Addressing Asymmetry in Multilingual Neural Machine Translation with Fuzzy Task Clustering

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Abstract

Multilingual neural machine translation (NMT) enables positive knowledge transfer among multiple translation tasks with a shared underlying model, but a unified multilingual model usually suffers from capacity bottleneck when tens or hundreds of languages are involved. A possible solution is to cluster languages and train individual model for each cluster. However, the existing clustering methods based on language similarity cannot handle the asymmetric problem in multilingual NMT, \textit{i.e.}, one translation task \textit{A} can benefit from another translation task \textit{B} but task \textit{B} will be harmed by task \textit{A}. To address this problem, we propose a fuzzy task clustering method for multilingual NMT. Specifically, we employ task affinity, defined as the loss change of one translation task caused by the training of another, as the clustering criterion. Next, we cluster the translation tasks based on the task affinity, such that tasks from the same cluster can benefit each other. For each cluster, we further find out a set of auxiliary translation tasks that benefit the tasks in this cluster. In this way, the model for each cluster is trained not only on the tasks in the cluster but also on the auxiliary tasks. During training, we design a dynamic task sampling strategy that eliminates the negative influence of auxiliary tasks while exploiting the positive knowledge of them. We conduct extensive experiments for one-to-many, many-to-one, and many-to-many translation scenarios to verify the effectiveness of our method.

1 Introduction

Neural machine translation (NMT) has achieved great success in recent years (Sutskever et al., 2014; Bahdanau et al., 2015; Vaswani et al., 2017). The conventional bilingual translation model well handles the translation task for a single language pair, but it is infeasible to train an individual model for each language pair since there are thousands of languages in the world. To improve the computational efficiency, researchers propose multilingual NMT that enables one model to handle multiple translation tasks (Ha et al., 2016; Johnson et al., 2017). Apart from the benefits for training and deployment, the shared underlying neural network in multilingual NMT also brings knowledge transfer among similar languages (Tan et al., 2019).

Despite its simplicity, multilingual NMT model often suffers from representation bottleneck caused by language interference (Wang et al., 2020b; Wang and Zhang, 2022) when massive number of languages involved (Aharoni et al., 2019), which leads to performance degradation compared to bilingual translation models. Several methods have been proposed to break the bottleneck, such as designing language specific modules (Wang et al., 2019; Sachan and Neubig, 2018), hidden units (Wang et al., 2018) or routing path (Zhang et al., 2021). Among them, the most intuitive approach is grouping the languages into several clusters and training one multilingual NMT model for each cluster. These methods use similarity between language representations as clustering criterion, in which the representations come from language embedding vectors of a pretrained universal multilingual model or sparse language vectors of a multilingual knowledge base (Tan et al., 2019; Oncevay et al., 2020).

|          | A  | B* | C* |
|----------|----|----|----|
| en-it     | 32.6 | 34.3 | 28.1 |
| en-nl     | 31.6 | 34.3 | 38.8 |
| en-de     | 25.9 | 37.9 | 22.2 |
| en-fr     | 34.3 | 34.3 | 13.6 |
| en-zh     | 25.3 | 10.4 | 25.3 |

Table 1: Three kinds of task relationship. (A): Tasks benefit from each other when jointly trained. (B): Tasks are negatively influenced by each other. (C): The task en-zh benefits from en-ja but en-zh is harmful to en-ja. The models are trained on the IWSLT’17 dataset and results with * are reported in Xu and Yvon (2021).
However, language similarity is not enough for modeling the relationship among translation tasks because of two reasons. First, a translation task includes a source language and a target language, while the language similarity only consider the feature of a single language. Second, the similarity metric cannot handle the asymmetric relationship between translation tasks. Zamir et al. (2018); Wang et al. (2022) show the asymmetry in multi-task learning and multilingual translation in which one task may benefit from another but not vice versa. Table 1 shows the three kinds of task relationships in multilingual NMT. Case (A) and (B) represent symmetric relationship in which the influence of the two tasks on each other are both positive or both negative. While in case (C), the relationship is asymmetric in which the task en-zh can benefit from the task en-ja but en-ja is harmed by en-zh when the two tasks are jointly trained.

In this work, we propose a fuzzy task clustering method for multilingual NMT to address the asymmetric problem among translation tasks. We use the task affinity (Fifty et al., 2021) as the clustering criterion, which measures the loss change of one task caused by the training of another task. We first train a universal multilingual model to obtain the affinity between each two tasks. Then we cluster tasks based on the affinity score such that tasks within each cluster can symmetrically benefit each other. For each cluster, we also select a set of auxiliary tasks that asymmetrically benefit the tasks in this cluster. Finally, we build separate models for each cluster, and train the model on both the tasks in the cluster and the corresponding auxiliary tasks. In this way, the model for each cluster can exploit the auxiliary tasks to facilitate training and improve the model quality. Compared to previous language clustering based methods, the proposed method improves positive knowledge transfer between tasks by introducing auxiliary tasks. To further address the increased burden of model training due to auxiliary tasks involved, we therefore propose a dynamic data sampling strategy, in which the sampling weights of auxiliary tasks gradually decrease to allow the optimization process to focus more on the tasks that used in inference.

To summarize, our method has the following advantages:

- The clustering criterion in our method directly measures the effect on one translation task when training another, which can better model the relationship between tasks compared to language similarity.
- The fuzzy clustering paradigm introduces auxiliary tasks for each cluster, breaking the barrier between clusters and improving positive knowledge transfer.

2 Problem Formulation

2.1 General Formulation

Given a set of translation tasks $T = \{\tau_1, \ldots, \tau_N\}$, we group the tasks into $K \in \{k \in \mathbb{N}^+ | k \leq N\}$ clusters $C$:

$$C = \left\{ c_1, \ldots, c_k \mid c_k \neq \emptyset, \forall k \quad \bigcup_{k=1}^{K} c_k = T \right\} \quad (1)$$

For each cluster $c_k$, we find out a set of auxiliary tasks from other clusters that benefit the tasks in $c_k$. By combining the auxiliary tasks and tasks in $c_k$, we obtain another cluster $g_k$. The set of $g_k$ is denoted as:

$$G = \left\{ g_1, \ldots, g_K \mid \bigcup_{k=1}^{K} g_k = T \quad c_k \subseteq g_k, \forall k \right\} \quad (2)$$

where the tasks $\tau \in g_k \setminus c_k$ are the auxiliary tasks of $c_k$.

We then build a multilingual NMT model $M_k$ for each cluster $c_k$ to handle the translation tasks in $c_k$. The model $M_k$ is trained on $g_k$, which consists of both the tasks from $c_k$ and the corresponding auxiliary tasks, by minimizing the cross-entropy loss:

$$\arg \min_{M_k} \sum_{\tau \in g_k} \sum_{(x,y) \in \tau} - \log p(y|x, M_k) \quad (3)$$

where $(x, y)$ is a sentence pair from task $\tau$.

For a predefined quality measure $Q(\tau|M)$ of a model $M$ on task $\tau$, our goal is to find the optimal clusters $C$ and $G$ that maximize the inference performance of all tasks:

$$\arg \max_{C \cup G, K} \sum_{k=1}^{K} \sum_{\tau \in c_k} Q(\tau|M_k) \quad (4)$$

2.2 Specialized Cases

We can see in this section that bilingual, multilingual, and clustering based methods are special cases of our formulation.
Bilingual Translation When $K = N$, namely we assign only one translation task for each cluster and train individual model for each task, the problem degrades into bilingual translation. The bilingual model for each cluster is trained with Equation (3).

Multilingual Translation When $K = 1$, a universal multilingual NMT model is trained for all tasks as in Johnson et al. (2017). To distinguish different languages, a special token called language tag is appended at the beginning of each source sentence.

Language Clustering for Multilingual NMT When $1 < K < N$, $\mathcal{C} = \mathcal{G}$, the tasks are grouped into separate clusters without auxiliary tasks. For example, Tan et al. (2019) first train a universal multilingual NMT model to obtain language embedding vectors. Based on the the embedding vectors, they cluster the languages into different groups and train individual model for each cluster.

3 Method

In this section, we first describe the translation task affinity used for modeling the asymmetric relationship between tasks (Section 3.1), followed by the translation task clustering method that clusters the tasks and finds out the auxiliary tasks for each cluster (Section 3.2). We finally build a model for each cluster and train the model with dynamic data sampling strategy (Section 3.3).

3.1 Translation Task Affinity

We first focus on the quality measure $Q(\tau|M)$ of a model $M$ on task $\tau$. A popular choice for modeling and optimizing the quality of a translation model is cross-entropy loss (Bahdanau et al., 2015; Vaswani et al., 2017). A lower cross-entropy indicates a better model. Therefore, we use the negative cross-entropy, namely the log-probability, to measure the quality of $M$ on task $\tau$:

$$Q(\tau|M) = \sum_{(x,y) \in \tau} \log p(y|x, M)$$

(5)

Obviously, training one model $M$ for each task $\tau$ is a possible solution for Equation (4), since the training objective in Equation (3) is identical to maximizing $Q(\tau|M)$.

Previous works find out that the performance on some tasks can be improved when jointly trained (Tan et al., 2019; Standley et al., 2020; Chiang et al., 2022). Therefore, we want to find out which task can benefit another under the quality measure $Q(\tau|M)$ in multilingual training. Formally, given two tasks $\tau_i$ and $\tau_j$, the affinity $Z_{j \rightarrow i}$ from $\tau_j$ to $\tau_i$ is defined by:

$$Z_{j \rightarrow i} = Q(\tau_i|M_1) - Q(\tau_i|M_2)$$

(6)

where $M_1$ is trained on tasks $\tau_i$ and $\tau_j$, while $M_2$ is trained on task $\tau_i$. A positive value $Z_{j \rightarrow i} > 0$ indicates that the task $\tau_j$ brings positive knowledge transfer to task $\tau_i$, while a negative value indicates that the task $\tau_j$ is harmful to task $\tau_i$. Note that $Z_{j \rightarrow i} \neq Z_{i \rightarrow j}$, and thus we call it asymmetric task affinity.

However, exhaustively searching over all possible combinations of $|T|$ tasks requires training $2^{|T|} - 1$ models, which is unaffordable. We therefore turn to an efficient approximation that measures, at each training step, the change of one task’s loss caused by the optimization of another task (Fifty et al., 2021). The affinity from task $j$ to task $i$ at step $t$ is defined as:

$$\hat{Z}_{j \rightarrow i}^t = \log p(y|x, M^{t+1}) - \log p(y|x, M^t)$$

(7)

where $(x, y)$ is a sentence pair sampled from task $\tau_i$, and $M^{t+1}$ is obtained by one-step training on task $\tau_j$ of model $M^t$.

Similar to Tan et al. (2019), we first train a universal model for all the language pairs. During training, we calculate the affinity $\hat{Z}_{j \rightarrow i}^t$ with randomly and uniformly sampled tasks $\tau_j$ and $\tau_i$ at $t$-th step. The affinity is then accumulated across all steps:

$$Z_{j \rightarrow i} \approx \hat{Z}_{j \rightarrow i} = \sum_{t=1}^T \hat{Z}_{j \rightarrow i}^t$$

(8)

With the affinity matrix $Z \in \mathbb{R}^{|T| \times |T|}$, our goal in Equation (4) becomes maximizing the overall inter-task affinity as proved in Section A:

$$\arg\max_{C, G, |K|} \sum_{k=1}^K \sum_{\tau_i \in G_k} \sum_{\tau_j \in C_k} Z_{j \rightarrow i}$$

(9)

1In Fifty et al. (2021), they consider the ratio of the loss change to eliminate the scale discrepancy among different task losses: $Z_{j \rightarrow i} = 1 - \frac{L_{i}(x,y, M^{t+1})}{L_{i}(x,y, M^t)}$. Since the task loss scales are similar in multilingual translation, we only consider the absolute loss change.

In multilingual NMT, a single batch can contain sentence pairs from multiple tasks (Johnson et al., 2017), which is unsuitable for Equation (7). We therefore iteratively use batches contain multiple tasks to stabilize training, and batches contain only one task to calculate $Z_{j \rightarrow i}$. 

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3.2 Translation Task Clustering

We now describe how to solve Equation (9). Similar to reduction from Set-Cover that chooses a subset covering all the tasks to minimize the overall cost (Standley et al., 2020), this problem is NP-hard in general. We therefore propose a greedy approximation that iteratively constructs the clusters $\mathcal{C}$ and $\mathcal{G}$ to minimize the overall affinity.

As shown in Figure 1(b), we first initialize $\mathcal{C}$ with $N$ clusters, where each cluster contains only one task. With the affinity matrix $Z$, we build the corresponding $N$ clusters of $\mathcal{G}$:

$$g_k = c_k \cup \{ \tau_j | Z_{j \rightarrow i} > 0 \} \; \forall k = 1, \ldots, N$$ (10)

where $\tau_j \in c_k$.

We define the score function $S(c_k, g_k)$ to measure the cluster affinity of $c_k$ and corresponding $g_k$:

$$S(c_k, g_k) = \frac{1}{|g_k|} \sum_{i \in c_k} \sum_{\tau_j \in g_k} Z_{j \rightarrow i}$$ (11)

where $\frac{1}{|g_k|}$ is the normalization term for the number of tasks. We also define the rule of the union of two clusters $c_1$ and $c_2$ in $\mathcal{C}$, and $g_1$ and $g_2$ in $\mathcal{G}$:

$$c_1 \cup c_2 = \{ \tau | \tau \in c_1 \text{ or } \tau \in c_2 \}$$

$$g_1 \cup g_2 = (c_1 \cup c_2) \cup \left\{ \tau_j | \tau_j \in g_1 \text{ or } \tau_j \in g_2, Z_{j \rightarrow i} > 0, \forall \tau_i \in c_1 \cup c_2 \right\}$$ (12)

As shown in Figure 1(c-e), for each two clusters, we form a union of them based on the above union rule and calculate the cluster affinity. The clusters with maximum overall affinity are selected. The clustering step is repeated until no union of two clusters can further improve the overall affinity, i.e., for any of two clusters $c_1$ and $c_2$, we have:

$$S(c_1 \cup c_2, g_1 \cup g_2) \leq S(c_1, g_1) + S(c_2, g_2)$$ (13)

After iteration\(^3\), the Equation (4) is solved and we obtain $K$ clusters in $\mathcal{C}$ as well as $K$ corresponding clusters in $\mathcal{G}$. We train one multilingual NMT model (Johnson et al., 2017) for the tasks in each cluster, where each model $M_k$ is trained with tasks in $g_k$ and is used for inference of tasks in $c_k$.

\(^3\)In most of our experiments, the iteration can stop with a proper number of resulting $K$ clusters. However, there is no theoretical guarantee for convergence and it may degrade into bilingual ($K = N$) or universal ($K = 1$) models. In practice, early-stop can be adopted when $K$ satisfies a predefined constraints (Standley et al., 2020).

![Figure 1: An example of clustering 3 tasks. Based on the affinity matrix (a), we first initialize the clusters $\mathcal{C}$ and $\mathcal{G}$ (b), and then make union of each of two clusters (c-e). In this example, (c) brings highest overall affinity (1.95) and no union of two clusters can further improve the affinity (1.2 if the three tasks belong to one cluster). Thus the clusters in (c) is the clustering result.](image)

3.3 Training with Dynamic Data Sampling

We now focus on the training of model $M_k$. The training objective, as described in Equation (3), is to minimize the overall cross-entropy loss for tasks in $g_k$. Since the training tasks in $g_k$ contain both the inference tasks in $c_k$ and other auxiliary tasks $g_k \setminus c_k$, the objective brings positive knowledge transfer and can improve the translation quality compared to that only trained with tasks in $c_k$. However, it also introduces extra burden for the model due to more auxiliary tasks involved.

We therefore propose a dynamic data sampling strategy that gradually decreases the weights of auxiliary tasks and focuses more on inference tasks. We start from the temperature based sampling (Conneau et al., 2020) that samples training data from each task $\tau \in g_k$ according to the data size of each task $|D_\tau|$ and a temperature term $\rho$:

$$P_k(\tau) = \frac{q^{1/\rho}_\tau}{\sum_{\pi \in g_k} q^{1/\rho}_\pi} \text{ where } q_\tau = \frac{|D_\tau|}{\sum_{\pi \in g_k} |D_\pi|}$$ (14)

We re-scale the sampling distribution $P(\tau)$ for the auxiliary tasks $\tau \in g_k \setminus c_k$ as a function of the training epoch $E$:

$$P_k(\tau) = \begin{cases} \frac{1 - \lambda E}{1 - \lambda} P_k(\tau) & \text{if } \tau \notin c_k \\ P_k(\tau) & \text{if } \tau \in c_k \end{cases}$$ (15)

where $\lambda$ is the decay rate of the sampling weight. The term $\frac{q_\tau}{q_k}$ considers the number of auxiliary tasks. If there are too many auxiliary tasks for
training the model, namely $|g_k| \gg |c_k|$, the weight of each auxiliary task should be smaller. Other dynamic data sampling and task weighting methods can also be used for prioritizing the inference tasks in $c_k$ (Lin et al., 2019; Wang et al., 2020a; Mahapatra and Rajan, 2020).

4 Experiment Setup

4.1 Dataset

We evaluate our method on the TED 2020 Parallel Sentences Corpus collected by Reimers and Gurevych (2020). The dataset contains sentences from TED talks with their translations in more than 100 languages provided by a global community of volunteers.

For one-to-many (O2M) translation and many-to-one (M2O) translation scenarios, we select 28 languages (es, fr, ar, zh, ko, ru, tr, it, ja, he, pt, ro, vi, nl, hu, fa, pl, de, el, sr, bg, uk, hr, cs, id, th, sv, sk) ↔ English that contain more than 100K sentence pairs\(^4\) and the data statistics are shown in Supplementary Materials (Section B). We randomly select 4,000 sentence pairs as validation set and 4,000 sentence pairs as test set for each language pair. We use byte-pair encoding (BPE) (Sennrich et al., 2016) to encode all sentences and learn the BPE operation using sentencepiece (Kudo and Richardson, 2018), which results in a shared subword vocabulary containing 32K sub-word symbols.

For many-to-many (M2M) translation, we select 10 languages (es, fr, ar, ko, ru, tr, it, ja, he, pt) from the TED 2020 Parallel Sentences Corpus. Each two languages contains about 300K parallel sentences, which results in 90 translation directions. We preprocess the data in the same way as in O2M and M2O setting.

The multilingual datasets are sampled with temperature based strategy with $\rho = 5$, and the sampling weight decay rate in our method is set to $\lambda = 0.5$.

4.2 Model Settings

We conduct the experiments using the Transformer model (Vaswani et al., 2017) and implement our method based on the fairseq codebase\(^5\). For the O2M and M2O experiments, we use a 4-layer model\(^6\) with embedding size 512 and FFN layer dimension 1024. For the M2M experiment, we adopt the transformer_iwslt_de_en configuration which represents 6-layer model. Each mini-batch contains roughly 16,384 tokens. All models are trained with Adam optimizer (Kingma and Ba, 2015) on Nvidia 3090 GPUs. We use 2 GPUs for O2M and M2O translation, and 4 GPUs for M2M translation. We use SacreBLEU to measure the translation quality (Papineni et al., 2002; Post, 2018) and test the statistical significance by bootstrap resampling (Koehn, 2004).

4.3 Systems

The following methods are used in our experiments.

Bilingual (Bi.) We train a Transformer model for each task, which results in $N$ individual models for $N$ translation directions (Vaswani et al., 2017).

Multilingual (Multi.) We train a universal multilingual Transformer model for all translation directions (Johnson et al., 2017).

Language Embedding Clustering (LEC) We cluster the languages based on the language embedding and train one multilingual model for each cluster. The number of clusters $K$ is obtained with elbow method following Tan et al. (2019).

Hard Task Affinity Clustering (HTAC) We use the affinity instead of language embedding for clustering and no auxiliary tasks are used for training, namely we set $\lambda = +\infty$ in Equation (15), which is equivalent to $G = C$.

Fuzzy Task Affinity Clustering (FTAC) We use the affinity for clustering and incorporate auxiliary tasks with dynamic data sampling during training.

5 Results and Analyses

5.1 Clustering Results

For the LEC method (Tan et al., 2019), we obtain 9 clusters in O2M translation: \{sk, cs, hr, sr, pl\}, \{sv, uk\}, \{th, el, hu, vi, he, ar\}, \{id\}, \{bg, ro\}, \{de, fa, nl, pt, it, tr, fr, es\}, \{ru\}, \{zh\}, \{ja, ko\}. In M2O translation, there are 11 clusters: \{sk, cs\}, \{sv\}, \{th\}, \{id, vi\}, \{hr, bg, sr\}, \{uk, pl, ru\}, \{el\}, \{de, hu, nl, tr\}, \{fa, he, ar\}, \{ro, pt, it, fr, es\}, \{ja, ko, zh\}.

\(^4\)We remove Brazilian Portuguese (pt-br) and Traditional Chinese (zh-tw) since they are similar to Portuguese (pt) and Simplified Chinese (zh-cn). We use zh to indicate zh-cn for simplicity.

\(^5\)https://github.com/pytorch/fairseq

\(^6\)We use 4-layer model because some bilingual models cannot converge with 6-layer setting.
Table 2: The clustering results of our method for one-to-
many translation. Each language X denotes a translation
task en→X.

| k | cₖ (en→X) | gᵢ \ cₖ (en→X) |
|---|----------|----------------|
| 1 | sr, hr   | fr, uk, bg, sv, el, pl, cs, es, it, sk |
| 2 | zh, ko   | tr, vi, th |
| 3 | pl, sk, cs | hu, ru, he, fr |
| 4 | sv, nl, de | zh, id, sk, hr |
| 5 | he, hu   | sv, ja, sk, de, ar |
| 6 | el, bg, uk | sk, es, fa, sr, th |
| 7 | ro, id, es, fr, pt, it | sv, cs, de, hr, sr, pl |
| 8 | ar, fa   | hu, vi, de, nl |
| 9 | tr, vi   | ja, zh, ar, th, ko |
| 10| th, ru   | ja, zh, el, ar, he, ko |

Table 3: The clustering results of our method for many-
to-one translation. Each language X denotes a translation
task X→en.

| k | cₖ (X→en) | gᵢ \ cₖ (X→en) |
|---|----------|----------------|
| 1 | hu       | sk, ar, ro, pt, pl, hr, sv, ru, th, uk, fa, id, zh, it, fr, de, ja, ko, cs, he |
| 2 | zh, ko, ja, th | ar, uk, de, hu |
| 3 | ar, el, fa, he | ru, cs, pl, ro, es, hr, uk, sr, ja, id, bg |
| 4 | tr, pl, cs, sk | ru, sr, ko, ja |
| 5 | bg, hr   | sk, ru, cs, pl, fa, nl, el, id |
| 6 | es, ro, fr, nl, pt | sk, id, bg |
| 7 | de, sr, uk | sk, sv, ru, cs, pl, ro, ar, hr, fa, nl, ko, it, zh, el, id, he |
| 8 | id, vi   | th, fr, pl, hr, uk, de, fa, sr, ko, it, ja, zh, tr, he |
| 9 | sv, it, ru | sk, fr, pl, uk, nl, ja, pt, he |

For our task affinity based method (FTAC), we first show the task affinity in one-to-many and
many-to-one scenarios in Figure 2. Obviously, the left part (O2M) and the right part (M2O) share
one common pattern that the cells on the diagonal line are darker, which indicates that each task
contributes more on itself. Besides, there are more differences between O2M and M2O models which
leads to several interesting findings:

- We find that the cells on the diagonal line in O2M are darker than M2O models, and the
cells beyond diagonal line are lighter in O2M model. The observation indicates that a task
in O2M model relies more on itself and the positive knowledge transfer relies more on the
target language. Thus the tasks in M2O translation can benefit each other and reduce the generation burden.

- The affinities between tasks better correlates with linguistic similarity in O2M model. For example, the Serbian (sr) and Croatian (hr)
are similar languages and the affinity between en→sr and en→hr is quite high. Similar to
language embedding (Tan et al., 2019), the affinity also captures the regional, cultural,
and historical influences in O2M model (see the affinities between ja, ko, and zh).

- The affinities in M2O model cannot reflect linguistic proximities. As claimed above, the
positive knowledge transfer mainly occurs in the decoder to facilitate generation. The differences in the target side between M2O trans-
lation tasks are imperceptible and affected by factors like data sizes, training schedule or
optimization.

Based on the affinity matrix, we cluster the languages using the method described in Section 3.2
and show the clustering results for O2M multiling-
ual translation in Table 2 and M2O translation in

Figure 2: The task affinity between English to 28 languages (O2M, Left) and 28 languages to English (M2O, Right). Each cell (i, j) represents the affinity Zᵢ→j of task τᵢ to task τⱼ.
Table 3. We find that the clusters in M2O translation contain more auxiliary tasks, which proves that the M2O translation can benefit more from multilingual training.

For many-to-many translation, we show the affinity heatmap and clustering results in Supplementary Materials (Section C).

5.2 O2M and M2O Translation Quality

We present the translation quality of different methods in Table 4. By comparing different methods, several observations can be found.

- Our FTAC method can well address the asymmetry in multilingual NMT and outperforms the Multi, baseline in all translation tasks.

- Clustering methods perform better in O2M translation. The LEC method outperforms the multilingual baseline by 2.9 BLEU in O2M translation but only 0.2 BLEU in M2O translation. Similarly, the HTAC method achieves improvements of 3.2 BLEU and 0.8 BLEU in O2M and M2O respectively. The results prove that the burden of generation caused by number of target languages involved is important in O2M translation, and the problem can be well addressed by clustering the tasks into different groups.

- Clustering based on task affinity performs better than based on language embedding. Compared to LEC method, HTAC achieves improvements of 0.3 BLEU in O2M setting and 0.6 BLEU in M2O setting.

- The asymmetry feature of task affinity that leads to fuzzy clustering is important, and the auxiliary tasks in each cluster brings large improvements, especially for M2O setting. The FTAC method with auxiliary tasks outperforms the HTAC method without auxiliary tasks by 0.5 BLEU and 0.9 BLEU in O2M and M2O respectively.

| Table 4: BLEU scores of one-to-many (O2M, Left) and many-to-one (M2O, Right) translation with different methods. The column $\Delta_1$ and $\Delta_2$ are the improvements of FTAC compared to LEC and Multi, respectively. † and ‡ indicate the corresponding improvement is statistically significant with $p < 0.01$ and 0.05 respectively. |
Table 5: Many-to-many (M2M) translation quality measured by BLEU score. We compare our method (FTAC) with the multilingual baseline (Multi.). The BLEU scores of FTAC and the improvements $\Delta$ are reported with the format of $\text{FTAC}/\Delta$.  

| Method | es→fr | en→fr | es→ko | en→ko | es→ru | en→ru | es→vi | en→vi | es→ja | en→ja | es→he | en→he | es→pt | en→pt |
|--------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|
| Result | 35.9/4.3 | 12.2/3.8 | 16.7/3.9 | 16.9/3.9 | 15.0/4.4 | 30.3/4.0 | 15.2/5.3 | 18.8/6.2 | 31.3/6.3 |
| fr→es | 28.9/4.6 | 11.4/2.6 | 16.6/3.4 | 16.3/4.5 | 14.0/4.1 | 28.3/-4.1 | 14.7/5.3 | 18.3/5.3 | 28.8/5.2 |
| fr→fr | 23.8/2.4 | 27.8/4.0 | - | 15.2/2.4 | 14.0/3.3 | 12.3/3.2 | 21.8/3.8 | 13.3/3.2 | 25.5/4.5 |
| fr→ko | 15.5/2.4 | 22.4/2.3 | 6.8/1.6 | - | 10.4/2.0 | 9.8/2.1 | 15.6/2.5 | 14.4/3.0 | 10.0/2.2 |
| fr→ru | 20.3/3.5 | 27.1/3.4 | 8.2/1.9 | 14.9/1.9 | - | 11.2/2.3 | 20.0/3.1 | 13.3/3.8 | 13.2/3.6 |
| fr→tr | 21.0/3.4 | 26.9/3.0 | 9.4/2.2 | 15.4/2.8 | 12.6/2.9 | - | 19.8/3.6 | 14.0/3.6 | 13.9/3.0 |
| fr→it | 30.2/3.6 | 34.9/3.3 | 11.3/3.5 | 16.7/3.8 | 16.4/4.4 | 14.1/2.3 | - | 14.8/5.0 | 18.2/5.1 |
| fr→ja | 13.1/1.5 | 19.8/2.2 | 5.7/1.3 | 13.4/1.8 | 8.6/0.3 | 8.6/1.2 | 13.6/1.8 | - | 7.8/1.9 |
| fr→he | 26.8/4.8 | 31.9/5.6 | 11.8/3.2 | 16.4/2.2 | 16.4/3.8 | 13.5/2.6 | 24.7/4.3 | 14.5/2.6 | - |
| fr→pt | 32.5/4.8 | 36.3/3.7 | 11.9/4.4 | 17.1/4.6 | 16.4/4.9 | 14.2/5.3 | 30.2/5.4 | 14.5/5.3 | 18.7/6.1 |

Table 6: Results of different sampling strategies for auxiliary task data in one-to-many translation (measured by average BLEU).
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Table 7: The data size (K) of languages X→English used in M2O and O2M translation.

| Language | es | fr | ar | ko | ru | tr |
|----------|----|----|----|----|----|----|
| Data Size | 431 | 397 | 399 | 384 | 371 | 368 |

Table 8: The data size (K) used in many-to-many (M2M) translation.

| Language | es | fr | ar | zh | ko | ru | tr |
|----------|----|----|----|----|----|----|----|
| Data Size | 370 | 363 | 349 | 326 | 325 | 323 | 317 |

Table 9: BLEU score of many-to-one (M2O) translation with different data sampling strategies.

| HTAC | Rand. | Temp. | Fix. | FTAC |
|------|-------|-------|------|------|
| es→en | 46.4 | 45.1 | 46.8 | 47.4 |
| fr→en | 40.5 | 39.2 | 40.5 | 41.0 |
| ar→en | 36.5 | 34.4 | 36.8 | 36.4 |
| zh→en | 25.8 | 24.8 | 25.7 | 25.6 |
| ko→en | 23.2 | 22.0 | 22.8 | 22.8 |
| ru→en | 28.8 | 27.8 | 28.2 | 27.2 |
| tr→en | 29.5 | 28.3 | 28.9 | 29.8 |
| it→en | 41.0 | 39.6 | 40.4 | 39.5 |
| ja→en | 19.0 | 17.8 | 18.6 | 18.5 |
| he→en | 40.7 | 38.5 | 40.8 | 41.4 |
| pt→en | 44.3 | 42.8 | 44.4 | 44.9 |
| ro→en | 39.9 | 38.7 | 40.7 | 40.7 |
| vi→en | 32.2 | 32.1 | 31.0 | 31.4 |
| nl→en | 38.8 | 37.5 | 38.8 | 38.9 |
| hu→en | 27.1 | 27.5 | 25.8 | 27.6 |
| fa→en | 33.0 | 31.6 | 33.2 | 32.6 |
| pl→en | 27.3 | 25.9 | 26.8 | 27.5 |
| de→en | 35.8 | 37.0 | 36.9 | 36.3 |
| el→en | 41.5 | 39.1 | 40.8 | 40.9 |
| sr→en | 42.0 | 40.7 | 40.3 | 40.5 |
| bg→en | 42.8 | 40.3 | 42.5 | 41.2 |
| uk→en | 31.4 | 30.9 | 31.5 | 30.6 |
| hr→en | 43.6 | 39.5 | 43.3 | 41.2 |
| cs→en | 36.3 | 33.4 | 34.6 | 36.0 |
| id→en | 34.6 | 33.7 | 32.7 | 34.0 |
| th→en | 28.1 | 26.6 | 27.4 | 27.9 |
| sv→en | 43.4 | 41.6 | 42.9 | 42.3 |
| sk→en | 37.4 | 33.5 | 35.7 | 37.3 |

A The Clustering Objective

We want to maximize the overall performance of all tasks by finding the clusters $C$ and $G$:

$$\arg\max_{C,G,K} \sum_{k=1}^{K} \sum_{\tau_i \in c_k} Q(\tau_i|M_k)$$

$s.t. M_k = \arg\min_{M_k} \sum_{\tau_j \in g_k, (x,y) \in \tau_j} -\log p(y|x,M_k)$ \hspace{1cm} (16)

Assume that the quality $Q(\tau_i|M_k)$ on task $\tau_i$ with the model trained on tasks $\tau_j \in g_k$ is an approximation of the average of the model qualities on task $\tau_i$ with the models trained on task $\tau_j$ and task $\tau_i$:

$$Q(\tau_i|M_k) \approx \frac{1}{|g_k|} \sum_{\tau_j \in g_k} Q(\tau_i|M_{\tau_j})$$ \hspace{1cm} (17)

where $M_{\tau_i,\tau_j}$ is the model trained on tasks $\tau_j$ and $\tau_i$. Then the objective becomes:

$$\arg\max_{C,G,K} \sum_{k=1}^{K} \sum_{\tau_i \in c_k} Q(\tau_i|M_k)$$

$$\approx \arg\max_{C,G,K} \sum_{k=1}^{K} \sum_{\tau_i \in c_k} \frac{1}{|g_k|} \sum_{\tau_j \in g_k} Q(\tau_i|M_{\tau_i,\tau_j})$$

$$\approx \arg\max_{C,G,K} \sum_{k=1}^{K} \sum_{\tau_i \in c_k} \sum_{\tau_j \in g_k} (Q(\tau_i|M_{\tau_i,\tau_j}) - Q(\tau_i|M_{\tau_i}))$$

$$= \arg\max_{C,G,K} \sum_{k=1}^{K} \sum_{\tau_i \in c_k} \sum_{\tau_j \in g_k} Z_{\tau_j \rightarrow \tau_i}$$ \hspace{1cm} (19)
Table 10: The clustering results of our method for many-to-many translation.

| k | cs_1 | cs_2 | ... |
|---|------|------|-----|
| 1 | ja-ru | it-ru | ... |
| 2 | en-es | es-it | ... |
| 3 | ko-he | ja-he | ... |
| 4 | ru-tr | tr-ar | ... |
| 5 | he-ja | ja-ja | ... |
| 6 | ko-he | tr-he | ... |
| 7 | ru-ar | ar-fr | ... |
| 8 | es-it | it-en | ... |
| 9 | ru-he | he-en | ... |
| 10 | es-fr | fr-es | ... |
| 11 | ja-ar | ar-fr | ... |
| 12 | tr-pt | pt-tr | ... |

B Data Statistics and Pre-processing

In our experiments, we use the data from the TED 2020 Parallel Sentences Corpus, which contains sentences from TED talks with their translations provided by a global community of volunteers.

For one-to-many and many-to-one translation, we select 28 languages and the data statistics are shown in Table 7. For many-to-many translation, we select 10 languages and the data statistics are shown in Table 8.

For the data pre-processing, we use Jieba for segmenting Chinese sentences, Mecab for Japanese and Korean, and Moses for other languages.

C M2M Clustering

We show the task affinities of many-to-many (M2M) translation in Figure 3 and the clustering results in Table 10. From figure 3, we find that the tasks with the same target languages share higher affinities compared to the tasks with the same source languages. From the clustering results in Table 10, we also find that the tasks with the same target languages are more likely to be in the same cluster or serve as auxiliary tasks.

D The Effects of Auxiliary Tasks

The detailed BLEU scores of different data sampling strategies for auxiliary tasks are shown in Table 9.

E Results on OPUS dataset

In our experiments, we randomly split the data into training/validation/test set. However, there can be overlap between sentences in train and test/validation sets of different language pairs. For example, one English sentence X in the test set of task en-de may occur in the training set of en-fr. To make the results more convincing, we evaluate the

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7 https://github.com/UKPLab/sentence-transformers/blob/master/docs/datasets/TED2020.md
8 https://www.ted.com/participate/translate
9 https://github.com/fxsjy/jieba
10 https://taku910.github.io/mecab/
11 https://github.com/moses-smt/mosesdecoder
Figure 3: The affinity heatmap between tasks in many-to-many translation. The orders of tasks in X and Y axes are identical to the tasks of $c_k$ in Table 10.

| Language Pair | Multi. | LEC | FTAC | $\Delta_1$ | $\Delta_2$ |
|---------------|-------|-----|------|-----------|-----------|
| es→en        | 25.1  | 27.0| 28.9 | +1.9      | +3.8      |
| fr→en        | 16.1  | 18.4| 20.0 | +1.6      | +3.9      |
| ar→en        | 19.2  | 21.3| 23.3 | +2.0      | +4.1      |
| zh→en        | 10.0  | 10.9| 11.5 | +0.6      | +1.5      |
| ko→en        | 12.6  | 14.5| 15.1 | +0.6      | +2.5      |
| ru→en        | 15.4  | 16.4| 17.7 | +1.3      | +2.3      |
| tr→en        | 21.1  | 22.2| 24.3 | +2.1      | +3.2      |
| it→en        | 20.6  | 23.1| 23.8 | +0.7      | +3.2      |
| ja→en        | 11.9  | 12.9| 14.1 | +1.2      | +2.2      |
| he→en        | 28.9  | 30.9| 33.7 | +2.8      | +4.8      |
| pt→en        | 24.8  | 27.0| 28.3 | +1.3      | +3.5      |
| ro→en        | 27.3  | 28.6| 30.6 | +2.0      | +3.3      |
| vi→en        | 19.9  | 22.8| 23.2 | +0.4      | +3.3      |
| nl→en        | 21.3  | 23.2| 24.6 | +1.4      | +3.3      |
| hu→en        | 19.3  | 20.1| 22.2 | +2.1      | +2.9      |
| fa→en        | 13.1  | 15.4| 17.0 | +1.6      | +3.9      |
| pl→en        | 20.0  | 20.7| 22.7 | +2.0      | +2.7      |
| de→en        | 13.7  | 16.8| 17.3 | +0.5      | +3.6      |
| el→en        | 22.2  | 25.3| 24.1 | -1.2      | +1.9      |
| sr→en        | 24.0  | 26.9| 25.7 | -1.2      | +1.7      |
| bg→en        | 23.8  | 25.6| 26.1 | +0.5      | +2.3      |
| uk→en        | 21.4  | 22.3| 22.4 | +0.1      | +1.0      |
| hr→en        | 23.6  | 27.0| 26.2 | -0.8      | +2.6      |
| cs→en        | 20.7  | 22.5| 23.3 | +0.8      | +2.6      |
| id→en        | 24.9  | 29.5| 28.8 | -0.7      | +3.9      |
| th→en        | 16.9  | 18.0| 18.9 | +0.9      | +2.0      |
| sv→en        | 17.7  | 19.6| 20.8 | +1.2      | +3.1      |
| sk→en        | 20.5  | 22.6| 22.7 | +0.1      | +2.2      |
| Average      | 19.9  | 21.8| 22.8 | +0.9      | +2.9      |

Table 11: BLEU score of many-to-one (M2O) translation on the OPUS test set.