure for future predictions.

For example, for the translation in line 10 in Figure 3, we only keep $S_8$, if the parsing score of $S_8$ is higher than $S'_8$, although they are not comparable. Another complicate example is shown in Figure 4, within the translation step 15, there are many alternatives with different parsing structures for the same translation (“a meeting with”) in the third column, but we can only choose the top one in the final.

### 3.4 Grouping: Regrouping Hypothesis by $N(S)$ in Each Bin

In order to do comparable sorting and pruning, our basic idea is to regroup those hypotheses in a same bin into small groups by $N(S)$. For each translation, we first apply all the possible parsing actions, and generate all dependency structures. Then we regroup all the hypothesis with different dependency structures based on the size of $N(S)$.

For example, Figure 4 shows two bins with two different translation steps (15 and 16). In bin 15, the graph shows the parsing movements after we scan three new words (“a”, “meeting”, and “with”). The parsing $\&$h action happens from a parsing state in one column to another state in the next column, while
Figure 4: Multi-beam structures of two bins with different translation steps (15 and 16). The first three columns show the parsing movements in bin 15. Each dashed box is a group based on the number of reduce actions over the new translation strings (“a meeting with” for bin 15, and “Sharon” for bin 16). $G_2$ means two reduce actions have been applied. After this regrouping, we perform the pruning in two phases: 1) keep top $b$ states in each group, and labeled each group with the state with the highest parsing score in this group; 2) sort the different groups, and keep top $g$ groups.

re happens from a state to another state in the same column. The third column in bin 15 lists some partial dependency structures that have all new words parsed. Here each dashed box is a group of hypothesis with a same $N(S)$, e.g. the $G_2$ contains all the dependency structures that have two reduce actions after parsed all the new words. Then, we sort and prune each group by the beam size $b$, and each group labeled as the highest hypothesis in this group. Finally, we sort those groups and only keep top $g$ groups for the future predictions. Again, in Figure 4, we can keep the whole group $G_3$ and partial group of $G_2$ if $b = 2$.

In our experiments, we set the group size $g$ to 5.

### 3.5 Log-linear Model

We integrate our dependency parser into the log-linear model as an additional feature. So the decoder searches for the best translation $e^*$ with a latent tree structure (evaluated by our $S_{LM}$) according to the following equation:

$$
    e^* = \arg\max_{e \in E} \exp(S_{LM}(e) \cdot w_s + \sum_i f_i \cdot w_i)
$$

where $S_{LM}(e)$ is the dependency parsing score calculated by our parser, $w_s$ is the weight of $S_{LM}(e)$, $f_i$ are the features in the baseline model and $w_i$ are the weights.
4 Experiments

4.1 Data Preparation

The training corpus consists of 1.5M sentence pairs with 38M/32M words of Chinese/English, respectively. We use the NIST evaluation sets of MT06 as our development set, and MT03, 04, 05, and 08 (newswire portion) as our test sets. We word-aligned the training data using GIZA++ with refinement option “grow-diag-and” (Koehn et al., 2003), and then parsed the Chinese sentences using the Berkeley parser (Petrov and Klein, 2007). We applied the algorithm of Galley et al. (2004) to extract tree-to-string translation rules. Our trigram word language model was trained on the target side of the training corpus using the SRILM toolkit (Stolcke, 2002) with modified Kneser-Ney smoothing. At decoding time, we again parse the input sentences using the Berkeley parser, and convert them into translation forests using rule pattern-matching (Mi et al., 2008).

Our baseline system is the incremental tree-to-string decoder of Huang and Mi (2010). We use the same feature set shown in Huang and Mi (2010), and tune all the weights using minimum error-rate training (Och, 2003) to maximize the BLEU score on the development set.

Our dependency parser is an implementation of the “arc-standard” shift-reduce parser (Nivre, 2004), and it is trained on the standard split of English Penn Treebank (PTB): Sections 02-21 as the training set, Section 22 as the held-out set, and Section 23 as the test set. Using the same features as Huang and Sagae (2010), our dependency parser achieves a similar performance as Huang and Sagae (2010). We add the structured language model as an additional feature into the baseline system.

We evaluate translation quality using case-insensitive IBM BLEU-4, calculated by the script mteval-v13a.pl. We also report the TER scores.

4.2 Complete Comparisons on MT08

To explore the soundness of our approach, we carry out some experiments in Table 2. With a beam size 100, the baseline decoder achieves a BLEU score of 21.06 with a speed of 1.7 seconds per sentence.

Since our dependency parser is trained on the English PTB, which is not included in the MT training set, there is a chance that the gain of BLEU score is due to the increase of new n-grams in the PTB data. In order to rule out this possibility, we use the tool SRILM to train another tri-gram language model on English PTB and use it as a secondary language model for the decoder. The BLEU score is 21.10, which is similar to the baseline result. Thus we can conclude that any gain of the following +SLM experiments is not because of the using of the additional English PTB.

Our second experiment re-ranks the 100-best translations of the baseline with our structured language model trained on PTB. The improvement is less than 0.2 BLEU, which is not statistically significant, as the search space for re-ranking is relatively small compared with the decoding space.

As shown in Section 3, we have three different ways to integrate an SLM to the baseline system:

- **naïve**: adding the parsing signature to the translation signature;
- **best-parse**: keeping the best dependency structure for each translation;
- **grouping**: regrouping the hypothesis by \( N(S) \) in each bin.

The naïve approach achieves a BLEU score of 19.12, which is significantly lower than the baseline. The main reason is that adding parsing signatures leads to very restricted translation variance in each beam. We also tried to increase the beam size to 1000, but we do not see any improvement.

The fourth line in Table 2 shows the result of the best-parse (Hassan et al., 2009). This approach only slows the speed by a factor of two, but the improvement is not statistically significant. We manually looked into some dependency trees this approach generates, and found this approach always introduce local parsing errors.

The last line shows our efficient beam grouping scheme with a grouping size 5, it achieves a significant improvement with an acceptable speed, which is about 6 times slower than the baseline system.
<table>
<thead>
<tr>
<th>System</th>
<th>BLEU</th>
<th>Speed</th>
</tr>
</thead>
<tbody>
<tr>
<td>baseline</td>
<td>21.06</td>
<td>1.7</td>
</tr>
<tr>
<td>+SLM</td>
<td></td>
<td></td>
</tr>
<tr>
<td>re-ranking</td>
<td>21.23</td>
<td>1.73</td>
</tr>
<tr>
<td>naïve</td>
<td>19.12</td>
<td>2.6</td>
</tr>
<tr>
<td>best-parse</td>
<td>21.30</td>
<td>3.4</td>
</tr>
<tr>
<td>grouping (g=5)</td>
<td>21.64</td>
<td>10.6</td>
</tr>
</tbody>
</table>

Table 2: Results on MT08. The bold score is significantly better than the baseline result at level $p < 0.05$.

<table>
<thead>
<tr>
<th>System</th>
<th>MT03</th>
<th>MT04</th>
<th>MT05</th>
<th>MT08</th>
<th>Avg.</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>BLEU</td>
<td>(T-B)/2</td>
<td>BLEU</td>
<td>(T-B)/2</td>
<td>BLEU</td>
</tr>
<tr>
<td>baseline</td>
<td>19.94</td>
<td>10.73</td>
<td>22.03</td>
<td>18.63</td>
<td>19.92</td>
</tr>
<tr>
<td>+SLM</td>
<td><strong>21.49</strong></td>
<td><strong>9.44</strong></td>
<td>22.33</td>
<td>18.38</td>
<td><strong>20.51</strong></td>
</tr>
</tbody>
</table>

Table 3: Results on all test sets. Bold scores are significantly better than the baseline system ($p < 0.5$).

4.3 Final Results on All Test Sets

Table 3 shows our main results on all test sets. Our method gains an average improvement of 0.7 points in terms of (T-B)/2. Results on NIST MT 03, 05, and 08 are statistically significant with $p < 0.05$, using bootstrap re-sampling with 1000 samples (Koehn, 2004). The average decoding speed is about 10 times slower than the baseline.

5 Related Work

The work of Schwartz et al. (2011) is similar in spirit to ours. We are different in the following ways. First, they integrate an SLM into a phrase-based system (Koehn et al., 2003), we pay more attention to a syntax-based system. Second, their approach slowdowns the speed at near 2000 times, thus, they can only tune their system on short sentences less than 20 words. Furthermore, their results are from a much bigger beam (10 times larger than their baseline), so it is not clear which factor contributes more, the larger beam size or the SLM. In contrast, our approach gains significant improvements over a state-of-the-art tree-to-string baseline at a reasonable speed, about 6 times slower. And we answer some questions beyond their work.

Hassan et al. (2009) incorporate a linear-time CCG parser into a DTM system, and achieve a significant improvement. Different from their work, we pay more attention to the dependency parser, and we also test this approach in our experiments. As they only keep 1-best parsing states during the decoding, they are suffering from the local parsing errors.

Galley and Manning (2009) adapt the maximum spanning tree (MST) parser of McDonald et al. (2005) to an incremental dependency parsing, and incorporate it into a phrase-based system. But this incremental parser remains in quadratic time.

Besides, there are also some other efforts that are less closely related to ours. Shen et al. (2008) and Mi and Liu (2010) develop a generative dependency language model for string-to-dependency and tree-to-tree models. But they need parse the target side first, and encode target syntactic structures in translation rules. Both papers integrate dependency structures into translation model, we instead model the dependency structures with a monolingual parsing model over translation strings.

6 Conclusion

In this paper, we presented an efficient algorithm to integrate a structured language model (an incremental shift-reduce parser in specific) into an incremental tree-to-string system. We calculate the structured language model scores incrementally at the decoding step, rather than re-scoring a complete translation. Our experiments suggest that it is important to design efficient pruning strategies, which have been
overlooked in previous work. Experimental results on large-scale data set show that our approach significantly improves the translation quality at a reasonable slower speed than a state-of-the-art tree-to-string system.

The structured language model introduced in our work only takes into account the target string, and ignores the reordering information in the source side. Thus, our future work seeks to incorporate more source side syntax information to guide the parsing of the target side, and tune a structured language model for both BLEU and parsing accuracy. Another potential work lies in the more efficient searching and pruning algorithms for integration.

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