Guiding Non-Autoregressive Neural Machine Translation
Decoding with Reordering Information

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Abstract

Non-autoregressive neural machine translation (NAT) generates each target word in parallel and has achieved promising inference acceleration. However, existing NAT models still have a big gap in translation quality compared to autoregressive neural machine translation models due to the enormous decoding space. To address this problem, we propose a novel NAT framework ReorderNAT which explicitly models the reordering information in the decoding procedure. We further introduce deterministic and non-deterministic decoding strategies that utilize reordering information to narrow the decoding search space in our proposed ReorderNAT. Experimental results on various widely-used datasets show that our proposed model achieves better performance compared to existing NAT models, and even achieves comparable translation quality as autoregressive translation models with a significant speedup.

1 Introduction

Neural machine translation (NMT) models with encoder-decoder framework (Sutskever et al., 2014; Bahdanau et al., 2014) significantly outperform conventional statistical machine translation models (Koehn et al., 2003, 2007) on translation quality. Despite their success, the state-of-the-art NMT models usually suffer from the slow inference speed, which has become a bottleneck to apply NMT in real-world translation systems. The slow inference speed of NMT models is due to their autoregressive property, i.e., decoding the target sentence word-by-word according to the translation history.

Recently, Gu et al. (2017) introduced non-autoregressive NMT (NAT) which can simultaneously decode all target words to break the bottleneck of the autoregressive NMT (AT) models.

To this end, NAT models (Gu et al., 2017; Wei et al., 2019; Wang et al., 2019; Guo et al., 2019; Shao et al., 2019) usually directly copy the source word representations to the input of the decoder, instead of using previous predicted target word representations. Hence, the inference of different target words are independent, which enables parallel computation of the decoder in NAT models. NAT models could achieve 10-15 times speedup compared to AT models while maintaining considerable translation quality.

However, existing NAT systems ignore the dependencies among target words and simultaneously generate all target words, which makes the search space in the decoding procedure too large to be well modeled. Specially, when decoding a target word, in order to determine which part of source sentence it is translated from, the NAT models need to search in a large global hypothesis space to infer what is expressed by its previous and latter words in the translation. Consequently, the large decoding space issue makes NAT models generate translation conditioned on less or inaccurate source information, thus leading to missing, repeated and even wrong translations. This problem is not severe for AT models because it only needs to decode a target word in a small local hypothesis space conditioned on previously translated words.

In this paper, to address this issue, we propose a novel NAT framework named ReorderNAT which explicitly models the reordering information to guide the decoding of NAT. To be specific, as shown in Figure 1, ReorderNAT first reorders the source sentence into a pseudo-translation formed by source words but in the target language structure, and then translate the pseudo-translation into target language to obtain the final translation. We further introduce two guiding decoding strategies which utilizes the reordering information (i.e.

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Figure 1: The framework of our ReorderNAT model. Different from original NAT models, our model adds a reordering module between the encoder module and decoder module to explicitly model the reordering information. For original NAT model, the decoder inputs are the copied embeddings of source sentence (No.1 dashed arrow), and for ReorderNAT model, the decoder inputs are the embeddings of pseudo translation.

The search space in decoding procedure of ReorderNAT is much smaller than the whole decoding space of original NAT: (1) the decoding space of reordering module in generating pseudo-translation is limited on the permutation of the source words; (2) with the guide of reordering information, for each target word, what it is expressed can be nearly narrow to the corresponding word of pseudo-translation in the same position. Therefore, ReorderNAT could effectively reduce the decoding search space by introducing the reordering information in NAT.

Experimental results on several widely-used public benchmarks show that our proposed ReorderNAT model achieves significant and consistent improvements compared to existing NAT models by explicitly model the reordering information to guide the decoding. Moreover, by introducing a simple but effective AT decoder to model reordering information, our ReorderNAT immensely narrows the translation quality gap between AT and NAT models, while maintains the considerable speedup (nearly six times faster). We will release all source codes and related resources of this work for further research explorations.

2 Background

Non-autoregressive neural machine translation (NAT) is first proposed by Gu et al. (2017) to alleviate the slow decoding issue of autoregressive neural machine translation (AT) models, which could simultaneously generate target words by removing their dependencies. Formally, given a source sentence \( X = \{x_1, \cdots, x_n\} \) and a target sentence \( Y = \{y_1, \cdots, y_m\} \), NAT models the translation probability from \( X \) to \( Y \) as a product of conditionally independent target word probability:

\[
P(Y | X) = \prod_{i=1}^{m} P(y_i | X). \tag{1}
\]

 Instead of utilizing the previous translation history, NAT models usually copy the sequence of source word representations as the input of the decoder. Hence, when translating a sentence, NAT models could predict all target words with their maximum likelihood individually by breaking the dependency among the target words, and therefore the decoding procedure of NAT models is in parallel and has very low translation latency.

However, since NAT models discard the sequential dependencies among words in the target sentence, it suffers from the potential performance degradation due to the explosion of decoding search space. To be specific, when decoding a target word, the NAT model must be able to figure out not only what target-side information does the word describe but also what is expressed by other target words. With the explosion of decoding search space, NAT models cannot effectively learn the intricate translation patterns from source sentences to target sentences, which leads to inferior translation quality.
3 Methodology

In this section, we introduce a novel NAT model named ReorderNAT, which aims to break the explosion of search space in the decoding procedure of NAT models.

3.1 ReorderNAT

As shown in Figure 1, ReorderNAT employs a reordering module to explicitly model the reordering information in the decoding. Formally, ReorderNAT first translates the source sentence \( X \) into a pseudo-translation \( Z = \{z_1, \ldots, z_m\} \) which reorders source sentence structure into the target language, and then translates the pseudo-translation to target sentence \( Y \). ReorderNAT models the overall translation probability as:

\[
P(Y | X) = \sum_Z P(Z | X) P(Y | Z, X),
\]

where \( P(Z | X) \) is modeled by the reordering module and \( P(Y | Z, X) \) is modeled by the decoder module. The encoder module in ReorderNAT is a multi-layer Transformer, which is the same as original NAT, and thus we do not introduce it in detail.

3.1.1 Reordering Module

The reordering module determines the source-side information of each target word by learning to translate the source sentence into the pseudo-translation. We propose two feasible implementations of the reordering module:

1. NAT Reordering Module: Intuitively, the pseudo-translation probability can also be modeled as NAT:

\[
P(Z | X) = \prod_{i=1}^{m} P(z_i | X),
\]

where \( P(z_i | X) \) is a one-layer Transformer.

2. AT Reordering Module: Moreover, we find that AT models are more suitable for modeling the reordering information compared to NAT models, and even a light AT model with similar decoding speed to a large NAT model could achieve better performance in modeling reordering information. Hence, we also introduce a light AT model to model the pseudo-translation probability as:

\[
P(Z | X) = \prod_{i=1}^{m} P(z_i | z_{<i}, X),
\]

where \( z_{<i} = \{z_1, \ldots, z_{i-1}\} \) indicates the pseudo-translation history, and \( P(z_i | z_{<i}, X) \) is a one-layer recurrent neural network.

3.1.2 Decoder Module

The decoder module generates the target translation with the guiding of pseudo-translation, which regards the translation of each word as NAT:

\[
P(Y | Z, X) = \prod_{i=1}^{m} P(y_i | Z, X).
\]

As shown in Figure 1, the encoder module and the decoder module can be viewed as a seq-to-seq model which translate the source sentence to target sentence. Different with the original NAT, the inputs of our decoder module is the embeddings of pseudo-translation instead of copied embeddings of source sentence, which is used to guide the decoding direction.

3.2 Guiding Decoding Strategy

ReorderNAT explicitly models reordering information of NAT and aims to utilize it to alleviate the issue of explosive decoding search space of NAT. Now the remaining problem is how to perform decoding with the guide of reordering information. We propose to utilize the pseudo-translation as a bridge to guide the decoding of the target sentence, which can be formulated as:

\[
Y^* = \arg \max_Y P(Y | X)
\]

\[
= \arg \max_Y \sum_Z P(Y | Z, X) P(Z | X).
\]

It is intractable to obtain an exact solution for maximizing Eq. 6 due to the high time complexity. Inspired by the pre-ordering works in statistical machine translation, we propose a deterministic guiding decoding (DGD) strategy and a non-deterministic guiding decoding (NDGD) strategy to solve this problem.

The DGD strategy first generates the most probable pseudo-translation of the source sentence and then decodes the target translation conditioned on it:

\[
Z^* = \arg \max_Z P(Z | X),
\]

\[
Y^* = \arg \max_Y P(Y | Z^*, X).
\]

The DGD approach is simple and effective, but it brings in some noise in the approximation.

Different from the DGD strategy which utilizes a deterministic pseudo-translation to guide, the NDGD strategy, regards the probability distribution \( Q \) of the pseudo-translation as a latent variable, and models the translation as generating the
target sentence according to the latent variable $Q$, i.e., Eq. 6 is re-formulated as:

$$
Y^* = \arg \max_Y P(Y|Q, X),
$$

(8)

where the probability distribution $Q$ is defined as:

$$
Q(Z) = P(Z|X) = \frac{\exp(s(Z)/T)}{\sum_{Z'} \exp(s(Z')/T)},
$$

(9)

where $s(\cdot)$ is a score function of pseudo-translation (the input of softmax layer in the decoder) and $T$ is a temperature coefficient. Since the latent variable $Q$ can be viewed as a non-deterministic form of the pseudo-translation, the translation with the NDGD strategy is also guided by the pseudo-translation.

To be specific, as shown in Figure 1, the major difference between DGD and NDGD strategy is the inputs of decoder module (No. 2 dashed arrow), where the DGD strategy directly utilizes the word embeddings of generated pseudo-translation and the NDGD strategy utilizes the weighted word embeddings of the word probability of pseudo-translation. The detailed architecture of ReorderNAT model is introduced in Appendix A due to the space limit.

### 3.3 Decoding Search Space of ReorderNAT

In ReorderNAT, the decoding space of generating pseudo-translation with reordering module is much smaller than that of the whole translation in NAT since the decoding vocabulary is limited in the words in the source sentence. Therefore, ReorderNAT could easily capture the reordering information compared to the original NAT by explicitly modeling with pseudo-translation as internal supervision. Besides, the decoding search space of generating the final translation with decoder module is also much small. The reason is that the search space of the $i$-th word of the final translation can be narrowed to the translation of $z_i$ to some extent since $z_i$ is the $i$-th word in the pseudo-translation which indicates the corresponding source information of $y_i$.

### 3.4 Training

In the training process, for each training sentence pair $(X, Y) \in D$, we first generate its corresponding pseudo-translation $\hat{Z}$: we use a word alignment tool to align each word $y_i$ to a source word $x_{y_i}$, and we set $z_i = x_{y_i}$. And then ReorderNAT is optimized by maximizing a joint loss:

$$
L = L_R + L_T,
$$

(10)

where $L_R$ and $L_T$ indicate the reordering and translation losses respectively. Formally, for both DGD and NDGD approaches, the reordering loss $L_R$ is defined as:

$$
L_R = \sum_{(X, \hat{Z}, Y) \in D} \log P(\hat{Z}|X).
$$

(11)

For the DGD approach, the translation loss is defined as an overall maximum likelihood of translating pseudo-translation into the target sentence:

$$
L_T = \sum_{(X, \hat{Z}, Y) \in D} \log P(Y|\hat{Z}, X),
$$

(12)

For the NDGD approach, the translation loss is defined as an overall maximum likelihood of decoding the target sentence from the conditional probability of pseudo-translation:

$$
L_T = \sum_{(X, \hat{Z}, Y) \in D} \log P(Y|Q, X).
$$

(13)

In particular, we use the trained model for the DGD approach to initialize the model for the NDGD approach since if Q is not well trained, $L_D$ will converge very slowly.

### 4 Experiments

#### 4.1 Datasets

The main experiments are conducted on three widely-used machine translation tasks: WMT14 En-De (4.5M pairs), WMT16 En-Ro (610k pairs) and IWSLT16 En-De (196k pairs). For WMT14 En-De task, we take newstest-2013 and newstest-2014 as validation and test sets respectively. For WMT16 En-Ro task, we employ newsdev-2016 and newstest-2016 as validation and test sets respectively. For IWSLT16 En-De task, we use test2013 for validation. We also conduct our experiments on Chinese-English translation which differs more in language structure. The training set consists of 1.25M sentence pairs extracted from the LDC corpora. We choose NIST 2002 (MT02) dataset as our validation set, and NIST 2003 (MT03), 2004 (MT04), 2005 (MT05), 2006 (MT06) and 2008 (MT08) datasets as our test sets.

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1. We set the word alignment tool to link each target word to exact one source word.
4.2 Experimental Settings

We use fast_align tool\(^2\) to generate the pseudo-translation in our experiments. We follow most of the model hyperparameter settings in (Gu et al., 2017; Lee et al., 2018; Wei et al., 2019) for fair comparison. For IWSLT16 En-De, we use a 5-layer Transformer model \(d_{\text{model}} = 278, d_{\text{hidden}} = 507, n_{\text{head}} = 2, p_{\text{dropout}} = 0.1\) and anneal the learning rate linearly (from \(3 \times 10^{-4}\) to \(10^{-5}\)) as in (Lee et al., 2018). For WMT14 En-De, WMT16 En-Ro and Chinese-English translation, we use a 6-layer Transformer model \(d_{\text{model}} = 512, d_{\text{hidden}} = 512, n_{\text{head}} = 8, p_{\text{dropout}} = 0.1\) and adopt the warm-up learning rate schedule (Vaswani et al., 2017) with \(t_{\text{warmup}} = 4000\). For the GRU reordering module, we set it to have the same hidden size with the Transformer model in each dataset. We employ label smoothing of value \(\epsilon_{ls} = 0.15\) and utilize the sequence-level knowledge distillation (Kim and Rush, 2016) for all datasets.

4.3 Baselines

In the experiments, we compare ReorderNAT (NAT) and ReorderNAT (AT) which utilize an NAT reordering module and an AT reordering module respectively with several baselines.

We select three models as our autoregressive baselines: (1) Transformer\(_{\text{full}}\) (Vaswani et al., 2017), the hyperparameters are described in experimental settings. (2) Transformer\(_{\text{one}}\), a lighter version of Transformer, of which decoder layer number is 1. (3) Transformer\(_{\text{gru}}\), which replaces the decoder of Transformer\(_{\text{full}}\) with GRU (Cho et al., 2014).

We also include several typical NAT models as our baselines: (1) NAT-FT (Gu et al., 2017), which copies source inputs using fertilities as the decoder inputs and predicts the target words in parallel. (2) NAT-FT+NPD (Gu et al., 2017), an NAT-FT model which adopts noisy parallel decoding (NPD) during inference. We set the sample size of NPD to 10 and 100. (3) NAT-IR (Lee et al., 2018), which iteratively refines the translation for multiple times. We set the number of iterations to 1 and 10. (4) NAT-REG (Wang et al., 2019), an NAT model using repeated translation and similarity regularizations. (5) NAT-FS (Shao et al., 2019), which serializes the top decoder layer and generates the target sentence autoregressively. (6) imitate-NAT (Wei et al., 2019), which forces the NAT model to imitate an AT model during training. (7) imitate-NAT+LPD (Wei et al., 2019), an imitate-NAT model which adopts length parallel decoding.

4.4 Effect of Temperature Coefficient \(T\)

The hyperparameter of temperature coefficient \(T\) controls the smoothness of the \(Q\) distribution (see Eq. 9). As shown in Figure 2, we find that \(T\) affects on the BLEU scores on the IWSLT16 validation set to some extent. While \(T = 0.1\) decreases BLEU scores, \(T = 0.2\) improves translation quality significantly and consistently. However, increasing \(T\) further to \(T = 0.5\) or 1, results in worse translation quality compared to \(T = 0.2\) after training 150k steps. Hence, we set \(T = 0.2\) for the NDGD strategy in our experiments.

4.5 Effect of Guiding Decoding Strategy

We also investigate the effect of two proposed guiding decoding strategies including DGD and NDGD on IWSLT16 validation set. In Table 1, we can find that the NDGD strategy has better performance compared to the DGD strategy for both ReorderNAT (AT) and ReorderNAT (NAT) since the NDGD strategy could effectively reduce the information loss of the DGD strategy. However, we also find that the NDGD strategy does not bring

\(^2\)https://github.com/clab/fast_align

\begin{table}[h]
\centering
\begin{tabular}{|c|c|c|}
\hline
Model & Decoding Strategy & IWSLT16 En→De \tabularnewline \hline
ReorderNAT (NAT) & DGD & 24.94 \tabularnewline & NDGD & 25.29 \tabularnewline \hline
ReorderNAT (AT) & DGD & 30.15 \tabularnewline & NDGD & 30.26 \tabularnewline \hline
\end{tabular}
\caption{Effect of guiding decoding strategy on the IWSLT16 validation set (The results on all datasets are in the appendix).}
\end{table}
ReorderNAT (NAT) and retain low translation latency (about 1.00x speedup). It is also worth mentioning that although RoNAT (AT)) achieves state-of-the-art performance on most of the benchmark datasets, RoNAT (AT) with small AT GRU reordering module performs much better than large NAT model (25.83 vs. 29.61) in WMT14’s De → En task, 31.99 vs. 32.60 in WMT16’s Ro → En task, 30.26 vs. 31.18 in IWSLT’s En → De task). It is also worth mentioning that although ReorderNAT utilizes a small AT model to better capture reordering information, it could still maintain low translation latency (about 16x speedup of ReorderNAT (NAT) and 6x speedup of ReorderNAT (AT))). Compared to Transformer$_{one}$ and Transformer$_{gru}$, ReorderNAT (AT) uses a much smaller vocabulary in the AT reordering module, which is limited to the words in the source sentence and makes it faster.

(2) ReorderNAT (NAT) and ReorderNAT (NAT)+LPD also gain significant improvements compared to most existing NAT model, and even overcome the state-of-the-art NAT model imitate-NAT on WMT14 by explicitly modeling the reordering information. It verifies that the reordering information explicitly modeled by ReorderNAT could effectively guide its decoding direction.

(3) A small AT model with close latency to large NAT models could perform much better in modeling reordering information. On all benchmark datasets, ReorderNAT (AT) with small AT GRU reordering module achieves much better translation quality than that with large NAT model (25.35 vs. 29.31, 32.86 vs. 32.60) in WMT14, while maintains acceptable latency (2.42x and 3.10x speedup respectively). The reason is that a major potential performance degradation of NAT models compared to AT models comes from the difficulty of modeling the sentence structure difference between source and target language, i.e., reordering information, which is neglected for most of existing NAT models but can be well modeled by the small AT decoder.

Table 2: Overall results of AT and NAT models in BLEU score on the test set of WMT14 and WMT16, and validation set of IWSLT16. AT-TM and NAT-TM indicate the AT Transformer and NAT Transformer decoder block respectively. AT-GRU indicates the AT GRU decoder block. NAT-TM-imitate indicates the NAT Transformer decoder block with the imitation module.

| Model                  | Decoder Architecture | WMT14 En→De | WMT14 De→En | WMT16 En→Ro | WMT16 Ro→En | IWSLT16 En→De | Speedup |
|------------------------|----------------------|-------------|-------------|-------------|-------------|---------------|---------|
| Transformer$_{full}$   | AT-TM × N            | 27.29       | 31.70       | 32.86       | 32.60       | 31.18         | 1.00x   |
| Transformer$_{one}$    | AT-TM × 1            | 25.35       | 29.31       | 30.61       | 31.23       | 29.52         | 2.42x   |
| Transformer$_{gru}$    | AT-GRU × 1           | 25.83       | 30.49       | 30.41       | 31.23       | 29.26         | 3.10x   |
| NAT-FT                 | NAT-TM × N           | 17.69       | 21.47       | 27.29       | 29.06       | 26.52         | 15.6x   |
| NAT-FT+NPD (s=10)      | NAT-TM × N           | 18.66       | 22.41       | 29.02       | 30.76       | 27.44         | 7.68x   |
| NAT-FT+NPD (s=100)     | NAT-TM × N           | 19.17       | 23.20       | 29.79       | 31.44       | 28.16         | 2.36x   |
| NAT-IR (iter = 1)      | NAT-TM × N           | 13.91       | 16.77       | 24.45       | 25.73       | 22.20         | 8.90x   |
| NAT-IR (iter = 10)     | NAT-TM × N           | 21.61       | 25.48       | 29.32       | 30.19       | 27.11         | 1.50x   |
| NAT-REG                | NAT-TM × N           | 20.65       | 24.77       | -           | -           | 27.02         | 15.10x  |
| NAT-FS                 | NAT-TM × N-1+AT-TM × 1 | 22.27   | 27.25       | 30.57       | 30.83       | 27.78         | 3.75x   |
| imitate-NAT            | NAT-TM-imitate × N   | 22.44       | 25.67       | 28.61       | 28.90       | 28.41         | 18.60x  |
| imitate-NAT+LPD        | NAT-TM-imitate × N   | 24.15       | 27.28       | 31.45       | 31.81       | 30.68         | 9.70x   |

4.6 Overall Results

We compare ReorderNAT (NAT) and ReorderNAT (AT) that utilizes an NAT reordering module and an AT reordering module respectively with all baseline models. All the results are shown in Table 2. From the table, we can find that:

(1) ReorderNAT (AT) achieves state-of-the-art performance on most of the benchmark datasets, which is even close to the AT model with smaller than 1 BLEU gap. (31.13 vs. 31.70 in WMT14’s De → En task, 31.99 vs. 32.60 in WMT16’s Ro → En task, 30.26 vs. 31.18 in IWSLT’s En → De task). It is also worth mentioning that although ReorderNAT utilizes a small AT model to better capture reordering information, it could still maintain low translation latency (about 16x speedup of ReorderNAT (NAT) and 6x speedup of ReorderNAT (AT))). Compared to Transformer$_{one}$ and Transformer$_{gru}$, ReorderNAT (AT) uses a much smaller vocabulary in the AT reordering module, which is limited to the words in the source sentence and makes it faster.

(2) ReorderNAT (NAT) and ReorderNAT (NAT)+LPD also gain significant improvements compared to most existing NAT model, and even overcome the state-of-the-art NAT model imitate-NAT on WMT14 by explicitly modeling the reordering information. It verifies that the reordering information explicitly modeled by ReorderNAT could effectively guide its decoding direction.

(3) A small AT model with close latency to large NAT models could perform much better in modeling reordering information. On all benchmark datasets, ReorderNAT (AT) with small AT GRU reordering module achieves much better translation quality than that with large NAT model (25.83 vs. 29.61) in WMT14, while maintains acceptable latency (2.42x and 3.10x speedup respectively). The reason is that a major potential performance degradation of NAT models compared to AT models comes from the difficulty of modeling the sentence structure difference between source and target language, i.e., reordering information, which is neglected for most of existing NAT models but can be well modeled by the small AT decoder.
4.7 Results on Chinese-English Translation

To show the effectiveness of modeling reordering information in NAT, we compare ReorderNAT with baselines on Chinese-English translation since the language structure between Chinese and English is more different than that between German and English (En-De). From Table 3, we can find that in Chinese-English translation, ReorderNAT (AT) achieves much more improvements (6-7 BLEU scores) compared to ReorderNAT (NAT) and imitate-NAT. The reason is that the problem of explosive decoding search space is more severe in Chinese-English translation, which could effectively alleviate by ReorderNAT.

4.8 Translation Quality over Sentence Lengths

Figure 3 shows the BLEU scores of translations generated by AT transformer model (Transformer), our Reorder-NAT model without reordering module (NAT), our Reorder-NAT model with AT reordering module (Reorder-NAT (AT)) and with NAT reordering module (Reorder-NAT (NAT)) on the IWSLT16 validation set with respect to input sentence lengths. From the figure, we can observe that:

1. The ReorderNAT (AT) model achieves significant improvement compared to the NAT model, and nearly comparable performance to AT Transformer model for all lengths. It verifies that the reordering information modeled by ReorderNAT could effectively reduce the decoding space and improve the translation quality of the model.

2. Our ReorderNAT model achieves much better translation performance than the NAT model for sentences longer than 15 words. The reason is that the size of the global hypothesis space for NAT’s decoding is correlated to the sentence length and therefore the problem of large decoding space is more serious for longer input sentences.

4.9 Case Study

Table 4 shows example translations of original NAT model and ReorderNAT model. We find that the problem of missing translation and repeated translation are severe in the translation (both 5 occurrences) of original NAT model, while this problem is effectively alleviated in ReorderNAT model. Moreover, we find that most of the missing, repeated or wrong word in the translation of ReorderNAT come from the errors in the pseudo-translation, which demonstrates that NAT model could well translate the pseudo-translation which has the target sentence structure to the final translation, and the remaining problem of NAT lies on the modeling reordering information.

5 Related Work

5.1 Non-Autoregressive Neural Machine Translation

Gu et al. (2017) first proposed the non-autoregressive neural machine translation (NAT), which could make parallel decoding for neural machine translation (NMT) available and significantly accelerate the inference of NMT. However, its performance degrades greatly since it discards the sequential dependencies among words in the target sentence and leads to enormous search space in decoding. In recent years, a variety of works have been investigated to improve the performance of NAT in various aspects including (Guo et al., 2019; Shao et al., 2019) which enhance the representation of decoder via source information or sequential target information; (Wang et al., 2019; Libovický and Helcl, 2018) which attempt to solve the multi-modality problem in NAT; (Lee et al., 2018; Ghazvininejad et al., 2019)
Source: eventually, after a period of six months of brutal war and a toll rate of almost 50,000 dead, we managed to liberate our country and to topple the tyrant.

Reference: schließlich, nach einem Zeitraum von sechs Monaten brutalen Krieges und fast 50,000 Toten, gelang es uns, unser Land zu befreien und den Tyran nen zu strafen.

NAT: Translation: schließlich, nach einer Zeit von sechs Monaten brutalen Krieges und einer Z rate von fast 50,000 Toten, schafften wir es, unser Land zu befreien und den Tyran en zu strafen.

ReorderNAT (NAT): Pseudo-Translation: schließlich, nach einer Zeit von sechs Monaten brutal, Krieg eines Z rate fast 50,000, schafften wir es, unser Land zu befreien und den Tyran en zu strafen.

ReorderNAT (AT): Translation: schließlich, nach einer Zeit von sechs Monaten brutalen Krieges und einer Z rate von fast 50,000 Toten, schafften wir es, unser Land zu befreien und den Tyran en zu strafen.

Table 4: Examples of translations of NAT baseline and ReorderNAT. We use red color to label the missing word, yellow color to label the repeat word and green color to label the wrong word. We use _ to concatenate sub-words.

which employ an iterative decoding strategy to improve translation quality; and (Akoury et al., 2019; Kaiser et al., 2018; Wang et al., 2018) which combine AT and NAT models by first autoregressively predicting a short sequence, and want to take a trade-off between decoding speed and translation quality; (Li et al., 2018; Wei et al., 2019) which attempts to guide the learning of NAT models with AT models to narrow the decoding space of NAT models. Different from existing improvement on NAT models, we propose to explicitly model reordering information in NAT models, which could effectively reduce the decoding search space of NAT models and improve translation quality.

5.2 Modelling Reordering Information in Machine Translation

Re-ordering model is a key component in statistical machine translation (SMT), which handles the difference of language structure between source and target language. There has been a large amount of works focusing on word pre-ordering in SMT, including deterministic pre-ordering approaches (Xia and McCord, 2004; Collins et al., 2005; Wang et al., 2007; Li et al., 2007), which find a single optimal reordering of the source sentence; and non-deterministic pre-ordering approaches (Kanthak et al., 2005; Zhang et al., 2007) which encode multiple alternative reorderings into a word lattice and remain the choosing strategy of best path in the decoder. In neural machine translation (NMT), it has been shown that the attention mechanism (Bahdanau et al., 2014) could implicitly capture the reordering information to some extent. Zhang et al. (2017) presented three distortion models to further incorporate reordering knowledge into attention-based NMT models. Chen et al. (2019) introduced a reordering mechanism for NMT models to learn the reordering embedding of a word based on its contextual information. Except for incorporating reordering knowledge in attention mechanism, researchers proposed to learn to pre-reorder the source-side word orders according to the sentence structure in target language with neural networks (Du and Way, 2017; Kawara et al., 2018; Zhao et al., 2018). To the best of our knowledge, it is the first time that reordering knowledge is incorporated into non-autoregressive neural machine translation models.

6 Conclusion and Further Work

In this work, we find that a key factor leading to the inferior performance of NAT is its explosive decoding space. To address this problem, we propose a novel NAT framework named ReorderNAT which explicitly models the reordering information in the decoding procedure. We further introduce deterministic and non-deterministic guiding decoding strategies to utilize the reordering information to narrow the potential decoding search space. Experimental results on public benchmarks show that our ReorderNAT model achieves better performance than existing NAT models, and even achieves comparable translation quality as AT model with a significant speedup. We believe to well model the reordering information is a po-
tential way towards better NAT.

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A Appendices

A.1 Model Architecture

In this section, we will introduce the details of the encoder, reorder and decoder modules in Figure 4 respectively. Formally, we denote the embedding of the source sentence $X$ as $\text{Emb}(X)$.

A.1.1 Encoder and Decoder Blocks

We first introduce the encoder and decoder blocks used in three modules.

In our proposed ReorderNAT model, we employ a Transformer encoder block (Vaswani et al., 2017) as our encoder block, which is composed by a multi-head self attention layer and a feed-forward layer. It could be formulated as:

$$E(H) = \text{FFN}(\text{Self-Att}(H)),$$

where $H$ is the input embeddings of the encoder block, $\text{FFN}(\cdot)$ is the feed-forward layer and $\text{Self-Att}(\cdot)$ is the multi-head self-attention layer.

We employ two types of decoder blocks:

1. Transformer decoder block (Vaswani et al., 2017), which is composed by a multi-head self-attention layer, a multi-head inter-attention layer and a feed-forward layer. It is defined as:

$$D(H, S) = \text{FFN}(\text{Inter-Att}(S, (\text{Self-Att}(H)))),$$

where $H$ is the input embeddings of the decoder block, $\text{Inter-Att}(\cdot)$ is the multi-head inter-attention layer.

2. GRU decoder block, which consists of a multi-head inter-attention layer and a GRU layer. It is defined as:

$$D(H, S) = \text{Inter-Att}(S, (\text{GRU}(H))),$$

where $\text{GRU}(\cdot)$ is a gated recurrent unit (Cho et al., 2014).

A.1.2 Encoder Module

In the ReorderNAT model, we feed the input sentence embedding $\text{Emb}(X)$ into an $N$-layer encoder block and obtain the hidden representation $S = E^N(\text{Emb}(X))$. $E^N(\cdot)$ indicates stacking $N$ layers of encoder block $E(\cdot)$ of the source sentence $X$. 

A.1.3 Reordering Module

In the reordering module, we employ an NAT model with Transformer decoder block or an AT model with GRU decoder block as the pseudo-translation decoder. Formally, for the NAT Reordering Module, we utilize the uniform copied embeddings as (Gu et al., 2017) for the input of the decoder, and then obtain the hidden representation \( R \) in word-reordering module:

\[
R = D(\text{Uniform-Copy}(\text{Emb}(X)), S). \tag{17}
\]

After obtaining the decoder hidden state \( R \), the conditional probability \( P(z_i|X) \) of the \( i \)-th word in the pseudo-translation is computed as:

\[
P(z_i|X) = \text{Softmax}(R_i), \tag{18}
\]

where \( R_i \) is the \( i \)-th column of \( R \).

For the AT Reordering Module, we use a greedy search algorithm to decode the pseudo-translation word-by-word. When decoding the \( i \)-th word \( z_i \) in the pseudo-translation, we obtain its hidden representation as:

\[
R_i = \text{GRU}(R_{i-1}, [C_{i-1}; \text{Emb}(z_{i-1}^*)]), \tag{19}
\]

where \( z_{i-1}^* \) is the previous word in the decoded pseudo-translation and \( C_{i-1} \) is calculated by the inter-attention to the encoder representation. After obtaining the hidden representation, the conditional probability \( P(z_i|X) \) is also calculated as Eq. 18.

A.1.4 Decoder Module

In the decoder module, we employ an NAT model with \( N-1 \) layers of Transformer decoder block. We utilize two types of input representation for deterministic guiding decoding (DGD) strategy and non-deterministic guiding decoding (NDGD) strategy. Formally, for DGD strategy, we use the word embeddings of the predicted pseudo-translation \( Z^* \) as the input of the decoder, and then obtain the final translation probability:

\[
P(Y|Z^*, X) = \text{Softmax}(D^{N-1}(\text{Emb}(Z^*), S)), \tag{20}
\]

where \( D^{N-1}(\cdot) \) indicates stacking \( N-1 \) layers of Transformer decoder block \( D(\cdot) \).

For NDGD strategy, we use the weighted word embeddings of the conditional probability \( Q \) (i.e. \( Q(Z) = P(Z|X) \)) of pseudo-translation as the input of the decoder, and then obtain the final translation probability:

\[
P(Y|Q, X) = \text{Softmax}(D^{N-1}(Q^T\text{Emb}(X), S)), \tag{21}
\]

A.2 Other Experiment Results

A.2.1 Effect of Guiding Decoding Strategy

We show the results of ReorderNAT (NAT) and ReorderNAT (AT) with DGD and NDGD in Table A.2.

A.2.2 Effect of #Layer of Decoder Module

To compare the NAT and AT baselines with the same model complexity, we utilize \( N-1 \) layers of Transformer decoder blocks for the decoder module in the experiments. However, we argue that the decoding space of decoder module is quite small and may be modeled by smaller architecture. To verify our assumption, we compare the translation quality of ReorderNAT model with different Transformer layer numbers in decoder module on the IWSLT16 validation set. Figure 5 shows the results, from which we can see that our ReorderNAT model also performs well with smaller de-
| Model               | Decoding Strategy | IWSLT16 En→De | WMT14 En→De | WMT14 De→En | WMT16 En→Ro | WMT16 Ro→En |
|---------------------|-------------------|---------------|-------------|-------------|-------------|-------------|
| ReorderNAT (NAT)    | DGD               | 24.94         | 22.79       | 27.28       | 28.47       | 29.04       |
|                     | NDGD              | 25.29         | 21.05       | 25.92       | 29.30       | 29.50       |
| ReorderNAT (AT)     | DGD               | 30.15         | 26.49       | 31.17       | 31.52       | 31.95       |
|                     | NDGD              | 30.26         | 26.51       | 31.13       | 31.70       | 31.99       |

Table 5: Effect of guiding decoding strategy.

| Model               | MT2* | MT3 | MT4 | MT5 | MT6 | MT8 |
|---------------------|------|-----|-----|-----|-----|-----|
| **Autoregressive Models** |      |     |     |     |     |     |
| Transformer$_{full}$| 46.11| 43.74| 45.59| 44.11| 44.09| 35.07|
| Transformer$_{one}$ | 43.60| 41.24| 43.39| 41.62| 41.07| 31.67|
| Transformer$_{gru}$ | 43.68| 40.55| 43.02| 40.73| 40.32| 31.09|
| **Non-Autoregressive Models** |      |     |     |     |     |     |
| imitate-NAT         | 33.77| 32.29| 34.83| 31.96| 31.84| 24.10|
| imitate-NAT+LPD     | 37.73| 36.53| 39.11| 35.97| 36.19| 27.29|
| ReorderNAT (NAT)    | 37.99| 36.03| 38.17| 36.07| 36.28| 27.99|
| ReorderNAT (NAT) + LPD | 41.58| 39.15| 41.67| 39.71| 39.58| 30.44|
| ReorderNAT (AT)     | 44.74| 42.74| 44.35| 43.44| 42.64| 33.74|

Table 6: BLEU scores on Chinese-English translation. * indidates the validation set.

Figure 5: Effect of the Transformer layer number of word translation module on the IWSLT16 validation set.

A.2.3 All Results on Chinese-English Translation

We show all results on all datasets including MT2, MT3, MT4, MT5, MT6 and MT8 in Table 6.