Unsupervised Neural Machine Translation for Low-Resource Domains via Meta-Learning

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Abstract
Unsupervised machine translation, which utilizes unpaired monolingual corpora as training data, has achieved comparable performance against supervised machine translation. However, it still suffers from data-scarce domains. To address this issue, this paper presents a novel meta-learning algorithm for unsupervised neural machine translation (UNMT) that trains the model to adapt to another domain by utilizing only a small amount of training data. We assume that domain-general knowledge is a significant factor in handling data-scarce domains. Hence, we extend the meta-learning algorithm, which utilizes knowledge learned from high-resource domains, to boost the performance of low-resource UNMT. Our model surpasses a transfer learning-based approach by up to 2-4 BLEU scores. Extensive experimental results show that our proposed algorithm is pertinent for fast adaptation and consistently outperforms other baseline models.

1 Introduction
Unsupervised neural machine translation (UNMT) leverages unpaired monolingual corpora for its training, without requiring an already labeled, parallel corpus. Recently, the state of the art in UNMT (Conneau and Lample, 2019; Song et al., 2019; Ren et al., 2019) has achieved comparable performances against supervised neural machine translation (NMT) approaches. Instead of not using parallel corpus, training the UNMT model requires a significant amount of monolingual sentences (e.g., 1M-3M sentences). However, the prerequisite limits UNMT’s applicability to low-resource domains, especially for the domain-specific document translation tasks. Since those documents require their knowledge for translation, the monolingual data themselves are scarce and expensive.

Yet, UNMT for low-resource domains is not an actively explored field. One naive approach is to train a model on high-resource domains (e.g., economy and sports) while hoping the model will generalize on an unseen low-resource domain (e.g., medicine). However, recent studies have shown that non-trivial domain mismatch can significantly cause low translation accuracy on supervised NMT tasks (Koehn and Knowles, 2017).

Another reasonable approach is transfer learning, particularly, domain adaptation, which has shown performance improvements in the supervised NMT literature (Freitag and Al-Onaizan, 2016; Zeng et al., 2019). In this approach, the model is first pretrained using data from existing domains and then finetuned by a new domain. However, this approach can suffer from overfitting and catastrophic forgetting due to a small amount of training data and a large domain gap.

As an effective method for handling a small amount of training data, meta-learning has shown its superiority in various NLP studies such as dialog generation, machine translation, and natural language understanding (Qian and Yu, 2019; Gu et al., 2018; Dou et al., 2019). In general, the meta-learning approach is strongly affected by the number of different tasks where tasks are defined as languages or domains from the aforementioned studies. However, in practice, previous studies may struggle to gather data to define tasks because they rely on a supervised model that requires labeled corpora. In this respect, we argue that applying a meta-learning approach to the unsupervised model is more feasible and achievable than the supervised model because it can define multiple different tasks with unlabeled corpora. Therefore, we newly introduce a meta-learning approach for UNMT, called MetaUMT, for low-resource domains by defining

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each task as a domain.

The objective of MetaUMT is to find the optimal initialization of the model parameters for neural machine translation that can quickly adapt to a new domain even with only a small amount of monolingual data. As shown in Fig. 1 (a), we define two different training phases, i.e., a meta-train and a meta-test phase, and simulate the domain adaption process in order to obtain optimal initial parameters. To be specific, the meta-train phase adapts to a domain while the meta-test phase optimizes initial parameters by leveraging adapted parameters obtained from the meta-train phase. After obtaining optimal initial parameters through these two phases, we fine-tune the model using a target domain, i.e., low-resource domain.

Although the initial parameters optimized through MetaUMT are suited to adapt to the low-resource domain, these parameters may not fully maintain the knowledge of high-resource domains. For instance, in the meta-test phase, MetaUMT optimizes initial parameters using the adapted parameters; however, it discards meta-train knowledge used to update adapted parameters in the meta-train phase. Moreover, instead of validating the same domain used in the meta-train phase, we hope to inject generalizable knowledge into initial parameters by utilizing another domain in the meta-test phase. This prevents overfitting from the data scarcity issue.

As shown in Fig. 1 (b), we propose an improved meta-learning approach called MetaGUMT for low-resource UNMT by explicitly promoting common knowledge across multiple source domains as well as generalizable knowledge from one particular domain to another. In other words, we do not only encourage the model to find the optimal initial parameters that can quickly adapt to a target domain with low-resource data, but also encourage the model to maintain common knowledge, e.g., general words such as determiners, conjunctions, and pronouns, which is applicable from multiple source domains. Furthermore, due to a small number of training data in a low-resource domain, the model can suffer from overfitting; however, we attempt to handle overfitting by leveraging generalizable knowledge that is available from one domain to another. Our proposed meta-learning approach demonstrates a consistent efficacy against other baseline models.

Overall, our contributions can be summarized as follows: (1) We apply a meta-learning approach for UNMT. To the best of our knowledge, this is the first study to use a meta-learning approach for UNMT, where this approach is more suitable to a UNMT task than a supervised one; (2) We empirically demonstrate that our enhanced method, MetaGUMT, shows fast convergence on both pre-training (i.e., meta-learning with source domains) and finetuning (i.e., adapting to a target domain); (3) The model trained with MetaGUMT consistently outperforms all baseline models including MetaUMT. This demonstrates that finding optimal initial parameters that incorporate high-resource domain knowledge and generalizable knowledge is significant to handle a low-resource domain.

2 Related Work

Our study leverages two components from the natural language processing (NLP) domain: low-resource NMT and meta-learning. In this section, we discuss previous studies by concentrating on the main components.

2.1 Low-Resource Neural Machine Translation

Based on the success of attention-based models (Luong et al., 2015; Vaswani et al., 2017), NMT obtain significant improvement in numerous language datasets, even showing human-like performances (Wu et al., 2016) in different datasets. However, the performance of NMT models depends on a size of parallel sentences from the source and target language (Koehn and Knowles, 2017). To address this problem, diverse approaches have been proposed, which are categorized into two different directions: (1) utilizing monolingual datasets and (2) transferring the knowledge from high-resource domains to a low-resource domain.

Recent studies point out the difficulty of gathering the parallel data, whereas the monolingual datasets are relatively easy to collect. To facilitate the monolingual corpora, several studies apply dual learning (He et al., 2016), back-translation (Sennrich et al., 2016b), and pretraining the model with the bilingual corpora (Hu et al., 2019a; Wei et al., 2020). Furthermore, as a challenging scenario, recent studies propose the UNMT methods without using any parallel corpus (Lample et al., 2018a; Artetxe et al., 2018; Yang et al., 2018). The UNMT models show comparable performances by extending the back-translation method (Conneau et al., 2018) and incorporating the methods for good ini-
Figure 1: An illustration of high-level training process for both MetaUMT and MetaGUMT. In the case of MetaUMT, the training process is divided into two different phases, a meta-train phase and a meta-test phase. In the meta-train phase, \( \theta \) adapts to a specific domain by leveraging the meta-train loss, i.e., \( \mathcal{L}[D_{tr}^N] \), to obtain adapted parameters, i.e., \( \phi_N \). \( N \) represents the number of domains; \( tr \) indicates meta-train data. In the meta-test phase, we optimize initial parameters \( \theta \) through \( \phi \) using the meta-test losses, i.e., \( \sum \mathcal{L}[D_{ts}^N] \), where \( ts \) indicates meta-test data.

tialization, such as the shared byte pair encoding (BPE) (Lample et al., 2018b) and the cross-lingual representations (Conneau and Lample, 2019), following the ones of the supervised NMT. However, theses approaches still require plenty of monolingual or parallel dataset to adapt the model to the target domain. Secondly, a few studies concentrate on transferring the knowledge from the rich-resources corpora into the low-resource one. Several models (Chu and Wang, 2018; Hu et al., 2019b) show better performances than when trained with the low-resource corpora only. Despite the improvements by the transfer learning approaches, these approaches apply in constraint conditions, which are one or both of target domains or source domain corpus are the parallel corpus. For example, if we intend to create a translation system of a particular language in a particular domain, there may be fewer sentences in-domain as far as parallel out-of-domain data is scarce.

To address the issues, we define a new task as the unsupervised domain adaptation on the low-resource dataset. Our work is a more challenging one than any other previous studies, since we assume that both the low-resource target domain and the source domain corpora are monolingual.

2.2 Meta Learning

Given a small amount of training data, most of machine learning models are prone to overfitting, thus failing to find a generalizable solution. To handle this issue, meta-learning approaches seek for how to adapt quickly and accurately to a low-resource task, and show impressive results in various domains (Finn et al., 2017; Javed and White, 2019). The meta-learning approaches aim to find the optimal initialization of the model parameters which adapts the model to the low-resource dataset in a few iterations of training (Finn et al., 2017; Ravi and Larochelle, 2016). Owing to the success of the meta learning, recent studies apply the meta-learning to the low-resource NMT tasks, including multi-lingual NMT (Gu et al., 2018) and the domain adaptation (Li et al., 2020). These studies assume that all the training corpora consist of the parallel sentences. On the other hand, a recent work (Li et al., 2018) utilizes the meta learning approach to find a generalized model for multiple target tasks. However, it is not focused on adapting a specific target task since its main goal is to handle the target task without using any low-resource data.

Our study attempts to address the low-resource UNMT by exploiting meta-learning approaches. Moreover, we present two novel losses that encourage incorporating high-resource knowledge and generalizable knowledge into the optimal initial parameters. Our proposed approaches show significant performance improvements in adapting to a low-resource target domain.

3 Unsupervised Neural Machine Translation

In this section, we first introduce the notation of the general UNMT models. We then describe the three steps for the UNMT task: initialization, language modeling, and back-translation. On these three steps, we illustrate how each step contributes to improving the performance of UNMT.

**Notations.** We denote \( S \) and \( T \) as a source and a target monolingual language datasets. \( x \) and \( y \) represent the source and the target sentences from \( S \) and \( T \). We assume the NMT model is parameterized by \( \theta \). We also denote \( M_{s \rightarrow s} \) and \( M_{t \rightarrow t} \) as language models in a source and a target languages, respectively, while denoting \( M_{s \rightarrow t} \) and \( M_{t \rightarrow s} \) as the machine translation models from the source to the
target language, and vice versa.

**Initialization.** A recent UNMT model (Lample et al., 2018b) is based on a shared encoder and decoder architecture for the source and the target language. Due to the shared encoder and decoder for each language, initializing the model parameters of the shared encoder and decoder is an important step for competitive performances (Conneau et al., 2018; Lample et al., 2018a; Artetxe et al., 2018; Yang et al., 2018). Conneau and Lample (2019) propose the XLM (cross-lingual language model) to initialize parameters, showing the significantly improved performances for UNMT. Among various initialization methods, we leverage the XLM as our initialization method.

**Language modeling.** We use a denoising auto-encoder (Vincent et al., 2008) to train the UNMT model, reconstructing an original sentence from a noisy one in a given language. The objective function is defined as follows:

\[
L_{\text{lm}} = E_{x \sim S}[- \log M_{s \rightarrow t}(x|C(x))] + E_{y \sim T}[- \log M_{t \rightarrow s}(y|C(y))],
\]

where \(C\) is a noise function described in (Lample et al., 2018b), which randomly drops or swaps words in a given sentence. By reconstructing the sentence from the noisy sentence, the model learns the language modeling in each language.

**Back-translation.** Back-translation helps the model learn the mapping functions between the source and the target language by using only those monolingual sentences. For example, we sample a sentence \(x\) and \(y\) from source language \(S\) and target language \(T\). To make pseudo-pair sentences from the sampled source sentence, we deduce the target sentence from the source sentence, such that \(y' = M_{s \rightarrow t}(x)\). Finally, we get the pseudo parallel sentence, i.e., \((x, y')\). Similarly, we obtain \((x', y)\), where \(x'\) is the translation of a target sentence, i.e., \(M_{t \rightarrow s}(y)\). We do not back-propagate when we generate the pseudo-parallel sentence pairs. In short, the back-translation objective function is

\[
L_{\text{bt}} = E_{y \sim T}[- \log M_{s \rightarrow t}(y | x')] + E_{x \sim S}[- \log M_{t \rightarrow s}(x | y')].
\]

4 Proposed Approach

This section first explains our formulation of a low-resource unsupervised machine translation task where we can apply a meta-learning approach. Afterwards, we elaborate on our proposed methods, MetaUMT and MetaGUMT. We utilize the meta-learning approach to address a low-resource challenge for unsupervised machine translation. Moreover, we extend MetaUMT into MetaGUMT to explicitly incorporate learned knowledge from multiple domains.

4.1 Problem Setup

Finn et al. (2017) assume multiple different tasks to find the proper initial parameters that can quickly adapt to a new task using only a few training examples. In this paper, we consider tasks in the meta-learning as domains, where \(D_{\text{out}} = \{D_0^{\text{out}}, ..., D_n^{\text{out}}\}\) represents \(n\) out-domain datasets (i.e., source domain datasets), and \(D_{\text{in}}\) indicates an in-domain dataset (i.e., a target domain dataset),
which can be the dataset in an arbitrary domain not included in $D_{out}$. Each domain in both $D_{out}$ and $D_{in}$ is assumed to be composed of unpaired language corpora, and we create $D_{in}$ as a low-resource monolingual dataset. To adapt our model to the low-resource in-domain data, we finetune the UNMT model by minimizing both the losses described in Eqs. (1) and (2) with $D_{in}$.

### 4.2 MetaUMT

In order to obtain an optimal initialization of model parameters, allowing the model to quickly adapt to the new domain with only a small number of monolingual training data, MetaUMT uses two training phases, the meta-train phase and the meta-test phase. During the meta-train phase, the model first learns a domain-specific knowledge by updating initial model parameters $\theta$ to temporary model parameters $\phi$, i.e., adapted parameters. Then, in the meta-test phase, the model learns the adaptation by optimizing $\theta$ with respect to $\phi$. From the domain adaption perspective, two phases simulate the domain adaption process. The model first adapts to a specific domain through the meta-train phase, and this adaption is evaluated in the meta-test phase.

**Meta-train phase.** We obtain $\phi$ for each $i$-th out-domain datasets by using one-step gradient descent, i.e.,

$$
\phi = \theta - \alpha \nabla_{\theta} L_{D_{out}}^{s} (\theta),
$$

where $L_{D_{out}}^{s}$ is represented as

$$
L_{D_{out}}^{s} = L_{D_{out}}^{lm} (\theta) + L_{D_{out}}^{bt} (\theta).
$$

$D_{out}$ is the $i$-th out-domain dataset and $\alpha$ is the learning rate for the meta-train phase. As previously discussed in Section 3, the language modeling and back-translation losses are essential in facilitating the unsupervised machine translation. Hence, $L_{D_{out}}^{s}$ consists of $L_{D_{out}}^{lm}$ and $L_{D_{out}}^{bt}$, where each loss function is computed with $D_{out}^{i}$.

**Meta-test phase.** The objective of the meta-test phase is to update $\theta$ using each $\phi$ learned from the meta-train phase by using each $L_{D_{out}^{i}}^{s}$. We call this update as a meta-update, defined as

$$
\theta \leftarrow \theta - \beta \nabla_{\theta} \sum_{i=0}^{n} L_{D_{out}^{i}}^{s} (\phi^{i}),
$$

where $\beta$ is another learning rate in the meta-test phase. Since Eq. (5) requires the second-order gradient, the equation is simplified with the first-order gradient by replacing the second-order term. Finn et al. (2017) showed that the first-order approximation of the meta-learning maintains the performance while minimizing the computational cost.

### 4.3 MetaGUMT

To handle a data scarcity issue from a meta-learning perspective, it is critical to be able to make the initialized model to adapt to a data-scarce domain. However, since a small amount of training data in the new domain may cause the model to overfit and prevent utilizing high-resource domain knowledge, it is important to incorporate high-resource domain knowledge and generalizable knowledge into optimal initial parameters. To address this issue, we extend the existing meta-learning approach via two novel losses, which we call an aggregated meta-train loss and a cross-domain loss. The former contributes to incorporating those high-resource domain knowledge into optimal initial parameters, while the latter encourages our model, after trained using a particular domain, to still generalize well to another domain, i.e., cross-domain generalization.

**Meta-train phase.** As shown in Fig. 2 (C), via Eqs. (3) and (4), we obtain $\phi$ from each $i$-th out-domain datasets. Since this phase is exactly same with the meta-train phase of MetaUMT, we leave out the details.

**Meta-test phase.** The aggregated meta-train loss, which refers to Fig. 2 (D), is computed using all out-domain datasets, i.e.,

$$
L_{ag} = \sum_{i=1}^{n} L_{D_{out}^{i}}^{s} (\phi).
$$

This loss term allows the model to learn the source domain knowledge potentially applicable to a target domain. Moreover, to alleviate the overfitting after adapting to the low-resource domain, we introduce a cross-domain loss, which is in Fig. 2 (D), as

$$
L_{cd} = \sum_{i=1}^{n} L_{D_{cd}^{i}}^{s} (\phi),
$$

where $L_{D_{cd}^{i}}^{s} = L_{D_{out}^{i}}^{s} (\phi) + L_{D_{other}^{i}}^{s} (\phi)$, i.e., computing the cross-domain loss with the data from $D_{out}^{i}$ as well as those from other domains than $D_{out}^{i}$ called $L_{D_{other}^{i}}^{s}$.
To obtain the optimal initialization $\theta$ for model parameters, we define our total loss function, which is Fig. 2 (E), as the sum of the two of our losses, i.e.,

$$\theta \leftarrow \theta - \beta \nabla_{\theta}(L_{cd} + L_{ag}).$$  \hspace{1cm} (8)  

In summary, our aggregated meta-train and cross-domain losses encourage our model to accurately and quickly adapt to an unseen target domain. The overall procedure is described in Algorithm A.1.

5 Experiments

This section first introduces experiment settings and training details. Afterwards, we show empirical results on various scenarios.

5.1 Dataset and Preprocessing

We conduct eight different domains for our experiments (Appendix T.3). Each domain dataset is publicly available on OPUS (Tiedemann, 2012). We utilize the eight different domains into out-domain ($D_{\text{out}}$) and in-domain datasets ($D_{\text{in}}$). To build the monolingual corpora of in-domain and out-domain datasets, we divide each corpus into monolingual ones and shuffle these monolingual corpora. Each of two monolingual corpora contains the equal number of sentences for each language (e.g., English and German). For our low-resource scenarios, we sample 5,000 tokens from a selected in-domain corpus for each language. Note that out-domain dataset represents full monolingual corpora.

5.2 Experimental Settings

As our base model, we use a Transformer (Vaswani et al., 2017) is initialized by a masked language model from XLM (Conneau and Lample, 2019) using our out-domain datasets. All the models consist of six layers, 1,024 units, and eight heads.

We establish and evaluate various baseline models as follows: 1. UNMT model is only trained with in-domain monolingual data, composed of 5,000 words for each language. 2. Supervised neural machine translation model (NMT) is trained with in-domain parallel datasets, which we arrange in parallel with the two in-domain monolingual corpora. 3. Unadapted model is pretrained with only the out-domain datasets and evaluated on the in-domain datasets. 4. Transfer learning model is a finetuned model, which is pretrained with the out-domain datasets and then finetuned with a low-resource in-domain dataset. 5. Mixed finetuned model (Chu et al., 2017) is similar to a Transfer learning model, but it utilizes both in-domain and out-domain datasets for finetuning. That is, the training batch is sampled evenly from in-domain and out-of-domain datasets.

5.3 Experimental Results

In order to verify the effectiveness of leveraging the high-resource domains (i.e., source domains) to handle the low-resource domains (i.e., target domain), we compare the unsupervised and supervised models with ours and other baseline models. The unsupervised model is trained on in-domain data which significantly suffers from data scarcity in that it only uses low-resource in-domain data. Although the unsupervised and supervised models are initialized by XLM, as shown in Table 1, those models show the worst performance in all the cases. This result indicates that when the small size of an in-domain corpus is given, it is appropriate to utilize the out-domain datasets rather than to train only with low-resource data. In addition, the performance of the unadapted model is far behind model from XLM (Conneau and Lample, 2019) using our out-domain datasets.
against other models, such as the mixed finetuned model, transfer learning model, MetaUMT, and MetaGUMT. This implies that we need an adequate strategy of leveraging the high-resource domains to improve the performance.

We further compare the performance between our proposed approaches (i.e., MetaUMT and MetaGUMT) and the other two finetuning models (i.e., the transfer learning and the mixed finetuned models). Our methods exhibit the leading performances in both directions of translation (en ↔ de). They consistently achieve improvements of 2-4 BLEU score in most of the settings. Furthermore, MetaGUMT consistently obtains better BLEU scores and converges faster than MetaUMT does. We assert that our proposed losses, i.e., the aggregated meta-train and the cross-domain losses, help the model to easily adjust to the unseen in-domain dataset, and thus accelerate the convergence speed.

5.4 Performances and Adaptation Speed in Finetuning Stage

As shown in Fig. 3 (A), we compare our proposed methods with the transfer learning approach by varying the sizes of an in-domain monolingual corpus. The smaller training data is, the wider the gap between the performances of the two approaches and the transfer learning model becomes. It means that the meta-learning is an effective approach to alleviate the performance degradation, preventing the model from overfitting in the low-resource data.

Compared to the transfer learning model, MetaUMT demonstrates a better performance than other methods in various settings. However, MetaGUMT exhibits even better performances consistently in all settings owing to our proposed losses (Eq. (8)). The transfer learning approach shows the worst performance except for the unadapted model, even though it exploits the in-domain corpus after being pretrained with the out-domain datasets.

Additionally, we analyze the number of iterations required for a model to converge given an in-domain dataset. As shown in Fig. 3 (B), the meta-learning approaches rapidly converge after only a few iterations, even faster than the transfer learning one does. As the number of in-domain training words increases, the transfer learning approach requires a much larger number of iterations until convergence than our meta-learning approaches do. It can be seen that MetaUMT and MetaGUMT rapidly adapt to an unseen domain. Moreover, owing to the encapsulated knowledge from the high-resource domains, MetaGUMT converges within a relatively earlier iteration than MetaUMT does.

In summary, the meta-learning-based methods quickly converge in the low-resource domain, improving the performances up to 2.2-4.1 BLEU score over the transfer learning method in various low-resource settings. This indicates that the meta-learning-based approaches are suitable to alleviate the data deficiency issue on scarce domains. Furthermore, our proposed losses (Eq. (8)) enhance the capabilities of aggregating domain general knowledge and finding adequate initialization.

5.5 Number of Iterations until Convergence in Pretraining Stage

An advantage of our meta-learning approaches is that they can find an optimal initialization point from which the model can quickly adapt to a low-resource in-domain dataset. The transfer learning model requires twice more iterations until convergence than ours do. As shown in Fig. 3 (C), MetaUMT and MetaGUMT not only converge quickly but also outperform the other base-
We empirically show the effectiveness of the cross-domain and aggregated meta-train losses, as shown in Table 3. First, compared to MetaUMT, MetaGUMT is effective in achieving a proper initialization at an earlier iteration. These results indicate that our additional losses, i.e., the cross-domain and aggregated meta-train losses, are beneficial in boosting up the ability for finding an optimal initialization point when training the model with the out-domain datasets.

### 5.6 Analysis of MetaGUMT losses

We assume that the domain generalization ability and high-resource domain knowledge is helpful for the UNMT model to translate the low-resource domain sentences. At first, to identify whether the model encapsulates the high-resource knowledge from multiple sources, we evaluate our model on out-domain datasets (i.e., $D_{\text{out}}$) with initial $\theta$. As shown in Table 2, MetaGUMT shows remarkable performances than MetaUMT in all domains, even better than the transfer learning models. On the other hands, MetaUMT demonstrates poor performances in $D_{\text{out}}$. Compare to MetaUMT, MetaGUMT uses aggregated meta-train loss such that MetaGUMT is able to encapsulates the high-resource domain knowledge. As shown in Table 1, MetaGUMT shows the superior performances that MetaGUMT is capable to leverage the encapsulated knowledge when finetuning the low-resource target domain. Secondly, our cross-domain loss encourages the model to have generalization capability after adapting the low-resource target domain. As ‘Unseen’ column in Table 2, MetaGUMT outperforms the other models. It can be seen that our model has the domain generalization ability after finetuning stage due to the cross-domain loss in the meta-test phase.

### 5.7 Ablation Study

We empirically show the effectiveness of the cross-domain and aggregated meta-train losses, as shown in Table 3. First, compared to MetaUMT that does not use any of the two losses, incorporating the cross-domain loss improves the average BLEU score by 0.21. The cross-domain loss acts as a regularization function that prevents the model to overfit during the finetuning stage. Second, the aggregated meta-train loss, another critical component of our model, allows the model to utilize the high-resource domain knowledge in the finetuning stage. This also improves the average BLEU score by 0.37 from MetaUMT. Lastly, combining both cross-domain and aggregated meta-train losses significantly enhance the result in both directions of translation ($E \leftrightarrow D_e$), indicating that they are complementary to each other.

### 6 Conclusions

This paper proposes novel meta-learning approaches for low-resource UNMT, called MetaUMT, which leverages multiple source domains to quickly and effectively adapt the model to the target domain even with a small amount of training data. Moreover, we introduce an improved method called MetaGUMT, which enhances cross-domain generalization and maintains high-resource domain knowledge. We empirically show that our proposed approach consistently outperforms the baseline methods with a nontrivial margin.

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**Table 2: BLEU scores evaluated on out-domain and in-domain data with initial $\theta$ and finetuned $\theta$, respectively. ‘$D$’ denotes the domain, ‘Unseen’ indicates the new domain evaluated with finetuned $\theta$. Since the transfer and mixed finetuned model use the same initial $\theta$, we leave its corresponding row as ‘-’.

| Parameter | Initial $\#$ | Finetuned $\#$ |
|-----------|--------------|----------------|
| D         | $D_{\text{out}}$ | $D_{\text{in}}$ |
| Medical   |               |                |
| Law       |               |                |
| Koran     |               |                |
| EUB       |               |                |
| IT        |               |                |
| GV        |               |                |
| Subtitles |               |                |
| Europarl  |               |                |

**Table 3: Effectiveness of each cross-domain and aggregated meta-train loss.

| Cross-domain | Aggregated meta-train | $\Delta$ |
|--------------|-----------------------|----------|
| ✓            | ✓                     |          |
| ✓            | ✓                     |          |
| ✓            | ✓                     |          |

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A Implementation Details

In order to preprocess datasets, we utilize Moses (Koehn et al., 2007) to tokenize the sentences. We then use byte-pair encoding (BPE) (Sennrich et al., 2016a) to build a shared sub-word vocabulary using fastBPE with 60,000 BPE codes. Based on this shared sub-word vocabulary, constructed from the out-domain datasets, we split words into sub-word units for the in-domain dataset. We implement all of the models using PyTorch library, and then train them in four nvidia V100 gpus for pretraining and finetuning. We evaluate all the experiments based on the BLEU script. The number of convergence iteration of each algorithm is defined based on the best validation epoch, which shows no more improvement of validation score even if we run 10 more epochs. Moreover, we have conducted comprehensive experiments to obtain our main result table (Table. 1 and Table. T.1) on different domains by training the model with 10 different sampled words each time.

For optimizing each algorithms, we choose the Adam optimizer (Kingma and Ba, 2014) for pretraining stage, as well as the Adam warmup optimizer (Vaswani et al., 2017) for finetuning stage. The learning rate is set to $10^{-4}$, optimized within the range of $10^{-2}$ to $10^{-5}$. In all experiments, the number of tokens per batch is set as 1,120 and the dropout rate is set as 0.1. In meta-learning approaches, we set the learning rates of alpha and beta commonly as 0.0001 in all experiments.

B Additional results

Due to the page limits, in this section, we provide a few additional results that include other domain combinations shown in Table. T.1. Clearly, our proposed approaches still significantly outperform other baseline models on various domain settings.

B.1 Impact of the Number of Source Domains

We examine how the performances change against the different number of source domains for each approach. As shown in Table. T.2, MetaGUMT consistently outperforms the transfer, the mixed-finetune, and MetaUMT approaches. As the size of the source domains increases, so does the performance gap between ours and the transferring based models, transferring and mixed-finetune models. This indicates that the meta-learning based approaches are highly affected by the size of domains in the meta-train phase, and also, if the number of source domains are large enough to capture the general knowledge, the meta-learning based approaches are suitable to handle the low-resource target task, i.e., domain.

B.2 Performances and Adaptation Speed in Finetuning Stage for a Law domain

As shown in Fig B.1 and Fig B.2, MetaGUMT consistently outperforms other methods even though the number words are increasing. Through this experiment, we attempt to show the robustness of our methods, MetaUMT and MetaGUMT, against others, transferring and mixed-finetune models. The models are pretrained on Subtitles, EUbookshop, Europarl, GlobalVoices, Medical, and Koran datasets and then finetuned on a Law dataset.

C Comparison between MetaGUMT and MetaUMT algorithms

Here, we provide additional details of MetaUMT for understating the difference between the MetaGUMT and MetaUMT. We describe the overall algorithms of MetaUMT (A.2) and MetaGUMT (A.1). As shown in Algorithms. A.2, MetaUMT has only difference in line 10.

D Statistics of Datasets

As shown in Table. T.3, W/S indicates the number of words per sentence in a domain.

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https://github.com/glample/fastBPE
https://pytorch.org/
https://github.com/moses-smt/mosesdecoder/blob/master/scripts/generic/multi-bleu.perl

Figure B.1: A performance comparison with respect to the number of words for adaptation on a Law domain.
Table T.1: Extended results on various domain settings. The column ‘epoch’ indicates the converged number of epochs for each in-domain dataset. Since the unadapted model does not involve an additional finetuning step, we leave the epoch column as blank.

Table T.2: Effectiveness of the different number of source domains between meta-learning based approaches and the transfer learning approach.

Algorithm A.1 MetaGUMT

Require: \(\alpha, \beta\): step sizes

1. Pretrain \(\theta\) by using XLM
2. while not done
3. for all \(D_{out}\) do
4. Evaluate \(\nabla_{\theta} L_{D_{out}}^{lm}(\theta)\) with respect to source and target language sentences from \(D_{out}\)
5. Back-translation generates source and target language sentences using the current translation model
6. Evaluate \(\nabla_{\theta} L_{D_{out}}^{bt}(\theta)\) with using pseudo-generated sentences
7. Sum each gradient:
   \(\nabla_{\theta} L_{D_{out}}^{s} = \nabla_{\theta} L_{D_{out}}^{lm}(\theta) + \nabla_{\theta} L_{D_{out}}^{bt}(\theta)\)
8. Compute adapted parameters with one-step gradient descent:
   \(\phi^{i} = \theta - \alpha \nabla_{\theta} L_{D_{out}}^{s}(\theta)\)
9. end for
10. Update \(\theta \leftarrow \theta - \beta \nabla_{\theta}(\mathcal{L}_{cd} + \mathcal{L}_{ag})\)
11. end while

Table T.3: Statistics of each corpora.
Algorithm A.2 MetaUMT

Require: $\alpha, \beta$: step sizes

1: Pretrain $\theta$ by using XLM
2: while not done do
3:   for all $D_{out}^i$ do
4:     Evaluate $\nabla_{\theta} L_{D_{out}^i}^{lm} (\theta)$ with respect to source and target language sentences from $D_{out}^i$
5:     **Back-translation** generates source and target language sentences using the current translation model
6:     Evaluate $\nabla_{\theta} L_{D_{out}^i}^{bt} (\theta)$ with using pseudo-generated sentences
7:     Sum each gradient:
   \[ \nabla_{\theta} L_{D_{out}^i}^{s} = \nabla_{\theta} L_{D_{out}^i}^{lm} (\theta) + \nabla_{\theta} L_{D_{out}^i}^{bt} (\theta) \]
8:     Compute adapted parameters with one-step gradient descent:
   \[ \phi^i = \theta - \alpha \nabla_{\theta} L_{D_{out}^i}^{s} (\theta) \]
9:   end for
10: $\theta \leftarrow \theta - \beta \nabla_{\theta} \sum_{i=0}^{n} L_{D_{out}^i}^{s} (\phi^i)$
11: end while