Don’t Take It Literally: 
An Edit-Invariant Sequence Loss for Text Generation

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Abstract

Neural text generation models are typically trained by maximizing log-likelihood with the sequence cross entropy loss, which encourages an exact token-by-token match between a target sequence with a generated sequence. Such training objective is sub-optimal when the target sequence not perfect, e.g., when the target sequence is corrupted with noises, or when only weak sequence supervision is available. To address this challenge, we propose a novel Edit-Invariant Sequence Loss (EISL), which computes the matching loss of a target n-gram with all n-grams in the generated sequence. EISL draws inspirations from convolutional networks (ConvNets) which are shift-invariant to images, hence is robust to the shift of n-grams to tolerate edits in the target sequences. Moreover, the computation of EISL is essentially a convolution operation with target n-grams as kernels, which is easy to implement with existing libraries. To demonstrate the effectiveness of EISL, we conduct experiments on three tasks: machine translation with noisy target sequences, unsupervised text style transfer, and non-autoregressive machine translation. Experimental results show our method significantly outperforms cross entropy loss on these three tasks.

1 Introduction

Neural text generation models have ubiquitous applications in natural language processing, including machine translation [1, 36, 38, 52], summarizations [21, 30], dialogue systems [15], etc. They are typically based on the encoder-decoder architectures [36, 38] and are trained by maximizing the conditional log-likelihood of the output sequence conditioning on the inputs with the cross entropy (CE) loss. The CE loss can be easily factorized into individual loss terms and can be optimized efficiently with stochastic gradient descent. Due to its computational efficiency and ease to implement, the training paradigm has played an important role in building successful large text generation models [14, 27].

Code is released at https://github.com/guangyliu/EISL

Figure 1: Invariance exists in both image and text, e.g., image is invariant to translation (top), and text is invariant to different forms of edits (bottom).
However, the CE loss only minimizes the negative log-likelihood of ground truth of input-output pairs, while all other sequences are equally penalized through normalization. This is counter-intuitive since for a given target sentence, many possible paraphrases are semantically close, hence should not be treated as negative samples. For example, as shown in Figure 1, a cat is on the red blanket should be treated equally with on the red blanket there is a cat. A model trained with CE loss fails short on modeling this type of invariance for text.

The problem is even more exaggerated when the supervision from target sequence is not perfect. On one hand, there could be some noises in the target sequence which makes itself not a valid sentence. As the last example shown in Figure 1, there is a repetition error in the target sequence, which is common in human generated text. With the CE loss, the model learns to copy all tokens including the error, but will instead assign a high loss for a grammatically correct sequence. Exact tokens matching makes the CE loss very sensitive to noise in the target. On the other hand, there are many settings with weak supervision from target sequences. Unsupervised text style transfer task requires to transfer a sentence with positive sentiment to negative without a target negative sequence. Using CE loss to transfer sentences to different styles naturally fails since it encourages the model to copy every token.

Prior works have tried to address this problem using reinforcement learning (RL) algorithms [23, 41]. For example, policy gradient was employed to optimize sequence rewards such as BLEU metric [17, 28]. Such algorithms will assign high rewards to sentences that are close to the target sentence. Though valid objective to optimize, policy optimization faces significant challenges in practice. The high variance from the gradient estimate makes models extremely hard to train and almost all previous attempts rely on fine-tuning from models trained with CE loss.

Instead, we designed an alternative loss that can overcome CE’s weakness, but reserves all good properties such as being end-to-end differentiable, easy to implement, hence can be used as a drop-in replacement or combined with CE. The loss is based on the observation that a viable candidate sequence shares many sub-sequences with the target. Our loss, called edit-invariant sequence loss (EISL), computes the loss for every target n-gram across all n-grams in a candidate sequence. Regardless of the position of n-gram in the candidate sequence, the loss for the target n-gram remains the same, hence EISL is invariant to the shift of positions. EISL is motivated by the translation invariant properties of ConvNets on images and captures the edit invariant properties of n-grams in calculating the loss. The CE loss can be seen as a special case of EISL: when n equals to the sequence length, EISL calculates the exact sequence matching loss and is equivalent to CE. Moreover, the computations of EISL is essentially a convolution operation of candidate sequence using target n-grams as kernels, which is very easy to implement with existing deep learning libraries. Figure 2 shows the invariance property of EISL.

To demonstrate the effectiveness of EISL loss, we conduct experiments on three tasks: machine translation with the noisy target, unsupervised text style transfer and non-autoregressive machine translation. Experiments demonstrate EISL loss can be easily incorporated with a series of sequence models and outperforms CE across the board.
2 Related Work

Deep neural sequence models such as recurrent neural networks [19, 36] and transformers [38] have achieved great progress in many text generation tasks like machine translation [1, 38]. These models are typically trained with the maximum-likelihood objective, which can lead to sub-optimal performance due to CE’s exact sequence matching assumption. There are lots of works trying to overcome this weakness. For examples, some works [17, 28, 29, 31, 34] proposed to use policy gradient or minimum risk training to optimize the expected BLEU metric. Due to the high variance and unstableness in training, a variety of training tricks are used in practice. Casas et al. [2], Zhukov and Kretov [45] made the initial attempts to develop differentiable BLEU objectives, making soft approximations to the count of n-gram matching in the original BLEU formulation. Wieting et al. [41] introduced a new reward function based on semantic similarity for the translation system. Another line of research that is relevant to our work is learning with noisy labels in classification. There are lots of researchers attempting to propose techniques to improve classifier’s performance in face of noises in labels [40, 43, 44]. For text generation, Nicolai and Silfverberg [22] proposed student forcing to substitute teacher forcing, which can avoid the influence of noise in target sequence during decoding. Kang and Hashimoto [11] proposed loss truncation, which adaptively removed high loss examples, considered as invalid data, to improve text generation. To the best of our knowledge, our work is the first to investigate sequence training with noisy targets in a principled manner.

3 Edit-Invariant Sequence Loss

In this section, we first review the CE loss for sequence learning and point out its weakness, especially when the target sequence is edited. We then introduce the EISL loss which gives a model the flexibility to learn from sub-sequences in a target sequence.

We first establish notations for the sequence generation setting. Let \((x, y^*)\) be a paired data sample where \(x\) is the input and \(y^* = (y^*_1, ..., y^*_T)\) be the ground truth target sequence. Further define \(y = (y_1, ..., y_T)\) as a candidate sentence. Our goal is to build a model \(p_{\theta}(y|x)\) that scores a candidate sequence \(y\) with parameter \(\theta\). In the sequel, we omit the condition \(x\) for simplicity.

3.1 The Cross Entropy Sequence Loss Dilemma

The standard approach to learn the sequence model is to minimize the negative log-likelihood (NLL) of the target sequence:

\[
L_{CE}(\theta) = -\log p(y^*).
\]

The cross entropy loss assumes exact matching of a candidate sequence \(y\) with the target sequence \(y^*\), so it only maximizes the probability of the target sequence \(y^*\) but penalizes all other possible sequence outputs that are close but different with \(y^*\).

The assumption is problematic in several aspects. First, for a given target sentence, there are many ways to paraphrase the sentence such as word reordering, synonyms replacement, active to passive rewriting, etc. All paraphrases are viable candidate sequences and should not be treated as negative samples. The paraphrases share many sub-sequences, which may appear in different positions. Similar to the translation invariant properties of images, a shift translation of sub-sequence in text does not change the meaning of a sentence. Hence a loss that is invariant to the shift of sub-sequences in the target sequence is preferred in modeling variations of sequences. Moreover, the shift-invariant property is desirable especially when the target sequence is corrupted with noise or only weak sequence supervision is available. In the example in Figure 3, the word is repeated twice, which is one of the common errors in typing. Using CE loss in the noisy target setting teaches the model to learn the errors as well. Instead, a loss that is invariant to the shift of sub-sequences assigns a high probability to a correct sentence that does not match with the noisy target exactly, hence enables the model to select the right information to learn regardless of the positions.

3.2 Edit-Invariant Sequence Loss

Motivated by the convolution operation that enables translation invariant in image (Figure 3, left), we propose an edit-invariant sequence loss function as shown in Figure 3 (right). For a given 4-gram on
We define the EISL loss as the summation of negative log-likelihood of each reference.

We now derive EISL loss mathematically. Define \( y_{a:b} = (y_a, \ldots, y_{b-1}) \) as a sub-sequence of \( y \) that starts from index \( a \) and ends at index \( b-1 \), which is of length \( b-a \). Let \( C(y^*_{i:i+n}, y) \) be the number of times the \( i \)-th \( n \)-gram of the reference, i.e., \( y^*_{i:i+n} \), occurs in \( y \):

\[
C(y^*_{i:i+n}, y) = \sum_{i' = 1}^{T-n+1} \mathbb{1}(y^*_{i:i+n} = y_{i':i'+n}),
\]

where \( \mathbb{1}(. \cdot) \) is the indicator function that takes value 1 if an \( n \)-gram matches, otherwise takes 0. For a text generation model, we would like to maximize the occurrence of an \( n \)-gram from the reference in the target sequence. For a given probabilistic model \( p_\theta(y) \), the expected value of \( C(y^*_{i:i+n}, y) \) can be computed as follow:

\[
\mathbb{E}_{y \sim p(y)}[C(y^*_{i:i+n}, y)] = \sum_{i' = 1}^{T-n+1} \mathbb{E}_{p(y_{i':i'+n})} \left[ \mathbb{1}(y^*_{i:i+n} = y_{i':i'+n}) \right]
 = \sum_{i' = 1}^{T-n+1} p(y^*_{i:i+n} = y_{i':i'+n}).
\]

We define the EISL loss as the summation of negative log-likelihood of each reference \( n \)-gram at all positions as:

\[
\mathcal{L}^n_{\text{EISL}}(\theta) = - \sum_{i' = 1}^{T-n+1} \log p(y^*_{i:i+n} = y_{i':i'+n}).
\]

Alternatively, we can see EISL loss as a direct generalization of CE loss on the \( n \)-gram level: we sum the CE loss of an \( n \)-gram over all candidate sequence positions.

### EISL as convolution

We show the above expected count can be computed using convolution. Denote \( V \) as the vocabulary size. Let \( P = [p_1, p_2, \ldots, p_T] \), where \( p_i \in \mathbb{R}^V \) is the probability output after softmax at \( i \)-th position. Define \( g^*_i = p(y^*_{i:i+n} = y_{i':i'+n}) \) as the probability of the \( i \)-th \( n \)-gram matches the \( n \)-gram at \( i' \)-th position at candidate sequence. We can vectorize the probability to get \( g_i = [g^*_i, \ldots, g^*_{i+T-n+1}]^T \). As shown in Figure 4, we can get \( \log g_i \) by applying convolution on \( \log P \) with \( y^*_{i:i+n} \) as kernels:

\[
\log g_i = \text{Conv}(\log P, \text{Onehot}(y^*_{i:i+n})),
\]

where \( \text{Onehot}(. \cdot) \) maps each token to its corresponding one-hot representation and \( \text{Conv}(. \cdot, \cdot) \) is the convolution operation with the first argument as input and the second argument as the kernel. We transform \( P \) into log domain because we want to turn the probability multiplication into log probability summations, where Conv can be directly applied.

As shown in Figure 4, \( \log P \) is of shape \( V \times T \) and \( \text{Onehot}(y^*_{i:i+n}) \) is of shape \( V \times n \), so \( \text{Conv}(\log P, \text{Onehot}(y^*_{i:i+n})) \) is an one-dimensional convolution on the sequence axis. Formally,
Figure 4: As convolution is a common operation for translation invariance in image, we adopt a convolution to achieve the translation invariance in text. The input is the distribution from the model output in log domain, kernel represents the convolution kernel and $*$ is the convolution operation. In this 3-gram example, there are 5 kernels, which correspond to the 5 rows on the right.

The $i'$-th convolutional output is:

$$
\log g_i' = \text{Conv}(\log P, \text{Onehot}(y_i'_{i+n})) = \sum_{j=1}^{n} \log p_{i'+j-1} \cdot \text{Onehot}(y_{i+j-1}) = \sum_{j=1}^{n} \log p(y_{i+j-1} = y_{i'+j-1})
$$

Therefore loss can be calculated as follow:

$$
\mathcal{L}_{\text{EISL}}^n(\theta) = - \sum_{i'=1}^{T-n+1} \log p(y_{i'+i+n} = y_{i'+i'+n}) = -1 \cdot \log g_i,
$$

where 1 is an all one vector of size $T - n + 1$.

**Position Selection** In practice, a given $n$-gram mostly appears in one position only. Minimizing the gram matching loss over all positions makes the model assign equal probabilities at all locations, which causes the training to collapse easily. We adapt the loss to enable the model to learn the positions of reference $n$-grams in an unsupervised manner. We first normalize the probability vector $g_i$ by Gumbel softmax [10], denoted as $q_i = \text{Gumbel}_\text{softmax}(g_i)$, which we use as the weight for every $n$-gram candidate. Then we multiply the weight with the original log probability to get a new loss as:

$$
l_i = -q_i \cdot \log g_i.
$$

This loss can be treated as the entropy of the unnormalized probabilities $g_i$ and by optimizing the loss, we aim to minimize the entropy of the vector $g_i$, which has minimal value if the mass of the probability is assigned to one location only. Intuitively, if $g_i'$ is large, then it is more likely $i'$ is the correct position for the reference $n$-gram, hence the weight for this position should also be large. This is like the greedy exploitation in reinforcement learning [20]. However, to overcome overexploitation, we introduce noises through Gumbel softmax, which controls the randomness in the weight assignment. The noise in Gumbel softmax helps balance the exploitation and exploration trade-off in position selection for the model.

Finally, we average the losses for all reference $n$-grams to get the EISL loss as:

$$
\mathcal{L}_{\text{EISL}}^n(\theta) = \frac{1}{T^* - n + 1} \sum_{i=1}^{T^* - n + 1} l_i^n = \frac{1}{T^* - n + 1} \sum_{i=1}^{T^* - n + 1} q_i^n \cdot \log g_i^n
$$

In experiments, we could combine different $n$ depending on tasks:

$$
\mathcal{L}_{\text{EISL}}(\theta) = \sum_n w_n \cdot \mathcal{L}_{\text{EISL}}^n(\theta),
$$

where $w_n$ denotes the weight of loss for $n$-gram.
3.3 Connections with Common Techniques

3.3.1 CE as a special case of EISL

A nice property of EISL is that it subsumes the standard CE loss as a special case. To see this, set $n = T^*$ (the target sequence length), and we have:

$$L_{\text{EISL}}^{T^*} = -l_1^{T^*} = -\log g_1^{T^*} = -\log p(y^* = y) = L_{\text{CE}}.$$  \hspace{1cm} (8)

The connection shows the generality of EISL. As a generalization of CE, it enables learning at arbitrary $n$-gram granularity.

3.3.2 Connections between BLEU and EISL

Though both our method and BLEU [25] metric use $n$-grams as the basis in the calculation, they have significant differences. To see that, let us first take a review of the BLEU metric. Specifically, BLEU is defined as a weighted geometric mean of $n$-gram precisions:

$$\text{BLEU} = \text{BP} \cdot \exp \left( \sum_{n=1}^{N} w_n \log \text{prec}_n \right),$$ \hspace{1cm} (9)

where BP is a brevity penalty depending on the lengths of $y$ and $y^*$; $N$ is the maximum $n$-gram order (typically $N = 4$); $\{w_n\}$ are the weights which usually take $1/N$; and $\text{prec}_n$ is the $n$-gram precision defined as:

$$\text{prec}_n = \frac{\sum_{s \in \text{gram}_n(y)} \min(C(s, y), C(s, y^*))}{\sum_{s \in \text{gram}_n(y)} C(s, y)},$$ \hspace{1cm} (10)

where \text{gram}_n(y) is the set of unique $n$-gram sub-sequences of $y$; and $C(s, y)$ is the number of times a gram $s$ occurs in $y$ as defined in Eq. 1. The conventional formulation above enumerates over unique $n$-grams in $y$. In contrast, we enumerate over token indexes in calculating the $n$-gram matching loss. BLEU considers the $n$-gram precisions and has a penalty term while EISL simply maximizes the log probability of $n$-gram matchings.

The non-differentiability of BLEU makes it hard to optimize directly, hence most prior attempts resort to reinforcement learning algorithms and use BLEU as the reward [17, 28]. There are also some works trying to introduce differentiable BLEU metric using approximation like [45]. However, such losses are often too complicated and are yet to be demonstrated to perform well in practice.

4 Experiments

In this section, we present the experimental results on three text generation settings: learning from noisy text, learning from weak sequence supervision and non-autoregressive generation models that require flexibility in generation orders to test EISL’s effectiveness.

4.1 Learning from Noisy Text

To test the robustness to noise, we propose a new task named Translation with Noisy Target, in which we train the models with noisy sequence targets and evaluate with clean sequence targets.

Setup We use German-to-English (de-en) dataset from Multi30k [4], which contains 29k training instances. As inspired by Shen et al. [33], to simulate various noises in the real data, we introduce four types of noises: shuffle, repetition, blank, and the synthetical noise, i.e., the combination of the aforementioned three types of noise. The noises are only added to the training target sequences. We use a Transformer-based pretrained model BART-base [14], containing 6 layers in the encoder and decoder. We train the model using the Adam optimizer with learning rate $3 \times 10^{-5}$ with polynomial decay and the maximum number of tokens is 6000 in one step. The models are trained on one Tesla V100 DGXS with 32GB memory. EISL starts with $T^*$-gram training using teacher forcing for fast initialization, where $T^*$ is the target length. Then we switch to 1-gram and 2-gram EISL with weight 0.8 : 0.2 and we adopt greedy decoding both in training and evaluation. We use fairseq [24] to

\[\text{https://github.com/pytorch/fairseq}\]
Results
The results are presented in Figure 5. The proposed EISL loss provides significantly better performance than CE loss and PG on all the noise types, especially on the high-level noise end. For synthetic noise as shown in Figure 5(d), it’s interesting to see that CE and PG completely fail when the noise level is beyond 6, but model trained with EISL has high BLEU score, demonstrating EISL can select useful information to learn despite high noise. This validates that the proposed EISL is much less sensitive to the noise than the traditional CE loss and policy gradient training method. The results of different n-gram are shown in Figure 5(e). As the noise increases, the importance of lower grams, e.g., 1-gram, is more obvious. The results confirm that CE loss which only considers the whole sentence matching may struggle to survive on noisy data.

4.2 Learning from Weak Supervisions: Style Transfer
We experiment on two types of style transformations: sentiment and political slant, to verify EISL can learn from weak sequence supervisions.

Setup
We use the Yelp review dataset and political dataset. Yelp contains almost 250k negative sentences and 380K positive sentences, of which the ratio of training, valid and test is 7 : 1 : 2. Li et al. [16] annotated 1000 sentences as ground truth for better evaluation. The political dataset is comprised of top-level comments on Facebook posts from all 412 members of the United States Senate and House who have public Facebook pages [39]. The data set contains 270K democratic sentences and 270K republican sentences. And there exists no ground truth for evaluation. The data preprocessing follows Tian et al. [37].

The structured content preserving model [37] is adopted as the base model. We use the Adam optimizer with learning rate $5 \times 10^{-4}$, the batch size is 128 and the model is trained on one Tesla V100 DGXS 32GB. We compare the results between the base model and the model with EISL. Specifically, on top of the base model, we add the EISL loss (a combination of 2, 3 and 4-gram with the same weights 1/3) to reduce the discrepancy between the transferred sentence generated by language model and the original sentence. We assign EISL loss with weight 0.5.
| Model          | Accuracy(%) | BLEU | BLEU(human) | PPL  | POS distance |
|---------------|-------------|------|-------------|------|--------------|
| Hu et al. [9] | 86.7        | 58.4 | -           | 177.7| -            |
| Shen et al. [32] | 73.9      | 20.7 | 7.8         | 72   | -            |
| He et al. [8] | 87.9        | 48.4 | 18.7        | 31.7 | -            |
| Dai et al. [3] | 87.7        | 54.9 | 20.3        | 73   | -            |
| Tian et al. [37] | 88.8      | 65.71| 22.56       | 42.07| 0.352        |
| with EISL     | 88.8        | 68.51| 23.17       | 41.56| 0.275        |

Table 1: Top: automatic evaluations on the Yelp review dataset. The BLEU (human) is calculated using the 1000 human annotated sentences as ground truth from Li et al. [16]. The POS distance denotes the noun difference between the original and transferred sentences. The smaller the POS distance, the better the performance. The first four results are from the original papers. Bottom: human evaluation statistics of base model vs. with EISL. The results denotes the percentages of inputs for which the model has better transferred sentences than other model.

Following previous work, we compute automatic evaluation metrics: accuracy, BLEU score, perplexity (PPL) and POS distance. For accuracy, we adopt a CNN-based classifier, trained on the same training data, to evaluate whether the generated sentence possesses the target style. Then we measure BLEU score and BLEU(human) score of transferred sentences against the original sentences and ground truth, respectively. PPL metric is evaluated by GPT-2 [27] base model after finetuning on the corresponding dataset, with the goal to assess the fluency of the generated sentence. POS distance is used to measure the model’s semantics preserving ability [37].

We also perform human evaluations on Yelp data to further test the transfer quality. We first randomly select 100 sentences from the test set, use these sentences as input and generate sentences from the base model [37] and our model. Then for each original sentence, we present the outputs of the base model and ours in random order. The three annotators are asked to evaluate which sentence is preferred as the transferred sentence of the original sentence, in terms of content preservation and sentiment transfer. They can choose either output or select the same quality. We measure the percentage of times each model outperforms the other.

**Results** As sentiment results are shown in Table 1, the BLEU gets improved from 65.71 to 68.51 with EISL loss. On the premise of the correctness of sentiment transfer, EISL loss plays a critical role to guarantee lexical preservation. In the meanwhile, all of BLEU(human), PPL, and POS distance get improved. It is not surprising that EISL loss helps generate sentences more fluently and select the more appropriate words conditions on the content information. As the human evaluation results are shown in Table 1, the model with EISL loss performs better, in accord with the automatic metrics. After analyzing the generated samples, we found EISL loss could drive the model to adopt the words which fit the scene better and could understand more semantics but not just replace some keywords.

We report the results of political data in Table 2. Our method outperforms all models on BLEU, PPL, and POS distance with comparable accuracy. For a more fair comparison with the base model, our EISL loss improves the base model on all four metrics, including the accuracy.

The above results demonstrate the effectiveness of our EISL for weak supervision task, which could improve not only transfer accuracy, but fluency and content preservation.

### 4.3 Learning Non-Autoregressive Generation

Non-autoregressive neural machine translation (NAT) [6] is proposed to predict tokens simultaneously in a single decoding step, which aims at reducing the inference latency. The non-autoregressive nature makes it extremely hard for models to keep the order of words in the sentences, hence CE often struggles with NAT problems. In experiments, we show EISL is superior to CE in NAT which requires modeling flexible generation order of the text.
| Model                  | Accuracy(%) | BLEU | PPL | POS distance |
|------------------------|-------------|------|-----|--------------|
| Prabhhumoye et al.     | 86.5        | 7.38 | -   | 7.298        |
| Hu et al.              | 90.7        | 47.5 | -   | 3.524        |
| Tian et al.            | 88          | 59.63| 28.46| 2.348        |
| with EISL              |             | 60.26| 27.85| 2.191        |

Table 2: The results on the political dataset. The first two results are reported by Tian et al. [37].

| Decoding method | Model                  | WMT14 en-de KD | WMT14 en-de |
|-----------------|------------------------|----------------|-------------|
|                 |                        | CE            | EISL        | CE          | EISL        |
| Autoregressive  | Transformer base       | 27.48         |             |             |
| Fully NAT       | Vanilla-NAT            | 17.9          | 22.2        | 9.12        | 15.46       |
|                 | NAT-CRF                | 21.88         | 22.43       | -           | -           |
|                 | iNAT (iter=10)         | 24.24         | 24.22       | -           | -           |
|                 | iNAT (iter=11)         | 16.67         | 22.59       | -           | -           |
|                 | LevT (max iter=10)     | 26.91         | 26.97       | 23.99       | 24.4        |
|                 | LevT (max iter=11)     | 17.84         | 23.61       | 9.91        | 18.47       |
|                 | CMLM (max iter=10)     | 25.4          | 25.58       | -           | -           |
|                 | CMLM (max iter=11)     | 17.12         | 23.05       | -           | -           |

Table 3: The results of EISL applied to non-autoregressive models. KD means that the models are trained on the dataset after knowledge distillation.

**Setup** We use English-to-German (en-de) dataset from WMT14 [18], which contains 4.5M training instances. We tested our proposed EISL loss on both fully NAT models (Vanilla-NAT [6] and NAT-CRF [35]) and iterative NAT models (iNAT [13], LevT [7] and CMLM [5]). We use the Adam optimizer with learning rate $5 \times 10^{-4}$ with inverse square root scheduler. We apply sequence-level knowledge distillation to the dataset, which can reduce the complexity of the dataset, making it easier for the model to learn and improving the performance. The models are first trained by $T$-gram EISL for fast initialization, then focus on 2-gram, 3-gram, and 4-gram with the same weights. Fairseq[24] is adopted to conduct the experiments. We average the last 5 checkpoints as the final model and compare the results with models trained by CE.

**Results** Table 3 summarizes the experiment results. The proposed EISL can improve the model performance on both KD and original datasets. For fully NAT models, EISL can improve model performance directly. For iterative NAT models, if we restrict the iteration step to a small level, EISL can significantly outperform the baseline. And with the increasing of iteration steps, e.g., iter=10, the difference fades away. However, as studied in Kasai et al. [12], iterative NAT models do not hold the intrinsic advantage of speed when using many decoding iterations since Transformer baselines with a shallow decoder can achieve comparable speedup and only at the sacrifice of minor performance drop. Therefore, comparing with CE, EISL possesses great generation capacity, especially with limited decoding steps.

5 Conclusions and future work

We have developed an Edit-Invariant Sequence Loss (EISL) for end-to-end training of neural text generation models. The proposed method is insensitive to the shift of $n$-grams in target sequences, hence suitable for training with noisy data and weak supervisions, where CE loss fails easily. We show CE loss is a special case of EISL and build the connection of EISL with BLEU metric and convolution operation, which both have the invariant property. Experiments on translation with noisy target, text style transfer, and non-autoregressive neural machine translation demonstrate the superiority of our method. One limitation is the noisy data is not from the real-life. In the future, we plan to carry out experiments on real noisy text data to investigate EISL’s performance in practice.
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