Reference Language based Unsupervised Neural Machine Translation

Zuchao Li\textsuperscript{1,2,3}, Hai Zhao\textsuperscript{1,2,3,∗}, Rui Wang\textsuperscript{1,∗}, Masao Utiyama\textsuperscript{4}, Eiichiro Sumita\textsuperscript{4}

\textsuperscript{1}Department of Computer Science and Engineering, Shanghai Jiao Tong University
\textsuperscript{2}Key Laboratory of Shanghai Education Commission for Intelligent Interaction and Cognitive Engineering, Shanghai Jiao Tong University, Shanghai, China
\textsuperscript{3}MoE Key Lab of Artificial Intelligence, AI Institute, Shanghai Jiao Tong University
\textsuperscript{4}National Institute of Information and Communications Technology (NICT), Kyoto, Japan

charlee@sjtu.edu.cn, zhaohai@cs.sjtu.edu.cn, \{wangrui, mutiyama, eiichiro.sumita\}@nict.go.jp

Abstract

Exploiting common language as an auxiliary for better translation has a long tradition in machine translation, which lets supervised learning based machine translation enjoy the enhancement delivered by the well-used pivot language, in case that the prerequisite of parallel corpus from source language to target language cannot be fully satisfied. The rising of unsupervised neural machine translation (UNMT) seems completely relieving the parallel corpus curse, though still subject to unsatisfactory performance so far due to vague clues available used for its core back-translation training. Further enriching the idea of pivot translation by freeing the use of parallel corpus other than its specified source and target, we propose a new reference language based UNMT framework, in which the reference language only shares parallel corpus with the source, indicating clear enough signal to help the reconstruction training of UNMT through a proposed reference agreement mechanism. Experimental results show that our methods improve the quality of UNMT over that of a strong baseline in terms of only one auxiliary language, demonstrating the usefulness of the proposed reference language based UNMT with a good start.

1 Introduction

Recently, the application of neural machine translation (NMT) (Sutskever et al., 2014; Bahdanau et al., 2015) to standard benchmarks has achieved great success (Wu et al., 2016; Gehring et al., 2017; Vaswani et al., 2017) because of advances in deep learning and the availability of large-scale parallel corpora. However, the applicability of MT systems is limited because of the reliance on large parallel corpora for the majority of language pairs. In real-world situations, the majority of language pairs have very few parallel data, although large volumes of monolingual data are available for each language. UNMT removes the dependence on parallel corpora, relying only on monolingual corpora in each language (Reddi et al., 2018; Lample et al., 2018a,b; Conneau and Lample, 2019).

UNMT uses translation symmetry for dual learning in each language direction. Existing UNMT models are mainly built on the encoder–decoder schema. The essence of UNMT is to learn unsupervised cross-lingual word alignment and/or sentence alignment. For unsupervised word alignment, the most popular methods are word embedding mapping (Conneau et al., 2017; Lample et al., 2018a; Sun et al., 2019), vocabulary sharing (Lample et al., 2018b) and language modeling (Conneau and Lample, 2019). Weight sharing can also be adopted in the encoder/decoder, adversarial training, and back-translation (BT) processes for unsupervised sentence alignment.

![Figure 1: Schemas of (a) pivot supervised NMT, (b) pivot UNMT, (c) our reference language-based UNMT.](image-url)
BT aims to train models using iteratively generated pseudo-parallel data, thus overcoming the lack of cross-language signals. Specifically, monolingual data in the source language are translated to the target language using a source-to-target translation model, then the pseudo-parallel data (including both the generated and the original data) are used to train the target-to-source translation model, and vice versa.

However, as the input sentences in the pseudo-parallel data are generated by unsupervised models, random errors and noises are inevitably introduced, resulting in low-quality parallel data for model training and bad translation performance. In addition, when vocabulary sharing UNMT models for two distant languages (that is, very little vocabulary overlap between the source language and target language) are trained with BT, the unsupervised model may generate the words in the source language instead of in the target language under source-to-target forward translation. As a result, although the reconstruction loss is small if the forward translation generation is very similar to the input, the model is not sufficiently optimized because the pseudo-parallel corpus contains very little cross-lingual sentence alignment information.

Multilingualism (Edwards, 2002; Clyne, 2017) is a powerful fact of life in communication across speech communities. In multilingualism, an important “lingua franca” (or common language) often serves as an aid to cross-group understanding, usually representing the language of a potent and prestigious society with a large number of users. For machine translation, the parallel corpora between languages and some lingua franca are usually more abundant. Thus, conventional pivot translation usually leverages a resource-rich language (mainly English) as the pivot to help the low/zero-resource translation (see Appendix A.1). Although UNMT no longer requires parallel corpora of languages, this feature is still worth exploring and can be used to enhance the current UNMT under low- or zero-resource scenarios. In addition, we can further use the transfer learning capabilities of the model to transfer the translation capabilities of languages and lingua francas to any two languages that need to be learned.

In this work, taking both merits of supervised NMT and UNMT on using the pivot language in pivot translation as shown in Figure 1, we propose the reference language-based UNMT framework in which the reference language shares a parallel corpus with only the source language (using only the target language is similar). In the framework, we use the feature of multilingualism and propose a reference agreement mechanism. Exploiting the accurate alignment clues between source and reference languages, we can more confidently enhance the source-target UNMT by taking into account the translation agreement within the source, reference, and target languages. Specifically, irrelevant parallel data play a role in controlling the quality of the pseudo-sentence pairs through a cross-lingual equivalence (translation agreement). The proposed mechanism is orthogonal to the common multilingual transfer learning methods and is different from the general pivot translation method. Empirical results on popular benchmarks and distant languages show that the reference agreement mechanism consistently improves the performance of UNMT systems. In addition, we explore the impact of multilingual information on the basis of our multilingual UNMT baseline and proposed method.

2 UNMT

UNMT is a recently proposed MT paradigm that attempts to achieve the co-growth of MT models in two directions while relying solely on monolingual data, such as English-to-French vs. French-to-English. It is a special kind of dual learning (He et al., 2016; Xia et al., 2017a,b) in the directions of languages. Currently, state-of-the-art UNMT models are based on a sequence-to-sequence encoder–decoder architecture using Transformer (Vaswani et al., 2017), which is similar to supervised NMT models.

For ease of expression, in the remainder of this paper, we denote the monolingual training data space of the source $S$ and target $T$ languages as $\phi_S$ and $\phi_T$. The parallel training data space between languages $S$ and $T$ is represented as $\phi_{S\rightarrow T}$. The translation direction symmetry of the UNMT model training implies that the translation direction problem $S \rightarrow T$ is the same as $T \rightarrow S^1$.

In general, the NMT model with parameters $\theta_{S\rightarrow T}$ models the conditional probability $P(t|s)$ of the translated sequence $t$. The model parameter $\theta_{S\rightarrow T}$ is trained to maximize the following

\[^1\text{In UNMT, translation is bidirectional, so the “source” and “target” language are only denoted as such for convenience of expression. Essentially, } S \text{ and } T \text{ are completely symmetrical and exchangeable.}\]
likelihood on the parallel training data space:

$$L(\theta_{S\to T}) = \mathbb{E}_{(s,t) \sim P(s \to t)} \left[ -\log P(t|s; \theta_{S\to T}) \right].$$  \hspace{1cm} (1)

As there is a lack of cross-lingual sentence alignment information, the current UNMT models reach a consensus over the use of the pseudo-parallel data generated iteratively with the BT method, despite their differences in structures and training methods. Specifically, for a monolingual sentence of the target language $t \in \phi_T$, a source translation $\tilde{s}$ is generated using the primal $T \to S$ translation model $P(\cdot|t, \theta_{T\to S})$, and then $\tilde{s}$ and $t$ form a pseudo-parallel pair $(\tilde{s}, t)$ for $S \to T$ model training. Similarly, the generated pseudo-parallel pair $(\tilde{t}, s)$ for a monolingual sentence $s$ in the source language is also used for training the $T \to S$ model.

The likelihood of the reconstructions $t \to \tilde{s} \to t$ and $s \to \tilde{t} \to s$ for the UNMT model is maximized over the BT process according to:

$$L(\theta_{S\to T}) = \mathbb{E}_{s \sim P(s \to \tilde{t}) \tilde{t} \sim P(\tilde{t}|s, \theta_{T\to S})} \left[ -\log P(t|\tilde{s}; \theta_{S\to T}) \right],$$ \hspace{1cm} (2)

$$L(\theta_{T\to S}) = \mathbb{E}_{\tilde{s} \sim P(\tilde{s}|t, \theta_{S\to T}) \tilde{t} \sim P(\tilde{t}|\tilde{s}, \theta_{T\to S})} \left[ -\log P(s|\tilde{t}; \theta_{T\to S}) \right].$$ \hspace{1cm} (3)

Finally, the BT process is optimized by minimizing the following objective function:

$$L_{BT}(S, T) = L(\theta_{S\to T}) + L(\theta_{T\to S}).$$ \hspace{1cm} (4)

## 3 Reference Language based UNMT

In this section, we introduce the reference language based UNMT framework and present our three kinds of reference agreement utilization approaches: reference agreement translation (RAT), reference agreement back-translation (RABT), and cross-lingual back-translation (XBT). These approaches are illustrated in Figure 2.

### 3.1 Framework and Reference Agreement

Figure 1(a) demonstrates the traditional pivot translation schema in supervised NMT, subfigure 1(b) show the pivot translation schema in UNMT, and subfigure 1(c) is our proposed reference language based UNMT framework. By applying pivot translation to UNMT, the special nature of any language pair in UNMT can be directly trained without any parallel data so as to translate to one another. Thus, traditional pivot translation schema ($S \to P \to T$) is not necessary in UNMT, while the practice of a third language (usually a common language) to enhance translation between language pairs is more suitable for UNMT. In order to distinguish from the pivot language in traditional pivot translation, we define the language used to enhance the performance of translation $S \to T$ in UNMT as the reference language $R$, regardless of whether the translation schema is $S \to R \to T$ as the bridge or $S \to T$ directly.

In this paper, the reference agreement refers to the cross-lingual equivalence (i.e., translation agreement) provided by bilingual parallel sentence pairs between the reference language and the source or target language of the translation.


3.2 Reference Agreement Translation

In the absence of supervision signals, the quality of machine translation across languages cannot be effectively evaluated. That is, a suitable cross-lingual quality evaluation function \( \text{quality}(s, t) \) cannot be defined in cases where only the source and target generation are provided. As a result, the quality of synthetic pseudo-parallel pairs \( \langle \hat{s}, \hat{t} \rangle \) and \( \langle \hat{t}, \hat{s} \rangle \) in BT cannot be guaranteed, which limits the performance of UNMT.

RAT refers to the simultaneous translation of the parallel sentences of languages \( S \) and \( R \) into the target language \( T \). The two translations should be in agreement (i.e., the same). Therefore, this agreement in the translations from different sources can be used to collaboratively evaluate the generated quality, and forms a new quality evaluation function \( \text{quality}(s, r, \hat{s}, \hat{r}) \).

Based on this premise, we propose two detailed implementations for the RAT approach, i.e., direct RAT (RAT-D) and indirect RAT (RAT-ID), which enable reference agreement functions with BT during the UNMT training process, resulting in improved translation agreement.

**RAT-D** As the two translations \( \hat{s}_S \) and \( \hat{t}_R \) from the parallel sentence pair \( \langle s, r \rangle \) should be the same, it is clear that their probability distributions \( \hat{d}_S = \mathbb{P}(\cdot|s; \theta_{S \rightarrow T}) \) and \( \hat{d}_R = \mathbb{P}(\cdot|r; \theta_{R \rightarrow T}) \) should ideally be consistent. We would like to minimize the distance of \( \hat{d}_S \) and \( \hat{d}_R \) so that the agreement is learned by the model. The Jensen–Shannon divergence (JSD) (Fuglede and Topsoe, 2004) is then used to compute the difference in the two distributions as the loss for RAT-D training. This is a symmetrized and smoothed version of the Kullback–Leibler divergence (KLD):

\[
L_{\text{RAT-D}}(S, T, R) = \text{JSD}(\hat{d}_S||\hat{d}_R) = \frac{1}{2} (\text{KLD}(\hat{d}_S||M) + \text{KLD}(\hat{d}_R||M)),
\]

where \( M = \frac{1}{2}(\hat{d}_S + \hat{d}_R) \), and the KLD of distribution \( Q \) from \( P \) is defined as:

\[
\text{KLD}(P||Q) = \sum_i p_i \log \left( \frac{p_i}{q_i} \right).
\]

Autoregressive NMT models generate translations from left-to-right and stop when an EOS token is generated or the generation exceeds the maximum length. This will lead to some length inconsistency between the two translation sequences and make the distributions incompatible for Equation 5. Therefore, in the training phase, we force the translation model to generate a sequence of length \( J \), which is determined as follows:

\[
J = \frac{1}{2} ((\alpha J_S + \beta) + (\alpha J_R + \beta)),
\]

where \( J_S \) and \( J_R \) are the lengths of the source language and reference language sentences, respectively; we set \( \alpha = 1.3 \) and \( \beta = 5 \) following previous work (Conneau and Lample, 2019).

**RAT-ID** Unlike the RAT-D implementation, which directly calculates the agreement loss on the output distributions, RAT-ID requires the two translation models to generate an agreed translation by taking votes. We use this agreed translation as the target, and form pseudo-parallel data from the input of each language to train both of the models. Specifically, for a parallel sentence pair \( \langle s, r \rangle \), we would ideally have \( \mathbb{P}(\cdot|s; \theta_{S \rightarrow T}) = \mathbb{P}(\cdot|r; \theta_{R \rightarrow T}) \), as stated for RAT-D. However, as the two models \( \theta_{S \rightarrow T} \) and \( \theta_{R \rightarrow T} \) are trained on different data, the agreement may be broken. Therefore, we combine the two models to obtain the agreed translation output \( \hat{i}_a \):

\[
\hat{i}_a \sim \mathbb{P}(\cdot|s, r; \theta_{S \rightarrow T}, \theta_{R \rightarrow T}).
\]

where \( \mathbb{P}(\cdot|s, r; \theta_{S \rightarrow T}, \theta_{R \rightarrow T}) \) is

\[
\prod_i \left[ \frac{1}{2} \left( \mathbb{P}(\cdot|s, \hat{i}_{<i}; \theta_{S \rightarrow T}) + \mathbb{P}(\cdot|r, \hat{i}_{<i}; \theta_{R \rightarrow T}) \right) \right].
\]

Finally, two synthetic sentence pairs \( \langle s, \hat{i}_a \rangle \) and \( \langle r, \hat{i}_a \rangle \) are used to train the models \( S \rightarrow T \) and \( R \rightarrow T \). Since the silver learning target is optimized, the smoothed cross-entropy loss \( \mathcal{L}_\epsilon \) is used instead of the ordinary cross-entropy loss \( \mathcal{L} \). The learning objective for RAT-ID can be written as follows:

\[
L_{\text{RAT-ID}}(S, T, R) = \mathcal{L}_\epsilon(\theta_{S \rightarrow T}) + \mathcal{L}_\epsilon(\theta_{R \rightarrow T}),
\]

where \( \epsilon \) is the smoothing control value indicating the uncertainty of the target for the model.

**Differences** RAT-D and RAT-ID are the same in principle, both attempting to move two independent output distributions closer to the (weighted) average distribution through the agreement mechanism. The difference is that RAT-D is applied to the two output distributions directly, the two models are required to generate fixed-length distributions before calculating the loss, and there is no interaction between the models.
in the generation process. The latter point causes an error propagation problem, whereby different errors made in the two translation processes make the context in each translation increasingly different, resulting in two distributions that differ significantly. RAT-ID addresses this issue by obtaining an agreed output prediction at each step, which ensures the context remains consistent in the two model generation processes.

3.3 Reference Agreement Back-translation

Motivated by the RAT-ID approach, the input language sentences and agreed translations form two synthetic parallel sentences. With these regularized pseudo-parallel sentences, we not only train the \( S \rightarrow T \) and \( R \rightarrow T \) forward-translation models (as the generation direction is the same as the training direction), but also train the BT models, i.e., \( T \rightarrow S \) and \( T \rightarrow R \). This gives the RABT training approach. The learning objective of RABT can be described as:

\[
\mathcal{L}_{\text{RABT}}(S, T, R) = \mathcal{L}(\theta_{S \rightarrow T}) + \mathcal{L}(\theta_{T \rightarrow R}).
\]  \hspace{1cm} (11)

3.4 Cross-lingual Back-translation

The traditional BT analyzed in Section 2 and illustrated in Figure 2(a) allows us to train a \( T \rightarrow S \) model with the help of an \( S \rightarrow T \) model, and vice versa. However, this mutually beneficial training is performed entirely within the same language pair. Multilingual UNMT (MUNMT) is a special case of UNMT that is capable of translating between multiple source and target languages. Although multiple language pairs are trained jointly in MUNMT, there is an obvious shortcoming for BT: translating between language pairs that do not occur together during training, i.e., lack of optimization across language pairs. Joint training across language pairs can be performed through forced high-order BT in UNMT, which is like \( L_1 \rightarrow L_2 \rightarrow ... \rightarrow L_{O+1} \rightarrow L_1 \), where \( O \) is the translation order indicating the number of bridge languages in BT. This approach may fail because decoding through multiple noisy channels (\( L_i \rightarrow L_{i+1} \)) accumulates latency and compounds errors, resulting in low-quality final pseudo-parallel data between \( L_{O+1} \) and \( L_1 \).

Although this high-order BT can expose multiple language pairs for simultaneous training, it also introduces the problem of uncontrollable intermediate translation quality. Therefore, we propose XBT based on the reference agreement. This method allows BT to maintain the first order while training across language pairs. XBT is a new training approach for UNMT that translates language \( S \) to \( T \) and then back-translates it to \( R \), or from \( R \) to \( T \) and then to \( S \), based on the reference agreement provided by the bilingual parallel data \( \phi_{S \rightarrow R} \) between languages \( S \) and \( R \). This training approach is illustrated in Figure 2(d). The objective function of XBT is:

\[
\mathcal{L}_{\text{XBT}}(S, T, R) = \mathcal{L}(\theta_{T \rightarrow S}) + \mathcal{L}(\theta_{R \rightarrow T}).
\]  \hspace{1cm} (12)

where \( T_S \) and \( T_R \) indicate language sentences translated from \( S \) and \( R \), respectively.

4 Experiments and Results

In this section, we empirically demonstrate the impact of reference agreement on several benchmarks, and compare our approach to current state-of-the-art methods.

4.1 Datasets

We consider multilingual UNMT of four languages: English (en), French (fr), Romanian (ro), and Chinese (zh). To compare the impact of the relative relationship between the chosen reference language and the considered language pairs on the UNMT performance, we constructed two language setting scenarios: English–French–Romanian (en-fr-ro) and English–Chinese–Romanian (en-zh-ro). In both scenarios, English–Romanian (en-ro) is the main language pair considered. French and Chinese are used as the reference languages, providing the parallel corpora of English–French (en-fr) and English–Chinese (en-zh), respectively, to aid the UNMT of English–Romanian. The reason for this setup is that both English and Romanian belong to the Indo-European language family, but English belongs to the Germanic branch, whereas Romanian and French belong to the Romance branch. Therefore, French was selected to evaluate the effect of the reference language being in the homologous family. Chinese belongs to the Sino-Tibetan language family and is a distant language from Romanian. It is selected to study the effect of the reference language being in a different language family.

For English, French, and Romanian, we used the same monolingual sentences as those extracted from the WMT News Crawl datasets for the period 2007–2017 by Conneau and Lample (2019) for a fair comparison, and limited the maximum number
Table 1: Comparison of the proposed method with previous work (BLEU). Overall best results are shown in bold (all of them are better than the corresponding baselines at significance level p < 0.01 (Collins et al., 2005)), the best ones in each group are underlined. PBSMT + NMT: (Lample et al., 2018b), XLM: (Conneau and Lample, 2019), MASS: (Song et al., 2019). In the results of ro→zh and zh→ro, in the form x[y], x represent the result of in-domain test set, and y is the result of out-of-domain test set.
multilingual. Therefore, MUNMT is the baseline for comparison. We adopt a multi-language joint vocabulary and training with a shared encoder and decoder for language model pre-training, denoising, and BT on the basis of our backbone UNMT (XLM). Thus, the MUNMT model can take advantage of the multilingualism.

**MUNMT + RNMT** Furthermore, as we use parallel corpus that exist between the reference language and the unsupervised translation language, for a fairer comparison, we consider supervised neural machine translation training as an optimization target on the basis of MUNMT, so that supervised and unsupervised training are performed jointly. This baseline is named MUNMT + RNMT.

### 4.3 Implementation Details

The Moses scripts (Koehn and Knowles, 2017) were used for tokenization of en, fr, and ro, and the jieba toolkit⁴ was used for word segmentation on zh. In particular, following Sennrich et al. (2016), we removed diacritics from ro. For zh, to avoid confusion between Hong Kong Standard Traditional Chinese (zh\_hk: QED), Taiwan Standard Traditional Chinese (zh\_tw: Bibleuedin), and Simplified Chinese (zh: Tanzil and monolingual training data), we used opencc⁵ to convert zh\_hk and zh\_tw to simplified Chinese. In all our baselines, the byte pair encoding (BPE) code size is set to 60k, and the model hyperparameters are consistent with those of XLM. The smoothing value $\epsilon$ in RAT-ID is set to 0.1.

### 4.4 Results and Analysis

This section examines the effectiveness of the proposed reference agreement approach. The main results are presented in Table 1. Row #4 reports the replicated results of the XLM architecture (Conneau and Lample, 2019) based on the training of each language pair individually. Judging from the results, our UNMT basically reproduces XLM results, and makes some improvements over the original (probably because of differences in data sampling). Thus, our approach offers a strong baseline performance. Compared with the current state-of-the-art method MASS (Song et al., 2019), our baseline performance is slightly lower. This is because MASS adopts the new masked sequence to sequence the pre-training method, and the improvement of our method is orthogonal to the pre-training improvement, which will not affect the evaluation of our method.

For MUNMT baseline as shown in #5, the results are basically consistent with the UNMT results we replicated in #4, with some slight fluctuations, indicating that the joint training of language pairs alone cannot make full use of multilingualism. Compared with MUNMT, MUNMT + RNMT (#10) is a very strong method to use the irrelevant parallel corpus brought by the reference language.

As shown in Table 2, the performance (perplexity/accuracy) of all languages joint pre-training is worse than the pre-training on individual language pairs. However, for distant language pairs, adding a close reference language for joint pre-training will improve performance compared to pre-training only on the distant language pair. Therefore, in #5 and #10, the performance of en-ro in en-fr-ro and en-ro-zh is inconsistent due in part to pre-training. Similarly, comparing the performance of en-ro and ro-zh in UNMT and MUNMT, it can be seen that the performance of ro-zh in MUNMT is better than UNMT, indicating that transfer learning plays a role in joint training. The en-ro performance becomes worse, indicating that the close language pairs joint training with a distant language will result in a decline in its UNMT results.

For the four specific implementations of proposed approaches, the effect of RAT-D (#6 and #11) is not obvious compared to the baselines, which verifies the reasons for the inconsistent context caused by the error propagation in the generation we analyzed. RAT-ID, RABT and XBT have achieved performance improvements over strong baselines, showing the effectiveness of our proposed approaches. Among them, RAT-ID and RABT both use agreed translation and their inputs to form pseudo-parallel data for training the model, RAT-ID uses the noisy synthetic data as the target, while RABT uses it as the source. From the results in #7 and #12, it can be seen that although it can be improved with the help of smoothing mechanism, the improvement is weaker than RABT in #8 and #13 which using golden as the target. Compared with RABT and XBT, the gap between the two is relatively small. XBT has a greater average improvement, indicating that agreement across language pairs is more effective.

⁴[https://github.com/fxsjy/jieba](https://github.com/fxsjy/jieba)
⁵[https://github.com/BYVoid/OpenCC](https://github.com/BYVoid/OpenCC)
in MUNMT than agreement within language pair.

In Table 1, we also report the results of different domains between ro-zh, where the results of in-domain are significantly higher than the results of out-of-domain, indicating that the domain problem is also important for UNMT. Our approaches have also obtained consistent improvements over different domains, further verifying the effectiveness of the method. In addition, the analysis of intermediate translation quality in BT is presented in Appendix A.2.

5 Ablation

In order to analyze the influence of the scale of reference and source language parallel data on the performance of MUNMT and proposed approaches, we compared the performance of en → ro on five different parallel corpus sizes: 1K, 10K, 100K, 1M, 10M together with UNMT baseline, and the results are shown in Figure 3. Since RAT-D is not as effective as RAT-ID as demonstrated in Section 4.4, it is excluded in this comparison.

It shows that although MUNMT + RNMT has been a very strong method to use irrelevant parallel corpus brought by reference language compared to the MUNMT, the reference agreement mechanism we proposed can still improve on various parallel data scales, which verifies the generalization of our method. In addition, in the case of low-resource irrelevant parallel data, RABT shows a better growth effect than XBT, and when the parallel resources grow to a certain extent, XBT will exceed the effect of RABT, indicating that agreement training for cross-language pairs requires more parallel data than agreement within a language pair. And the effect of back-translation enhancement in all cases is better than that of forward-translation, which shows that the golden target is better than the silver target in UNMT. Finally, in the case of low resources, our methods have achieved a relatively greater improvement, indicating that our method can mine the information of irrelevant parallel data to a greater extent for enhancing UNMT.

6 Related Work

UNMT (Artetxe et al., 2017; Lample et al., 2018a,b; Conneau and Lample, 2019; Song et al., 2019) has attracted widespread attention in academic research, as only large-scale monolingual corpora are required for training. Conneau and Lample (2019) extended the generative language model pre-training approach to multiple languages and showed that cross-lingual pre-training could be effective for MUNMT. As discussed by Arivazhagan et al. (2019), MUNMT usually performs worse than pivot-based supervised NMT. However, the pivot-based method always falls into a computationally expensive scenario of quadratic growth in the number of source languages, and suffers from the error propagation problem. Arivazhagan et al. (2019) addressed the zero-shot generalization problem in which a lack of parallel data means that some translation directions have not been optimized during training in supervised multilingual NMT. Leng et al. (2019) propose a multi-hop UNMT that automatically selects a good translation path for a distant language pair during UNMT. Baijun et al. (2019) proposed an effective cross-lingual pre-training approach called BRLM that makes use of the source–pivot data to pre-train the language model.

7 Conclusion

In this work, we take both merits of supervised NMT and UNMT on using the pivot language in pivot translation, we propose the reference language-based UNMT framework, in which a reference agreement mechanism with diverse implementations is introduced to better leverage the reference agreement in parallel data brought by the reference language to reduce the uncontrol problem in back-translation. The experimental results show that we were able to get an improvement over the strong baseline and reached a new state-of-the-art
on popular benchmark WMT16 en-ro and others.

References

Ahmed Abdelali, Francisco Guzman, Hassan Sajjad, and Stephan Vogel. 2014. The AMARA corpus: Building parallel language resources for the educational domain. In Proceedings of the Ninth International Conference on Language Resources and Evaluation (LREC’14), pages 1856–1862, Reykjavik, Iceland. European Language Resources Association (ELRA).

Roee Aharoni, Melvin Johnson, and Orhan Firat. 2019. Massively multilingual neural machine translation. In Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers), pages 3874–3884, Minneapolis, Minnesota. Association for Computational Linguistics.

Naveen Arivazhagan, Ankur Bapna, Orhan Firat, Roee Aharoni, Melvin Johnson, and Wolfgang Macherey. 2019. The missing ingredient in zero-shot neural machine translation. arXiv preprint arXiv:1903.07091.

Mikel Artetxe, Gorka Labaka, and Eneko Agirre. 2017. Learning bilingual word embeddings with (almost) no bilingual data. In Proceedings of the 55th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), pages 451–462, Vancouver, Canada. Association for Computational Linguistics.

Dzmitry Bahdanau, Kyunghyun Cho, and Yoshua Bengio. 2015. Neural machine translation by jointly learning to align and translate. In International Conference on Learning Representations.

Ji Baijun, Zhang Zhirui, Duan Xiangyu, Zhang Min, Chen Boxing, and Luo Weihua. 2019. Cross-lingual pre-training based transfer for zero-shot neural machine translation. arXiv preprint arXiv:1912.01214.

Yong Cheng, Qian Yang, Yang Liu, Maosong Sun, and Wei Xu. 2017. Joint training for pivot-based neural machine translation. In Proceedings of the 26th International Joint Conference on Artificial Intelligence, pages 3974–3980. AAAI Press.

Christos Christodoulopoulos and Mark Steedman. 2015. A massively parallel corpus: the bible in 100 languages. Language resources and evaluation, 49(2):375–395.

Michael Clyne. 2017. Multilingualism. The handbook of sociolinguistics, pages 301–314.

Michael Collins, Philipp Koehn, and Ivona Kučerová. 2005. Clause restructuring for statistical machine translation. In Proceedings of the 43rd Annual Meeting on Association for Computational Linguistics, ACL ’05, pages 531–540, Stroudsburg, PA, USA. Association for Computational Linguistics.

Alexis Conneau and Guillaume Lample. 2019. Cross-lingual language model pretraining. In Advances in Neural Information Processing Systems, pages 7057–7067.

Alexis Conneau, Guillaume Lample, Marc’Aurelio Ranzato, Ludovic Denoyer, and Hervé Jégou. 2017. Word translation without parallel data. arXiv preprint arXiv:1710.04087.

John Edwards. 2002. Multilingualism. Routledge.

Bent Fuglede and Flemming Topsoe. 2004. Jensen-Shannon divergence and hilbert space embedding. In International Symposium on Information Theory, 2004. ISIT 2004. Proceedings., page 31. IEEE.

Jonas Gehring, Michael Auli, David Grangier, Denis Yarats, and Yann N Dauphin. 2017. Convolutional sequence to sequence learning. In Proceedings of the 34th International Conference on Machine Learning-Volume 70, pages 1243–1252. JMLR. org.

Di He, Yingce Xia, Tao Qin, Liwei Wang, Nenghai Yu, Tie-Yan Liu, and Wei-Ying Ma. 2016. Dual learning for machine translation. In Advances in Neural Information Processing Systems, pages 820–828.

Yunus Kim, Petre Petrov, Pavel Petrushkov, Shahram Khadivi, and Hermann Ney. 2019. Pivot-based transfer learning for neural machine translation between non-English languages. In Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP), pages 866–876, Hong Kong, China. Association for Computational Linguistics.

Philipp Koehn and Rebecca Knowles. 2017. Six challenges for neural machine translation. In Proceedings of the First Workshop on Neural Machine Translation, pages 28–39, Vancouver. Association for Computational Linguistics.

Guillaume Lample, Alexis Conneau, Ludovic Denoyer, et al. 2018a. Unsupervised machine translation using monolingual corpora only. In International Conference on Learning Representations.

Guillaume Lample, Myle Ott, Alexis Conneau, Ludovic Denoyer, and Marc’Aurelio Ranzato. 2018b. Phrase-based & neural unsupervised machine translation. In Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing, pages 5039–5049, Brussels, Belgium. Association for Computational Linguistics.

Yichong Leng, Xu Tan, Tao Qin, Xiang-Yang Li, and Tie-Yan Liu. 2019. Unsupervised pivot translation for distant languages. In Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics, pages 175–183.
Florence, Italy. Association for Computational Linguistics.

Pierre Lison and Jörg Tiedemann. 2016. Opensubtitles2016: Extracting large parallel corpora from movie and tv subtitles. In Proceedings of the Tenth International Conference on Language Resources and Evaluation (LREC 2016), pages 923–929.

Chao-Hong Liu, Catarina Cruz Silva, Longyue Wang, and Andy Way. 2018. Pivot machine translation using chinese as pivot language. In China Workshop on Machine Translation, pages 74–85. Springer.

Michael Paul, Hiroyuki Yamamoto, Eiichiro Sumita, and Satoshi Nakamura. 2009. On the importance of pivot language selection for statistical machine translation. In Proceedings of Human Language Technologies: The 2009 Annual Conference of the North American Chapter of the Association for Computational Linguistics, Companion Volume: Short Papers, pages 221–224, Boulder, Colorado. Association for Computational Linguistics.

Sashank J. Reddi, Satyen Kale, and Sanjiv Kumar. 2018. Unsupervised neural machine translation. In International Conference on Learning Representations.

Rico Sennrich, Barry Haddow, and Alexandra Birch. 2016. Edinburgh neural machine translation systems for WMT 16. In Proceedings of the First Conference on Machine Translation: Volume 2, Shared Task Papers, pages 371–376, Berlin, Germany. Association for Computational Linguistics.

Kaitao Song, Xu Tan, Tao Qin, Jianfeng Lu, and Tie-Yan Liu. 2019. Mass: Masked sequence to sequence pre-training for language generation. In International Conference on Machine Learning, pages 5926–5936.

Haipeng Sun, Rui Wang, Kehai Chen, Masao Utiyama, Eiichiro Sumita, and Tiejun Zhao. 2019. Unsupervised bilingual word embedding agreement for unsupervised neural machine translation. In Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics, pages 1235–1245, Florence, Italy. Association for Computational Linguistics.

I Sutskever, O Vinyals, and QV Le. 2014. Sequence to sequence learning with neural networks. Advances in Neural Information Processing Systems.

Jörg Tiedemann. 2012. Parallel data, tools and interfaces in OPUS. In Proceedings of the Eighth International Conference on Language Resources and Evaluation (LREC’12), pages 2214–2218, Istanbul, Turkey. European Language Resources Association (ELRA).

Masao Utiyama and Hitoshi Isahara. 2007. A comparison of pivot methods for phrase-based statistical machine translation. In Human Language Technologies 2007: The Conference of the North American Chapter of the Association for Computational Linguistics; Proceedings of the Main Conference, pages 484–491, Rochester, New York. Association for Computational Linguistics.

Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N Gomez, Łukasz Kaiser, and Illia Polosukhin. 2017. Attention is all you need. In Advances in Neural Information Processing Systems, pages 5998–6008.

Hua Wu and Haifeng Wang. 2007. Pivot language approach for phrase-based statistical machine translation. In Proceedings of the 45th Annual Meeting of the Association of Computational Linguistics, pages 856–863, Prague, Czech Republic. Association for Computational Linguistics.

Yonghui Wu, Mike Schuster, Zhifeng Chen, Quoc V Le, Mohammad Norouzi, Wolfgang Macherey, Maxim Krikun, Yuan Cao, Qin Gao, Klaus Macherey, et al. 2016. Google’s neural machine translation system: Bridging the gap between human and machine translation. arXiv preprint arXiv:1609.08144.

Yingce Xia, Jiang Bian, Tao Qin, Nenghai Yu, and Tie-Yan Liu. 2017a. Dual inference for machine learning. In International Joint Conferences on Artificial Intelligence, pages 3112–3118.

Yingce Xia, Tao Qin, Wei Chen, Jiang Bian, Nenghai Yu, and Tie-Yan Liu. 2017b. Dual supervised learning. In Proceedings of the 34th International Conference on Machine Learning-Volume 70, pages 3789–3798. JMLR. org.

Michal Ziemski, Marcin Junczys-Dowmunt, and Bruno Pouliquen. 2016. The united nations parallel corpus v1.0. In Proceedings of the Tenth International Conference on Language Resources and Evaluation (LREC’16), pages 3530–3534, Portorož, Slovenia. European Language Resources Association (ELRA).
A Appendices

A.1 Pivot Translation

Recent state-of-the-art NMT models are heavily dependent on a large number of bilingual language resources. Large-sized bilingual text datasets are usually readily available between common and other languages. However, for language pairs that are used less frequently, few or no bilingual resources may be available. Pivot translation was proposed to overcome the resource limitations for certain language pairs.

Instead of a direct translation between two languages for which few or no bilingual resources are available, the pivot translation approach makes use of a third language (namely the pivot language). This third language is more appropriate because of the availability of more bilingual corpora and/or its relatedness to either the source or the target language.

Pivot translation has long been studied in statistical machine translation (Wu and Wang, 2007; Utiyama and Isahara, 2007; Paul et al., 2009), supervised NMT (Cheng et al., 2017; Liu et al., 2018; Kim et al., 2019), and UNMT (Leng et al., 2019) as a means of improving the performance of low/zero-resource translations.

Formally, for the translation from language $S$ to $T$, the chosen pivot language is denoted as $P$. The translation schema can be described as follows:

$$S \rightarrow P_1 \rightarrow \ldots \rightarrow P_K \rightarrow T,$$

(13)

where $K$ is the number of pivot languages.

Recently, the development of UNMT seems to have lessened the importance of pivot translation. UNMT no longer requires bilingual parallel data between two languages, so the low/zero-resource translation problem for less-common language pairs is partially solved. However, the performance of UNMT between some distant languages in different language groups or families is still not promising, which leads researchers to reconsider pivot translation based on UNMT.

A.2 Analysis of Intermediate Translation Quality in BT

In order to verify the problem of uncontrollable intermediate quality in the back-translation we mentioned, we performed experiments on the distant language pair zh-ro and reports the results of translation direction $ro \rightarrow zh$. The reason for choosing $ro$-zh is that Chinese and Romanian characters can be directly distinguished by using unicode encoding. We define BT-BLEU as the BLEU of $s \in S$ with the $\tilde{s}$ generated in the $S \rightarrow T \rightarrow S$ back-translation process which we introduce it in the evaluation phase. Calculate the ratio of the generated Chinese token (subword) to the total number of generated tokens to reflect the intermediate quality of the back-translation from the side. The experimental results are shown in Table 3.

|               | BLEU | BT-BLEU | RATIO   |
|---------------|------|---------|---------|
| UNMT          | 10.92| 31.47   | 2.17%   |
| MUNMT         | 11.55| 31.98   | 2.01%   |
| MUNMT + RABT  | 12.95| 32.52   | 1.69%   |
| MUNMT + XBT   | 13.66| 33.16   | 1.62%   |

Table 3: Intermediate Translation Quality in BT.