TOWARD NEURAL PHRASE-BASED MACHINE TRANSLATION

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ABSTRACT

In this paper, we present Neural Phrase-based Machine Translation (NPMT). Our method explicitly models the phrase structures in output sequences using Sleep-WAke Networks (SWAN), a recently proposed segmentation-based sequence modeling method. To mitigate the monotonic alignment requirement of SWAN, we introduce a new layer to perform (soft) local reordering of input sequences. Different from modern neural machine translation (NMT) approaches, NPMT does not use any attention-based decoding mechanisms. Instead, it directly outputs phrases in a sequential order. Our experiments show that NPMT achieves superior performances on IWSLT 2014 German-English/English-German and IWSLT 2015 English-Vietnamese translation tasks compared with strong NMT baselines. We also observe that our method produces meaningful phrases in output languages.

1 INTRODUCTION

Human languages often exhibit strong compositional patterns. For example, consider understanding the following sentence, "machine learning is part of artificial intelligence". It may become easier to comprehend if we segment it as "[machine learning] [is] [part of] [artificial intelligence]", where the words in the bracket '[]' are regarded as "phrases". These phrases have their own meanings, and can often be reused in other contexts.

The goal of this paper is to explore the use of phrase structures aforementioned for neural network-based machine translation systems (Sutskever et al., 2014; Bahdanau et al., 2015). To this end, we develop a neural machine translation method that explicitly models phrases in target language sequences. On one hand, traditional phrase-based statistical machine translation (SMT) approaches have been shown to consistently outperform word-based ones (Koehn et al., 2003; Koehn, 2009; Lopez, 2008). On the other hand, modern neural machine translation (NMT) methods (Sutskever et al., 2014; Bahdanau et al., 2015; Luong et al., 2015) do not have an explicit treatment on phrases, but they still work surprisingly well and have been deployed to industrial systems (Zhou et al., 2016; Wu et al., 2016).

The proposed Neural Phrase-based Machine Translation (NPMT) method tries to explore the advantages from both kingdoms. It builds upon Sleep-WAke Networks (SWAN), a segmentation-based sequence modeling technique described in Wang et al. (2017a), where segments (or phrases) are automatically discovered given the data. However, SWAN requires monotonic alignments between inputs and outputs and this is often not a good assumption in many langauge pairs. To mitigate this issue, we introduce a new layer to perform (soft) local reordering on input sequences. Experimental results show that NPMT outperforms attention-based NMT baselines in terms of the BLEU score (Papineni et al., 2002) on IWSLT 2014 German-English/English-German and IWSLT 2015 English-Vietnamese translation tasks. We believe our method is one step towards the full integration of the advantages from neural machine translation and phrase-based SMT.

This paper is organized as follows. Section 2 presents the neural phrase-based machine translation model. Section 3 demonstrates the usefulness of our approach on several language pairs. We conclude our work with some discussions in Section 4.

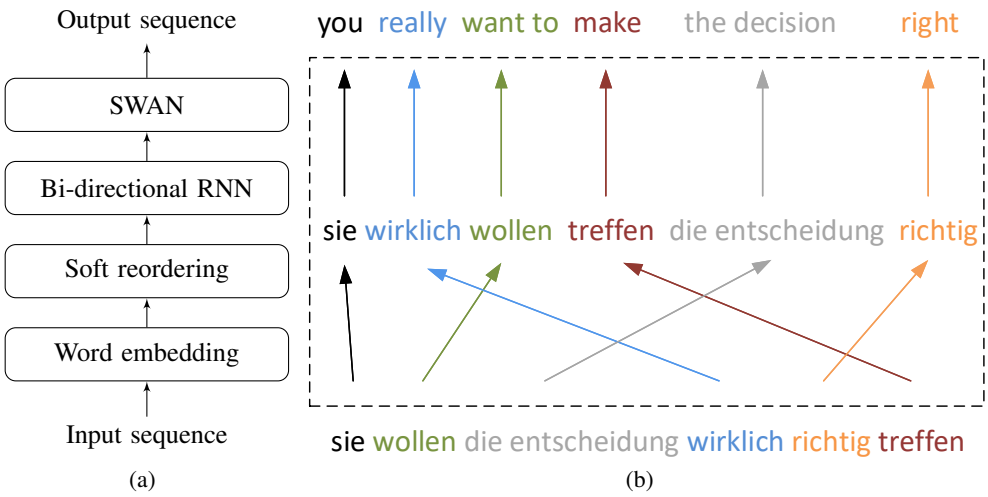

Figure 1: (a) The overall architecture of NPMT. (b) An illustration of using NPMT in German-English translation. Ideally, phrases in the source sentence (German) are first reordered. Given the new order, phrases can be translated one by one to the target phrases. These translated phrases then compose the target sentence (English). Phrase boundaries in the target language are not predefined, but automatically discovered by the model. No attention-based decoders are used here.

2 Neural Phrase-based Machine Translation

We first give an overview of the proposed NMPT architecture and some related work on incorporating phrases into NMT. We then describe the two key building blocks in NPMT, 1) SWAN and 2) the soft reordering layer which alleviates the monotonic alignment requirement of SWAN. In the context of machine translation, we use "segment" and "phrase" interchangeably.

2.1 The overall architecture of NMPT

Figure 1 shows the overall architecture of NPMT. The input sequence is first turned into embedding representations and then they go through a (soft) reordering layer (described below in Section 2.3). We then pass these "reordered" activations to the bi-directional RNN layers, which are finally fed into the SWAN layer to directly output target language in terms of segments (or phrases). While it is be possible to replace bi-directional RNN layers with other layers (Gehring et al., 2017), in this paper, we have only explored this particular setting to demonstrate our proposed idea.

We only explicitly consider output segments using SWAN while input segments are implicitly modeled via empty segments in SWAN. This is conceptually different from the traditional phrase-based SMT where both inputs and outputs are phrases (or segments). We leave the option of exploring explicit input segments as future work.

There have been several works that have proposed new ways to incorporate phrases into attention-based neural machine translation, such as Tang et al. (2016); Wang et al. (2017b); Dahlmann et al. (2017). These approaches typically use predefined phrases (obtained by external methods, e.g., phrase-based SMT) to guide or modify the existing attention-based decoder. The major difference of our approach is that, in NPMT, we do not use any attention-based decoding mechanisms and our phrase structures for the target language are automatically discovered from the training data. Another line of related work is a segment to segment neural transduction model, or SSNT from Yu et al. (2016) and shows promising results on a Chinese-to-English translation task under a noisy channel framework (Yu et al., 2017). In SSNT, the segments are implicit and the monotonic alignments between the inputs and outputs are achieved using latent variables. They are marginalized out during training using dynamic programming.

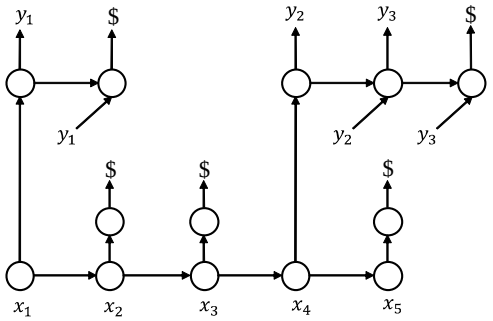

Figure 2: Courtesy to Wang et al. (2017a). Symbol \$ indicates the end of a segment. SWAN emits one particular segmentation of $y_{1:3} = \pi(a_{1:5})$, where $\{a_1 = \{y_1, \$\}, a_2 = \{\$\}, a_3 = \{\$\}, a_4 = \{y_2, y_3, \$\}, a_5 = \{\$\}\}$. Here x_1 wakes (emitting segment a_1) and x_4 wakes (emitting segment a_4) while x_2, x_3 and x_5 sleep (emitting empty segments a_2, a_3 and a_5 respectively).

2.2 Modeling phrases with SWAN

Here we review the SWAN model proposed in Wang et al. (2017a). SWAN defines a probability distribution for the output sequence given an input sequence. It models all valid output segmentations of the output sequence as well as the monotonic alignments between the output segments and the input sequence. Empty segments are allowed in the output segmentations. It does not make any assumption on the lengths of input or output sequence.

Assume input sequence is $x_{1:T'}$ and output sequence is $y_{1:T}$. Let $\mathcal{S}_y$ denote the set containing all valid segmentations of $y_{1:T}$, with the constraint that the number of segments in a segmentation is the same as the input sequence length, T'. Let a_t to denote a segment or phrase in the target sequence. Empty segments are allowed to ensure that we can correctly align segment a_t to input element x_t. Otherwise, we might not have a valid alignment for the input and output pair. See Figure 2 for an example of the emitted segmentation of $y_{1:T}$. The probability of the sequence $y_{1:T}$ is defined as the sum of the probabilities of all the segmentations in $\mathcal{S}_y \triangleq \{a_{1:T'} : \pi(a_{1:T'}) = y_{1:T}\}$, [1]

$$p(y_{1:T}|x_{1:T'}) \triangleq \sum_{a_{1:T'} \in S_y} \prod_{t=1}^{T'} p(a_t|x_t), \tag{1}$$

where the $p(a_t|x_t)$ is the segment probability given input element x_t, which is modeled using a recurrent neural network (RNN) with an additional softmax layer. $\pi(\cdot)$ is the concatenation operator and the symbol \$, end of a segment, is ignored in the concatenation operator $\pi(\cdot)$. (An empty segment, which only contains \$ will thus be ignored as well.) Since $|S_y|$ is exponentially large, direct summation quickly becomes infeasible when T or T' is not small. Instead, Wang et al. (2017a) developed an exact dynamic programming algorithm to tackle the computation.[2] The key idea is that although the number of possible segmentations is exponentially large, the number of possible segments is polynomial—$O(T^2)$. In other words, it is possible to first compute all possible segment probabilities, $p(a_t|x_t), \forall a_t, x_t$, and then use dynamic programming to calculate the output sequence probability $p(y_{1:T}|x_{1:T'})$ in Eq. (1). The feasibility of using dynamic programming is due to a property of segmentations—a segmentation of a subsequence is also part of the segmentation of the entire sequence. In practice, a maximum length for a segment a_t is also enforced to reduce the computational complexity, since the length of useful segments is often not very long. Wang et al. (2017a) also discussed a way to carry over information across segments using a separate RNN, which we will not elaborate here. We refer the readers to the original paper for the algorithmic details.

[1] If predefined phrase structure information is provided for the target language in advance, we can incorporate it into SWAN by restricting the size of $\mathcal{S}_y$. We leave the exploration of this option as future work.

[2] The computational complexity of SWAN is still high even with the dynamic programming algorithm. This is the reason that it takes a longer time to train our method for larger datasets such as in WMT translation tasks (weeks for a moderate model size). In the meantime, we are actively looking into the algorithms that can significantly speed up SWAN.

SWAN defines a conditional probability for an output sequence given an input one. It can be used in many sequence-to-sequence tasks. In practice, a sequence encoder like a bi-directional RNN can be used to process the raw input sequence (like speech signals or source language) to obtain $x_{1:T'}$ that is to be passed into SWAN for decoding. For example, Wang et al. (2017a) demonstrated the usefulness of SWAN in the context of speech recognition.

Greedy decoding for SWAN is straightforward. We first note that $p(a_t|x_t)$ is modeled as an RNN with an additional softmax layer. Then for each x_t in $x_{1:T'}$, we can use a left-to-right greedy decoding algorithm (Sutskever et al., 2014) for $p(a_t|x_t)$ to produce an output segment (possibly empty). We then concatenate these output segments to form the greedy decoding of the entire output sequence. See Wang et al. (2017a) for the algorithmic details of the beam search decoder.

2.3 Local reordering of input sequences

SWAN assumes a monotonic alignment between the output segments and the input elements. For speech recognition experiments in Wang et al. (2017a), this is a reasonable assumption. However for machine translation, this might be too strict. In neural machine translation literature, attention mechanisms were proposed to address alignment problems (Bahdanau et al., 2015; Luong et al., 2015; Raffel et al., 2017). But it is not clear how to apply a similar attention mechanism to SWAN due to the use of segmentations for output sequences.

We first note that in NPMT, a bi-directional RNN encoder for the source language can partly mitigate the alignment issue for SWAN, since it can access every source word. However, we found it is not enough to obtain the best performance. Here, we propose a new reordering layer that does (soft) local reordering of the input sequence. Together with SWAN, we obtain promising results on the IWSLT 2014 German-English/English-German, and IWSLT 2015 English-Vietnamese machine translation tasks. One additional advantage of using SWAN is that since SWAN does not using attention mechanism, decoding can be much faster, removing the need to query the entire input source for every output word (Raffel et al., 2017).

We now describe the details of the local reordering layer as shown in Figure 3(a). Let the input to the local reordering layer be $e_{1:T'}$ and the output of this layer is $h_{1:T'}$. We compute h_t as

$$h_t = \tanh\left(\sum_{i=0}^{2\tau} \sigma\left(w_i^T[e_{t-\tau};\ldots;e_t;\ldots;e_{t+\tau}]\right) e_{t-\tau+i}\right). \tag{2}$$

where $\sigma(\cdot)$ is the sigmoid function and $2\tau + 1$ is the local reordering window size. Notation $[e_{t-\tau};\ldots;e_t;\ldots;e_{t+\tau}]$ is the concatenation of vectors $e_{t-\tau},\ldots,e_t,\ldots,e_{t+\tau}$. For $i = 0,\ldots,2\tau$, notation w_i is the parameter for sigmoid function at position i of the input window. It decides the weight of $e_{t-\tau+i}$ through gate $\sigma\left(w_i^T[e_{t-\tau};\ldots;e_t;\ldots;e_{t+\tau}]\right)$. The final output h_t is a weighted linear combination of the input elements, $e_{t-\tau},\ldots,e_t,\ldots,e_{t+\tau}$, in the window followed by a non-linear transformation by the $\tanh(\cdot)$ function.

Figure 3(b) illustrates how local reordering works. Here we want to (soft) select an input element from a window given all information available in this window. Suppose we have two adjacent windows, (e_1, e_2, e_3) and (e_2, e_3, e_4). If we pick e_3 in the first window and e_2 in the second, e_2 and e_3 are effectively reordered. We design our layer differently from the typical attention mechanism (Bahdanau et al., 2015) in two ways because we do not have a query to begin with as in standard attention mechanisms. First, we do not normalize the weights for the input elements $e_{t-\tau},\ldots,e_t,\ldots,e_{t+\tau}$. This provides the reordering capability and can shut off everything if needed. Second, the weight of any position i in the reordering window is determined by all input elements $e_{t-\tau},\ldots,e_t,\ldots,e_{t+\tau}$ in the window. We provides an example of the reordering layer gates in Appendix A.

One related work to this layer is the Gated Linear Units (GLU) (Dauphin et al., 2017) which can control the information flow of the output of a traditional convolutional layer. But GLU does not have the ability to choose which input elements from the convolution window. And in our experiments, we found neither GLU nor traditional convolutional layer helped our setup of using SWAN. Another related work is the self-attention mechanism (Vaswani et al., 2017); this could potentially provide a soft reordering capability and we leave the exploration of this in the future work.

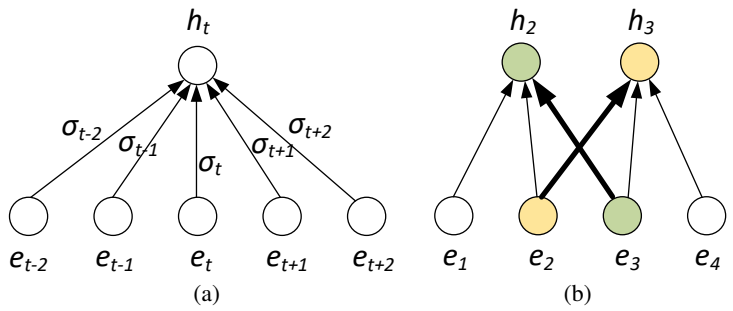

Figure 3: (a) Example of a local reordering layer of window size $\tau = 5$ to compute h_t. Here $\sigma_{t-3+i} \triangleq \sigma(w_i^T[e_{t-2}; e_{t-1}; e_t; e_{t+1}; e_{t+2}])$, $i = 1, \ldots, 5$, are the gates that decides how much information h_t should accept from those elements from this input window. Note that all information available in this input window helps decides each gate. (b) An illustration of the reordering layer that swaps information between e_2 and e_3 and contributes to h_3 and h_2, respectively.

3 Experiments

In this section, we evaluate our model on the IWSLT 2014 German-English (Cettolo et al., 2014), IWSLT 2014 English-German, IWSLT 2015 English-Vietnamese machine translation tasks. We note that, in this paper, we limited the application of our model to relatively small datasets to demonstrate the usefulness of our method. We plan to explore more large scale experiments in future work.

3.1 IWSLT14 German-English

We evaluate our model on the German-English machine translation track of the IWSLT 2014 evaluation campaign (Cettolo et al., 2014). The data comes from translated TED talks, and the dataset contains roughly 153K training sentences, 7K development sentences, and 7K test sentences. We use the same preprocessing and dataset splits as in Ranzato et al. (2015); Wiseman & Rush (2016); Bahdanau et al. (2017).

We report our IWSLT 2014 German-English experiments using one reordering layer with window size 7, two-bi-directional GRU encoder (Gated recurrent unit, Chung et al. (2014)) with 256 hidden units, and a two-unidirectional GRU decoder with 512 hidden units. We add dropout with a rate of 0.5 in the GRU layer. We chose GRU since baselines for comparisons were using GRU. The maximum segment length is set to 6. Batch size is set as 32 and the Adam algorithm (Kingma & Ba, 2014) is used for optimization with initial learning rate as 0.001. For decoding, we use greedy search and beam search with a beam size of 10. As reported in Maas et al. (2014); Bahdanau et al. (2017), we find that penalizing candidate sentences that are too short was required to obtain the best results. All hyperparameters are chosen based on the development set. NPMT takes about 2–3 days to run to convergence (40 epochs) on a 4 M40 GPU machine. The results are summarized in Table 1. In addition to previous reported baselines in the literature, we also explored the best hyperparameter using the same model architecture (except the reordering layer) using sequence-to-sequence model with attention as reported as LL* of Table 1.

NPMT achieves state-of-the-art results on this dataset as far as we know. Compared to the supervised sequence-to-sequence model, LL (Bahdanau et al., 2017), NPMT achieves 2.4 BLEU gain in the greedy setting and 2.25 BLEU gain using beam-search. Our results are also better than those from the actor-critic based methods in Bahdanau et al. (2017). But we note that our proposed method is orthogonal to the actor-critic method. So it is possible to further improve our results using the actor-critic method.

We also run two following experiments to verify the sources of the gain. The first is to add a reordering layer to the original sequence-to-sequence model with attention, which gives us BLEU scores of 25.55 (greedy) and 26.91 (beam search). The second is to remove the reordering layer from NPMT, which gives us BLEU scores of 27.79 (greedy) and 29.28 (beam search). This shows that the reordering layer and SWAN are both important for the effectiveness of NPMT.

	BLEU	
	Greedy	Beam Search
MIXER (Ranzato et al., 2015)	20.73	21.83
LL (Wiseman & Rush, 2016)	22.53	23.87
BSO (Wiseman & Rush, 2016)	23.83	25.48
LL (Bahdanau et al., 2017)	25.82	27.56
LL*	26.17	27.61
RF-C+LL (Bahdanau et al., 2017)	27.70	28.30
AC+LL (Bahdanau et al., 2017)	27.49	28.53
NPMT (this paper)	**28.57**	**29.92**
NPMT+LM (this paper)	–	**30.08**

Table 1: Translation results on the test set. MIXER Ranzato et al. (2015) uses a convolutional encoder and simpler attention. LL (attention model with log likelihood) and BSO (beam search optimization) of Wiseman & Rush (2016), and LL, RF-C+LL, and AC+LL of Bahdanau et al. (2017) use a one-layer GRU encoder and decoder with attention. (RF-C+LL and AC+LL are different settings of actor-critic algorithms combined with LL.) LL* stands for attention model with log likelihood with the same word embedding size, and encoder and decoder size as NPMT.

In greedy decoding, we can estimate the *average segment length*[3] for the output. The average segment length is around 1.4–1.5, indicating phrases with more than one word are being decoded. Figure 2 shows an example of the input and decoding results with NPMT. We can observe phrase-level translation being captured by the model (e.g., "danke" $\rightarrow$ "thank you"). The model also knows when to *sleep* before outputting a phrase (e.g., "das" $\rightarrow$ \$). We use the index of words in the source sentence to indicate where the output phrases are from. Table 2 shows some sampled examples. We can observe there are many informative segments in the decoding results, e.g., "tens of thousands of", "the best thing", "a little", etc. There are also mapping from phrase to phrase, word to phrases, and phrase to word in the examples. Following the analysis, we show the most frequent phrase mappings in Appendix B.

We also explore an option of adding a language-model score during beam search as the traditional statistical machine translation does. This option might not make much sense in attention-based approaches, since the decoder itself is usually a neural network language model. In SWAN, however, there is no language models directly involved in the segmentation modeling,[4] and we find it useful to have an external language model during beam search. We use a 4-order language model trained using KenLM implementation (Heafield et al., 2013) for English target training data. So the final beam search score we use is

$$Q(y) = \log p(y|x) + \lambda_1 \text{word_count}(y) + \lambda_2 \log p_{\text{lm}}(y), \tag{3}$$

where we empirically find that $\lambda_1 = 1.2$ and $\lambda_2 = 0.2$ gives good performance, which is tuned on the development set. If no external language models are used, we set $\lambda_2 = 0$. This scoring function is similar to the one for speech recognition in Hannun et al. (2014).

3.2 IWSLT14 English-German

We also evaluate our model on the opposition direction, English-German, which translates from a more segmented text to a more inflectional one. Following the setup in Section 3.1, we use the same dataset with the opposite source and target languages. We use the same model architecture,

[3]The average segment length is defined as the length of the output (excluding end of segment symbol \$) divided by the number of segments (not counting the ones only containing \$).

[4]In Wang et al. (2017a), SWAN does have an option to use a separate RNN that connects the segments, which can be seen as a language model. However, different from speech recognition experiments, we find in machine translation experiments, adding this separate RNN leads to a worse performance. We suspect this is because that a RNN language model can be easier to learn than the segmentation structures and SWAN gets stuck in that local mode. This is further evidenced by the fact that the average segment length is much shorter with a separate RNN in SWAN.

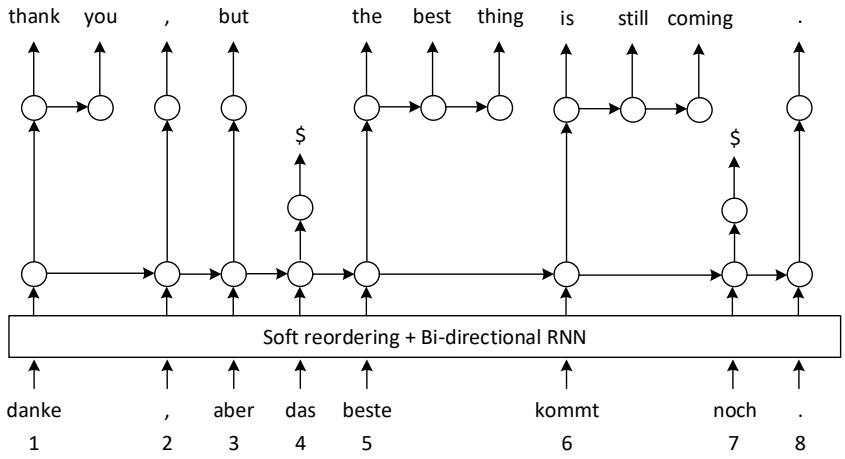

Figure 4: An example of NPMT greedy decoding output for German-English translation. The example corresponds to the first example of Table 2. Note that for illustrating the input and output segments, we do not take into account of the behavior of the reordering layer and bi-directional RNN—the index mappings from source to target assumes monotonic alignments so some of them might be inaccurate.

source	^{1}danke ^{2}, ^{3}aber ^{4}das ^{5}beste ^{6}kommt ^{7}noch ^{8}.
greedy decoding	^{1}thank you • ^{2}, • ^{3}but • ^{5}the best thing • ^{6}is still coming • ^{8}.
target ground truth	thanks . i haven 't come to the best part .
source	^{1}sie ^{2}können ^{3}einen ^{4}schalter ^{5}dazwischen ^{6}einfügen ^{7}und ^{8}so ^{9}haben ^{10}sie ^{11}einen ^{12}kleinen ^{13}UNK ^{14}erstellt ^{15}.
greedy decoding	^{1}you can put • ^{4}a switch • ^{5}in between • ^{7}and • ^{8}so • ^{10}they created • ^{12}a little • ^{13}UNK ^{14}.
target ground truth	you can put a knob in between and now you 've made a little UNK .
source	^{1}sie ^{2}wollen ^{3}die ^{4}entscheidung ^{5}wirklich ^{6}richtig ^{7}treffen ^{8}, ^{9}wenn ^{10}es ^{11}für ^{12}alle ^{13}ewigkeit ^{14}ist ^{15}, ^{16}richtig ^{17}?
greedy decoding	^{1}you really want to make • ^{4}the decision • ^{6}right • ^{8}, • ^{9}if • ^{10}it 's • ^{11}for • ^{12}all • ^{13}eternity • ^{15}, • ^{16}right • ^{17}?
target ground truth	you really want to get the decision right if it 's for all eternity , right ?
source	^{1}es ^{2}gibt ^{3}zehntausende ^{4}maschinen ^{5}rund ^{6}um ^{7}die ^{8}welt ^{9}die ^{10}kleine ^{11}stücke ^{12}von ^{13}dna ^{14}herstellen ^{15}können ^{16}, ^{17}30 ^{18}bis ^{19}50 ^{20}buchstaben ^{21}lang ^{22}aber ^{23}es ^{24}ist ^{25}ein ^{26}UNK ^{27}prozess ^{28}, ^{29}also ^{30}je ^{31}länger ^{32}man ^{33}ein ^{34}stück ^{35}macht ^{36}, ^{37}umso ^{38}mehr ^{39}fehler ^{40}passieren ^{41}.
greedy decoding	^{1}there are • ^{3}tens of thousands of • ^{4}machines • ^{6}around • ^{8}the world • ^{9}can make • ^{10}little • ^{11}pieces • ^{12}of • ^{13}dna • ^{16}, • ^{17}30 • ^{18}to • ^{19}50 • ^{20}letters • ^{21}long • ^{22}, but • ^{23}it 's • ^{26}a more UNK • ^{27}process • ^{28}, • ^{29}so • ^{31}the longer • ^{32}you make • ^{34}a piece • ^{36}, • ^{38}the more • ^{39}mistakes • ^{40}happen • ^{41}.
target ground truth	there are tens of thousands of machines around the world that make small pieces of dna – 30 to 50 letters - in length - and it 's a UNK process , so the longer you make the piece , the more errors there are .

Table 2: Examples of German-English translation outputs with their segmentations. We label the index of the words in the source sentence and we use those indexes to indicate where the output segment is emitted. For example, in greedy decoding results, "$^{i}\texttt{word}_1, \ldots, \texttt{word}_m$" denotes i-th word in the source sentence emits words $\texttt{word}_1, \ldots, \texttt{word}_m$ during decoding (assuming monotonic alignments). The "•" represents the segment boundary in the target output. See Figure 4 for a visualization of row 1 in this table.

optimization algorithm and beam search size as the German-English translation task. NPMT takes about 2–3 days to run to convergence (40 epochs) on a 4 M40 GPU machine.

Given there is no previous sequence-to-sequence attention model baseline for this setup, we create a strong one and tune hyperparameters on the development set. The results are shown in Table 3. Based on the development set, we set $\lambda_1 = 1$ and $\lambda_2 = 0.15$ in Eq. (3). Our model outperforms sequence-to-sequence model with attention by 2.46 BLEU and 2.49 BLEU in greedy and beam search cases. We can also use a 4-order language model trained using KenLM implementation for German target training data, which further improves the performance. Some sampled examples are shown in Table 4. Several informative segments/phrases can be found in the decoding results, e.g., "some time ago" $\rightarrow$ "vor enniger zeit".

	BLEU	
	Greedy	Beam Search
Sequence-to-sequence with attention	21.26	22.59
NPMT (this paper)	**23.62**	**25.08**
NPMT+LM (this paper)	–	**25.36**

Table 3: Translation results on IWSLT 2014 English-German test set.

source	^{1}how ^{2}would ^{3}you ^{4}guys ^{5}describe ^{6}your ^{7}brand ^{8}?
greedy decoding	^{1}wie • ^{2}würdet • ^{3}sie • ^{6}ihre marke • ^{8}beschreiben ?
target ground truth	wie würdet ihr eure marke beschreiben ?
source	^{1}if ^{2}the ^{3}museum ^{4}has ^{5}given ^{6}us ^{7}the ^{8}image ^{9}, ^{10}you ^{11}click ^{12}on ^{13}it ^{14}.
greedy decoding	^{1}wenn • ^{2}das museum • ^{6}uns • ^{7}das bild • ^{9}gegeben hat ,• ^{10}klicken sie • ^{13}darauf • ^{14}.
target ground truth	wenn das museum uns das bild gegeben hat , klicken sie darauf .
source	^{1}they ^{2}are ^{3}frustrated ^{4}as ^{5}hell ^{6}with ^{7}it ^{8}, ^{9}but ^{10}they ^{11}'re ^{12}not ^{13}complaining ^{14}about ^{15}it ^{16}, ^{17}they ^{18}'re ^{19}fixing ^{20}it ^{21}.
greedy decoding	^{1}sie sind • ^{3}frustriert • ^{8}, • ^{9}aber • ^{10}sie UNK sich • ^{12}nicht • ^{15}darüber • ^{16}, • ^{17}sie reparieren • ^{20}es • ^{21}.
target ground truth	sie sie sind fürchterlich frustriert mit ihr , aber sie beschweren sich nicht darüber , sie reparieren sie . ?
source	^{1}now ^{2}some ^{3}time ^{4}ago ^{5}, ^{6}if ^{7}you ^{8}wanted ^{9}to ^{10}win ^{11}a ^{12}formula ^{13}1 ^{14}race ^{15}, ^{16}you ^{17}take ^{18}a ^{19}budget ^{20}, ^{21}and ^{22}you ^{23}bet ^{24}your ^{25}budget ^{26}on ^{27}a ^{28}good ^{29}driver ^{30}and ^{31}a ^{32}good ^{33}car ^{34}.
greedy decoding	^{2}vor einiger zeit • ^{6}wenn • ^{7}man • ^{11}eine formel • ^{15}gewinnen will , • ^{18}ein budget • ^{21}und • ^{23} , dass • ^{24}ihr budget • ^{27}auf einem guten • ^{29}fahrer • ^{30}und • ^{31}ein gutes • ^{33}auto • ^{34}.
target ground truth	vor einiger zeit war es so , dass wenn sie ein formel 1 rennen gewinnen wollten , dann nahmen sie ihr budget und setzten ihr geld auf einen guten fahrer und ein gutes auto .

Table 4: Examples of English-German translation outputs with their segmentations. The meanings of the superscript indexes and the "•" symbol are the same as those in Table 2.

3.3 IWSLT15 English-Vietnamese

In this section, we evaluate our model on the IWSLT 2015 English to Vietnamese machine translation task. The data is from translated TED talks, and the dataset contains roughly 133K training sentence pairs provided by the IWSLT 2015 Evaluation Campaign (Cettolo et al., 2015). Following the same preprocessing steps in Luong & Manning (2015); Raffel et al. (2017), we use the TED tst2012 (1553 sentences) as a validation set for hyperparameter tuning and TED tst2013 (1268 sentences) as a test set.

We use the one reordering layer with window size 7, two-bi-directional LSTM (Long short-term memory, Hochreiter & Schmidhuber (1997)) encoder with 512 hidden units, and a three-unidirectional LSTM decoder with 512 hidden units. We add dropout with a rate of 0.4 in the LSTM layer. We chose LSTM since baselines for comparisons were using LSTM. The maximum segment length is set to 7. Batch size is set as 48 and the Adam algorithm Kingma & Ba (2014) is used for optimization with initial learning rate as 0.001. For decoding, we use greedy decoding and beam search with a beam size of 10. The results are shown in Table 5. Based on the development set, we set $\lambda_1 = 0.7$ and $\lambda_2 = 0.15$ in Eq. (3). NPMT takes about one day to run to convergence

(15 epochs) on a 4 M40 GPU machine. Our model outperforms sequence-to-sequence model with attention by 1.41 BLEU and 1.59 BLEU in greedy and beam search cases. We also use a 4-order language model trained using KenLM implementation for Vietnamese target training data, which further improves the BLEU score. Note that our reordering layer relaxes the monotonic assumption as in Raffel et al. (2017) and is able to decode in linear time. Empirically we outperform models with monotonic attention. Table 6 shows some sampled examples.

	BLEU	
	Greedy	Beam Search
Hard monotonic (Raffel et al., 2017)	23.00	-
Luong & Manning (2015)	-	23.30
Sequence-to-sequence model with attention	25.50	26.10
NPMT (this paper)	**26.91**	**27.69**
NPMT+LM (this paper)	–	**28.07**

Table 5: Translation results on IWSLT 2015 English-Vietnamese tst2013 test set. The result of the sequence-to-sequence model with attention is obtained from an open source model provided by the authors.[6]

source	^{1}And ^{2}I ^{3}figured ^{4}, ^{5}this ^{6}has ^{7}to ^{8}stop ^{9}.
greedy decoding	^{1}Và • ^{2}tôi • ^{3}nhận ra rằng • ^{4}, • ^{5}điều này • ^{6}phải• ^{8}dừng lại ^{9}.
target ground truth	Và tôi nhận ra rằng điều đó phải chấm dứt .
source	^{1}So ^{2}great ^{3}progress ^{4}and ^{5}treatment ^{6}has ^{7}been ^{8}made ^{9}over ^{10}the ^{11}years ^{12}.
greedy decoding	^{1}Vì vậy , • ^{2}tiến bộ• ^{4}và • ^{5}điều trị • ^{6}đã • ^{7}được • ^{8}tạo ra • ^{9}trong • ^{10}những • ^{11}năm • ^{12}.
target ground truth	Trong suốt những năm qua đã có sự tiến bộ to lớn trong quá trình điều trị .
source	^{1}The ^{2}passion ^{3}that ^{4}the ^{5}person ^{6}has ^{7}for ^{8}her ^{9}own ^{10}growth ^{11}is ^{12}the ^{13}most ^{14} important ^{15} thing ^{16}.
greedy decoding	^{1}Niềm đam mê • ^{3}rằng • ^{5}người • ^{6} có • ^{7} cho • ^{8}sự phát triển • ^{10}của cô ấy • ^{11}là • ^{13}điều • ^{14}quan trọng • ^{15}nhất • ^{16}.
target ground truth	Cái khát vọng của người phụ nữ có cho sự phát triển của bản thân là thứ quan trọng nhất .
source	^{1}We ^{2}have ^{3}eight ^{4}species ^{5}of ^{6}UNK ^{7}that ^{8}occur ^{9} in ^{10}Kenya ^{11}, ^{12}of ^{13}which ^{14}six ^{15}are ^{16}highly ^{17}threatened ^{18}with ^{19} extinction ^{20}.
greedy decoding	^{1}Chúng ta • ^{2}có • ^{3}8 • ^{4}loài • ^{6} UNK • ^{8}xảy ra • ^{9}ở • ^{10}Kenya • ^{11}, • ^{14}6 • ^{17}bị đe doạ • ^{19}tuyệt chủng • ^{20}.
target ground truth	Chúng ta có 8 loài kền kền xuất hiện tại Kenya , trong đó có 6 loài bị đe doạ với nguy cơ tuyệt chủng cao .

Table 6: Examples of English-Vietnamese translation outputs with their segmentations. The meanings of the superscript indexes and the "•" symbol are the same as those in Table 2.

4 CONCLUSION

We studied NPMT, a neural phrase-based machine translation system that models phrase structures in the target language using SWAN. We also introduced a local reordering layer to mitigate the monotonic alignment requirement in SWAN. Our experimental results showed promising results on a IWSLT German-English, English-German, English-Vietnamese translation tasks. The results suggest that NPMT can potentially be extended to explore the structures in other challenging sequence-to-sequence problems. In future work, we plan to explore two major directions: 1) speed up NPMT and apply it to larger datasets and more language pairs, 2) investigate how to learn input and output phrases simultaneously.

[6]https://github.com/tensorflow/nmt

REFERENCES

Dzmitry Bahdanau, Kyunghyun Cho, and Yoshua Bengio. Neural machine translation by jointly learning to align and translate. In *International Conference on Learning Representations*, 2015.

Dzmitry Bahdanau, Philemon Brakel, Kelvin Xu, Anirudh Goyal, Ryan Lowe, Joelle Pineau, Aaron C. Courville, and Yoshua Bengio. An actor-critic algorithm for sequence prediction. In *International Conference on Learning Representations*, 2017.

Mauro Cettolo, Jan Niehues, Sebastian Stüker, Luisa Bentivogli, and Marcello Federico. Report on the 11th IWSLT evaluation campaign, IWSLT 2014. In *Proceedings of IWSLT*, 2014.

Mauro Cettolo, Jan Niehues, Sebastian Stüker, Luisa Bentivogli, Roldano Cattoni, and Marcello Federico. The IWSLT 2015 evaluation campaign. In *International Conference on Spoken Language*, 2015.

Junyoung Chung, Caglar Gulcehre, KyungHyun Cho, and Yoshua Bengio. Empirical evaluation of gated recurrent neural networks on sequence modeling. *arXiv preprint arXiv:1412.3555*, 2014.

Leonard Dahlmann, Evgeny Matusov, Pavel Petrushkov, and Shahram Khadivi. Neural machine translation leveraging phrase-based models in a hybrid search. In *Proceedings of the 2017 Conference on Empirical Methods in Natural Language Processing*, pp. 1422–1431, 2017.

Yann N Dauphin, Angela Fan, Michael Auli, and David Grangier. Language modeling with gated convolutional networks. In *International Conference on Machine Learning (ICML)*, 2017.

Jonas Gehring, Michael Auli, David Grangier, Denis Yarats, and Yann N Dauphin. Convolutional sequence to sequence learning. In *ICML*, 2017.

Awni Hannun, Carl Case, Jared Casper, Bryan Catanzaro, Greg Diamos, Erich Elsen, Ryan Prenger, Sanjeev Satheesh, Shubho Sengupta, Adam Coates, et al. Deep speech: Scaling up end-to-end speech recognition. *arXiv preprint arXiv:1412.5567*, 2014.

Kenneth Heafield, Ivan Pouzyrevsky, Jonathan H. Clark, and Philipp Koehn. Scalable modified Kneser-Ney language model estimation. In *Proceedings of the 51th Annual Meeting of the Association for Computational Linguistics: Short Papers-Volume 2*, pp. 690–696, 2013.

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

Diederik Kingma and Jimmy Ba. Adam: A method for stochastic optimization. *arXiv preprint arXiv:1412.6980*, 2014.

Philipp Koehn. *Statistical Machine Translation*. Cambridge University Press, 2009.

Philipp Koehn, Franz Josef Och, and Daniel Marcu. Statistical phrase-based translation. In *Proceedings of the 2003 Conference of the North American Chapter of the Association for Computational Linguistics on Human Language Technology-Volume 1*, pp. 48–54. Association for Computational Linguistics, 2003.

Adam Lopez. Statistical machine translation. *ACM Computing Surveys (CSUR)*, 40(3):8, 2008.

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

Minh-Thang Luong, Hieu Pham, and Christopher D Manning. Effective approaches to attention-based neural machine translation. *arXiv preprint arXiv:1508.04025*, 2015.

Andrew L. Maas, Awni Y. Hannun, Daniel Jurafsky, and Andrew Y. Ng. First-pass large vocabulary continuous speech recognition using bi-directional recurrent DNNs. *CoRR*, abs/1408.2873, 2014.

Kishore Papineni, Salim Roukos, Todd Ward, and Wei-Jing Zhu. BLEU: a method for automatic evaluation of machine translation. In *Proceedings of the 40th annual meeting on association for computational linguistics*, pp. 311–318. Association for Computational Linguistics, 2002.

Colin Raffel, Thang Luong, Peter J Liu, Ron J Weiss, and Douglas Eck. Online and linear-time attention by enforcing monotonic alignments. In *International Conference on Machine Learning (ICML)*, 2017.

Marc'Aurelio Ranzato, Sumit Chopra, Michael Auli, and Wojciech Zaremba. Sequence level training with recurrent neural networks. *CoRR*, abs/1511.06732, 2015.

Ilya Sutskever, Oriol Vinyals, and Quoc V Le. Sequence to sequence learning with neural networks. In *Advances in Neural Information Processing Systems*, pp. 3104–3112, 2014.

Yaohua Tang, Fandong Meng, Zhengdong Lu, Hang Li, and Philip LH Yu. Neural machine translation with external phrase memory. *arXiv preprint arXiv:1606.01792*, 2016.

Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N Gomez, Lukasz Kaiser, and Illia Polosukhin. Attention is all you need. *arXiv preprint arXiv:1706.03762*, 2017.

Chong Wang, Yining Wang, Po-Sen Huang, Abdelrahman Mohamed, Dengyong Zhou, and Li Deng. Sequence modeling via segmentations. In *International Conference on Machine Learning (ICML)*, 2017a.

Xing Wang, Zhaopeng Tu, Deyi Xiong, and Min Zhang. Translating phrases in neural machine translation. In *Proceedings of the 2017 Conference on Empirical Methods in Natural Language Processing*, pp. 1432–1442. Association for Computational Linguistics, 2017b.

Sam Wiseman and Alexander M. Rush. Sequence-to-sequence learning as beam-search optimization. *CoRR*, abs/1606.02960, 2016.

Yonghui Wu, Mike Schuster, Zhifeng Chen, Quoc V Le, Mohammad Norouzi, Wolfgang Macherey, Maxim Krikun, Yuan Cao, Qin Gao, Klaus Macherey, et al. Google's neural machine translation system: Bridging the gap between human and machine translation. *arXiv preprint arXiv:1609.08144*, 2016.

Lei Yu, Jan Buys, and Phil Blunsom. Online segment to segment neural transduction. In *Proceedings of the 2016 Conference on Empirical Methods in Natural Language Processing*, pp. 1307–1316, 2016.

Lei Yu, Phil Blunsom, Chris Dyer, Edward Grefenstette, and Tomas Kocisky. The neural noisy channel. In *International Conference on Learning Representations*, 2017.

Jie Zhou, Ying Cao, Xuguang Wang, Peng Li, and Wei Xu. Deep recurrent models with fast-forward connections for neural machine translation. *Transactions of the Association for Computational Linguistics*, 4:371–383, 2016. ISSN 2307-387X.

A REORDERING LAYER ANALYSIS

To further understand the behavior of the reordering layer, we examine the values of the gate $\sigma\left(w_i^T[e_{t-\tau};\ldots;e_t;\ldots;e_{t+\tau}]\right)$ in Eq. (2). We study the NPMT English-German model in Section 3.2. In Figure 5, we show an example that translates from "can you translate it ?" to "können man es übersetzen ?", where the mapping between words are as follows: "can $\rightarrow$ können", "you $\rightarrow$ man", "translate $\rightarrow$ übersetzen", "it $\rightarrow$ es" and "? $\rightarrow$?". Note that the example needs to be reordered from "translate it" to "es übersetzen". Each row of Figure 5 represents a window of size 7 that is centered at a source sentence word. The values in the matrix represent the gate values for the corresponding words. The gate values will later be multiplied with the embedding $e_{t-\tau+i}$ of Eq. (2) and contribute to the hidden vector h_t. The y-axis represents the word/phrases emitted from the corresponding position. We can observe that the gates mostly focus on the central word since the first part of the sentence only requires monotonic alignment. Interestingly, the model outputs "$" (empty) when the model has the word "translate" in the center of the window. Then, the model outputs "es" when the model encounters "it". Finally, in the last window (top row), the model not only has a large gate value to the center input "?", but the model also has a relatively large gate value to the word "translate" in order to output the translation "übersetzen ?". This shows an example of the reordering effect achieved by using the gating mechanism of the reordering layer.

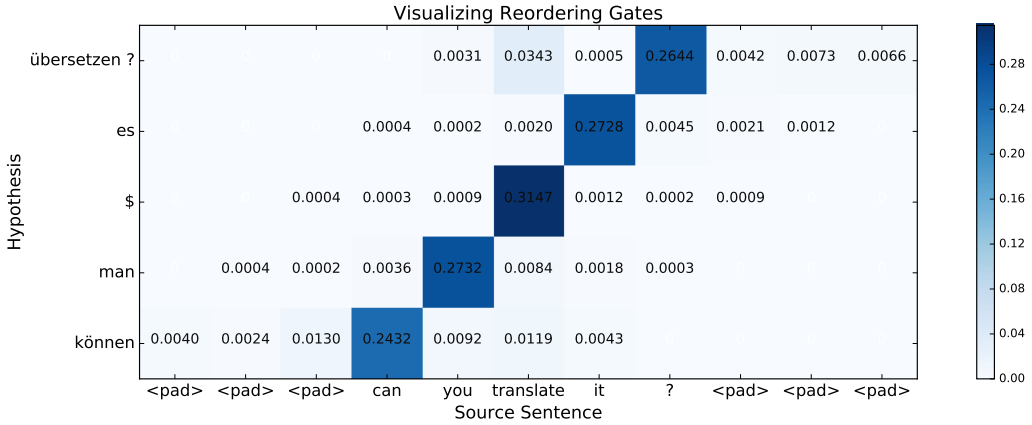

Figure 5: Visualizing reordering gates in the NPMT English-German translation model.

B PHRASE MAPPING EXAMPLES

Following the examples of Table 2, we analyze the decoding results on the test set of the German-English translation task. Given we do not have explicit input segments in NPMT, we assume input words that emit "$" symbol are within the same group as the next non-'$' word. For example, in Figure 4, input words "das beste" are considered as an input segment. We then can aggregate all the input, output segments (phrases) and sort them based on the frequency. Tables 7 and 8 show the most-frequent input, output phrase mappings.

Table 7: German-English phrase mapping results. We show the top 10 input, output phrase mappings in five categories ("One" stands for single word and "Many" stands for multiple words.). In the last column, Many → Many*, we remove the phrases with the "UNK" word as the "UNK" appears often.

One → One	**One → Many**	**Many → One**	**Many → Many**	**Many → Many***
, → ,	es → it 's	, dass → that	die UNK → the UNK	wissen sie → you know
. → .	UNK → the UNK	in der → in	der UNK → the UNK	in diesem → in this
und → and	und → , and	UNK . → .	ein UNK → a UNK	die welt → the world
UNK → UNK	das → this is	UNK , → ,	das UNK → the UNK	ist es → it 's
aber → but	das, → that 's	, die → that	eine UNK → a UNK	" . → . "
" → "	UNK → a UNK	ist . → .	in UNK → in UNK	ein paar → a few
ist → is	ich → i think	in den → in	den UNK → the UNK	gibt es → there 's
der → of	es → it was	ist , → ,	wissen sie → you know	der welt → the world
von → of	dies → this is	sind . → .	in diesem → in this	die frage → the question
mit → with	es → there 's	, wenn → if	dem UNK → the UNK	haben wir → we have

Table 8: German-English longer phrase mapping results. We show the top 5 input, output phrase mappings for two categories: input and output phrases with three words, and input and output phrases with four words.

Phrases with 3 words	**Phrases with 4 words**
auf der ganzen → all over the	auf der ganzen → a little bit of
gibt eine menge → a lot of	weiß nicht , was → what 's going to be
dann hat er→ he doesn 't have	tun , das wir → we can 't do
, die man → you can do	tat , das ich → i didn 't do
das können wir → we can do that	zu verbessern , die → that can be done