Advancements in Reordering Models for Statistical Machine Translation

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Abstract

In this paper, we propose a novel reordering model based on sequence labeling techniques. Our model converts the reordering problem into a sequence labeling problem, i.e. a tagging task. Results on five Chinese-English NIST tasks show that our model improves the baseline system by 1.32 BLEU and 1.53 TER on average. Results of comparative study with other seven widely used reordering models will also be reported.

1 Introduction

The systematic word order difference between two languages poses a challenge for current statistical machine translation (SMT) systems. The system has to decide in which order to translate the given source words. This problem is known as the reordering problem. As shown in (Knight, 1999), if arbitrary reordering is allowed, the search problem is NP-hard.

Many ideas have been proposed to address the reordering problem. Within the phrase-based SMT framework there are mainly three stages where improved reordering could be integrated:

In the preprocessing: the source sentence is reordered by heuristics, so that the word order of source and target sentences is similar. (Wang et al., 2007) use manually designed rules to reorder parse trees of the source sentences. Based on shallow syntax, (Zhang et al., 2007) use rules to reorder the source sentences on the chunk level and provide a source-reordering lattice instead of a single reordered source sentence as input to the SMT system. Designing rules to reorder the source sentence is conceptually clear and usually easy to implement. In this way, syntax information can be incorporated into phrase-based SMT systems. However, one disadvantage is that the reliability of the rules is often language pair dependent.

In the decoder: we can add ***constraints*** or ***models*** into the decoder to reward good reordering options or penalize bad ones. For reordering constraints, early work includes ITG constraints (Wu, 1995) and IBM constraints (Berger et al., 1996). (Zens and Ney, 2003) did comparative study over different reordering constraints. This paper focuses on reordering models. For reordering models, we can further roughly divide the existing methods into three genres:

- *The reordering is a classification problem.* The classifier will make decision on next phrase's relative position with current phrase. The classifier can be trained with maximum likelihood like Moses lexicalized reordering (Koehn et al., 2007) and hierarchical lexicalized reordering model (Galley and Manning, 2008) or be trained under maximum entropy framework (Zens and Ney, 2006).
- *The reordering is a decoding order problem.* (Mariño et al., 2006) present a translation model that constitutes a language model of a sort of bilanguage composed of bilingual units. From the reordering point of view, the idea is that the correct reordering is a suitable order of translation units. (Feng et al., 2010) present a simpler version of (Mariño et al., 2006)'s model which utilize only source words to model the decoding order.
- *The reordering can be solved by outside heuristics.* We can put human knowledge into the decoder. For example, the simple jump model using linear distance tells the decoder that usually the long range reordering should be avoided. (Cherry, 2008) uses information from dependency trees to make the decoding process keep syntactic cohesion. (Feng et al., 2012) present a method that utilizes predicate-argument structures from semantic role labeling results as soft constraints.

In the reranking framework: in principle, all

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the models in previous category can be used in the reranking framework, because in the reranking we have all the information (source and target words/phrases, alignment) about the translation process. (Och et al., 2004) describe the use of syntactic features in the rescoring step. However, they report the syntactic features contribute very small gains. One disadvantage of carrying out reordering in reranking is the representativeness of the N-best list is often a question mark.

In this paper, we propose a novel tagging style reordering model which is under the category *"The reordering is a decoding order problem"*. Our model converts the decoding order problem into a sequence labeling problem, i.e. a tagging task. The remainder of this paper is organized as follows: Section 2 introduces the basement of this research: the principle of statistical machine translation. Section 3 describes the proposed model. Section 4 briefly describes several reordering models with which we compare our method. Section 5 provides the experimental configuration and results. Conclusion will be given in Section 6.

2 Translation System Overview

In statistical machine translation, we are given a source language sentence $f_1^J = f_1 \dots f_j \dots f_J$. The objective is to translate the source into a target language sentence $e_1^I = e_1 \dots e_i \dots e_I$. The strategy is to choose the target sentence with the highest probability among all others:

$$\hat{e}_i^{\hat{I}} = \arg\max_{I, e_1^I} \{Pr(e_1^I | f_1^J)\} \tag{1}$$

We model $Pr(e_1^I|f_1^J)$ directly using a log-linear combination of several models (Och and Ney, 2002):

$$Pr(e_1^I|f_1^J) = \frac{\exp\Big(\sum\limits_{m=1}^{M} \lambda_m h_m(e_1^I, f_1^J)\Big)}{\sum\limits_{I', {e'}_1^{I'}} \exp\Big(\sum\limits_{m=1}^{M} \lambda_m h_m({e'}_1^{I'}, f_1^J)\Big)} \tag{2}$$

The denominator is to make the $Pr(e_1^I|f_1^J)$ to be a probability distribution and it depends only on the source sentence f_1^J. For search, the decision rule is simply:

$$\hat{e}_i^{\hat{I}} = \arg\max_{I, e_1^I} \Big\{ \sum_{m=1}^{M} \lambda_m h_m(e_1^I, f_1^J) \Big\} \tag{3}$$

The model scaling factors λ_1^M are trained with Minimum Error Rate Training (MERT). In this paper, the phrase-based machine translation system is utilized (Och et al., 1999; Zens et al., 2002; Koehn et al., 2003).

3 Tagging-style Reordering Model

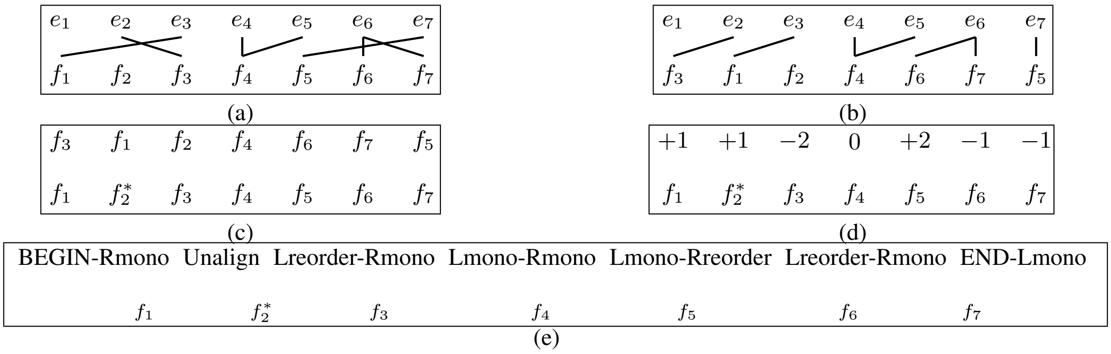
In this section, we describe the proposed novel model. First we will describe the training process. Then we explain how to use the model in the decoder.

3.1 Modeling

Figure 1 shows the modeling steps. The first step is word alignment training. Figure 1(a) is an example after GIZA++ training. If we regard this alignment as a translation result, i.e. given the source sentence f_1^7, the system translates it into the target sentence e_1^7, then the alignment link set $\{a_1 = 3, a_3 = 2, a_4 = 4, a_4 = 5, a_5 = 7, a_6 = 6, a_7 = 6\}$ reveals the decoding process, i.e. the alignment implies the order in which the source words should be translated, e.g. the first generated target word e_1 has no alignment, we can regard it as a translation from a NULL source word; then the second generated target word e_2 is translated from f_3. We reorder the source side of the alignment to get Figure 1(b). Figure 1(b) implies the source sentence decoding sequence information, which is depicted in Figure 1(c). Using this example we describe the strategies we used for special cases in the transformation from Figure 1(b) to Figure 1(c):

- ignore the unaligned target word, e.g. e_1
- the unaligned source word should follow its preceding word, the unaligned feature is kept with a $*$ symbol, e.g. f_2^* is after f_1
- when one source word is aligned to multiple target words, only keep the alignment that links the source word to the first target word, e.g. f_4 is linked to e_5 and e_6, only $f_4 - e_5$ is kept. In other words, we use this strategy to guarantee that every source word appears only once in the source decoding sequence.
- when multiple source words are aligned to one target word, put together the source words according to their original relative positions, e.g. e_6 is linked to f_6 and f_7. So in the decoding sequence, f_6 is before f_7.

Now Figure 1(c) shows the original source sentence and its decoding sequence. By using the strategies above, it is guaranteed that the source sentence and its decoding sequence have the ex-



(a)
e_1 e_2 e_3 e_4 e_5 e_6 e_7
f_1 f_2 f_3 f_4 f_5 f_6 f_7
(b)
e_1 e_2 e_3 e_4 e_5 e_6 e_7
f_3 f_1 f_2 f_4 f_6 f_7 f_5
(c)
f_3 f_1 f_2 f_4 f_6 f_7 f_5
f_1 f_2^* f_3 f_4 f_5 f_6 f_7
(d)
$+1$ $+1$ -2 0 $+2$ -1 -1
f_1 f_2^* f_3 f_4 f_5 f_6 f_7
(e)
BEGIN-Rmono Unalign Lreorder-Rmono Lmono-Rmono Lmono-Rreorder Lreorder-Rmono END-Lmono
f_1 f_2^* f_3 f_4 f_5 f_6 f_7

Figure 1: modeling process illustration.

actly same length. Hence the relation can be modeled by a function $F(f)$ which assigns a value for each source word f. Figure 1(d) manifests this function. The positive function values mean that compared to the original position in the source sentence, its position in the decoding sequence should move rightwards. If the function value is 0, the word's position in original source sentence and its decoding sequence is same. For example, f_1 is the first word in the source sentence but it is the second word in the decoding sequence. So its function value is $+1$ (move rightwards one position).

Now Figure 1(d) converts the reordering problem into a sequence labeling or tagging problem. To make the computational cost to a reasonable level, we do a final step simplification in Figure 1(e). Suppose the longest sentence length is 100, then according to Figure 1(d), there are 200 tags (from -99 to +99 plus the unalign tag). As we will see later, this number is too large for our task. We instead design nine tags. For a source word f_j in one source sentence f_1^J, the tag of f_j will be one of the following:

Unalign f_j is an unaligned source word

BEGIN-Rmono $j = 1$ and f_{j+1} is translated *after* f_j (Rmono for right monotonic)

BEGIN-Rreorder $j = 1$ and f_{j+1} is translated *before* f_j (Rreorder for right reordered)

END-Lmono $j = J$ and f_{j-1} translated *before* f_j (Lmono for left monotonic)

END-Lreorder $j = J$ and f_{j-1} translated *after* f_j (Lreorder for left reordered)

Lmono-Rmono $1 < j < J$ and f_{j-1} translated *before* f_j and f_j translated *before* f_{j+1}

Lreorder-Rmono $1 < j < J$ and f_{j-1} translated *after* f_j and f_j translated *before* f_{j+1}

Lmono-Rreorder $1 < j < J$ and f_{j-1} translated *before* f_j and f_j translated *after* f_{j+1}

Lreorder-Rreorder $1 < j < J$ and f_{j-1} translated *after* f_j and f_j translated *after* f_{j+1}

Up to this point, we have converted the reordering problem into a tagging problem with nine tags. The transformation in Figure 1 is conducted for all the sentence pairs in the bilingual training corpus. After that, we have built an "annotated" corpus for the training. For this supervised learning task, we choose the approach conditional random fields (CRFs) (Lafferty et al., 2001; Sutton and Mccallum, 2006; Lavergne et al., 2010) and recurrent neural network (RNN) (Elman, 1990; Jordan, 1990; Lang et al., 1990).

For the first method, we adopt the linear-chain CRFs. However, even for the simple linear-chain CRFs, the complexity of learning and inference grows quadratically with respect to the number of output labels and the amount of structural features which are with regard to adjacent pairs of labels. Hence, to make the computational cost as low as possible, two measures have been taken. Firstly, as described above we reduce the number of tags to nine. Secondly, we add source sentence part-of-speech (POS) tags to the input. For features with window size one to three, both source words and its POS tags are used. For features with window size four and five, only POS tags are used.

As the second method, we use recurrent neural network (RNN). RNN is closely related with Multilayer Perceptrons (MLP) (Rumelhart et al., 1986), but the output of one ore more hidden layers is reused as additional inputs for the network in the next time step. This structure allows the RNN to learn whole sequences without restricting itself to a fixed input window. A plain RNN has only access to the previous events in the input sequence. Hence we adopt the bidirectional RNN (BRNN) (Schuster and Paliwal, 1997) which reads the input sequence from both directions before making the prediction. The long short-term memory (LSTM) (Hochreiter and Schmidhuber, 1997) is applied to counter the effects that long distance dependencies are hard to learn with gradient descent. This is often referred to as vanishing gradient problem (Bengio et al., 1994).

3.2 Decoding

Once the model training is finished, we make inference on develop and test corpora which means that we get the labels of the source sentences that need to be translated. In the decoder, we add a new model which checks the labeling consistency when scoring an extended state. During the search, a sentence pair (f_1^J, e_1^I) will be formally splitted into a segmentation S_1^K which consists of K phrase pairs. Each $s_k = (i_k; b_k, j_k)$ is a triple consisting of the last position i_k of the kth target phrase $\tilde{e}_k$. The start and end position of the kth source phrase $\tilde{f}_k$ are b_k and j_k. Suppose the search state is now extended with a new phrase pair $(\tilde{f}_k, \tilde{e}_k)$: $\tilde{f}_k := f_{b_k} \ldots f_{j_k}$ and $\tilde{e}_k := e_{i_{k-1}+1} \ldots e_{i_k}$. We have access to the old coverage vector, from which we know if the new phrase's left neighboring source word f_{b_k-1} and right neighboring source word f_{j_k+1} have been translated. We also have the word alignment within the new phrase pair, which is stored during the phrase extraction process. Based on the old coverage vector and alignment, we can repeat the transformation in Figure 1 to calculate the labels for the new phrase. The added model will then check the consistence between the calculated labels and the labels predicted by the reordering model. The number of source words that have inconsistent labels is the penalty and is then added into the log-linear framework as a new feature.

4 Comparative Study

The second part of this paper is comparative study on reordering models. Here we briefly describe those models which will be compared to later.

4.1 Moses lexicalized reordering model

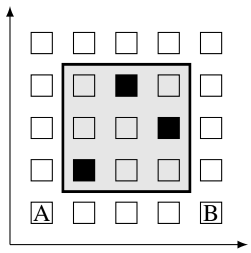


Figure 2: lexicalized reordering model illustration.

Moses (Koehn et al., 2007) contains a word-based orientation model, which has three types of reordering: (m) monotone order, (s) switch with previous phrase and (d) discontinuous. Figure 2 is an example. The definitions of reordering types are as follows:

monotone for current phrase, if a word alignment to the bottom left (point A) exists and there is no word alignment point at the bottom right position (point B) .

swap for current phrase, if a word alignment to the bottom right (point B) exists and there is no word alignment point at the bottom left position (point A) .

discontinuous all other cases

Our implementation is same with the default behavior of Moses lexicalized reordering model. We count how often each extracted phrase pair is found with each of the three reordering types. The add-0.5 smoothing is then applied. Finally, the probability is estimated with maximum likelihood principle.

4.2 Maximum entropy reordering model

Figure 3 is an illustration of (Zens and Ney, 2006) . j is the source word position which is aligned to the last target word of the current phrase. $j^{'}$ is the last source word position of the current phrase. $j^{''}$ is the source word position which is aligned to the first target word position of the next phrase. (Zens and Ney, 2006) proposed a maximum entropy classifier to predict the orientation of the next phrase given the current phrase. The orientation class $c_{j,j^{'},j^{''}}$ is defined as:

$$c_{j,j^{'},j^{''}} = \begin{cases} \text{left,} & \text{if } j^{''} < j \\ \text{right,} & \text{if } j^{''} > j \text{ and } j'' - j' > 1 \\ \text{monotone,} & \text{if } j^{''} > j \text{ and } j'' - j' = 1 \end{cases} \tag{4}$$

The orientation probability is modeled in a log-linear framework using a set of N feature functions $h_n(f_1^J, e_1^I, i, j, c_{j,j^{'},j^{''}})$, $n = 1, \ldots, N$. The whole model is:

$$p_{\lambda_1^N}(c_{j,j^{'},j^{''}} | f_1^J, e_1^I, i, j) = \frac{\exp(\sum_{n=1}^{N} \lambda_n h_n(f_1^J, e_1^I, i, j, c_{j,j^{'},j^{''}}))}{\sum_{c^{'}} \exp(\sum_{n=1}^{N} \lambda_n h_n(f_1^J, e_1^I, i, j, c^{'}))} \tag{5}$$

Different features can be used, we use the source and target word features to train the model.

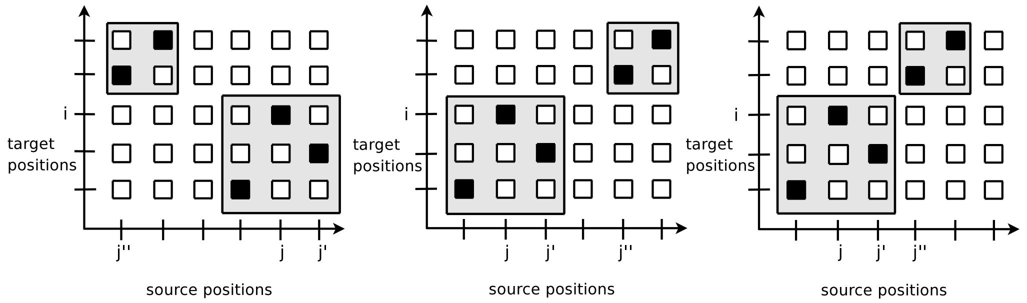


Figure 3: phrase orientation: left, right and monotone. j is the source word position aligned to the last target word of current phrase. $j^{'}$ is the last source word position of current phrase. $j^{''}$ is the source word position aligned to the first target word position of the next phrase.

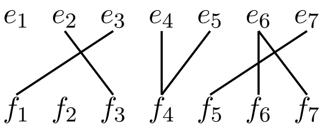

e_1 e_2 e_3 e_4 e_5 e_6 e_7
f_1 f_2 f_3 f_4 f_5 f_6 f_7

Figure 4: bilingual LM illustration. The bilingual sequence is e_1-, e_2-f_3 , e_3-f_1 , e_4-f_4 , e_5-f_4 , e_6-f_6-f_7 , e_7-f_5 .

4.3 Bilingual LM

The previous two models belong to *“The reordering is a classification problem”*. Now we turn to *“The reordering is a decoding order problem”*. (Mariño et al., 2006) implement a translation model using n-grams. In this way, the translation system can take full advantage of the smoothing and consistency provided by standard back-off n-gram models. Figure 4 is an example. The interpretation is that given the sentence pair (f_1^7, e_1^7) and its alignment, the correct translation order is e_1-, e_2-f_3 , e_3-f_1 , e_4-f_4 , e_5-f_4 , e_6-f_6-f_7 , e_7-f_5 . Notice the bilingual units have been ordered according to the target side, as the decoder writes the translation in a left-to-right way. Using the example we describe the strategies used for special cases:

- keep the unaligned target word, e.g. e_1-
- remove the unaligned source word, e.g. f_2
- when one source word aligned to multiple target words, duplicate the source word for each target word, e.g. e_4-f_4 , e_5-f_4
- when multiple source words aligned to one target word, put together the source words for that target word, e.g. e_6-f_6-f_7

After the operation in Figure 4 was done for all bilingual sentence pairs, we get a decoding sequence corpus. We build a 9-gram LM using SRILM toolkit (Stolcke, 2002) with modified Kneser-Ney smoothing.

The model is added as an additional feature in Equation (2). To use the bilingual LM, the search state must be augmented to keep the bilingual unit decoding sequence. In search, the bilingual LM is applied similar to the standard target side LM. The bilingual sequence of phrase pairs will be extracted using the same strategy in Figure 4 . Suppose the search state is now extended with a new phrase pair $(\tilde{f}, \tilde{e})$. $\tilde{F}$ is the bilingual sequence for the new phrase pair $(\tilde{f}, \tilde{e})$ and $\tilde{F}^i$ is the i^{th} unit within $\tilde{F}$. $\tilde{F}^{'}$ is the bilingual sequence history for current state. We compute the feature score $h_{bilm}(\tilde{F}, \tilde{F}^{'})$ of the extended state as follows:

$$h_{bilm}(\tilde{F}, \tilde{F}^{'}) = \lambda \cdot \sum_{i=1}^{|\tilde{F}|} \log p(\tilde{F}^i | \tilde{F}^{'}, \tilde{F}^1, \cdots, \tilde{F}^{i-1}) \tag{6}$$

λ is the scaling factor for this model. $|\tilde{F}|$ is the length of the bilingual decoding sequence.

4.4 Source decoding sequence LM

(Feng et al., 2010) present an simpler version of the above bilingual LM where they use only the source side to model the decoding order. The source word decoding sequence in Figure 4 is then f_3 , f_1 , f_2 , f_4 , f_6 , f_7 , f_5 . We also build a 9-gram LM based on the source word decoding sequences. The usage of the model is same as bilingual LM.

4.5 Syntactic cohesion model

The previous two models belong to *“The reordering is a decoding order problem”*. Now we turn to *“The reordering can be solved by outside heuristics”*. (Cherry, 2008) proposed a syntactic cohesion model. The core idea is that the syntactic structure of the source sentence should be preserved during translation. This structure is represented by a source sentence dependency tree. The algorithm is as follows: given the source sentence and its dependency tree, during the translation process, once a hypothesis is extended, check if the source dependency tree contains a subtree T such that:

- Its translation is already started (at least one node is covered)
- It is interrupted by the new added phrase (at least one word in the new source phrase is not in T)
- It is not finished (after the new phrase is added, there is still at least one free node in T)

If so, we say this hypothesis violates the subtree T, and the model returns the number of subtrees that this hypothesis violates.

4.6 Semantic cohesion model

(Feng et al., 2012) propose two structure features from semantic role labeling (SRL) results. Similar to the previous model, the SRL information is used as soft constraints. During decoding process, the first feature will report how many event layers that one search state violates and the second feature will report the amount of semantic roles that one search state violates. In this paper, the two features have been used together. So when the semantic cohesion model is used, both features will be triggered.

4.7 Tree-based jump model

(Wang et al., 2007) present a pre-reordering method for Chinese-English translation task. In Section 3.6 of (Zhang, 2013), instead of doing hard reordering decision, the author uses the rules as soft constraints in the decoder. In this paper, we use the similar method as described in (Zhang, 2013). Our strategy is: firstly, we parse the source sentences to get constituency trees. Then we manipulate the trees using heuristics described by (Wang et al., 2007) . The leaf nodes in the revised tree constitute the reordered source sentence. Finally, in the log-linear framework (Equation 2) a new jump model is added which uses the reordered source sentence to calculate the cost. For example, the original sentence $f_1f_2f_3f_4f_5$ is now converted by rules into the new sentence $f_1f_5f_3f_2f_4$. For decoding, we still use the original sentence. Suppose previously translated source phrase is f_1 and the current phrase is f_5 . Then the standard jump model gives cost $q_{Dist} = 4$ and the new tree-based jump model will return a cost $q_{Dist\_new} = 1$.

5 Experiments

In this section, we describe the baseline setup, the CRFs training results, the RNN training results and translation experimental results.

5.1 Experimental Setup

Our baseline is a phrase-based decoder, which includes the following models: an n-gram target-side language model (LM), a phrase translation model and a word-based lexicon model. The latter two models are used for both directions: $p(f|e)$ and $p(e|f)$. Additionally we use phrase count features, word and phrase penalty. The reordering model for the baseline system is the distance-based jump model which uses linear distance. This model does not have hard limit. We list the important information regarding the experimental setup below. All those conditions have been kept same in this work.

- lowercased training data from the GALE task (Table 1, UN corpus not included)
  alignment trained with GIZA++
- tuning corpus: NIST06
  test corpora: NIST02 03 04 05 and 08
- 5-gram LM (1 694 412 027 running words) trained by SRILM toolkit (Stolcke, 2002) with modified Kneser-Ney smoothing
  training data: target side of bilingual data.
- BLEU (Papineni et al., 2001) and TER (Snover et al., 2005) reported
  all scores calculated in lowercase way.
- Wapiti toolkit (Lavergne et al., 2010) used for CRFs; RNN is built by the RNNLIB toolkit.

	Chinese	**English**
Sentences	5 384 856	
Running Words	115 172 748	129 820 318
Vocabulary	1 125 437	739 251

Table 1: translation model and LM training data statistics

Table 1 contains the data statistics used for translation model and LM. For the reordering model, we take two further filtering steps. Firstly, we delete the sentence pairs if the source sentence length is one. When the source sentence has only one word, the translation will be always monotonic and the reordering model does not need to learn this. Secondly, we delete the sentence pairs if the source sentence contains more than three contiguous unaligned words. When this happens, the sentence pair is usually low quality hence not suitable for learning. The main purpose of the two filtering steps is to further lay down the computational burden. The label distribution is depicted in Figure 5. We can see that most words are monotonic. We then divide the corpus to three parts:

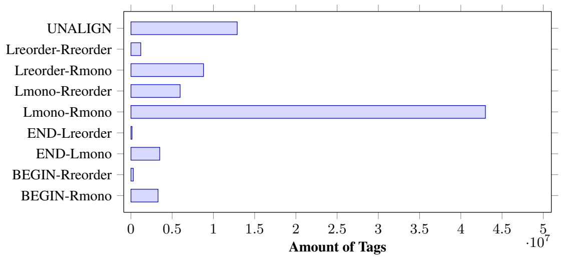


Figure 5: Tags distribution illustration.

train, validation and test. The source side data statistics for the reordering model training is given in Table 2 (target side has only nine labels).

	train	validation	test
Sentences	2 973 519	400 000	400 000
Running Words	62 263 295	8 370 361	8 382 086
Vocabulary	454 951	149686	150 007

Table 2: tagging-style model training data statistics

5.2 CRFs Training Results

The toolkit Wapiti (Lavergne et al., 2010) is used in this paper. We choose the classical optimization algorithm limited memory BFGS (L-BFGS) (Liu and Nocedal, 1989). For regularization, Wapiti uses both the ℓ^1 and ℓ^2 penalty terms, yielding the elastic-net penalty of the form

$$\rho_1 \cdot \parallel \theta \parallel_1 + \frac{\rho_2}{2} \cdot \parallel \theta \parallel_2^2 \tag{7}$$

In this work, we use as many features as possible because ℓ^1 penalty $\rho_1 \parallel \theta \parallel_1$ is able to yield sparse parameter vectors, i.e. using a ℓ^1 penalty term implicitly performs the feature selection. The computational costs are given here: on a cluster with two AMD Opteron(tm) Processor 6176 (total 24 cores), the training time is about 16 hours, peak memory is around 120G. Several experiments have been done to find the suitable hyperparameter ρ_1 and ρ_2, we choose the model with lowest error rate on validation corpus for translation experiments. The error rate of the chosen model on test corpus (the test corpus in Table 2) is 25.75% for token error rate and 69.39% for sequence error rate. Table 3 is the feature template we set initially which generates 722 999 637 features. Some examples are given in Table 4. After training 36 902 363 features are kept.

Feature Templates
1-gram source word features
x[-4,0], x[-3,0], x[-2,0], x[-1,0]
x[0,0], x[1,0], x[2,0], x[3,0], x[4,0]
1-gram source POS features
x[-4,1], x[-3,1], x[-2,1], x[-1,1]
x[0,1], x[1,1], x[2,1], x[3,1], x[4,1]
2-gram source word features
x[-1,0]/x[0,0], x[0,0]/x[1,0]
x[-1,1]/x[0,1], x[0,1]/x[1,1]
3-gram source word features
x[-1,0]/x[0,0]/x[1,0]
x[-2,0]/x[-1,0]/x[0,0]
x[0,0]/x[1,0]/x[2,0]
3-gram source POS features
x[0,1]/x[1,1]/x[2,1]
x[-2,1]/x[-1,1]/x[0,1]
x[-1,1]/x[0,1]/x[1,1]
4-gram source POS features
x[0,1]/x[1,1]/x[2,1]/x[3,1]
x[0,1]/x[-1,1]/x[-2,1]/x[-3,1]
x[-1,1]/x[0,1]/x[1,1]/x[2,1]
x[-2,1]/x[-1,1]/x[0,1]/x[1,1]
5-gram source POS features
x[0,1]/x[1,1]/x[2,1]/x[3,1]/x[4,1]
x[-4,1]/x[-3,1]/x[-2,1]/x[-1,1]/x[0,1]
x[-2,1]/x[-1,1]/x[0,1]/x[1,1]/x[2,1]
bigram output label feature
x[-1,2]/x[0,2]

Table 3: feature templates for CRFs training

Words	**POS**	**Label**	
基于	P	BEGIN-Rmono	
这	DT	Lmono-Rmono	
种	M	Lmono-Rmono	
看法	NN	Lmono-Rmono	
，	PU	Lmono-Rmono	
本人	PN	Lmono-Rmono	
是	VC	UNALIGN	≪ Current label
支持	VV	Lmono-Rmono	
修正案	NN	Lmono-Rmono	
的	DEC	UNALIGN	
。	PU	END-Lmono	

Table 4: feature examples. x[**row**,**col**] specifies a token in the input data. **row** specfies the relative position from the current label and **col** specifies the absolute position of the column. So for the current lable in this table, x$[-1, 2]/x[0, 2]$ is Lmono-Rmono/UNALIGN and x$[-1, 1]/x[0, 1]/x[1, 1]$ is PN/VC/VV.

5.3 RNN Training Results

We also applied RNN to the task as an alternative approach to CRFs. The here used RNN implementation is RNNLIB which has support for long short term memory (LSTM) (Graves, 2008). We used a one of k encoding for the input word and also for the labels. After testing several configurations over the validation corpus we used a network with LSTM 200 nodes in the hidden layer. The RNN has a token error rate of 27.31% and a sentence error rate of 77.00% over the test corpus in Table 2. The RNN is trained on a similar computer as above. RNNLIB utilizes only one thread. The training time is about three and a half days and peak memory consumption is 1G .

5.4 Comparison of CRFs and RNN errors

CRFs performs better than RNN (token error rate 25.75% vs 27.31%). Both error rate values are much higher than what we usually see in part-of-speech tagging task. The main reason is that the "annotated" corpus is converted from word alignment which contains lots of error. However, as we

Prediction Reference	Unalign	BEGIN-Rm	BEGIN-Rr	END-Lm	END-Lr	Lm-Rm	Lr-Rm	Lm-Rr	Lr-Rr
Unalign	687724	15084	850	7347	716	493984	107364	43457	9194
BEGIN-Rmono	3537	338315	6209	0	0	0	0	0	0
BEGIN-Rreorder	419	12557	17054	0	0	0	0	0	0
END-Lmono	1799	0	0	365635	3196	0	0	0	0
END-Lreorder	510	0	0	5239	7913	0	0	0	0
Lmomo-Rmono	188627	0	0	0	0	4032738	176682	150952	13114
Lreorder-Rmono	88177	0	0	0	0	369232	433027	27162	15275
Lmomo-Rreorder	32342	0	0	0	0	268570	24558	296033	10645
Lreorder-Rreorder	9865	0	0	0	0	34746	20382	16514	45342
Recall	50.36%	97.20%	56.79%	98.65%	57.92%	88.40%	46.42%	46.83%	35.74%
Precision	67.89%	92.45%	70.73%	96.67%	66.92%	77.56%	56.83%	55.42%	48.46%

Table 5: CRF Confusion Matrix. Abbreviations: Lmono(Lm) Lreorder(Lr) Rmono(Rm) Rreorder(Rr)

Prediction Reference	Unalign	BEGIN-Rm	BEGIN-Rr	END-Lm	END-Lr	Lm-Rm	Lr-Rm	Lm-Rr	Lr-Rr
Unalign	589100	17299	901	7870	1000	639555	82413	24277	3305
BEGIN-Rmono	1978	339686	6397	0	0	0	0	0	0
BEGIN-Rreorder	186	13812	16032	0	0	0	0	0	0
END-Lmono	2258	0	0	364121	4251	0	0	0	0
END-Lreorde	699	0	0	4693	8269	1	0	0	0
Lmomo-Rmono	142777	1	0	0	0	4232113	105266	78692	3264
Lreorder-Rmono	96278	0	1	0	0	491989	323272	14635	6698
Lmomo-Rreorder	31118	0	0	0	0	380483	18144	198068	4335
Lreorder-Rreorder	12366	0	1	0	0	50121	25196	17008	22157
Recall	43.13%	97.59%	53.39%	98.24%	60.53%	92.77%	34.65%	31.33%	17.47%
Precision	67.19%	91.61%	68.71%	96.66%	61.16%	73.04%	58.32%	59.54%	55.73%

Table 6: RNN Confusion Matrix. Abbreviations: Lmono(Lm) Lreorder(Lr) Rmono(Rm) Rreorder(Rr)

will show later, the model trained with both CRFs and RNN help to improve the translation quality.

Table 5 and Table 6 demonstrate the confusion matrix of the CRFs and RNN errors over the test corpus. The rows represent the correct tag that the classifier should have predicted and the columns are the actually predicted tags. E.g. the number 687724 in first row and first column of Table 5 tells that there are 687724 correctly labeled **Unalign** tags. The number 15084 in first row and second column of Table 5 represents that there are 15084 **Unalign** tags labeled incorrectly to **Begin-Rmono**. Therefore, numbers on the diagonal from the upper left to the lower right corner represent the amount of correctly classified tags and all other numbers show the amount of false labels. The many zeros show that both classifier rarely make mistake for the label "**BEGIN-**$*$" which only occur at the beginning of a sentence. The same is true for the "**END-**$*$" labels.

5.5 Translation Results

Results are summarized in Table 7. Please read the caption for the meaning of abbreviations. An **Index** column is added for score reference convenience (B for BLEU; T for TER). For the proposed model, significance testing results on both BLEU and TER are reported (B2 and B3 compared to B1, T2 and T3 compared to T1). We perform bootstrap resampling with bounds estimation as described in (Koehn, 2004). The 95% confidence threshold (denoted by ‡ in the table) is used to draw significance conclusions. We add a column **avg.** to show the average improvements.

From Table 7 we see that the proposed reordering model using CRFs improves the baseline by 0.98 BLEU and 1.21 TER on average, while the proposed reordering model using RNN improves the baseline by 1.32 BLEU and 1.53 TER on average. For line B2 B3 and T2 T3, most scores are better than their corresponding baseline values with more than 95% confidence. The results show that our proposed idea improves the baseline system and RNN trained model performs better than CRFs trained model, in terms of both automatic measure and significance test. To investigate why RNN has lower performance for the tagging task but achieves better BLEU, we build a 3-gram LM on the source side of the training corpus in Table 2 and perplexity values are listed in Table 8. The perplexity of the test corpus for reordering model comparison is much lower than those NIST corpora for translation experiments. In other words, there exists mismatch of the data for reordering model training and actual MT data. This could explain why CRFs is superior to RNN for labeling problem while RNN is better for MT tasks.

For the comparative study, the best method is the tree-based jump model (JUMPTREE). Our proposed model ranks the second position. The difference is tiny: on average only 0.08 BLEU (B3 and B10) and 0.15 TER (T3 and T10). Even with

Systems	NIST02	NIST03	NIST04	NIST05	NIST08	avg.	Index
BLEU scores							
baseline	33.60	34.29	35.73	32.15	26.34	-	B1
baseline+CRFs	34.53	35.19	36.56‡	33.30‡	27.41‡	0.98	B2
baseline+RNN	35.30‡	35.34‡	37.03‡	33.80‡	27.23‡	1.32	B3
baseline+LRM	34.87	34.90	36.40	33.43	27.45	0.99	B4
baseline+MERO	34.91	34.83	36.29	33.69	26.66	0.85	B5
baseline+BILM	35.21	35.00	36.83	33.64	27.39	1.19	B6
baseline+SRCLM	34.55	34.52	36.18	32.84	27.03	0.50	B7
baseline+SRL	35.05	34.93	36.71	33.22	26.89	0.93	B8
baseline+SC	34.96	34.52	36.37	33.35	26.90	0.79	B9
baseline+JUMPTREE	35.10	35.53	37.12	34.18	27.19	1.40	B10
baseline+LRM+MERO+BILM+SRCLM+SRL+SC+JUMPTREE	36.77	36.16	38.10	35.67	28.52	2.62	B11
baseline+LRM+MERO+BILM+SRCLM+SRL+SC+JUMPTREE+RNN	36.99	37.00	38.79	35.86	28.99	3.10	B12
TER scores							
baseline	61.36	60.48	59.12	60.94	65.17	-	T1
baseline+CRFs	60.14‡	58.91‡	57.91‡	59.77‡	64.30‡	1.21	T2
baseline+RNN	59.38‡	58.87‡	57.60‡	59.56‡	63.99‡	1.53	T3
baseline+LRM	60.07	59.08	58.42	59.74	64.50	1.05	T4
baseline+MERO	60.19	59.58	58.51	59.49	64.68	0.92	T5
baseline+BILM	60.23	59.93	58.59	60.09	64.72	0.70	T6
baseline+SRCLM	60.27	59.55	58.40	60.16	64.61	0.82	T7
baseline+SRL	60.05	59.55	58.14	59.69	64.74	0.98	T8
baseline+SC	59.90	59.37	58.27	59.69	64.44	1.08	T9
baseline+JUMPTREE	59.53	58.54	57.67	58.90	64.04	1.68	T10
baseline+LRM+MERO+BILM+SRCLM+SRL+SC+JUMPTREE	59.16	57.84	56.83	58.03	63.20	2.40	T11
baseline+LRM+MERO+BILM+SRCLM+SRL+SC+JUMPTREE+RNN	58.67	57.67	56.27	58.00	63.09	2.67	T12

Table 7: Experimental results. CRFs and RNN mean the tagging-style model trained with CRFs or RNN; LRM for lexicalized reordering model (Koehn et al., 2007) ; MERO for maximum entropy reordering model (Zens and Ney, 2006) ; BILM for bilingual language model (Mariño et al., 2006) and SRCLM for its simpler version source decoding sequence model (Feng et al., 2010) ; SC for syntactic cohesion model (Cherry, 2008) ; SRL for semantic cohesion model (Feng et al., 2012); JUMPTREE for our tree-based jump model based on (Wang et al., 2007).

	Running Words	OOV	Perplexity
Test in Table 2	8 382 086	33854	74.364
NIST02	22 749	195	176.806
NIST03	24 180	290	274.679
NIST04	49 612	320	170.507
NIST05	29 966	228	279.402
NIST08	32 502	511	408.067

Table 8: perplexity

a strong system (B11 and T11), our model is still able to provide improvements (B12 and T12).

6 Conclusion

In this paper, a novel tagging style reordering model has been proposed. By our method, the reordering problem is converted into a sequence labeling problem so that the whole source sentence is taken into consideration for reordering decision. By adding an unaligned word tag, the unaligned word phenomenon is automatically implanted in the proposed model. The model is utilized as soft constraints in the decoder. In practice, we do not experience decoding memory increase nor speed slow down.

We choose CRFs and RNN to accomplish the sequence labeling task. The CRFs achieves lower error rate on the tagging task but RNN trained model is better for the translation task. Experimental results show that our model is stable and improves the baseline system by 0.98 BLEU and 1.21 TER (trained by CRFs) and 1.32 BLEU and 1.53 TER (trained by RNN). Most of the scores are better than their corresponding baseline values with more than 95% confidence. We also compare our method with several other popular reordering models. Our model ranks the second position which is slightly worse than the tree-based jump model. However, the tree-based jump model relies on manually designed reordering rules which does not exist for many language pairs while our model can be easily adapted to other translation tasks. We also show that the proposed model is able to improve a very strong baseline system.

The main contributions of the paper are: propose the tagging-style reordering model and improve the translation quality; compare two sequence labeling techniques CRFs and RNN; compare our method with seven other reordering models. To our best knowledge, it is the first time that the above two comparisons have been reported .

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