Self-Distillation Mixup Training for Non-autoregressive Neural Machine Translation

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Abstract

Recently, non-autoregressive (NAT) models predict outputs in parallel, achieving substantial improvements in generation speed compared to autoregressive (AT) models. While performing worse on raw data, most NAT models are trained as student models on distilled data generated by AT teacher models, which is known as sequence-level Knowledge Distillation. An effective training strategy to improve the performance of AT models is Self-Distillation Mixup (SDM) Training, which pre-trains a model on raw data, generates distilled data by the pre-trained model itself and finally re-trains a model on the combination of raw data and distilled data. In this work, we aim to view SDM for NAT models, but find directly adopting SDM to NAT models gains no improvements in terms of translation quality. Through careful analysis, we observe the invalidation is correlated to Modeling Diversity and Confirmation Bias between the AT teacher model and the NAT student models. Based on these findings, we propose an enhanced strategy named SDMRT by adding two stages to classic SDM: one is Pre-Rerank on self-distilled data, the other is Fine-Tune on Filtered teacher-distilled data. Our results outperform baselines by 0.6~1.2 BLEU on multiple NAT models. As another bonus, for Iterative Refinement NAT models, our methods can outperform baselines within half iteration number, which means $2 \times$ acceleration.

1 Introduction

Autoregressive (AT) neural machine translation (Bahdanau et al., 2015) models decode tokens one-by-one, which ensure the robustness of the intrinsic language model but make the inference slow (§2.1). Recently, non-autoregressive (NAT) models generate all outputs in parallel. It speeds up the inference, but at the cost of breaking the dependency between adjacent tokens, leading to worse performance than standard AT models (§2.2).

Knowledge distillation (Hinton et al., 2015) is a method that trains a student model to perform better by learning from a stronger teacher model. This method has been proved to be necessary for NAT models training in (Zhou et al., 2020), and most NAT models are trained on distilled data generated by an AT teacher model to achieve competitive performance. This method of distilled data generation is called sequence-level knowledge distillation (Kim and Rush, 2016) (§2.3).

When the teacher model is the same as the student model, we call it Self-Distillation. Using the combination of the original data and the self distilled data to re-train the model itself is Self-Distillation Mixup (SDM) Training. (Freitag et al., 2017) has proved that SDM can improve the performance of AT models (§2.4).

In this work, we study a general training strategy to improve the NAT performance. A promising attempt to address this issue is to improve the AT teacher model by using some strategies such as SDM Training. The problem is that, higher quality distilled data generated by a better AT teacher model may not improve the performance of NAT student models generally (§3.1). Another approach is to adopt SDM Training to NAT models directly. But the second problem occurs that, classic SDM Training has no effect when NAT models are trained on AT-distilled data (§3.2).

We propose an enhanced training progress named Self-Distillation Mixup Training with Pre-Rerank and Fine-Tune (SDMRT). In the stage of distilled data generation, we use Rerank Algorithm (Lee et al., 2021) to reduce the Modeling Diversity between AT and NAT models. In the stage of model training, we Fine-Tune the NAT models on the filtered data to reduce the Confirmation Bias (§4).
Our contributions are as follows:

- We first apply SDM to NAT training and introduce an enhanced training strategy named SDMRT to significantly improve translation quality of multiple NAT models (§4.1; §5.2).

- We analyse why classic SDM fails on NAT models trained on AT-distilled data. Specifically, we theoretically demonstrate **Modeling Diversity** and **Confirmation Bias** between the AT teacher model and the NAT student models (§4.2; §5.3; §5.3).

- We carefully study the effect of different Rerank strategies on self-distilled data and Data-filtering methods on teacher-distilled data. Furthermore, we find our SDMRT can be regarded as an acceleration method to reduce iterations for Iterative Refinement NAT models (§5.3; §5.3; §5.3).

2 Background

2.1 Autoregressive NMT Models

Let $x$ denote the input sequence and $y$ denote the output sequence. Let $\mathcal{D}$ denote the original parallel data: $\mathcal{D} = \{\mathcal{X}; \mathcal{Y}\}$. In order to model the joint probability of the output sequence, autoregressive (AT) models usually generate each output token $y_t$ conditioned on the previously generated ones (Bahdanau et al., 2015). The formulation is as following:

$$p(y|x) = \prod_{t=1}^{T} p(y_t|y_{<t}; x)$$ (1)

2.2 Non-autoregressive NMT Model

Non-autoregressive (NAT) models (Du et al., 2021; Gu and Kong, 2021; Saharia et al., 2020) generate all outputs in parallel and break the dependency between the output tokens. The basic formulation of a NAT model independently factors the conditional distribution:

$$p(y|x) = \prod_{t=1}^{T} p(y_t|x)$$ (2)

According to the decoding strategy, NAT can be classified into two types, fully non-autoregressive models and iterative refinement models:

**Fully Non-autoregressive models**
- Vanilla NAT (Gu et al., 2018) Vanilla NAT (V-NAT) is the first NAT model. We use the simplified version where the decoder’s inputs are directly copied from the encoder without considering latent variables.
- NAT-CRF (Sun et al., 2019) NAT-CRF designs an efficient approximation for Conditional Random Fields (CRF) for decoder’s outputs.

**Iterative Refinement (IR) NAT models**
- iNAT (Lee et al., 2018) iNAT extends the vanilla NAT by iteratively refining the translation. At each refinement step, the outputs of the previous step would be taken as inputs.
- CMLM (Ghazvininejad et al., 2019) CMLM adopts a masked language model to progressively generate the sequence from entirely masked inputs. At each refinement step, the outputs of the previous step would be partially re-masked and taken as inputs.

2.3 Knowledge Distillation

Knowledge distillation (Hinton et al., 2015) was originally proposed for training a weaker student classifier on the targets predicted from a stronger teacher model. A typical approach is using the label probabilities produced by the teacher as “soft targets” $q_i = \exp(z_i/\tau)/\sum_j \exp(z_j/\tau)$ for training the student model, where $q_i$ and $z_i$ are the probability and the logit of class $i$ respectively and $\tau$ is the temperature. Prior work has shown the effectiveness of adopting knowledge distillation in adversarial defense, neural network compression, and fast inference for speech synthesis.

**Seq-Level KD** In the context of sequence generation, Kim and Rush (2016) extend knowledge distillation to the sentence level using “hard targets” from a pretrained large teacher model to train a small sequence generation model. More precisely, the teacher distribution $q(t|x)$ is approximated by its mode: $q(t|x) \approx 1\{t = \arg\max_{t \in T} q(t|x)\}$ with the following objectives:

$$L_{seq-KD} = -\mathbb{E}_{x \sim \mathcal{D}} \sum_{t \in T} q(t|x) \log p(t|x)$$
$$= -\mathbb{E}_{x \sim \mathcal{D}, \hat{y} = \arg\max_{t \in T} q(t|x)} \log p(t = \hat{y}|x)$$ (3)
where \( t \in T \) is the space of possible target sequences. This can also be seen as a special case of standard distillation over the sentence space when the temperature \( \tau \) approaches 0, which is equivalent to taking the arg max over all feasible translations. While the “hard target” \( \hat{y} \) is the most likely translation predicted by the teacher, in practice we use beam search as an approximation. As mentioned earlier, almost all the existing literature trains NAT models using sequence-level knowledge distillation from a pre-trained AT model to achieve competitive performance.

### 2.4 Self-Distillation Mixup Training

We clarify Self-Distillation Training and Self-Distillation Mixup Training in this section. The overview of these training strategies is shown in Figure 1.

![Figure 1: An overview of (a) Baseline Training, (b) Self-Distillation (SD) Training and (c) Self-Distillation Mixup (SDM) Training for an AT model.](image)

**Self-Distillation** As shown in Figure 1 (b), we define Self-Distillation (SD) as training a student model on the distilled data generated by the teacher model which is as same as the student model.

**Self-Distillation Mixup** The strategy of Mixup Training is transferred from Self-training (Arazo et al., 2020). Self-training is an algorithm to train a model to fit pseudo-labels predicted by another previously-learned model. It has been very successful for learning with unlabeled data while mixup training on the combinations of labeled data and pseudo-labeled data.

In NMT task, distilled data can be considered as pseudo-labels. As shown in Figure 1 (c), we define Self-Distillation Mixup (SDM) as training the student model on the combinations of original data and distilled data.

Prior research Freitag et al. (2017) has proved that SDM Training can improve the translation quality. We re-implement the results of AT performance under SD and SDM training strategies on IWSLT14 EN\( \rightarrow \)DE task.

**Table 1:** Results of AT performance under SD and SDM training strategies on IWSLT14 EN\( \rightarrow \)DE task.

| Setup          | Paralleled Data       | BLEU | \( \Delta \) BLEU |
|----------------|-----------------------|------|------------------|
| Baseline       | Raw Data (160K)       | 28.34|                  |
| SD             | Distilled Data (160K) | 28.29|-0.05             |
| SDM            | Raw Data + Distilled Data (320K) | 29.51| +1.17↑ |

**Table 2:** Results of several NAT models’ performance under AT-baseline teacher model and AT-SDM teacher model on IWSLT14 EN\( \rightarrow \)DE task.

| Teacher Model | Student Model | NAT-CRF | CMLM |
|---------------|---------------|---------|------|
| AT-Baseline   | 28.34         | 22.41   | 26.78|
| AT-SDM        | 29.51         | 21.83↓  | 26.83↑|

3 **Problem Formulation**

3.1 **Motivations**

NAT models relay more on the distilled data generated by AT models than the raw data. But prior research (Zhou et al., 2020) has proved that, higher quality distilled data does not necessarily improve the performance of NAT models. V-NAT (Gu et al., 2018) achieves better performance on distilled data generated by Transformer-small than Transformer-base/big. CMLM (Ghazvininejad et al., 2019) only achieves a little bit improvement of 0.22 BLEU when trained on distilled data by Transformer-big comparing with Transformer-base.

As mentioned in §2.4, a better AT model can be got by using SDM Training. We study several NAT models’ performance under AT-baseline teacher model and AT-SDM teacher model. We do this preliminary experiments on IWSLT14 EN\( \rightarrow \)DE task.

As shown in Table 2, we reach a conclusion consistent with prior research (Zhou et al., 2020) that, higher quality distilled data does not necessarily improve the performance of NAT models. The little bit difference between our experiments and theirs is that we generate distilled data by the same size AT teacher models with the different training strategies, while they use the different size teacher models with the same training strategies.

**Problem 1:** SDM can improve the performance of the AT teacher models and lead to
higher quality distilled data, but it cannot further improve the performance of NAT student models generally. We make some theoretical analysis in §4.2.

3.2 Straightforward but Failed Formulation

A straightforward way is to directly adopt SDM Training on NAT models. The overview of the training strategies is shown in Figure 2. We do experiments of all strategies on IWSLT14 EN→DE task.

Table 3: Results of several NAT models’ performance under classic SDM training on IWSLT14 EN→DE task.

| Arch     | Raw data baseline | SDM | AT-distilled data baseline | SDM |
|----------|-------------------|-----|---------------------------|-----|
| AT       | 28.34             | 29.51↑ | -                         | -   |
| NAT-CRF  | 18.41             | 19.61↑ | 22.41↑                    | 21.93↓ |
| CMLM     | 25.04             | 25.97↑ | 26.78↑                    | 26.67↓ |

Table 4: Results of several NAT models’ performance on Test Set and D-Test Set on IWSLT14 EN→DE task.

we re-evaluate the performance of the NAT models on D-Test Set and the results in Table 4 show SDM training worked on D-Test Set. So the key is the diversity between the distilled data and the original data. It is explicable but not expected to the original goal. Given these facts, we conclude that the straightforward formulation is not effective.

Problem 2: How to successfully use SDM Training for NAT models on distilled data, while the distilled data brings bias comparing with the original data?

4 Approach

4.1 Self-Distillation Mixup with Pre-Rerank and Fine-Tune Training

We add two stages to the classic SDM Training process. One is Pre-Rerank on self-distilled data, the other is Fine-Tune on filtered teacher-distilled data. The overall training process is seen in Figure 3. We define our enhanced training strategy as Self-Distillation Mixup with Pre-Rerank and Fine-Tune (SDMRT) Training.

Let \( \mathcal{D} \) denote the original parallel data: \( \mathcal{D} = \{X; Y\} \), where \( X \) is the original source-side corpus and \( Y \) is the original target-side corpus. Let \( \hat{\mathcal{D}} \) denotes the denoised parallel data: \( \hat{\mathcal{D}} = \{X; \hat{Y}\} \), where \( \hat{Y} \) is the distilled target-side corpus. For a clearer presentation, we summarise the SDMRT training process concretely in Appendix.

When translation model \( M \) generates \( k \)-candidates \( \hat{Y} = \{y_0, \ldots, y_{k-1}\} \) on the input sentence \( x \), we can use another model \( M_r \) to re-score the candidates instead of scoring them by the model \( M \) itself, which is known as Rerank. Reranking is an effective method to change the data distribution. We define the stage of re-score the self-distilled data in our SDMRT as Pre-Rerank. We demonstrate two rerank strategies. One is using Language Model trained on the original target-side corpus \( M_r = LM(\hat{Y}) \) to evaluate the Perplexity of the conditional candidates. The other is using Alignment Model such as an AT teacher model.
Mixup N-Distilled Data
Raw Data
AT model
Training
Generating
Mixup N-Distilled Data
Generating
Raw Data
AT model
Training
Generating
Rerank model
Filtered Distilled Data
NAT model
Fine-tune
Filtering

Figure 3: An overview of Self-Distillation Mixup Training with Pre-Rerank and Fine-Tune (SDMRT) Training on distilled data for a NAT model.

$M_r = AT(\mathcal{X}, \mathcal{Y})$ to score the Conditional Entropy between the source input and the prediction output.

Fine-Tune on filtered teacher-distilled data is an effective method to reduce the bias gap mentioned earlier. The key of the Fine-Tune stage in our SDMRT is to filter incorrect train set out. We calculate the score $T E R(\hat{y}, y)$ of the target-side of the teacher-distilled data $\hat{D}$, where $(x, \hat{y}) \in \hat{D}$; $(x, y) \in D$, and only keep the sentence pairs $(x, \hat{y})$ with TER score lower than $\tau$.

4.2 Theoretical Analysis

(Zhou et al., 2020) has used Bayesian Decision Theory to analyse distilled data with access to the true distribution. Furthermore, we use Bayesian Decision Theory to explain the reasons for the effectiveness and invalidity of SDM in §3.1 and §3.2. We also give the reasons why our SDMRT is effective.

Background: Bayesian Decision Theory In the problem of translations, let $x$ denote the input sequence and $y$ denote the output label sequence, where $x \in \mathcal{X}$ and $y \in \mathcal{Y}$. Let $\mathcal{H}$ denote all the possible hypothesis functions from the input to the output space: $\mathcal{H} = \{h : \mathcal{X} \rightarrow \mathcal{Y}\}$. Let $r(y|x)$ denote the conditional risk on the input $x$, which is the expected loss of predicting $y$ based on the posterior probabilities:

$$r(y|x) = \mathbb{E}_{P(y|x)}[L(y, y')]$$  \hspace{1cm} (4)

where $L(y, y')$ is the loss function that penalizes predicting the true target $y'$ as $y$. The classification task aims to find a hypothesis function $h$ that minimizes the overall risk $R$ given by

$$R(h) = \mathbb{E}_{P(x)}[r(h(x)|x)]$$  \hspace{1cm} (5)

This is known as the Bayes risk. To minimize the overall risk, obviously we need to minimize the conditional risk for each input $x$. The Bayesian decision rule states that the global minimum of $R(h)$ is achieved when the classifier makes predictions that minimize each conditional risk given $x$ and this gives the Bayes optimal classifier:

$$h^*(x) = \arg \min_{y \in \mathcal{Y}} r(y|x)$$  \hspace{1cm} (6)

We define $h^*$ as the best function in theory.

So the parallel data can be considered as $D = \{X; h^*(\mathcal{X})\}$. So:

- For baseline training, we train models on $\{X; h^*(\mathcal{X})\}$ and get $h_1$ close to $h^*$.
- For SD training, we train models on $\{X; h_1(\mathcal{X})\}$ and get another $h_1$.
- For SDM training, we train models on $\{X; h^*(\mathcal{X})\} \cup \{X; h_1(\mathcal{X})\}$ and get a new $h_2$ between $h^*$ and $h_1$, which means $h_2$ is closer to $h^*$.

Modeling Diversity Let $M$ denote a trainable network model and $\Theta$ denote the parameters of the model $M$. Then the $D$ can be defined as:

$$D = \{\mathcal{X}; h(\mathcal{X}, M^*, \Theta^*)\}$$  \hspace{1cm} (7)

where the theoretically best function $h^*$ can be replaced by the theoretically best model $M^*$ and the theoretically best parameters $\Theta^*$.

Let $M_s$ and $\Theta_s$ denote the student model and parameters. Let $M_t$ and $\Theta_t$ denote the teacher model and parameters. Then SDM Training can be considered to find the best $(M_s, \Theta_s)$ for:

$$\{\mathcal{X}; h(\mathcal{X}, M^*, \Theta^*)\} \cup \{\mathcal{X}; h(\mathcal{X}, M_t^*, \Theta_t^*)\}$$  \hspace{1cm} (8)
5 Experiments & Results

We evaluate our SDMRT Training strategy on five standard NMT benchmarks including WMT14 En↔De and WMT16 En↔Ro in both directions, and IWSLT14 En→De in single direction.

5.1 Experiments Setting

Datasets The sizes of the datasets are (train=4.5M / valid=3k / test=3k / dict=42k), (train=610k / valid=2k / test=2k / dict=40k) and (train=160k / valid=7k / test=6k / dict=10k) for WMT14 En↔De, WMT14 En↔Ro and IWSLT14 En→De respectively. We use Transformer-base (Vaswani et al., 2017) as teacher model to create the AT-distilled data, and initialize NAT model with the same model size. We use BPE (Sennrich et al., 2016b) to tokenize the sentences and create the vocabulary.

Model Configurations For WMT tasks, we use the following hyperparameters: $n_{layers} = 12$, $n_{heads} = 8$, $d_{hidden} = 512$, $d_{FFN} = 2048$, $lr = 5e^{-4}$, $n_{warmsup} = 10k$, $bz = 8192$, $n_{gpu} = 8$. For IWSLT tasks, smaller hyperparameters are set: $n_{layers} = 12$, $n_{heads} = 4$, $d_{hidden} = 512$, $d_{FFN} = 1024$, $lr = 5e^{-4}$, $n_{warmsup} = 6k$, $bz = 10240$, $n_{gpu} = 1$. Our models are trained on Tesla V100 GPUs. Adam (Kingma and Ba, 2015) is used as the optimizer and the inversed-sqrt scheduler is used for $lr$ decaying. All models are trained for 300k steps, and last 4 checkpoints are averaged. For the Pre-Rerank stage, we use AT teacher model to re-score the predictions instead of a language model. For the Fine-Tune stage, we filter the distilled data with TER score less than 0.8, and pre-train models for 240k steps and further-train for 60k steps. We implement models in the experiment with fairseq (Ott et al., 2019).

5.2 Main Results

Table 7 shows the translation performance of our SDMRT method. For all tasks, SDMRT forms

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| Metrics          | Original | Model Predictions |
|------------------|----------|-------------------|
|                  | AT       | NAT-CRF | CMLM     |
| Perplexity       | 23.59    | 28.78   | 127.59   | 37.22    |

Table 5: Average PPL of original Test Set and multiple model predictions on IWSLT14 EN→DE.

| Metrics          | AT       | NAT-CRF | CMLM     |
|------------------|----------|---------|----------|
| Frequency of     | 0.072%   | 0.937%  | 0.461%   |
| repeated tokens  | -        | 13.01×  | 6.42×    |

Table 6: The percentage of repeated tokens of different data on IWSLT14 EN→DE task.

in §5.3.
Table 7: Performance of BLEU (Papineni et al., 2002) score of multiple NAT models on WMT14 En$\rightarrow$De, WMT16 En$\rightarrow$Ro and IWSLT14 En$\rightarrow$De. Note that we train CMLM baseline using Transformer-base as teacher model, but their (Ghazvininejad et al., 2019) teacher model is Transformer-big. The results of CMLM* are under Transformer-big teacher model.

| Model                  | Iter | WMT14 | WMT16 | IWSLT14 |
|------------------------|------|-------|-------|---------|
|                        |      | En $\rightarrow$ De | De $\rightarrow$ En | En $\rightarrow$ Ro | Ro $\rightarrow$ En | En $\rightarrow$ De |
| **AT models**          |      | | | | | |
| Transformer-base(Vaswani et al., 2017) | -    | 27.3  | -     | -       | -       | -       |
| Transformer-base(Our Implementation) | -    | 27.67 | 31.17 | 34.37   | 33.98   | 28.34   |
| Transformer-big(Our Implementation) | -    | 28.83 | -     | -       | -       | -       |
| **NAT models**         |      | | | | | |
| V-NAT(Gu et al., 2018) | -    | 19.17 | 23.20 | 29.79   | 31.44   | -       |
| NAT-CRF(Sun et al., 2019) | -    | 23.32 | 25.75 | -       | -       | 26.39   |
| iNAT(Lee et al., 2018) | 10   | 21.61 | 25.48 | 29.32   | 30.19   | -       |
| CMLM*(Ghazvininejad et al., 2019) | 10   | 27.03 | 30.53 | 33.08   | 33.31   | -       |
| **Our Implementation** |      | | | | | |
| V-NAT                  | -    | 16.32 | 20.01 | 24.83   | 25.57   | 15.79   |
| NAT-CRF                | 10   | 23.76 | 25.56 | 29.31   | 29.17   | 22.41   |
| iNAT                   | 10   | 21.19 | 25.37 | 29.17   | 30.09   | 22.75   |
| CMLM                   | 10   | 26.03 | 29.61 | 32.94   | 33.07   | 26.78   |
| CMLM*                  | 10   | 27.06 | 30.94 | 33.07   | 33.36   | -       |

Table 8: SDM v.s. SDMRT on IWSLT14 En$\rightarrow$De task and WMT14 En$\rightarrow$De task.

| Model | WMT14 En$\rightarrow$De | IWSLT14 En$\rightarrow$De |
|-------|-------------------------|---------------------------|
| Baseline | 23.76 | 22.41 |
| CMLM | 26.03 | 26.78 |

**5.3 Study**

**SDM v.s. SDMRT on different NAT models**

As shown in Table 8, the performance of our SDMRT outperforms that of classic SDM. Surprisingly, NAT-CRF with SDM can achieve positive results on smaller datasets, while CMLM achieves positive results on larger datasets.

**SDM v.s. SDMRT on different steps of IR NAT models**

It is clear in Figure 4, SDM only has positive influence at the first several steps, but our SDMRT can improve translation quality at any step.

Table 9: BLEU scores of every step with maxiter=10 for CMLM model on WMT14 En$\rightarrow$De task. SDMRT can overstep baseline earlier in step of 5.

| STEP | Baseline | SDMRT | ΔBLEU  |
|------|----------|-------|--------|
| 1    | 19.54    | 21.58 | 2.04   |
| 5    | 25.57    | 26.24*| 0.67   |
| 10   | 26.03    | 26.77*| 0.74   |

Table 10: Re-visit average PPL of multiple models predictions on IWSLT14 En$\rightarrow$De.

| Metrics | Rerank | Original | NAT-CRF | CMLM |
|---------|--------|----------|---------|------|
| Perplexity | w/o   | 23.59    | 127.59  | 37.22 |
| w/      | -     | 76.55↓   | 30.47↓  |      |

**Acceleration for Iterative Refinement NAT**

For Iterative Refinement (IR) NAT such as CMLM, it usually requires more than 4 steps to make the refinement converge, which causes negative influence on the speedup. Table 9 shows, on AT-distilled data, our SDMRT training strategy can overstep baseline within 5 steps which means $2 \times$ acceleration compared to baseline.

**Re-visit Modeling Specificity**

Following the preliminary experiments before, we re-visit the average Perplexity of test set on IWSLT14 En$\rightarrow$De.
Figure 4: Results of different training strategies for CMLM model on IWSLT14 EN→DE task.

| Model   | SDM  | SDMRT |
|---------|------|-------|
| AT      | 0.072% | -     |
| NAT-CRF | 0.937% | 13.01× | 0.533%↓ | 7.40× |
| CMLM    | 0.461% | 6.42× | 0.195%↓ | 2.71× |

Table 11: Re-visit the percentage of repeated tokens of different data on IWSLT14 EN→DE task.

The results in Table 10 prove that the distribution of NAT models’ predictions under Rerank is more closer to that of original data.

Re-visit Confirmation Bias As mentioned earlier, confirmation bias in NMT is Multi-modality, and Multi-modality is typically characterized by token repetitions. We re-measure the frequency of repeated tokens. As shown in Table 11, the percentage of repeated tokens of with rerank stage sharply decreases, which proves that our SDMRT is an effective method.

AT-Rerank v.s. LM-Rerank We compare the effect of different rerank strategies. As shown in Table 12, AT-Rerank performs overall better than LM-Rerank. Specially, LM-Rerank can achieve similar performance as AT-Rerank for NAT-CRF model.

Effect of Data-Filtering on Fine-Tune Stage To measure the effect of filtered teacher-distilled data, we change our SDMRT training process and fine-tune the models on teacher-distilled data. The results in Table 13 prove that Data-Filtering is important in our SDMRT training process.

6 Conclusion

In this work, we empirically find directly adopting the classic Self-Distillation Mixup (SDM) Training strategy to NAT models is not as effective as in AT models. Through careful analysis, we observe Modeling Diversity and Confirmation Bias between the AT teacher model and the NAT student models, causing SDM theoretically invalid for NAT models when trained on AT-distilled data. Furthermore, we propose an enhanced training strategy named SDMRT and achieve new SOTA performance for multiple NAT models compared to the baselines. In addition, it’s demonstrated to be an effective method to reduce the iteration number for Iterative Refinement NAT.

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A Appendix
Algorithm 1 SDMRT Training

1: `procedure TRAIN_RERANK(D = {X; Y}):`
2:     `If ( M_r is Language Model )`
3:         Train randomly initialized M_r on Y
4:     `Elseif ( M_r is Alignment Model )`
5:         Train randomly initialized M_r on D
6:     `Return M_r`
7: `end procedure`

1: `procedure FILTER(D = {X; Y}, \hat{D} = {X; \hat{Y}}):`
2:     Filter \( D^* = \{(x, \hat{y}) \mid \text{TER}(\hat{y}, y) < \tau; (x, \hat{y}) \in \hat{D}; (x, y) \in D \} \)
3:     `Return D^*`
4: `end procedure`

1: `procedure TRAIN(D = {X; Y}):`
2:     Train randomly initialized M on D
3:     `Return M`
4: `end procedure`

1: `procedure RERANK_DIS(D = {X; Y}, M, M_r):`
2:     `For (x, y) in D:`
3:         Generate k-candidates \( Y = \{y_0', ..., y_{k-1}'\} \) by M(x)
4:         `If ( M_r is Language Model )`
5:             Select the best \( y' \) order by sorted \( \{M_r(y')|y' \in Y\} \)
6:         `Elseif ( M_r is Alignment Model )`
7:             Select the best \( y' \) order by sorted \( \{M_r(x, y')|y' \in Y\} \)
8:     `Return D' = \{(x, y')\}`
9: `end procedure`

1: `procedure FINE_TUNE(M, D = {X; Y}):`
2:     Further train M on D
3:     `Return M`
4: `end procedure`

1: `procedure SDMRT(D = {X; Y}, \hat{D} = {X; \hat{Y}}):`
2:     \( M_r \leftarrow \text{TRAIN_RERANK}(D) \)
3:     \( D^* \leftarrow \text{FILTER}(D, \hat{D}) \)
4:     \( M \leftarrow \text{TRAIN}(\hat{D}) \)
5:     \( \hat{D}_N \leftarrow \text{RERANK_DIS}(D, M, M_r) \)
6:     \( M \leftarrow \text{TRAIN}(\hat{D} \cup \hat{D}_N) \)
7:     \( M \leftarrow \text{FINE_TUNE}(M, D^*) \)
8:     `Return M`