Nearest Neighbor Non-autoregressive Text Generation

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Abstract

Non-autoregressive (NAR) models can generate sentences with less computation than autoregressive models but sacrifice generation quality. Previous studies addressed this issue through iterative decoding. This study proposes using nearest neighbors as the initial state of an NAR decoder and editing them iteratively. We present a novel training strategy to learn the edit operations on neighbors to improve NAR text generation. Experimental results show that the proposed method (NeighborEdit) achieves higher translation quality (1.69 points higher than the vanilla Transformer) with fewer decoding iterations (one-eighteenth fewer iterations) on the JRC-Acquis En-De dataset, the common benchmark dataset for machine translation using nearest neighbors. We also confirm the effectiveness of the proposed method on a data-to-text task (WikiBio). In addition, the proposed method outperforms an NAR baseline on the WMT’14 En-De dataset. We also report analysis on neighbor examples used in the proposed method.

1 Introduction

Non-autoregressive (NAR) models have gained popularity lately (Gu et al., 2018a; Ghazvininejad et al., 2019; Lee et al., 2020; Qian et al., 2021). Autoregressive (AR) generation models (Sutskever et al., 2014) need to iterate computations of forward propagation from the input to output layers of the decoder multiple times for all generated tokens, whereas NAR models predict multiple tokens simultaneously. Hence, NAR decoding is faster as only one forward propagation computation is required. However, due to the inherent difficulty in capturing the dependencies between generated tokens, the generation quality of NAR models is worse than that of AR models.

The primary solution to this problem is to repeat decoding processes including edit operations, e.g., token substitution (Ghazvininejad et al., 2019; Qian et al., 2021), insertion (Stern et al., 2019a), and deletion/insertion (Gu et al., 2019). Repeating generation processes decreases the dependencies between output tokens by learning the conditional distribution over the generated tokens (Gu and Kong, 2021). However, during the inference, the decoder must start the generation from scratch (or special tokens), which leads to a low-quality sentence generated in the first iteration. Moreover, Huang et al. (2022) have demonstrated that if the initial sentence generated is of low quality, it is difficult to recover even after several iterations. Therefore, it is preferable to begin the generation process with a high-quality sentence to improve performance.

Therefore, this paper proposes using the nearest neighbor as the initial state of the NAR decoder. The proposed method, NeighborEdit, retrieves the nearest neighbor of an input sentence and edits it to generate the output sentence. Thus, NeighborEdit can start the generation with a sentence that is close to that of the output. As generating from a neighbor example is easier than generating from scratch, we anticipate an improved generation quality with fewer iterations. Consider the following example where the English sentence “I have an apple.” is translated into the German sentence “Ich habe einen Apfel.” NeighborEdit first retrieves the nearest neighbor of the English sentence from the training data, “I have a banana. – Ich habe eine Banane.” The method then starts with the retrieved German sentence, deletes the words ‘eine’ and ‘Banane’ and inserts the words ‘einen’ and ‘Apfel,’ to complete the translation.

Traditionally, nearest neighbors have been utilized in various tasks, including part-of-speech tagging (Daelemans et al., 1996) and example-based machine translation (Nagao, 1984). Recently, nearest neighbors have been successfully applied to AR models, particularly to neural machine translation (Gu et al., 2018b; Xu et al., 2020; Khandel-
we consider a translation task for simplicity. A

Neighbo...reduces at the previous iteration. The model then selects

2.2 Recap: Levenshtein Transformer

Neighbo... and the output
target-centric policies (described in Section 3.1.1).

2.1 Problem Formulation

We consider a translation task for simplicity. A target sentence $y^*$ is generated from a source sentence $x$ and a neighbor example $z_0$. Here, we find the sentence $x'$ that is closest to the source sentence $x$ in the datastore, and let $z_0$ be the target sentence paired with $x'$.

2.1 Problem Formulation

We train the model using imitation learning, a type of reinforcement learning, to mimic the sequence of actions of an expert. We cast the sequence generation task as a Markov Decision Process defined by the tuple $(\mathcal{Y}, \mathcal{A}, \mathcal{E}, \mathcal{R}, z_0)$. Here, $y \in \mathcal{Y}$ is a partially constructed sequence during the decoding process, which we refer to as a canvas (Stern et al., 2019b; Wiseman et al., 2021). $\mathcal{A}$ is a set of actions (edit operations), $\mathcal{E}$ is the environment that receives a canvas $y$ and action $a$ and yields an edited sequence, and $\mathcal{R}$ is a reward function.

At the $k$-th iteration of decoding, the model receives canvas $y^{k-1}$ (of $n+1$ tokens) edited at the previous iteration. The model then selects the action $a^k$ to generate a new canvas $y^k = \mathcal{E}(y^{k-1}, a^k)$ (of $n+1$ tokens) and obtains the reward $r^k = \mathcal{R}(y^k)$. The policy $\pi$ to select the action $a^k$ is defined as the mapping from the decoder output $(h_0, h_1, ..., h_n)$ for the input canvas $y^{k-1}$ into action space $\mathcal{A}$. Generally, the policy $\pi$ is approximated by linear classifiers with parameter $\theta$.

2.2 Recap: Levenshtein Transformer

NeighborEdit adopts Levenshtein Transformer (Gu et al., 2019), an edit-based non-autoregressive encoder-decoder model, as the base architecture. More specifically, policy $\pi$ consists of three parts: (1) token deletion classifier $\pi^\text{del}_\theta$, (2) placeholder insertion classifier $\pi^\text{plh}_\theta$, and (3) token classifier $\pi^\text{tok}_\theta$.

2.2.1 Policy Classifier

(1) Deletion classifier $\pi^\text{del}_\theta$ predicts whether each token $y_i (i \in \{1, ..., n-1\})$ should be deleted ($d_i = 0$) or kept ($d_i = 1$) as a binary classification.

$$
\pi^\text{del}_\theta(d_i|i, y) = \text{softmax}(h_i \theta) \quad \forall i : i \in \{1, ..., n-1\}
$$

(2) Placeholder insertion classifier $\pi^\text{plh}_\theta$ predicts the number of placeholders $[\mathcal{PLH}]$ to be inserted $p_i \in \{0, ..., K_{\text{max}}\}$. The model inserts no placeholder between $y_1$ and $y_{i+1}$.

$$
\pi^\text{plh}_\theta(p_i|i, y) = \text{softmax}(h_i : h_{i+1}) B \quad \forall i : i \in \{0, ..., n-1\}
$$

Here, $[a; b]$ represents a concatenation of the vectors $a$ and $b$.

(3) Token classifier $\pi^\text{tok}_\theta$ predicts a token $t_i$ for filling the placeholder $[\mathcal{PLH}]$.

$$
\pi^\text{tok}_\theta(t|i, y) = \text{softmax}(h, C) \quad \forall i : y_i = [\mathcal{PLH}]
$$

In total, the policy classifier has the parameter $\theta = (\mathcal{A}, B, C)$. The model receives the canvas $y_{i=0} = <s>$ and $y_n = </s>$, which represent the beginning and end of a sentence. The value $n$ may change during the iteration process via token deletion and insertion.
We train the model parameters by minimizing the Levenshtein Transformer. Please refer to Gu et al. (2019) for more details of edited canvas $E_D$ and deletion target, respectively. Also, here, $y_{\text{ins}}$ and $y_{\text{del}}$ are the canvases of the insertion target and deletion target, respectively. Also, $y_{\text{ins}}^0$ represents the canvas after insertion $[\text{PLH}]$ to $y_{\text{ins}}$. The expert operations $\alpha^* \in \{d^*, p^*, t^*\}$ are used to minimize the Levenshtein distance $D$ (Levenshtein et al., 1966) between expert $e$ and edited canvas $E(y, a)$.

$$d^* = \arg \min_d D(e, E(y_{\text{del}}, d))$$

$$p^*, t^* = \arg \min_{p, t} D(e, E(y_{\text{ins}}, \{p, t\}))$$

Please refer to Gu et al. (2019) for more details of Levenshtein Transformer.

### 3 Proposed Method

As shown in Figure 1, the proposed method first retrieves the nearest neighbors from the datastore consisting of all parallel sentences in the training set (Section 3.2). The method then generates a sentence by deleting and inserting tokens on the retrieved neighbor (Section 3.1).

#### 3.1 Edit Operations on Neighbors

NeighborEdit is an NAR model based on Transformer (Vaswani et al., 2017). Given the source sentence $x$ as the input and a retrieved neighbor $z_0$ as the initial state of the decoder, the proposed model edits the neighbor by deleting and inserting tokens repeatedly. We focus on incorporating the retrieved neighbors $z_0$ into the decoding process.

##### 3.1.1 Oracle Policy for NeighborEdit

During imitation learning, the model learns the parameterized policy $\pi_0$ to mimic the actions of an oracle policy $\pi^\ast$. We designed a novel strategy to obtain an oracle policy to edit the neighbor $z_0$ to a target sentence effectively.

The basic idea of the policy is to reproduce the edit operations on the intermediate sequence that appears in the iteration during inference (the partially edited neighbor). Therefore, our policy focuses on the lexical difference between a neighbor and target sentence. However, if their similarity is too low, it is necessary to rewrite a sentence into a completely different sentence. The policy...
of complete rewriting is too difficult to learn. To alleviate this issue, we design a policy by mixing the neighbor-centric policy $\pi_n^*$ and target-centric policy $\pi_t^*$. The former utilizes the lexical similarity and difference between the neighbor $z_0$ and the target sentence $y^*$, whereas the latter uses the target sentence $y^*$ only. During training, the model randomly chooses $\pi_n^*$ or $\pi_t^*$ for each batch. Furthermore, when the similarity between the neighbor and target sentence $\sim(z_0, y^*)$ is less than a threshold $\beta$, the policy $\pi_n^*$ for the insertion switches to the $\pi_t^*$ for each instance\(^2\). In summary, our policy $\pi^*$ mixes the policies $\pi_n^*$ and $\pi_t^*$ as follows:

$$\pi^* = (\pi^* \text{for deletion}, \pi^* \text{for insertion})$$

$$= \begin{cases} 
(\pi_n^*, \pi_n^*) & (u < \alpha \land \sim(z_0, y^*) > \beta) \\
(\pi_n^*, \pi_t^*) & (u < \alpha \land \sim(z_0, y^*) \leq \beta) \\
(\pi_t^*, \pi_t^*) & (\text{otherwise}) 
\end{cases}$$

where $\alpha \in [0, 1]$ is a hyperparameter and $u$ is a value sampled from the uniform distribution of $[0, 1]$. Here, we define $\sim(z_0, y^*)$ as the token overlap ratio, the number of overlapped tokens divided by the number of tokens in the neighbor.

By the above training strategy, our policy enables the model to delete unfavorable tokens from the nearest neighbor and insert necessary tokens. Given a canvas $y$, we define the oracle policy $\pi^*$ to generate expert $e$ as follows.

**Deletion:** $\pi^*(y_{\text{del}})$ This edit operation removes unnecessary tokens from the canvas $y_{\text{del}}$. It is essential to delete all unnecessary tokens from the retrieved neighbor $z_0$. Furthermore, unnecessary tokens that the model inserted in the previous iteration need to be removed. Hence, we train the model to delete tokens from $z_0$ that do not appear in the target sentence $y^*$ or unnecessarily inserted tokens from $\mathcal{E}(y', (\tilde{p}, \tilde{i}))$.

$$\pi_n^*(z_0) = M(y^*, z_0)$$

$$\pi^*(\mathcal{E}(y', (\tilde{p}, \tilde{i}))) = M(y^*, y_{\text{del}})$$

The function $M(a, b)$ yields the common token subsequence between $a$ and $b$. For example, $M(\text{"ABCDE."}, \text{"ARE"})$ returns “AE.”

**Insertion:** $\pi^*(y_{\text{ins}})$ This operation inserts necessary tokens into the canvas $y_{\text{ins}}$ to generate $y^*$.

$$\pi_n^*(M(y^*, \mathcal{E}(z_0, \tilde{d}))) = y^* \overset{\tilde{d}}{\sim} \tilde{d} \sim \pi_{\text{del}}^{\text{del}}$$

$$\pi_t^*(\mathcal{E}(y^*, \tilde{d})) = y^* \overset{\tilde{d}}{\sim} \pi_{\text{RND}}^{\text{RND}}$$

Here, $\pi_{\text{RND}}$ is a policy of random token deletion. $\mathcal{E}(y^*, \tilde{d})$ presents a target sequence with some tokens deleted at random (based on $\pi_{\text{RND}}$). The intention of $M(y^*, \mathcal{E}(z_0, \tilde{d}))$ is to delete tokens in the nearest neighbor based on the policy of $\pi_{\text{del}}$ and insert necessary tokens that appear in $y^*$ but not in the deleted sequence.

### 3.1.2 Inference

The model receives the initial state (neighbors) and generates a sentence by repeatedly selecting and applying the most probable edit operation to the canvas $y$. We terminate the process when we reach the maximum number of iterations or when the output sequences from two consecutive iterations are identical.

However, the initial state may hurt the performance if no close example exists in the datastore. Therefore, this study employs a switching approach as well as the oracle policy. Specifically, if the similarity of the neighbor on the source side $\sim(z_0, \tilde{x})$ is less than the threshold $\beta$ (used in Equation (10)), we do not initialize the decoder with the neighbors but do with special tokens `<s>` instead, similarly to common NAR models.

### 3.2 Neighbor Retrieval

To obtain the nearest neighbor $z_0$, we retrieve the most similar example to a given input sentence from the datastore. The datastore contains all the parallel sentences in the training data. Existing retrieval methods for nearest neighbors can be divided into two major types: lexical matching (Xu et al., 2020; Gu et al., 2018b; Bulte and Tezcan, 2019) and distributional similarity (Khandelwal et al., 2021; Borgeaud et al., 2021).

**Lexical matching** Previous studies explored fuzzy matching and n-gram matching (Xu et al., 2020; Gu et al., 2018b; Bulte and Tezcan, 2019). This study uses token frequencies, as in Peng et al. (2019), because this method scales well with large amounts of data. Specifically, we define a similarity score $S_{\text{TFIDF}}$ for sentences $s_i$ and $s_j$ using the
cosine similarity of the TFIDF vector \( \text{tfidf}(\cdot) \).

\[
S_{\text{TFIDF}}(s_i, s_j) = \frac{\text{tfidf}(s_i) \cdot \text{tfidf}(s_j)}{||\text{tfidf}(s_i)|| ||\text{tfidf}(s_j)||} \quad (14)
\]

**Distributional similarity** We use the cosine similarity \( S_{\text{SentVec}} \) of the sentence vector extracted from an off-the-shelf encoder.

\[
S_{\text{SentVec}}(s_i, s_j) = \frac{h_i \cdot h_j}{||h_i|| ||h_j||} \quad (15)
\]

Here, \( h_i \) and \( h_j \) are the sentence vectors obtained by encoding the sentences \( s_i \) and \( s_j \), respectively. Since the proposed method edits neighbor examples at word level, it is preferable that a neighbor example has common words with a target sentence. Therefore, we retrieve \( k \) candidate neighbors based on \( S_{\text{SentVec}} \), and rerank the \( k \) candidates by using the lexical matching with \( S_{\text{TFIDF}}(s_i, s_j) \).

### 4 Experiment

#### 4.1 Experimental Settings

**Dataset** We used the JRC-Acquis English-German dataset\(^5\), which is a corpus of legal documents. Because the corpus includes quite a few semantically similar sentences, many previous studies utilizing nearest neighbors regard this corpus as the standard benchmark dataset (Li et al., 2016; Gu et al., 2018b; Xu et al., 2020; Cai et al., 2021). In this experiment, we preprocessed the data after excluding duplicate translation pairs, following Gu et al. (2018b).

**Models** We used Transformer (Vaswani et al., 2017) (base setting) as the strong AR baseline (AR). For the NAR baselines, we adopted Levenshtein Transformer (Gu et al., 2019) (LevenshteinT), GLAT+CTC (Qian et al., 2021), NAT-ITR (Lee et al., 2018), NAT-CRF (Sun et al., 2019), and CMLM (Ghazvininejad et al., 2019). We used a beam size of four during inference for the AR model. Implementing these models using fairseq (Ott et al., 2019)\(^4\), we trained them with a maximum of 100,000 steps and a total batch size of approximately 32,768 tokens per step.

**Neighbor retrieval** We used TFIDF and SentVec+TFIDF \((k=50)\) to retrieve neighbors from the datastore and chose the closest sentence for each input sentence. The encoder of SentVec+TFIDF is the SBERT model pre-trained on multilingual corpora\(^5\) (Reimers and Gurevych, 2019), which performs well in information retrieval tasks. We used faiss\(^6\), a fast library for nearest-neighbor retrieval.

**Evaluation** We assessed the quality of the generated sentences using a case-sensitive detokenized BLEU using SacreBLEU (Post, 2018) and ChrF (Popović, 2015). We also calculated the mean number of iterations and the mean time required to translate a sentence. The latter measured the mean latency while the model generated a sequence using a single batch and a single Tesla P100 GPU, similar to Xu and Carpuat (2021). Latency includes the time for nearest-neighbor retrieval (for NeighborEdit).

A more detailed description can be found in the Appendix.

#### 4.2 Experimental Result

We presented the main results on generation quality and decoding speed in Table 1 and the translation example in Appendix A.6.

NeighborEdit outperformed the NAR baselines significantly (more than +7.04 BLEU score and +3.59 ChrF score). Furthermore, the mean number of iterations was the lowest among the iterative NAR models. NeighborEdit was not the fastest in terms of latency because the proposed method decodes three times (once for deletion and twice for insertion) for one iteration. However, it is noteworthy that the proposed method significantly improved the generation quality.

Surprisingly, NeighborEdit outperformed even a strong AR baseline (more than +1.50 BLEU score) on this dataset. The mean number of iterations were less than one-eighteenth of the AR baseline, and the latency was reduced by a quarter.

These results indicate that incorporating neighbors into an NAR model is effective; NeighborEdit can consistently improve the generation quality without sacrificing the decoding speed. Furthermore, this finding raises another question regarding the way in which nearest neighbors are utilized in the proposed method. Therefore, we investigated the effect of the neighbors in the oracle policy and

\(^5\)https://opus.nlpl.eu/JRC-Acquis.php
\(^4\)https://github.com/pytorch/fairseq
\(^6\)https://github.com/facebookresearch/faiss
Table 1: BLEU, the mean number of iterations, and the mean latency [ms] on the JRC-Acquis dataset. Boldface numbers are the top scores among NAR models. The underline denotes significant gains over LevenshteinT at \( p < 0.05 \).

![Table 1](image)

Table 2: BLEU scores with or without neighbor in the oracle policy and decoder initialization on JRC-Acquis dataset. \( \dagger \): We displayed the best-performing value using SentVec+TFIDF, although the model can be initialized with TFIDF and SentVec+TFIDF.

![Table 2](image)

the decoder initialization separately. We also explored a RAND baseline that retrieves an example at random (regardless of input) for decoder initialization.

Table 2 shows that the performance significantly improved when we incorporate neighbors from both the oracle policy and decoder initialization. Moreover, random decoder initialization severely hurt the performance. These results imply that the key to performance improvement is choosing useful neighbors and incorporating them effectively to the oracle policy and decoder initialization.

4.3 Experiments on Other Datasets

We also experimented other datasets that have not been well explored in previous studies using nearest neighbors. In these experiments, we adopted Levenshtein Transformer as an NAR baseline.

4.3.1 Data-to-Text (WikiBio)

We evaluated the effectiveness of NeighborEdit in the task of data-to-text generation on WikiBio dataset\(^7\) (Lebret et al., 2016). In this task, the model receives a fact table describing a person and generates the biography. Because biographies are written in a similar manner, we can assume that certain patterns exist in the target side of this task. To obtain the nearest neighbor, we calculated the similarity score \( S_{TM} \) between two serialized infoboxes \( s_i \) and \( s_j \), similarly to Wiseman et al. (2021).

\[
S_{TM}(s_i, s_j) = F_1(values(s_i), values(s_j)) + 0.1 F_1(values(s_i), values(s_j))
\]

Here, \( fields(s) \) extracts the field types (e.g., ‘name’) from the infobox \( s \), \( values(s) \) extracts the unigrams that appear as values in the infobox \( s \) (e.g., ‘Obama’), and \( F_1 \) presents an F1-score. We call this retrieval TableMatch. We trained the models with a maximum of 300,000 steps and a batch size of approximately 16,384 tokens per step. We evaluated the models using BLEU, NIST\(^8\) and the mean number of iterations.

Table 3 reports the evaluation result. NeighborEdit improved the BLEU score compared to the NAR baseline (+1.87 points) and narrowed the performance gap with the AR baseline with fewer iterations. This demonstrates that the proposed method was effective on this dataset.

4.3.2 Machine Translation (WMT’14)

Thus far, we examined the performance of NeighborEdit on the datasets where nearest neighbors

\(^7\)https://rlebret.github.io/wikipedia-biography-dataset/

\(^8\)We used this evaluation script: https://github.com/tuetschek/e2e-metrics.
may be effective. In this section, we investigate the performance on the popular WMT’14 English-German dataset (Bojar et al., 2014). Unlike JRC-Acquis, this dataset covers a wide range of topics. We downloaded the dataset and preprocessed it using the fairseq scripts.\footnote{https://github.com/pytorch/fairseq/tree/main/examples/translation#WMT’14-english-to-german-convolutional} We trained the models with a maximum of 300,000 steps and a batch size of approximately 65,536 tokens per step.

Table 4 demonstrates that the proposed method using SentVec+TFIDF outperforms Levenshtein Transformer (+0.63 points). However, the performance gain of BLEU scores was smaller than that in the other datasets, and the number of iterations was larger. Although we also explored an AR model where a source sentence and its neighbor are concatenated in the Transformer architecture (+CONCAT), we could not observe a performance improvement. Therefore, we suspect that the WMT’14 En-De dataset may have a different characteristic to JRC-Acquis and WikiBio.

### 4.4 Analysis on Neighbor Examples

Figure 2 displays scatter plots between the similarity of an example and its neighbor \((x\text{-axis})\) and the sentence-BLEU of its translation \((y\text{-axis})\). For JRC-Acquis and WMT’14 datasets, the \(x\text{-axis}\) presents the cosine similarity of tf-idf vectors between a target sentence and its neighbor. However, the similarity measures of the source and target sides of the WikiBio dataset are completely different; therefore, the \(x\text{-axis}\) of Figure 2c shows F1 scores of overlapping field names and values (Equation 16) (source side); and Figure 2d shows the cosine similarity of tf-idf vectors between a target sentence and its neighbor (target side).

Figure 2a shows that the JRC-Acquis dataset contains many similar examples; the mean of cosine similarity is 0.521. We observe the tendency that BLEU scores are larger when retrieved examples have higher similarity values to target sentences.

In contrast, Figure 2b clearly indicates that the WMT’14 dataset does not include similar examples; the mean of cosine similarity is 0.105. This implies that NeighborEdit must edit retrieved examples a lot, beginning with distant examples. This difficulty has already been observed in the larger number of iterations in Table 4. In other words, NeighborEdit was not so effective for WMT’14 because most examples were dissimilar and few examples with a high similarity were useful.

In the WikiBio dataset, the mean similarity on the source side is as high as 99.15 (Figure 2c) because two infobox tables can be similar only if these tables include the same field names. In contrast, the mean similarity on the target side is 0.130 (Figure 2d). These plots indicate that the similarity distributions on the source and target sides are quite different because different similarity metrics are used for infobox tables and sentences. We followed the previous study to design the similarity metric of the source side in Section 4.3.1. However, it may be necessary to reconsider the similarity metric for the source side so that it reflects similar patterns of biographies, for example, by focusing more on the occupations of entities.

### 5 Related Work

#### 5.1 Non-autoregressive Generation

Text generation using NAR decoding has attracted attention in recent years (Ghazvininejad et al., 2019; Lee et al., 2020; Gu et al., 2019; Stern et al., 2019a; Lee et al., 2018). Common approaches for improving the performance are iterative decoding and knowledge distillation using AR models. A number of researchers have proposed non-left-to-right decoding, utilizing parallelism in NAR models (Ghazvininejad et al., 2019; Gu et al., 2019; Stern et al., 2019a). Inspired by these approaches,
we incorporated the nearest neighbor into the iterative decoding process to guide the generation.

5.2 Text Generation using Neighbors

Gu et al. (2018b) were the first to use nearest neighbors in an attention-based encoder-decoder model. Other studies utilized the neighbors at the token-level (Khandelwal et al., 2021; Zheng et al., 2021), chunk-level (Borgeaud et al., 2021), and sentence-level (Peng et al., 2019; Cao et al., 2018) for text generation. Our approach is motivated primarily by these successes. While token-level and chunk-level retrieval can obtain less noisy (i.e., close) neighbors, they need to repeat a retrieval for each time step, which slows down training and inference. In contrast, our method does not suffer from the slowdown, retrieving neighbors only once per input. We adjusted how neighbors were utilized during training and inference to reduce the influence of noisy neighbors retrieved at sentence level.

Some previous studies concatenated a source sentence and its neighbors as input or used two encoders for them (Xu et al., 2020; Bulte and Tezcan, 2019; Borgeaud et al., 2021). Although these methods are effective, they require additional mechanisms and parameters. In contrast, we incorporated neighbors without introducing additional components or parameters but only by changing the training strategy. To the best of our knowledge, this is the first study to incorporate neighbors into an NAR model.

6 Conclusion

This paper proposes NeighborEdit, which utilizes the nearest neighbors in an NAR decoder based on edit operations. The experimental results showed that NeighborEdit could improve the quality of the generated sentences with fewer iterations than existing NAR models on all datasets. We expect...
that NeighborEdit will be beneficial in domains with writing patterns, such as patents and parliamentary proceedings. Future work will include the design of improved oracle policies that can reproduce intermediate sequences during inference as well as the development of improved algorithms for sentence-level neighbor retrieval.

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A Appendix

| Dataset     | Train   | Validation | Evaluation |
|-------------|---------|------------|------------|
| JRC-Acquis  | 475,330 | 2,945      | 2,937      |
| WikiBio     | 582,659 | 72,831     | 72,831     |
| WMT’14      | 3,961,179 | 3,000   | 3,003      |

Table 5: Dataset statistics

A.1 Dataset Details

Table 5 lists the statistics of the datasets in the experiments. We did not use the distilled dataset (Kim and Rush, 2016) in this study.

A.2 Model Details and Hyperparameters

For Neighboredit, we set $d_{\text{model}} = 512$, $d_{\text{hidden}} = 2048$, $n_{\text{head}} = 8$, and $n_{\text{layer}} = 6$. In the proposed oracle policy in Section 3.1.1, we set the hyperparameter $\alpha$ to 0.6 for all settings. In addition, we set $\beta$ to 0.3 for all retrieval methods in JRC-Acquis, TableMatch in WikiBio, and TFIDF in the WMT’14. For SentVec+TFIDF in the WMT’14, we set to 1.0. These are the values automatically determined by the development data as well as other hyperparameters. A threshold value of 1.0 means that special tokens are used for initialization instead of neighbors for all data during inference. However, during training, Neighboredit uses the neighbors to learn the deletion operation, which led to improved performance in Table 4. For the policy classifier, we set $K_{\text{max}}$ to 255. Embeddings of the source and target sides are shared. Furthermore, the parameters of the three edit operations in the decoder are shared.

A.3 Neighbor Retrieval Details

For TFIDF, we first created high-dimensional sparse TFIDF vectors and reduced the dimension to 512 by using singular value decomposition (SVD). After the neighbors are retrieved by faiss, we reranked the Top-50 neighbor candidates by calculating the exact cosine similarity of the uncompressed TFIDF vectors between the candidates and source sentences to reduce information loss for the TFIDF. For SentVec, we use the vectors (512 dimensions) computed by the pre-trained encoder as they are. Nearest neighbor retrieval was much faster than the decoding process of the NAR model; thus, the decoding overhead by nearest-neighbor retrieval is negligible.

A.4 Training Details

We trained BPE (Sennrich et al., 2016) to construct a vocabulary with 20,000 joint operations for the JRC-Acquis and 40,000 joint operations for the WMT’14. For the WikiBio, we did not use the subword tokenization.

We followed the weight initialization scheme of BERT (Devlin et al., 2019). We used Adam (Kingma and Ba, 2015) optimizer with $\beta = (0.9, 0.98)$. For regulation, we set the dropout rate of 0.3 and the weight decay of 0.01. We linearly increased the learning rate from $1 \times 10^{-7}$ to $5 \times 10^{-4}$ in the initial 10,000 steps and then used the learning rate decay of square root. All models were trained on 4 NVIDIA Tesla P100 GPUs for the JRC-Acquis and WikiBio, and 16 NVIDIA V100 GPUs for the WMT’14.

A.5 Evaluation Details

We selected the checkpoints according to the BLEU scores of the development set. SacreBLEU hash is BLEU+case.mixed+numrefs.1+smooth.exp+tok.1_3a+version.1.5.1. For a statistical significance test, we adopted a paired bootstrap resampling (Dror et al., 2018).

A.6 Output examples

Figure 3 shows output examples of Levenshtein Transformer and NeighborEdit. The proposed method could generate correct sentences with fewer iterations by removing unnecessary words from the neighbor examples and filling the placeholders.
Source  
Capacity utilisation increased by 56% between 1996 and the IP.

Target  
Die Kapazitätsauslastung stieg von 1996 bis zum UZ um 56%.

Levenshtein Transformer

| Deletion 1 | Insertion 1 | Deletion 2 | Insertion 2 |
|------------|-------------|------------|-------------|
|            | [PLH] [PLH] [PLH] [PLH] [PLH] [PLH] [PLH] [PLH] [PLH] [PLH] [PLH] [PLH] [PLH] [PLH] [PLH] [PLH] [PLH] [PLH] [PLH] |            |            |
| (48)       | Die Kapazitätsauslastung stieg von 1996 bis dem UZ um 56%. | (48)       | Die Kapazitätsauslastung stieg von 1996 bis zu dem UZ um 56%. |
|            | (48)       | (48)       | (48)       |

NeighborEdit

| Neighbor (En) | Neighbor (De) |
|---------------|---------------|
| (56) Export prices of the two cooperating Thai producers have increased by 6% between 1996 and the IP. | (56) Die Ausfuhrpreise der beiden kooperierenden thailändischen Hersteller stiegen von 1996 bis zum Untersuchungszeitraum um 6% |
| Deletion 1 | Insertion 1 |
| ( ) Die von 1996 bis zum um %. | ( ) Die von 1996 bis zum um % |

Figure 3: An example of JRC-Acquis En-De translation by Levenshtein Transformer and NeighborEdit (proposed). We present inserted tokens in red color and deleted tokens in blue color. The proposed method could generate the correct sentence with a single iteration.