Reciprocal Supervised Learning Improves Neural Machine Translation

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Abstract

Despite the recent success on image classification, self-training has only achieved limited gains on structured prediction tasks such as neural machine translation (NMT). This is mainly due to the compositionality of the target space, where the far-away prediction hypotheses lead to the notorious reinforced mistake problem. In this paper, we revisit the utilization of multiple diverse models and present a simple yet effective approach named Reciprocal-Supervised Learning (RSL). RSL first exploits individual models to generate pseudo parallel data, and then cooperatively trains each model on the combined synthetic corpus. RSL leverages the fact that different parameterized models have different inductive biases, and better predictions can be made by jointly exploiting the agreement among each other. Unlike the previous knowledge distillation methods built upon a much stronger teacher, RSL is capable of boosting the accuracy of one model by introducing other comparable or even weaker models. RSL can also be viewed as a more efficient alternative to ensemble. Extensive experiments demonstrate the superior performance of RSL on several benchmarks with significant margins.\textsuperscript{1}

1 Introduction

Recently, self-training method has shown remarkable success in image recognition. Trained on noisy augmented data, an EfficientNet model finetuned with self-training can achieve 87.4\% top-1 accuracy on ImageNet, which is 1.0\% better than the state-of-the-art model that requires 3.5B weakly labeled images (Xie et al., 2019). Typically, in self-training we first train a base model on the labeled data, and then utilize the learned model to label unannotated data. Finally, both labeled and pseudo data are combined as the training set to yield the next level model. In the context of natural language processing, many works have successfully applied self-training technique including word sense disambiguation (Yarowsky, 1995) and parsing (McClosky et al., 2006; Reichart and Rappoport, 2007; Huang and Harper, 2009).

Nevertheless, the performance gains achieved through self-training are still limited for structured prediction tasks such as Neural Machine Translation (NMT) where the target space is vast. Originally designed for classification problems, previous work suggests that self-training can be effective only when the predictions on unlabeled samples are good enough, and otherwise it will suffer from the notorious reinforced mistakes (Zhu and Goldberg, 2009). However, this problem is common in NMT scenario, where the hypotheses generated from a single model are often far away from the ground-truth target due to the compositionality of the target space (He et al., 2019). Zhang and Zong (2016) found that training on this biased pseudo data may accumulate the mistakes at each time step and enlarge the error, and thus they propose to freeze the decoder parameters when training on the pseudo parallel data which may negatively impact the decoder model of NMT.

To overcome this issue, in this paper we borrow the reciprocal teaching concept (Rosenshine and Meister, 1994) from the educational field and revisit the core idea of classic ensemble approaches. Ensemble is built upon the assumption that different models have different inductive biases and better predictions can be made by majority voting. We propose to replace the self-supervision with Reciprocal-Supervision in NMT, leading to a novel co-EM (Expectation-Maximization) scheme (Nigam and Ghani, 2000) named RSL. In RSL, we use multiple separately learned models to provide diverse proper pseudo data, allowing us to enjoy the independence between different models and dramatically reduce the
error through strategic aggregation. More specifically, we first learn multiple different models on the parallel data. Then in the E-step all individual models are used to translate the monolingual data. And in the M-step the generated pseudo data produced by different models are combined to tune all student models.

RSL is inspired by the success of ensemble method. However, ensemble is resource-demanding during inference, which prevents its wide usage. Besides, it cannot make use of the large scale monolingual data from source side. RSL is also related to the data augmentation approaches for NMT. While most of previous works concentrate on monolingual data of target side such as back-translation (Edunov et al., 2018), we pay more attention to the source side. Knowledge distillation (KD) (Hinton et al., 2015; Mirzadeh et al., 2019) is another relevant research topic. However, KD is preliminary designed to improve a weak student model with a much stronger teacher model. By contrast, RSL boosts the performance of base models through reciprocal-supervision from other just comparable or even weaker learners. To the best of our knowledge, we are the first self-training framework with reciprocal-supervision, which can correct the bias of each model and fully utilize the monolingual data of source side language. More precisely, the advantages of RSL can be summarized as follows:

- As an architecture-free framework, RSL is flexible and promising, where a strong NMT model can benefit from any other comparable or even weaker models.
- RSL is efficient for translation. While involving multiple models during training, only one NMT model is required for inference.
- Orthogonal to other widely used techniques such as back translation, RSL is capable of making full use of the source side monolingual data.

Through extensive experiments, RSL achieves significant gains on several standard translation tasks including En→{Ro, De}. Surprisingly, we also have found that RSL with other much weaker learners could even outperform a strong BERT enhanced NMT model with big margins.

2 Proposed Method

In this section, we first briefly introduce the background of modern NMT systems. Then we present a detailed description of the proposed reciprocal-supervised learning framework. The whole framework is illustrated in Fig. 1. Note that, RSL is architecture-free, which can practically be adapted with arbitrary seq2seq models.

2.1 Preliminary

Neural Machine Translation (NMT) (Sutskever et al., 2014; Vaswani et al., 2017) is a sequence-to-sequence (seq2seq) (Bahdanau et al., 2015) learning framework to model the conditional probability $P(y|x)$ of the target translation $y$ given the source sentence $x$. Given a parallel corpus $D_{s,t}$ of source language $s$ and target language $t$, the training objective of the model is to minimize the negative likelihood of the training data:

$$L(\theta) = -\frac{1}{N} \sum_{(x,y) \sim D_{s,t}} \log P(y|x; \theta),$$  \hspace{1cm} (1)

where $P(y|x; \theta)$ is the NMT model and $\theta$ denotes the model parameter. $N$ is the amount of parallel training data in $D_{s,t}$. Recently, there are plenty of works attempting to improve the performance of NMT system by new network architectures and modifications (Luong et al., 2015; Gu et al., 2016; Hassan et al., 2018). Different from previous works, in this paper we take a step back and study how to make the most of multiple individual models by reciprocally learning.

2.2 Basic NMT Models

2.2.1 Diverse Parameterized Networks

Modern NMT models can be parameterized with diverse different network architectures, such as recurrent neural network (RNMT) (Sutskever et al.,
2014) and its variants (Hochreiter and Schmidhuber, 1997; Cho et al., 2014; Chung et al., 2014), convolutional neural network (Conv) (Gehring et al., 2017; Wu et al., 2019a) or self-attention based Transformer network (Vaswani et al., 2017; Ott et al., 2018), among which the recent self-attention based Transformer is the state-of-the-art architecture for NMT. In our RSL framework, we hope different network architectures can capture different linguistic knowledge, and then all the knowledge can be aggregated into a single NMT model through the proposed RSL approach.

2.2.2 Bidirectional Decoding Factorization
Seq2seq models are direction-sensitive. Usually, the inputs of the encoder and the outputs of the decoder are both from left to right, leading to the exposure bias problem (Bengio et al., 2015): during inference, true previous target tokens are unavailable and replaced by tokens predicted by the model itself, and thus mistakes made early can mislead subsequent translation, yielding unsatisfied translations with good prefixes but bad suffixes. To mitigate this issue in our inferred pseudo parallel data, we also involve right-to-left (R2L) decoding models (Zhang et al., 2019; Shan et al., 2019) together with common left-to-right (L2R) model. Precisely, for R2L models the references will be reversed during training, and for inference procedure the outputs are also reversed after decoding to recover the normal sequence.

2.3 Reciprocal-Supervised NMT
Suppose we have a parallel corpus $D_{s,t}$ of source language $s$ and target language $t$, and a monolingual corpus $D_{s}$ of language $s$. In our pipeline, we will first use the bilingual dataset $D_{s,t}$ to train multiple basic models $M_1, M_2, \ldots, M_k$ by standard maximum likelihood training method, where $k$ denotes the number of models. In practice, our basic models involve both different network architectures and different decoding factorizations. After training, we further tune them through the reciprocal-supervision from each other. In this procedure, both bilingual and monolingual data can be utilized. More specifically, the models are tuned with both the real parallel dataset $D_{s,t}$ and the supervision from other different models. Thus, the training objective consists of the standard maximum likelihood (MLE) term on real parallel dataset and the reciprocal-supervision agreement (RS) term with other models. We use Kullback-Leibler (KL) divergence to measure the gap between different models. More precisely, the training loss for the $i^{th}$ basic model can be written as:

$$\mathcal{L}_{MLE}(\theta_i) = -\frac{1}{N} \sum_{(x,y) \sim D_{s,t}} \log P(y|x; \theta_i),$$

$$\mathcal{L}_{RS}(\theta_i) = \frac{1}{M} \sum_{x \sim D_{s,t}} \sum_{j=1,j \neq i}^{k} \left( KL(P(y|x; \theta_j)||P(y|x; \theta_i)) + KL(P(y|x; \theta_i)||P(y|x; \theta_j)) \right)$$

(2)

$$\mathcal{L}(\theta_i) = \mathcal{L}_{MLE}(\theta_i) + \mathcal{L}_{RS}(\theta_i)$$

where $\theta_i$ denotes the parameters of the basic model $M_i$. $D_{s,t}'$ is the combination of source side language sentences of both bilingual dataset $D_{s,t}$ and monolingual dataset $D_{s}$. $N$ and $M$ are the sample numbers of parallel data $D_{s,t}$ and combined monolingual data $D_{s}'$ respectively in one training epoch. Note that, the proposed cooperative training framework is flexible, which can be adopted either with or without the monolingual corpus.

According to the definition of KL divergence that $KL(P||Q) = \sum_x P(x) \log \frac{P(x)}{Q(x)}$, we can get the gradient of $\mathcal{L}(\theta_i)$ with respect to $\theta_i$. More specifically, since $P(y|x; \theta_i)$ is irrelevant to parameter $\theta_i$, the partial derivative of $KL(P(y|x; \theta_j)||P(y|x; \theta_i))$ with respect to $\theta_i$ can be written as:

$$\frac{\partial KL(P(y|x; \theta_j)||P(y|x; \theta_i))}{\partial \theta_i} = \sum_{y \sim Y(x)} \frac{1}{\partial \theta_i} \left[ P(y|x; \theta_j) \log \frac{P(y|x; \theta_i)}{P(y|x; \theta_j)} \right]$$

$$= \sum_{y \sim Y(x)} P(y|x; \theta_j) \frac{\partial \log P(y|x; \theta_i)}{\partial \theta_i}$$

$$= - E_{y \sim P(y|x; \theta_j)} \frac{\partial \log P(y|x; \theta_i)}{\partial \theta_i},$$

(3)

where $Y(x)$ is the space of all possible target translations given the source sentence $x$. The term $\frac{\partial \log P(y|x; \theta_i)}{\partial \theta_i}$ are the standard gradients to maximize the log-likelihood within the seq2seq NMT system. And the expectation part $E_{y \sim P(y|x; \theta_j)}$ can be simply approximated by sampling from the $j^{th}$ NMT model. Therefore, minimizing this reciprocal-supervision term is equal to maximizing the log-likelihood on the pseudo sentence pairs generated from other basic model.

And similarly, the partial derivative of $KL(P(y|x; \theta_j)||P(y|x; \theta_i))$ with respect to $\theta_i$ is
calculated as follows:
\[
\frac{\partial KL(P(y|x; \theta_i) || P(y|x; \theta_j))}{\partial \theta_i} = - \sum_{y \sim Y(x)} \frac{1}{N} \partial_y \log P(y|x; \theta_i) \log \frac{P(y|x; \theta_i)}{P(y|x; \theta_j)}
\]
\[
= - E_{y \sim P(y|x; \theta_i)} \log \frac{P(y|x; \theta_i)}{P(y|x; \theta_i)} \log \frac{P(y|x; \theta_i)}{P(y|x; \theta_i)}
\]

(4)

Similarly, for the calculation of the expectation \(E_{y \sim P(y|x; \theta_i)}\), we can also sample from the \(i\)th NMT model itself. However, one should note that there are vital differences between the above two terms (Eq. 3 and Eq. 4): 1) Pseudo sentence pairs are generated from other models in the former term, but from the \(i\)th model itself in the latter one; 2) The latter term, used the density ratio \(P(y|x; \theta_i)/P(y|x; \theta_i)\) to re-weight the pseudo pairs generated from itself. Actually, the second KL term can be viewed a improved version of self-training, which employ the calculated weights to penalize the incorrect pseudo parallel data.

To sum up, the whole partial derivative of the objective function \(L(\theta_i)\) with respect to \(\theta_i\) can be written as:
\[
\frac{\partial L_{MLE}(\theta_i)}{\partial \theta_i} = - \frac{1}{N} \sum_{(x,y) \sim D_{s,t}} \log P(y|x; \theta_i)
\]
\[
\frac{\partial L_{RS}(\theta_i)}{\partial \theta_i}
\]
\[
= - \frac{1}{M} \sum_{s \sim S_j} \frac{1}{k} \left( E_{y \sim P(y|x; \theta_j)} \log \frac{P(y|x; \theta_j)}{P(y|x; \theta_i)} \right)
\]
\[
+ E_{y \sim P(y|x; \theta_j)} \log \frac{P(y|x; \theta_j)}{P(y|x; \theta_i)} \log \frac{P(y|x; \theta_j)}{P(y|x; \theta_i)}
\]
\[
\frac{\partial L(\theta_i)}{\partial \theta_i} = \frac{\partial L_{MLE}(\theta_i)}{\partial \theta_i} + \frac{\partial L_{RS}(\theta_i)}{\partial \theta_i}.
\]

(5)

In the final derivative \(\frac{\partial L_{MLE}(\theta_i)}{\partial \theta_i}\), the first MLE term can be easily optimized by standard maximum likelihood training on parallel data. For the second cooperative term, it can be approximately optimized by co-EM (Nigam and Ghani, 2000) algorithm, where we first estimate the expectation of target translation probability \(p(x|y)\) in the E-step, and then maximize the likelihood in the M-step. More specifically, in the E-step, we employ the multiple diverse NMT models to individually generate the target translations of source monolingual data, and then paired them to serve as the estimated new distribution of training data. In the following M-step, maximizing the likelihood is approximated by maximizing the log-likelihood of each individual model on the pseudo data. The above procedure will be repeated for several iterations until convergence, where the synthetic training data are re-produced with the updated NMT models.

3 Experiments

3.1 Experiment Setup

Dataset. We compare our model with its counterparts in both resource-poor and resource-rich scenarios. For the former scenario, we conduct experiments on WMT16 English-to/from-Romanian (WMT16 En↔Ro) low-resource task and IWSLT16 English-to/from-German (IWSLT16 En↔De) cross-domain task on TED talks. For the latter setting, we use WMT14 English-to/from-German (WMT14 En↔De) dataset. For all the settings, monolingual data are randomly picked from WMT News Crawl datasets. Furthermore, we also compare RSL with some state-of-the-art large scale training methods on more widely used benchmarks, including WMT14 English-to-German and French (WMT14 En→{De,Fr}) as well as WMT18 Chinese-to-English (WMT18 Zh→En). The statistics about all datasets are listed in Tab. 1. For data preprocessing, we use Moses scripts\(^2\) for sentence tokenization, and Jieba\(^3\) for Chinese sentence segmentation. Tokenized sentences of both source and target side are then segmented to sub-word units with Byte-Pair Encoding (BPE) (Sennrich et al., 2016b)\(^4\).

\(^2\)https://github.com/moses-smt/mosesdecoder
\(^3\)https://github.com/fxsjy/jieba
\(^4\)https://github.com/rsennrich/subword-nmt

| Dataset          | WMT14 EN↔DE | WMT16 EN↔RO | IWSLT16 EN↔DE | WMT14 EN↔FR | WMT18 ZH↔EN |
|------------------|-------------|-------------|--------------|-------------|-------------|
| Parallel         | 4.50M       | 0.62M       | 0.20M (TED)  | 36M         | 22M         |
| Non-parallel     | 5.00M       | 1.00M       | 0.20M (NEWS) | 72M         | 10M         |
| Dev/Test         | newstest2013/14 | newstest2015/16 | ts13/14     | newstest2013/14 | newstest2017/18 |

Table 1: Statistics of datasets.
Table 2: BLEU scores on both low-resource and rich-resource translation tasks. Transformer and Transformer-R2L are representative of basic models. +BT denotes using back translation to augment the training data, and +ST means further using the source side monolingual data through self-training. ML-NMT and RSL represent instead using the multi-agent learning and proposed reciprocal learning to utilize the source side data respectively.

| Model                  | WMT16 En-Ro | En-Ro | WMT14 En-De | De-En | WMT16 En-Ro | Ro-En | En-De | De-En |
|------------------------|-------------|-------|-------------|-------|-------------|-------|-------|-------|
| Transformer            | 32.1        | 33.2  | 27.5        | 32.8  | 28.6        | 31.3  |       |       |
| Transformer-R2L        | 31.7        | 32.7  | 26.9        | 32.1  | 27.8        | 30.9  |       |       |
| Transformer+BT         | 33.9        | 35.0  | 27.8        | 33.3  | 29.6        | 33.2  |       |       |
| Transformer+ST+BT      | 34.2        | 35.4  | 28.2        | 33.7  | 30.4        | 34.2  |       |       |
| RSL (ours)             | 35.0        | 36.2  | 28.7        | 34.1  | 31.1        | 35.0  |       |       |
| ML-NMT (Bi et al., 2019) | 34.5    | 35.6  | 28.3        | 33.7  | 30.6        | 34.4  |       |       |

Basic Models. In our implementation of RSL, we employ several NMT models with different architecture to conduct the reciprocal learning process, including transformer, convolutional models and hybrid models. **Transformer** (Vaswani et al., 2017; Ott et al., 2018) utilizes multi-head attention modules instead of recurrent units in encoder and decoder to summarize information of sentences. Besides, there are additional modules such as feed forward networks and layer normalization to consist stacked layers. Transformer has shown its capacity on sequence modeling in lots of works. **Convolutional models** have been successfully applied on seq2seq tasks where the encoder and decoder are stacked convolutional layers without recurrent units. ConvS2S (Gehring et al., 2017) is the first convolutional model with Gated Linear Units (GLU) and separate attention blocks interacting with the outputs of the encoder. DynamicConv (Wu et al., 2019b) further improves the performance with sophisticated designed dynamic convolution kernels. **Hybrid model** (Chen et al., 2018) implement RNMT+ that combines the advantages of both recurrent networks and self-attention mechanism. They further construct hybrid methods that use transformer or RNMT+ as encoder or decoder. In RSL, we use a Hybrid-RNMT+ model in which the encoder is transformer and the decoder is RNMT+, which shows the best performance among all hybrid models shown in their work.

Model Settings. All our models (Transformer, DynamicConv and Hybrid-RNMT+) are implemented with fairseq\(^5\) (Ott et al., 2019) in PyTorch (Paszke et al., 2019). For the hyperparameters we mainly follow their original papers, and we also adopted some settings from (Ott et al., 2018). More specifically, the dropout rate is set as 0.3 for all experiments, and all models are optimized with Adam (Kingma and Ba, 2014) following the default optimizer settings and learning rate schedule in (Ott et al., 2018). All the models are trained on 8 NVIDIA V100 GPUs with half-precision (FP16), and the batch size is set as 4096. During inference, we generate translations with a beam size of 5 and a length penalty of 0.6. For evaluation, we use sacreBLEU\(^6\) (Post, 2018) to report the case-sensitive detokenized BLEU score for WMT14 En-De, WMT14 En-Fr and WMT18 Zh-Ee, and uncased tokenized BLEU for other tasks.

3.2 Numerical Results

We first present the overall performances of RSL with its related baselines on several widely used datasets, and then make a comparison with several strong prior works:

- **Basic models**: In practice, we find Transformer shows the best performance among all basic models in both bidirectional decoding direction, and thus we take it as the representative of state-of-the-art basic models.
- **Previous semi-supervised approaches (+BT and +ST)**: These baselines are trained on the combination of both bilingual parallel data and pseudo data generated from monolingual sentences by back translation (+BT) or forward translation, i.e., self-training (+ST).
- **Multi-agent Learning NMT (ML-NMT)** (Bi et al., 2019): This recent proposed approach also introduces diverse agents in an interactive updating process, where each NMT agent

\(^5\)https://github.com/pytorch/fairseq \(^6\)https://github.com/mjpost/sacreBLEU
learns advanced knowledge from an ensemble model during the training time.

The main results are shown in Tab. 2. In practice, we use the aforementioned 6 different models (3 different architectures × 2 different decoding directions as shown in Section 2.2) as basic NMT models to conduct reciprocal-supervised learning. We can see from the table that: 1) RSL is robust in a range of different scenarios. Sophisticated designed experiments show that RSL is effective on several different tasks, including low-resource, rich-resource and cross-domain translations. These results suggest that as a generalized method, RSL is not over-fitted to any specific dataset or translation task. 2) RSL is orthogonal to the widely adopted back translation technique. Results show that RSL works well with the classic BT technique, which promotes its wide usage. 3) RSL can make the most of monolingual data. While both self-training, multi-agent learning and reciprocal-supervised learning can further boost the performance of BT enhanced models, RSL achieves much more noticeable gains. This meaningful observation roughly versifies the idea that diverse models are vital for higher quality pseudo data. This conjecture will be further discussed in Section 4.1.

For training efficiency, we take IWSLT task as an example for illustration: with 1 Tesla V100 for each model, Transformer converges in ~14 hours, Transformer+BT in ~21 hours, Transformer+ST+BT in ~22 hours, ML-NMT in ~34 hours and RSL in ~28 hours. In practice, we found that in RSL, it is the on-fly pseudo data sampling process that is time-consuming. One possible way to improve the efficiency may be to sample and save pseudo translations in advance for the training of next epoch.

Furthermore, we compare the performances of our RSL with some important prior works on more challenging tasks. Previous work includes:

| SYSTEMS          | En→De | En→Fr | Zh→En |
|------------------|-------|-------|--------|
| Transformer (2017) | 28.4  | 41.0  | 24.1   |
| WMT Winner (2018) | -     | -     | -      |
| BERT-NMT (2019)   | 30.1  | 42.3  | -      |
| MASS (2019)       | 28.9  | -     | -      |
| XLM (2019)        | 28.8  | -     | -      |
| mBERT (2018)      | 28.6  | -     | -      |
| ALM (2020)        | 29.2  | -     | -      |
| RSL              | 31.1  | 43.4  | 29.4   |

Table 3: The performance comparison with other large-scale pretrained works on WMT 2014 En→De, En→Fr and WMT 2018 Zh→En.

- WMT Winner (Wang et al., 2018) is the winner system of WMT18 Zh→En task, implemented with rerank and ensemble techniques over 48 models.
- BERT-NMT (Yang et al., 2019) is a BERT-enhanced NMT model. It introduces BERT features with three delicately designed tricks, which helps to capture the knowledge of large scale source side monolingual data through the pre-trained language model.
- MASS (Song et al., 2019) is a seq2seq method pretrained with billions of monolingual data.
- XLM (Lample and Conneau, 2019) utilizes large scale cross-lingual data to pre-train the NMT model.

The results are presented in Tab. 3. As shown in the table: RSL is much more efficient in making use of the monolingual data: while the pretrained language model is obtained through much larger monolingual or cross-lingual corpus, RSL shows better results on these three benchmark translation tasks with much less cost.

4 Analysis

To further verify our conclusions, in this section we conduct several ablation studies. The majority of these empirical studies are conducted on WMT14 En→De and En→Fr datasets.

4.1 Are Diverse Models Necessary?

This work is motivated by the conjecture of ensemble learning, which assumes different models can capture different patterns of the sequence. Thus, the prediction mistakes of each model can be corrected by others, leading to a better estimation of the synthetic corpus constructed upon the source monolingual data. In this section, we implement RSL with different basic models to investigate whether the diversity of basic models is necessary. The results are reported in 4.

Empirical results suggest that though increasing the number of models (6*Transformer) can boost the performance, the improvement is rather limited compared with involving more diverse models (L2R+R2L and Heterogeneous settings). To investigate the vital element behind diverse models, we further measure the difference between different basic models through BLEU score. More specifically, we use each model to translate the test set into target space, and then compute the BLEU score between the predictions of different models. The
Table 4: The performance of RSL on WMT 2014 En→De with different basic models. Note that, in this comparison we concentrate on the utilization of source side monolingual data, so all experiments are conducted without BT. L2R+R2L denotes RSL where basic models are Transformer and Transformer-R2L. Heterogeneous Models represents the standard implementation in Section 3 where basic model are 6 different models. To yield a fair comparison we also incorporate the setting that basic models are 6 Transformers or 3 bidirectional Transformers, which are obtained by training with different seeds.

BLEU scores between different architectures are about 56, and between different decoding direction are about 53. By contrast, the differences between the homogeneous models trained with different seeds are about 60, which is much higher. This observation indicates that heterogeneous models can produce more diverse hypotheses, which plays the vital role in our reciprocal learning framework.

However, this conclusion further leads to another interesting question: since the diversity is important, whether we can induce the diversity by sampling multiple pseudo data from a single model to improve the performance of self-training? We use a single Transformer model to generate multiple hypotheses for each source side monolingual sentence during inference, and take them all together to construct the pseudo data. However, the results are less satisfactory as shown in Tab. 5. We empirically found that many translations are of low quality when generating multiple predictions, which may hurt the performance of the NMT model during tuning on the generated pseudo data. These results suggest that involving the high training computation cost for multiple models is necessary to generate both diverse and good pseudo data, which is consistent with the well-known no free lunch theorem (Wolpert, 2012).

4.2 Direct Ensemble vs. RSL

RSL involves multiple models during reciprocal training, while uses just each individual model for inference. By contrast, in ensemble methods different models are separately trained, but are aggregated together during inference. Despite the high inference cost of ensemble method, it is interesting to compare the empirical performance of ensemble learning and the proposed RSL. The results are shown in Tab. 6. As shown in the table, RSL can achieve comparable performance against ensemble method with much less inference cost. Surprisingly, we found that ensemble over the reciprocal-supervised Learned models can further boost the performance. Our results suggest that: (1) The direct ensemble and RSL can be viewed as a trade-off between training and testing cost. (2) RSL is parallel to the ensemble method, and therefore better accuracy can be achieved by combining the two methods together.

4.3 Could RSL still be effective with much weaker models?

In this section, we investigate in RSL framework, whether a strong Transformer can still benefit from other much weaker NMT models. We first show the performances of our chosen weak models on

| Pseudo Data                  | BLEU   |
|------------------------------|--------|
| Beam Search (Top1)           | 29.0   |
| Beam Search (Top3)           | 28.6   |
| Diverse Beam Search (Top3)   | 28.8   |

Table 5: The performance of RSL with diverse generated pseudo data from single model. Topk means we generate k target predictions for each source side sentence. Beam Search and Diverse Beam Search (Vijayakumar et al., 2016) are two different decoding method, and the latter one is a diversity-promoting version of the former one.

| En → De | newstest14 | newstest15 |
|---------|------------|------------|
| Transformer       | 28.6       | 30.9       |
| Transformer w/ E  | 29.5       | 31.7       |
| Heterogeneous w/ E| 29.7       | 32.1       |
| RSL w/ E          | 29.6       | 31.9       |
| RSL w/ E          | **30.2**   | **32.5**   |

Table 6: The performance of ensemble and RSL. To yield a fair comparison with ensemble, all experiments are conducted without any source or target side monolingual data. Transformer w/ E means ensemble over 3 Transformers together, while Heterogeneous w/ E ensemble over the 3 different models in Section 3.1. RSL w/ E means ensemble all the models after the reciprocal-supervised learning procedure.
Table 7: The performances of our re-implemented base models on WMT 2014 tasks.

| Model        | En→De | En→Fr |
|--------------|-------|-------|
| ConvS2S      | 26.2  | 40.8  |
| Transformer  | 28.6  | 42.3  |
| Transformer-R2L | 27.8  | 41.8  |
| Hybrid-RNMT+ | 27.7  | 41.3  |

Table 7: The performances of our re-implemented base models on WMT 2014 tasks.

WMT 2014 En→De task in Tab. 7.

We conduct comprehensive experiments to study the capacity of RSL with weak NMT models. We first take each individual model as the teacher model and use the Transformer as the student model. The results are shown in Tab. 8. We can find that R2L model can bring more obvious performance with better diversities. For other L2R models, while a stronger teacher leads to a better student, it can still be improved with much weaker teachers. Combining Transformer and Transformer-R2L in RSL, we get better results than learning with a single heterogeneous model. When jointly training all four models with reciprocal supervision, even though ConvS2S and Hybrid-RNMT+ are weaker, adding them also can bring significantly higher results. These results suggest that RSL is flexible, where strong learners can even benefit from other weaker models.

4.4 Influence of Monolingual Data Size

In Figure 2 we follow the En→De task in Section 4.3 and show how the number of monolingual sentences affects the performance of RSL. For different basic models, though have distinct performances, they receive a similar impact from monolingual data size. Results also show that monolingual data which are roughly two to three times as many as parallel data can already obtain satisfactory performances in this task.

Table 8: The influence on Transformer with different reciprocal learners on WMT 2014 En→De. The single and avg denote the scores evaluated on the checkpoint before averaging and averaged checkpoint respectively, which we show here for better comparison. The BLEU score of basic Transformer is 28.6 for the averaged checkpoint. T + T-R2L denotes using two models of Transformer and Transformer-R2L.

| Teachers       | Student-Performance |       |       |
|----------------|---------------------|-------|-------|
|                | Single              | Avg   |       |
| ConvS2S        | 28.8                | 28.9  |       |
| Transformer    | 29.0                | 29.0  |       |
| Transformer-R2L| 29.2                | 29.3  |       |
| Hybrid-RNMT+   | 28.8                | 29.0  |       |
| T + T-R2L      | 29.6                | 29.7  |       |
| All Four Teachers | 29.8               | 30.1  |       |

Table 8: The influence on Transformer with different reciprocal learners on WMT 2014 En→De. The single and avg denote the scores evaluated on the checkpoint before averaging and averaged checkpoint respectively, which we show here for better comparison. The BLEU score of basic Transformer is 28.6 for the averaged checkpoint. T + T-R2L denotes using two models of Transformer and Transformer-R2L.

Figure 2: The BLEU score influence with different monolingual data size on En→De task. Four lines denote four different students. 0 monolingual data means the performance of basic models.

| Monolingual data size | BLEU score |
|-----------------------|------------|
| 0                     | 42.3       |
| 36M                   | 43.0       |
| 72M                   | 43.4       |

Table 9: The performances of RSL on WMT 2014 En→Fr translation task with respect to monolingual data size. The sizes are multiples of parallel data.

5 Conclusion

In this paper, we propose reciprocal supervised learning, an efficient and effective co-EM framework for neural machine translation. Different from previous methods, in RSL a strong NMT model can benefit from any comparable or even weaker models, and the source monolingual corpus can also be fully utilized seamlessly. Extensive experiments demonstrate the effectiveness and robustness of RSL and provide insights on why and how RSL can work well. RSL is a general framework and can be extended for more NLP tasks, e.g., Q&A, text summarization. One potential direction for future work is to design better objective functions and set learnable weights for pseudo data from different models. Second, how to make RSL more efficient is another interesting topic.
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A Related Work

Our work is highly related to several important research directions of NMT.

Improving NMT with Monolingual Data. NMT heavily relies on a large amount of bilingual data with parallel sentence pairs, which is expensive to collect. To overcome this obstacle, many works have been proposed to leverage the rich monolingual data to help the training in the semi-supervised setting. Gulcehre et al. (2015, 2017) incorporate external language models (trained separately on target monolingual data) into the NMT model, which improves the fluency in target language. Sennrich et al. (2016a) use the back translation (BT) approach to exploit target side monolingual data. They back translate the target side monolingual data to source side through an additional target-to-source NMT model learned on the bilingual dataset. Then the original bilingual data will be augmented with the synthetic parallel corpus for further training the source-to-target NMT model. (He et al., 2016; Xia et al., 2017; Wang et al., 2019) learns from non-parallel data in a round-trip game via dual learning, where the source sentence is first forward translated to the target space and then back translated to the source space. The reconstruction loss is used to benefit the training. Zhang et al. (2018) propose to jointly train the source-to-target and target-to-source NMT models, where two models can provide back-translated pseudo data for each other.

While target side monolingual data has been extensively studied (Poncelas et al., 2018; Cotterell and Kreutzer, 2018; Edunov et al., 2018; Burlot and Yvon, 2019), there exist few attempts to use the source side data. Ueffing (2006) and Zhang and Zong (2016) explored self-training (ST) in statistical and neural machine translation respectively, albeit with limited gains. Recently, He et al. (2019) shows that the perturbation on the input and hidden states is critical for self-training on NMT. However, this study is conducted on relatively small-scale monolingual data, and therefore ST remains unclear in the large-scale setting.

Ensemble and KD for NMT. Among various model aggregating methods in machine learning, the most effective and widely adopted methods for NMT is the token-level ensemble. In this approach, given the source sentences, a group of individually learned models cooperate together to generate the target sentence step by step. More specifically, the token-level ensemble method generates the target sequence by averaging the predicted probabilities of each token.

A commonly used KD approach is ensemble KD (Fukuda et al., 2017; Freitag et al., 2017; Liu et al., 2018; Zhu et al., 2018), where each individual NMT model distill the knowledge from an ensemble model. More recently, multi-agent learning (Bi et al., 2019) is proposed to distill the knowledge from a dynamic ensemble teacher model during training. By contrast, there is no teacher model and no ensemble procedure in RSL, and we just improve individual models together through reciprocal learning. Note that, for Bi et al. (2019), models such as conventional Statistical MT or NMT with right2left decoding direction cannot be aggregated with common models with token-level ensemble method, which means RSL is much more flexible.

A.1 Discussions

There are several essential differences between RSL and other widely used methods that involves multiple models.

Ensemble. In the scenario of NMT, a common implementation of ensemble is to average the probability of each token computed by different individual models and then decode with the averaged probabilities. Despite its success in state-of-the-art Neural NMT systems (Sutskever et al., 2014; Bahdanau et al., 2015; Vaswani et al., 2017; Hassan et al., 2018), in practice there are a few common challenges of ensemble methods, which prevent its wide usage: 1) High computational cost. For ensemble learning, all individual models have to conduct encoding and decoding, which is prohibitively time and memory consuming. This will be even worse in the context of NMT due to the large size of state-of-the-art networks like transformer (Kitaev et al., 2020). 2) Absence of monolingual data. Ensemble cannot make use of the large scale monolingual data from the source side. By contrast, RSL involves the co-EM procedure in reciprocal-supervised learning, which can enjoy the benefit of monolingual data.

Knowledge distillation (KD). KD (Hinton et al., 2015) is another related topic, where we usually first train a strong teacher model and use it to give soft label of the training data. Then a smaller model is trained with the soft label to distill the knowledge from the strong model. For NMT, when multiple models are provided, a typical practice is to take
the ensemble of all the models as the teacher model to translate the source side data into single pseudo data. By contrast, in RSL we just use individual models to translate the monolingual data into multiple proper target sentences, which encourage the basic models to learn more diverse patterns. Furthermore, compared with KD, the absence of the teacher role in RSL allows the strong models to benefit from other comparable or even much weaker models.