A Coverage Embedding Model for Neural Machine Translation

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Abstract

In this paper, we enhance the attention-based neural machine translation by adding an explicit coverage embedding model to alleviate issues of repeating and dropping translations in NMT. For each source word, our model starts with a full coverage embedding vector, and then keeps updating it with a gated recurrent unit as the translation goes. All the initialized coverage embeddings and updating matrix are learned in the training procedure. Experiments on the large-scale Chinese-to-English task show that our enhanced model improves the translation quality significantly on various test sets over the strong large vocabulary NMT system.

1 Introduction

Neural machine translation (NMT) has gained popularity in recent two years (Bahdanau et al., 2014; Jean et al., 2015; Luong et al., 2015), especially for the attention-based models of Bahdanau et al. (2014). The attention at each time step shows which source word the model should focus on to predict the next target word. However, the attention in each step only looks at the previous hidden state and the previous target word, there is no history or coverage information typically for each source word. As a result, this kind of model suffers from issues of repeating or dropping translations.

The traditional statistical machine translation (SMT) systems (e.g. (Koehn, 2004; Chiang, 2005)) address the above issues by employing a source side “coverage vector” to indicate explicitly which words have been translated, which parts have not yet. A coverage vector starts with all zero, which means no word has been translated. If a source word at position \( j \) got translated, the coverage vector remembers position \( j \) as 1, and they won’t use this source word in future translation. This mechanism avoids the repeating or dropping translation problems.

However, it is not easy to adapt the “coverage vector” to NMT directly, as the attentions are soft probabilities, not 0 or 1. Furthermore, traditional SMT approaches handle one-to-many fertility problem by using phrases or hiero rules (can predict several words in a row). But NMT systems can only predict one word at each step. In order to alleviate all those problems, in this paper, we borrow the basic idea of “coverage vector”, and introduce a coverage embedding vector for each source word. Starting from a full coverage embedding for a source word, if this word is translated, the embedding vector should come to empty. We model this procedure by using a gated recurrent unit (GRU) (Cho et al., 2014). When we start the translation, we initialize each source word at different position with its own coverage embedding, then, at each translation step, we feed the coverage embedding at each source position to the first layer of the attention model, and compute the attention probabilities. After we get attentions at each position, we update our coverage embedding model by feeding attentions back (Section 3). Large-scale experiments over Chinese-to-English on various test sets show that our method improves the translation quality significantly over the large vocabulary NMT system (Section 5).

2 Neural Machine Translation

As shown in Figure 1, attention-based neural machine translation (Bahdanau et al., 2014) is an encoder-decoder network. The encoder employs a bi-directional recurrent neural network to encode the source sentence \( \mathbf{x} = (x_1, \ldots, x_l) \), where \( l \) is the sentence length, into a sequence of hidden states \( \mathbf{h} = (h_1, \ldots, h_l) \), each \( h_i \) is a concatenation of a left-to-right \( \vec{h}_i \) and a right-to-left \( \hat{h}_i \).

\[
\vec{h}_i = \begin{bmatrix} \vec{h}_i^L \\ \vec{h}_i^R \end{bmatrix} = \begin{bmatrix} \vec{f}(x_i, \vec{h}_{i+1}) \\ \vec{f}(x_i, \hat{h}_{i-1}) \end{bmatrix},
\]

where \( \vec{f} \) is the left-to-right recurrence function, and \( \hat{f} \) is the right-to-left recurrence function.
where \( \hat{f} \) and \( \bar{f} \) are two gated recurrent units (GRU).

Given the encoded \( h \), the decoder predicts the target translation by maximizing the conditional log-probability of the correct translation \( y^* = (y^*_1, \ldots, y^*_m) \), where \( m \) is the sentence length. At each time \( t \), the probability of each word \( y_t \) from a target vocabulary \( V_y \) is:

\[
p(y_t|h, y^*_{t-1}, y^*_1) = g(s_t, y^*_1),
\]

where \( g \) is a two layer feed-forward neural network (\( o_t \) is an intermediate state) over the embedding of the previous word \( y^*_t \), and the hidden state \( s_t \). The \( s_t \) is computed as:

\[
s_t = q(s_{t-1}, y^*_t, H_t)
\]

\[
H_t = \left[ \sum_{i=1}^{l}(\alpha_{ti} \cdot \hat{f}_i) \right] / \left[ \sum_{i=1}^{l}(\alpha_{ti} \cdot \bar{f}_i) \right],
\]

where \( q \) is a GRU, \( H_t \) is a weighted sum of \( h \), the weights, \( \alpha \), are computed with a two layer feed-forward neural network \( r \):

\[
\alpha_{ti} = \frac{\exp\{r(s_{t-1}, h_t, y^*_t)\}}{\sum_{k=1}^{l} \exp\{r(s_{t-1}, h_k, y^*_t)\}}
\]

3 A Coverage Embedding Model

In traditional statistical machine translation (e.g. (Koehn, 2004; Chiang, 2005)), they employ a source side “coverage vector” to indicate explicitly which word has been translated. A coverage vector starts with all zero, which means no word has been translated. If a source word at position \( j \) got translated, the coverage vector remembers position \( j \) as 1, and we won’t use this source word in future translation. This mechanism avoids the repeating or dropping translation problems.

However, in attention-based NMT systems, there is no explicit “coverage vector”, as attentions in each step are probabilities. Furthermore, the intermediate state \( A_j \) only takes into account of encoding state \( h_t \), the previous target word \( y_{t-1} \), and the previous hidden state \( s_{t-1} \), there is no information from the history for this particular position \( j \). Thus, it is possible that an attention at position \( j \) will be repeated in different steps, or some positions never get any attention.

Our idea is to introduce a coverage embedding for each source word, and keep updating this embedding with a GRU at each time step.

Figure 2 shows the coverage embedding model. As different words have different fertilities (one-to-one, one-to-many, or one-to-zero), similar to word embeddings, we also initialize a special coverage embedding for each source word. For simplicity, the source vocabulary size of coverage embeddings is the same as the word embedding vocabulary size. At the beginning of translation, we initialize \( c_{0,1}, c_{0,2}, \ldots, c_{0,t} \) by looking up the coverage embedding matrix. Then, at time step \( t \), we feed \( c_{t-1,j} \) to the attention model (shown in red dotted line in Figure 1). After we get the attention \( \alpha_{t,j} \), we feed \( y_t \) and \( \alpha_{t,j} \) to the coverage model (shown in Figure 2),

\[
\begin{align*}
z_{t,j} &= \sigma(W^{zy}y_t + W^{za}\alpha_{t,j} + U^zc_{t-1,j}) \\
r_{t,j} &= \sigma(W^{ry}y_t + W^{ra}\alpha_{t,j} + U^rc_{t-1,j}) \\
\tilde{c}_{t,j} &= \tanh(W^z_y y_t + W^a \alpha_{t,j} + r_{t,j} \circ U c_{t-1,j}) \\
c_{t,j} &= z_{t,j} \circ c_{t-1,j} + (1 - z_{t,j}) \circ \tilde{c}_{t,j},
\end{align*}
\]

where, \( z_t \) is the update gate, \( r_t \) is the reset gate, \( \tilde{c}_t \) is the new memory content, and \( c_t \) is the final memory. The matrix \( W^{zy}, W^{za}, U^z, W^{ry}, W^{ra}, U^r, W^y, W^a \) and \( U \) are shared across different position \( j \). \( \circ \) is a pointwise operation.

The reason why we only pick \( y_t \) and \( \alpha_{t,j} \) as input is that coverage embedding \( c_{t,j} \) is highly related to the translation word \( y_t \) and the attention probability \( \alpha_{t,j} \) at this step \( t \) and source position \( j \). Other states, like \( s_{t-1,j} \), contain too much information, it may not be clear how much influence will be imposed to \( c_{t,j} \). So if \( y_t \) is close to the embedding \( c_{t-1,j} \), this means \( y_t \) and \( c_{t,j} \) are equivalent translations, thus, \( c_{t,j} \) will be close to empty. Similarly, if \( \alpha_{t,j} \) is very high, it also results in almost empty of \( c_{t,j} \). Hopefully, if \( y_t \) is partial translation of \( c_{t-1,j} \), it only remove partial information of \( c_{t-1,j} \). The same to the \( \alpha_{t,j} \). In this way, we enable coverage embeddings \( c_t \) to encode fertility information for each source word \( x \).

In order to check whether \( \alpha \) is important for coverage embedding \( c_t \), we run two models, one is with \( \alpha \) in the input (\( \alpha \rightarrow c \)), the other one is without \( \alpha \) (shown in the red dotted line in Figure 2).
In contrast, their work initializes the word coverage vector from a specific coverage embedding matrix, while we directly add fertility information to every hidden state. Tu et al. (2016) add an accumulate operation and a fertility function to simulate the process of one-to-many alignments. In our approach, we add fertility information directly to coverage embeddings, as each source word has its own embedding. Furthermore, we only feed the previous word, attention to coverage embedding layer, which is much simpler than theirs. The last difference is that we run experiments on 5 million and 11 million sentence pairs, which are significant larger than theirs. Finally, our baseline system is similar to the large vocabulary NMT of Jean et al. (2015) with candidate list decoding and UNK replacement, a much stronger baseline system.

Tu et al. (2016) propose some methods to add more connections between different hidden states in a baseline model. Feed the previous attention context directly to attention model. By contrast, we have an explicit model for coverage embedding. And they
run experiments only on 0.5 million sentence pairs, which are not large enough to train a good NMT system.

Cohn et al. (2016) augment the attention model with well-known features in traditional SMT, including positional bias, Markov conditioning, fertility and agreement over translation directions. This work is orthogonal to our work. And they only run experiments on smaller training sets and on reranking task only.

5 Experiments

5.1 Data Preparation

We run our experiments on Chinese to English task. We train our machine translation systems on two training sets. The first training corpus consists of approximately 5 million sentences available within the DARPA BOLT Chinese-English task. The corpus includes a mix of newswire, broadcast news, webblog and comes from various sources, which do not include HK Law, HK Hansard and UN data. The second training corpus includes HK Law, HK Hansard and UN data, the total number of training sentence pairs is 11 million. The Chinese text is segmented with a segmenter trained on CTB data using conditional random fields (CRF).

Our development set is the concatenation of several tuning sets (GALE Dev, P1R6 Dev, and Dev 12) initially released under the DARPA GALE program. The development set is 4491 sentences in total. Our test sets are NIST MT06 (1664 sentences), MT08 news (691 sentences), and MT08 web (666 sentences).

For all NMT systems, the full vocabulary sizes for the two training sets are 300k and 500k respectively. The coverage embedding vector size is 100. In the training procedure, we use AdaDelta (Zeiler, 2012) to update model parameters with a mini-batch size 80. Following Mi et al. (2016), the output vocabulary for each mini-batch or sentence is a sub-set of the full vocabulary. For each source sentence, the sentence-level target vocabularies are union of top 2k most frequent target words and the top 10 candidates of the word-to-word/phrase translation tables learned from ‘fast_align’ (Dyer et al., 2013). The maximum length of a source phrase is 4. In the training time, we add the reference in order to make the translation reachable.

Following Jean et al. (2015), We dump the alignments, attentions, for each sentence, and replace UNKs with the word-to-word translation model or the aligned source word.

Our traditional SMT system is a hybrid syntax-based tree-to-string model (Zhao and Al-onaizan, 2008), a simplified version of the joint decoding (Liu et al., 2009; Cmejrek et al., 2013). We parse the Chinese side with Berkeley parser, and align the bilingual sentences with GIZA++. Then we extract Hiero and tree-to-string rules on the training set. Our language models are trained on the English side of the parallel corpus, and on monolingual corpora (around 10 billion words from Gigaword (LDC2011T07) and Google News). We tune our system with PRO (Hopkins and May, 2011) to minimize \((\text{TER} - \text{BLEU})/2\) on the development set.

5.2 Results

Table 1 shows the final results of all systems. The traditional hybrid syntax-based system achieves 9.45, 12.90, and 17.72 on MT06, MT08 News, and MT08 Web sets respectively, 13.36 on average in terms of \((\text{TER} - \text{BLEU})/2\). The associated BLEU scores are 34.93, 31.12, and 23.45 respectively.

The large-vocabulary NMT (LVNMT), our baseline, achieves an average \((\text{TER} - \text{BLEU})/2\) score at 15.74, which is about 2 points worse than the hybrid system. But, interestingly, LVNMT performs slightly better on MT08 Web test set. This suggests that NMT has the potential ability of handling informal text better than traditional SMT systems, as NMT represents the source sentence as dense vectors instead of surface strings.

With the help of the coverage embedding model, without feeding the attentions back, we improve the scores by 1.1 points in average over LVNMT. If we feed attentions into our coverage embedding model, we further boost our performance by almost 0.4 points on average. Our best NMT system is only 1 point worse than the strong tree-to-string system, and we can get significantly better results on informal text set, like MT08 Web.

Table 2 shows the results of all the systems trained on 11 million sentence pairs, LVNMT achieves an average \((\text{TER} - \text{BLEU})/2\) at 13.27, which is about 2.5 points better than 5 million LVNMT. The result
Table 1: Single system results in terms of (TER-BLEU)/2 (the lower the better) on 5 million Chinese to English training set. NMT results are on a large vocabulary (300k) and with UNK replaced.

| system          | MT06   | MT08   | avg.  |
|-----------------|--------|--------|-------|
| Tree-to-string  | 0.95   | 34.93  | 9.45  |
| LVNMT           | 0.96   | 34.53  | 12.25 |
| Ours w/o $\alpha \rightarrow c$ | 0.94   | 35.42  | 10.90 |
| Ours w/ $\alpha \rightarrow c$ | 0.92   | 35.59  | 10.71 |

Table 2: Single system results in terms of (TER-BLEU)/2 (the lower the better) on 11 million Chinese to English training set. NMT results are on a large vocabulary (500k) and with UNK replaced.

| system          | MT06   | MT08   | avg.  |
|-----------------|--------|--------|-------|
| Tree-to-string  | 0.90   | 36.78  | 8.70  |
| LVNMT           | 0.96   | 36.59  | 9.78  |
| Ours w/ $\alpha \rightarrow c$ | 0.97   | 38.16  | 8.62  |

Table 3: Alignment F1 scores of different models.

| system           | prec. | rec.  | F1    |
|------------------|-------|-------|-------|
| MaxEnt           | 74.86 | 77.10 | 75.96 |
| LVNMT            | 47.88 | 41.06 | 44.21 |
| +coverage embedding | 51.11 | 41.42 | 45.76 |

In order to verify that our coverage embedding model improves the attention accuracy, we conduct alignment experiments over the LVNMT and our coverage model (with $\alpha \rightarrow c$). Table 3 shows the F1 scores on the alignment test set (447 hand aligned sentences). The MaxEnt model is trained on 67k hand-aligned data, and achieves an F1 score at 75.96. For NMT systems, we dump the alignment matrixes and covert them into alignments with following steps. For each target word, we sort the alphas$^1$, and add the max probability link if it is higher than 0.2. Results show that coverage embeddings improve the F1 score by 1.6 points over the LVNMT. But NMT scores are still far behind the MaxEnt model.

6 Conclusion

In this paper, we propose a simple, yet effective, coverage embedding model for attention-based NMT. Our model learns a special coverage embedding vector for each source word to start with. We keep updating those coverage embeddings as the translation goes. Experiments on the large-scale Chinese-to-English task show significant improvements over the strong LVNMT system.

References

D. Bahdanau, K. Cho, and Y. Bengio. 2014. Neural Machine Translation by Jointly Learning to Align and Translate. ArXiv e-prints, September.

David Chiang. 2005. A hierarchical phrase-based model for statistical machine translation. In Proceedings of ACL.

KyungHyun Cho, Bart van Merrienboer, Dzmitry Bahdanau, and Yoshua Bengio. 2014. On the properties of neural machine translation: Encoder-decoder approaches. CoRR, abs/1409.1259.

Martin Cmejrek, Haitao Mi, and Bowen Zhou. 2013. Flexible and efficient hypergraph interactions for joint hierarchical and forest-to-string decoding. In Proceedings of the 2013 Conference on Empirical Methods in
Chris Dyer, Victor Chahuneau, and Noah A. Smith. 2013. A simple, fast, and effective reparameterization of ibm model 2. In Proceedings of the 2013 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, pages 644–648, Atlanta, Georgia, June. Association for Computational Linguistics.

S. Feng, S. Liu, M. Li, and M. Zhou. 2016. Implicit Distortion and Fertility Models for Attention-based Encoder-Decoder NMT Model. ArXiv e-prints, January.

Mark Hopkins and Jonathan May. 2011. Tuning as ranking. In Proceedings of EMNLP.

Sébastien Jean, Kyunghyun Cho, Roland Memisevic, and Yoshua Bengio. 2015. On using very large target vocabulary for neural machine translation. In Proceedings of ACL, pages 1–10, Beijing, China, July.

Philipp Koehn. 2004. Pharaoh: a beam search decoder for phrase-based statistical machine translation models. In Proceedings of AMTA, pages 115–124.

Yang Liu, Haitao Mi, Yang Feng, and Qun Liu. 2009. Joint decoding with multiple translation models. In Proceedings of the Joint Conference of the 47th Annual Meeting of the ACL and the 4th International Joint Conference on Natural Language Processing of the AFNLP: Volume 2 - Volume 2. ACL ’09, pages 576–584, Stroudsburg, PA, USA. Association for Computational Linguistics.

Thang Luong, Hieu Pham, and Christopher D. Manning. 2015. Effective approaches to attention-based neural machine translation. In Proceedings of the 2015 Conference on Empirical Methods in Natural Language Processing, pages 1412–1421, Lisbon, Portugal, September. Association for Computational Linguistics.

Haitao Mi, Zhiguo Wang, and Abe Ittycheriah. 2016. Vocabulary manipulation for neural machine translation. In Proceedings of ACL, Berlin, Germany, August.

Z. Tu, Z. Lu, Y. Liu, X. Liu, and H. Li. 2016. Coverage-based Neural Machine Translation. ArXiv e-prints, January.

Matthew D. Zeiler. 2012. ADADELTA: an adaptive learning rate method. CoRR.

Bing Zhao and Yaser Al-onaizan. 2008. Generalizing local and non-local word-reordering patterns for syntax-based machine translation. In Proceedings of the Conference on Empirical Methods in Natural Language Processing, EMNLP ’08, pages 572–581, Stroudsburg, PA, USA. Association for Computational Linguistics.