Abstract

We propose a novel model for Neural Machine Translation (NMT). Different from the conventional method, our model can predict the future text length and words at each decoding time step so that the generation can be helped with the information from the future prediction. With such information, the model does not stop generation without having translated enough content. Experimental results demonstrate that our model can significantly outperform the baseline models. Besides, our analysis reflects that our model is effective in the prediction of the length and words of the untranslated content.

1 Introduction

Recent researches in machine translation focus on Neural Machine Translation, whose most common baseline is the sequence-to-sequence (Seq2Seq) model (Kalchbrenner and Blunsom, 2013; Sutskever et al., 2014; Cho et al., 2014) with attention mechanism (Bahdanau et al., 2014; Luong et al., 2015; Tu et al., 2016; Mi et al., 2016a; Meng et al., 2016; Xiong et al., 2017; Vaswani et al., 2017; Mi et al., 2016b; Lin et al., 2018c,b,a). In the Seq2Seq model, the encoder encodes the source text for a representation of the source text and decodes it for a translation that approximates the target. However, a salient drawback of this mechanism is that the decoding process should follow the sequential order, which cannot take the information in the untranslated content into consideration. Without the information about the untranslated content, the translation may end up with faults on semantic level (e.g., the translation ends by mistake with contents untranslated). The information about the “future generation” can provide indication for present generation, guaranteeing the loyalty of translation to the source text.

To tackle the problem, we propose a novel model that targets on the provision of the untranslated information for the decoder. Based on the conventional attention-based sequence-to-sequence (Seq2Seq) model, we implement a novel decoder that is able to generate more than the present word. At each time step, the model produces a conjecture of the bag of the following words (e.g., the model is to generate a sentence “the new plan can boost the economy”, when the model generates “the new plan”, it can predict the bag of the following words that is {can, boost, the, economy}). Moreover, the decoder can also predict the length of the untranslated content, so as to make sure that the translation does not end without having translated all the source information. Our proposed model can be effective in generating translation with the help of the prediction of the bag of words and text length of the untranslated content.

Our contributions are summarized as below: (1). We propose a novel model for NMT that targets on the prediction of the untranslated content, which guarantees that the system can generate translation that is loyal to the source text; (2). Experimental results demonstrate that our model can significantly outperform the baseline models. (3). The analysis reflects that our model can be effective in predicting the words and text length of the untranslated content.

2 Model

In the following, we introduce the details of our model, including the basic attention-based Seq2Seq model and our proposed Future-Prediction-Based model.

2.1 Seq2Seq with Attention

In our model, the encoder, a bidirectional LSTM (Hochreiter and Schmidhuber, 1997),
reads the embeddings of the input text sequence \( x = \{x_1, ..., x_n\} \) and encodes a sequence of source annotations \( h = \{h_1, ..., h_n\} \). The decoder, which is also an LSTM, decodes the final state \( h_n \) to a new sequence to approximate the target with the application of conventional attention mechanism (Bahdanau et al., 2014). The model is trained by maximum likelihood estimation (MLE) to minimize the difference between the generation and target.

### 2.2 Future-Prediction-Based Decoder

In the following, we introduce the details of our proposed future-prediction-based decoder, including the bag-of-words (BOW) predictor and the length predictor.

#### 2.2.1 Bag-of-Words Predictor

On top of the output of the LSTM decoder, we implement a Bag-of-Words (BOW) Predictor in order to predict the word set of the following text sequence to generate. Some studies (Ma et al., 2018) show that using Bag-of-Words as target can improve the performance of the model. With the objective of predicting the words in the future generation, the decoder can obtain more information about the target-side information. With the information about the future, it is less possible for the model to repeat the previous generation and generates translation far different from the target. Moreover, if the BOW predictor successfully predicts the word set, it can encourage the model not to generate words outside of the word set and avoids mistake. The details are in the following:

\[
\begin{align*}
    h_{t,k} &= f_k(C_t, o_{t-1,k}) \\
    g_{t,k} &= \text{sigmoid}(h_{t,k}) \\
    z_{t,k} &= g_{t,k} \cdot \tanh(C_t) + (1 - g_{t,k}) \cdot o_{t-1,k} \\
    o_{t,k} &= \text{Attention}(z_{t,k}, \text{context}) \\
    p_{t,k} &= \text{softmax}(W o_{t,k}) \\
    p_t &= \frac{1}{k} \sum_{i=1}^{k} p_{t,k}
\end{align*}
\]

where \( C_t \) refers to the cell state of LSTM and \( f_k(\cdot) \) refers to the \( k \)-th linear function. Since a single output is hardly able to predict all of the untranslated words, the model generates \( k \) outputs for improved prediction. The averaged \( p_t \) refers to the probability distribution of the untranslated words, which is used to compute the loss below.

As to the representation of the target word set, we use one-hot representation by assigning \( 1/m \) to the word indices and 0 to others for the construction of the representation vector, where \( m \) refers to the number of words in the target. Therefore, the model can be trained by minimizing negative log likelihood, where the loss \( L_{BOW} \) is illustrated below:

\[
L_{BOW} = -\frac{1}{N} \sum_{i=1}^{N} \sum_{t=1}^{T} \frac{1}{m} \log P(y_{t,i}^{(t)}|y_{<t,i}, x^{(t)}, \theta)
\]

With the purpose of helping the prediction at the next time step with the information about future generation, we retrieve the word embeddings of the words that the model predicts and generates a representation of the untranslated bag of words, which is shown below:

\[
e_{t,bow}^i = \sum_{i=1}^{N} p_{t-1}^i \cdot e_i
\]

where \( e_i \) refers to the word embedding, \( N \) refers to the vocabulary size and \( p_t \) is from 6. The \( e_{bow} \) is then added to the original input for the input of the next time step.

#### 2.2.2 Length Predictor

Similar to the BOW predictor, we use the output of the LSTM decoder \( s_t \) as input and implement an MLP as well as softmax function on top. Also, for further information about the translation, we implement attention mechanism for the output of the current time step to extract information from the previous generation, as mentioned above. We set the length of sequence that is untranslated to a one-hot representation vector whose size is \( k \), where \( k \) is a hyperparameter (e.g., suppose there are still 10 words to generate according to the target text, we assign 1 to the index 10 of the vector and 0 to the others). Therefore, this still can be trained with maximum likelihood by minimizing the following loss:

\[
L_{len} = -\log P(l_{y>t}|y_{<t}, x)
\]

where \( l \) refers to sequence length.

### 2.3 Training

Given the parameters \( \theta \) and source text \( x \), the model generates a sequence \( \hat{y} \). The learning process is to minimize the negative log-likelihood,
which is between the generated text $\tilde{y}$ and reference $y$, which in our context is the sequence in target language for machine translation:

$$L_{NLL} = -\frac{1}{N} \sum_{i=1}^{N} \sum_{t=1}^{T} \log P(y_t^{(i)} | \tilde{y}_{<t}^{(i)}, x^{(i)}, \theta)$$

(10)

Our total loss function can be illustrated below:

$$\mathcal{L} = \lambda_1 L_{NLL} + \lambda_2 L_{BOW} + \lambda_3 L_{len}$$

(11)

where $\lambda_1$, $\lambda_2$ and $\lambda_3$ are hyper-parameters. We set them to 1, 1, and 0.1 respectively in our experiments based on the model’s performance on the development set.

3 Experiment

We evaluate our proposed model on machine translation tasks and provide the analysis. We present the experimental details in the following, including the introduction to the datasets as well as our experimental settings.

3.1 Datasets

**English-German Translation** We implement our model on the dataset WMT 2014 with 4.5M sentence pairs as training data. The news-test 2013 is our development set and the news-test 2014 is our test set. Following Wu et al. (2016), we segment the data with byte-pair encoding (Sennrich et al., 2016) and we extract the most frequent 50K words for the dictionary.

**English-Vietnamese Translation** Following Luong and Manning (2015), we use the same preprocessed data for this task with 133K training sentence pairs (Cettolo et al., 2015) for training. The TED tst2012 with 1553 sentences and the the TED tst2013 with 1268 sentences are our development and test set respectively. We preserve casing, and we set the English dictionary size to 17K words and Vietnamese dictionary to 7K words. The case-sensitive BLEU score (Papineni et al., 2002) is the evaluation metric.

3.2 Setting

We implement the models in PyTorch on an NVIDIA 1080Ti GPU. Both the size of word embedding and the number of units of hidden layers are 512, and the batch size is 64. We use Adam optimizer (Kingma and Ba, 2014) with the default setting, $\alpha = 0.001$, $\beta_1 = 0.9$, $\beta_2 = 0.999$ and $\epsilon = 1 \times 10^{-8}$, to train the model. Gradient clipping is applied with the norm smaller than 10. Dropout (Srivastava et al., 2014) is used with the dropout rate set to 0.2 for both datasets, in accordance with the model’s performance on the development set. Based on the performance on the development set, we use beam search with a beam width of 10 to generate text.

3.3 Baselines

For the English-German translation, we compare with the baseline models in the following. ByteNet is the Seq2Seq model based on dilated convolution, which runs faster than conventional RNN-based model (Kalchbrenner et al., 2016). GNMT is the improved version of end-to-end translation system that tackles many detail problems in NMT (Wu et al., 2016). ConvS2S is the Seq2Seq model completely based on CNN and attention mechanism, which achieves outstanding performance in NMT.

For English-Vietnamese translation, the models to compared are presented below. RNNSearch The attention-based Seq2Seq model as mentioned above, and we present the results of (Luong and Manning, 2015).

For both datasets, we reimplement the baseline, the attention-based Seq2Seq model, which is named Seq2Seq.

4 Results and Analysis

In the following, we present our experimental results as well as our analysis of our proposed modules to figure out how it enhances the performance of the basic Seq2Seq model for NMT.

4.1 Results

Table 1 shows the results of our model as well as the baseline models on the English-German translation dataset.
Table 2: Results of the models on the English-Vietnamese translation.

| Model                                  | BLEU |
|----------------------------------------|------|
| RNNSearch                              | 26.10|
| Seq2Seq (our reimplementation)         | 25.90|
| FPB                                    | 27.70|

Table 3: Ablation test on the English-Vietnamese translation. Seq2Seq refers to our reimplementation of the attention-based Seq2Seq model.

| Model                              | BLEU |
|------------------------------------|------|
| Seq2Seq (our reimplementation)     | 25.90|
| +length predictor                  | 26.26|
| +BOW predictor                     | 27.38|
| FPB                                | 27.70|

Table 2 shows the results of the models on the English-Vietnamese translation dataset. It can be found that on the evaluation of BLEU score, our proposed model has significant advantage over the RNNSearch, which demonstrates that our proposed model is effective in improving the performance of the baseline. In the following, we conduct ablation test to evaluate the effect of each module and examine the performance of the BOW predictor in prediction accuracy of words.

4.2 Ablation Test

To evaluate the effects of each proposed module, we conduct an ablation test for our model to examine the individual effect of our BOW predictor and length predictor.

We present the results of the ablation test on Table 3. Compared with the basic attention-based Seq2Seq model, it can be found that the length predictor can bring a slight improvement for the baseline model, while the model only with the BOW predictor can outperform the baseline with a large margin. It is obvious that the BOW predictor brings contribution to the model’s performance, and we analyze its bag-of-words prediction accuracy in the next section. The combination of the two modules, which is our proposed model, can achieve the best performance.

4.3 Bag-of-Words Prediction

In this section, we present our analysis of the prediction accuracy of the BOW predictor. As the BOW predictor predicts words at each decoding time step, we evaluate its accuracy in various situations by evaluating its bag-of-words prediction accuracy with different lengths of untranslated words. For example, if there are still 20 words left for translation, we evaluate if the BOW predictor can predict the correct words without concerning sequential order.

Results shown in Figure 1 reflect our model’s performance on the prediction of the bag of words to translate at different time steps with diverse lengths of untranslated content. It can be found that with the increase of untranslated words, the prediction accuracy decreases. The phenomenon is reasonable as it is more difficult to predict the information about further future only with the information from the source-side context and the previous generation. However, even when the length of the untranslated words is relatively long (20 words), the model can still maintain a stable performance on the evaluation with the accuracy of around 50%. This demonstrates that our model possesses strong capability of predicting the word-level information about future generation.

5 Conclusion and Future Work

In this paper, we propose a novel model for NMT with the BOW predictor that predicts the words that are not translated and the length predictor that predicts the length of the untranslated words. Therefore, the model can receive information about the future from its conjecture to improve the quality of the current translation. Experimental results demonstrate that our model outcompetes the
baseline model on the English-Vietnamese translation dataset. Moreover, our analysis shows that our proposed modules can enhance the performance of the baseline individually, especially the BOW predictor, and we find that the BOW is able to predict words with high accuracy and the accuracy increases with the decline of the number of untranslated words.

References

Dzmitry Bahdanau, Kyunghyun Cho, and Yoshua Bengio. 2014. Neural machine translation by jointly learning to align and translate. CoRR, abs/1409.0473.

Mauro Cettolo, Jan Niehues, Sebastian Stüker, Luisa Bentivogli, Roldano Cattoni, and Marcello Federico. 2015. The iws1 2015 evaluation campaign. Proc. of IWSLT, Da Nang, Vietnam.

Kyunghyun Cho, Bart van Merrienboer, Çaglar Gülçehre, Dzmitry Bahdanau, Fethi Bougares, Holger Schwenk, and Yoshua Bengio. 2014. Learning phrase representations using RNN encoder-decoder for statistical machine translation. In EMNLP 2014, pages 1724–1734.

Sepp Hochreiter and Jürgen Schmidhuber. 1997. Long short-term memory. Neural Computation, 9(8):1735–1780.

Nal Kalchbrenner and Phil Blunsom. 2013. Recurrent continuous translation models. In EMNLP 2013, pages 1700–1709.

Nal Kalchbrenner, Lasse Espeholt, Karen Simonyan, Aáron van den Oord, Alex Graves, and Koray Kavukcuoglu. 2016. Neural machine translation in linear time. CoRR, abs/1610.10099.

Diederik P. Kingma and Jimmy Ba. 2014. Adam: A method for stochastic optimization. CoRR, abs/1412.6980.

Junyang Lin, Shuming Ma, Qi Su, and Xu Sun. 2018a. Decoding-history-based adaptive control of attention for neural machine translation. CoRR, abs/1802.01812.

Junyang Lin, Xu Sun, Xuancheng Ren, Muyu Li, and Qi Su. 2018b. Learning when to concentrate or divert attention: Self-adaptive attention temperature for neural machine translation. CoRR, abs/1808.07374.

Junyang Lin, Xu Sun, Xuancheng Ren, Shuming Ma, Jinsong Su, and Qi Su. 2018c. Deconvolution-based global decoding for neural machine translation. CoRR, abs/1806.03692.

Minh-Thang Luong and Christopher D Manning. 2015. Stanford neural machine translation systems for spoken language domains. In Proceedings of the International Workshop on Spoken Language Translation.

Thang Luong, Hieu Pham, and Christopher D. Manning. 2015. Effective approaches to attention-based neural machine translation. In EMNLP 2015, pages 1412–1421.

Shuming Ma, Xu Sun, Yizhong Wang, and Junyang Lin. 2018. Bag-of-words as target for neural machine translation. CoRR, abs/1805.04871.

Fandong Meng, Zhengdong Lu, Hang Li, and Qun Liu. 2016. Interactive attention for neural machine translation. In COLING 2016, pages 2174–2185.

Haitao Mi, Baskaran Sankaran, Zhiguo Wang, and Abe Ittycheriah. 2016a. Coverage embedding models for neural machine translation. In EMNLP 2016, pages 955–960.

Haitao Mi, Zhiguo Wang, and Abe Ittycheriah. 2016b. Supervised attentions for neural machine translation. In EMNLP 2016, pages 2283–2288.

Kishore Papineni, Salim Roukos, Todd Ward, and WeiJing Zhu. 2002. Bleu: a method for automatic evaluation of machine translation. In ACL, 2002, pages 311–318.

Rico Sennrich, Barry Haddow, and Alexandra Birch. 2016. Neural machine translation of rare words with subword units. In ACL 2016.

Nitish Srivastava, Geoffrey E. Hinton, Alex Krizhevsky, Ilya Sutskever, and Ruslan Salakhutdinov. 2014. Dropout: a simple way to prevent neural networks from overfitting. Journal of Machine Learning Research, 15(1):1929–1958.

Ilya Sutskever, Oriol Vinyals, and Quoc V. Le. 2014. Sequence to sequence learning with neural networks. In NIPS, 2014, pages 3104–3112.

Zhaopeng Tu, Zhengdong Lu, Yang Liu, Xiaohua Liu, and Hang Li. 2016. Modeling coverage for neural machine translation. In ACL 2016.

Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N. Gomez, Lukasz Kaiser, and Illia Polosukhin. 2017. Attention is all you need. CoRR, abs/1706.03762.

Yonghui Wu, Mike Schuster, Zhifeng Chen, Quoc V. Le, Mohammad Norouzi, Wolfgang Macherey, Maxim Krikun, Yuan Cao, Qin Gao, Klaus Macherey, Jeff Klingner, Apurva Shah, Melvin Johnson, Xiaobing Liu, Lukasz Kaiser, Stephan Gouws, Yoshikiyo Kato, Taku Kudo, Hideto Kazawa, Keith Stevens, George Kurian, Nishant Patil, Wei Wang, Cliff Young, Jason Smith, Jason Riesa, Alex Rudnick, Oriol Vinyals, Greg Corrado, Macduff Hughes, and Jeffrey Dean. 2016. Google’s
neural machine translation system: Bridging the gap between human and machine translation. *CoRR*, abs/1609.08144.

Hao Xiong, Zhongjun He, Xiaoguang Hu, and Hua Wu. 2017. Multi-channel encoder for neural machine translation. *CoRR*, abs/1712.02109.