Disentangling the Roles of Target-Side Transfer and Regularization in Multilingual Machine Translation

Yan Meng Christof Monz
Language Technology Lab
University of Amsterdam
{y.meng, c.monz}@uva.nl

Abstract

Multilingual Machine Translation (MMT) benefits from knowledge transfer across different language pairs. However, improvements in one-to-many translation compared to many-to-one translation are only marginal and sometimes even negligible. This performance discrepancy raises the question of to what extent positive transfer plays a role on the target-side for one-to-many MT. In this paper, we conduct a large-scale study that varies the auxiliary target-side languages along two dimensions, i.e., linguistic similarity and corpus size, to show the dynamic impact of knowledge transfer on the main language pairs. We show that linguistically similar auxiliary target languages exhibit strong ability to transfer positive knowledge. With an increasing size of similar target languages, the positive transfer is further enhanced to benefit the main language pairs. Meanwhile, we find distant auxiliary target languages can also unexpectedly benefit main language pairs, even with minimal positive transfer ability. Apart from transfer, we show distant auxiliary target languages can act as a regularizer to benefit translation performance by enhancing the generalization and model inference calibration.

1 Introduction

Multilingual Machine Translation (MMT) enables a single model to translate among multiple language pairs by joint training (Dong et al., 2015; Johnson et al., 2017). The improvements in translation quality, especially for low-resource languages, are generally attributed to transfer learning (Zoph et al., 2016; Lakew et al., 2018; Kocmi and Bojar, 2018; Stap et al., 2023). However, MMT suffers from a performance gap where the gains for one-to-many translation are not as substantial as for many-to-one translation (Dabre et al., 2020; Tang et al., 2020; Yang et al., 2021; Chiang et al., 2021; Chowdhery et al., 2022). Empirical studies (Johnson et al., 2017; Aharoni et al., 2019) also show little to no benefit for one-to-many translation compared to their bilingual baselines, leading to the hypothesis that positive transfer does not occur on the target-side (Arivazhagan et al., 2019).

The challenge of knowledge transfer for one-to-many translation is attributed to the inherent characteristics of translating into *distinct* target languages. The necessity for target language-specific representations in the translation process hinders knowledge transfer as transfer learning prefers language-invariant representations (Kudugunta et al., 2019). On the other hand, Arivazhagan et al. (2019) and Aharoni et al. (2019) list the increasing amounts of source language data and regularization induced by multiple target languages as possible reasons for the observed benefits in massively MMT scenarios.

Nevertheless, the extent to which positive knowledge transfer occurs on the target-side still remains unclear. Furthermore, a comprehensive analysis of the interplay between different factors, i.e., knowledge transfer, source data size, and regularization, for one-to-many translation is lacking. This hinders the optimization of MMT performance.

To understand the impact of knowledge transfer, we conduct comprehensive controlled experiments with varying target languages along two dimensions, i.e., linguistic similarity and corpus size. We select a set of bilingual out-of-English translation tasks, e.g., English into German, as main language pairs. Subsequently, we add different auxiliary target language pairs to each main language pair, considering variations in auxiliary language families, written scripts, data sizes, and the number of target languages. Our experimental results show a consistent positive correlation between the improvements and their translation task relatedness, i.e., increasing the amounts of similar target languages encourages more positive knowledge transfer for the main language pair than distant ones. These findings confirm the existence of knowledge transfer on the target-side and also clearly show factors

Proceedings of the 18th Conference of the European Chapter of the Association for Computational Linguistics Volume 1: Long Papers, pages 1828–1840
March 17-22, 2024

that influence target-side transfer, i.e., target data size, number of translation tasks, and linguistic similarity. The performance differences induced by various target languages also indicate their varying transfer ability.

Apart from knowledge transfer, we find distant auxiliary target languages can also yield substantial improvements, even with minimal transfer ability. Instead of transferring similar linguistic knowledge, we show that distant auxiliary target languages exhibit strong regularization abilities improving translation performance.To understand why language regularization plays a role, we show it benefits translation performance by reducing generalization errors and improving inference calibration. With introducing distant auxiliary target languages, the translation model is implicitly calibrated so that the confidences of its predictions are more aligned with the accuracies of its predictions.

In this paper, we show the interplay between knowledge transfer and regularization which is visualized in Figure 1. We observe that languages that are similar to the target language, in this example *Belarusian*, tend to benefit the target language by mostly transferring knowledge and only act as a regularizer to a very limited extent. The inverse holds for distant auxiliary languages. Overall, our paper provides a more comprehensive understanding of one-to-many translation, from the perspectives of target-side transfer and regularization. First, we show how positive knowledge transfer occurs on the target-side, by varying the linguistic similarity and data size of the auxiliary target language. Second, we point out the importance of regularization in one-to-many translation, by showing its effectiveness on generalization ability and inference confidence calibration.

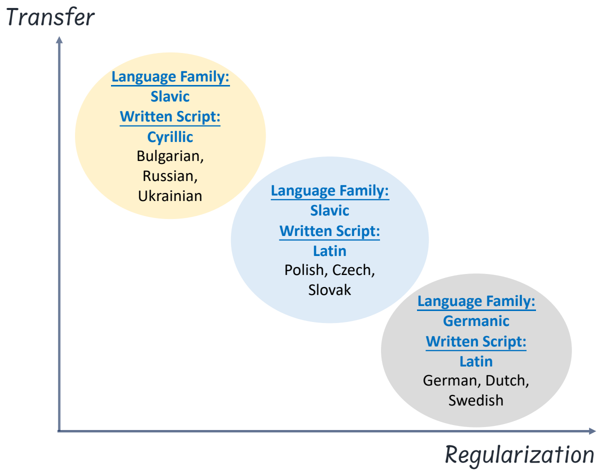


Figure 1: The interplay between knowledge transfer and regularization. For one example of main target language **Belarusian** (language family: Slavic, written script: Cyrillic) the level of knowledge transfer and regularization induced by different auxiliary target languages in MMT.

2 Background

In this section, we discuss some background on transfer learning and regularization in MMT.

2.1 Transfer Learning

Transfer learning is defined as improving a learner for a given task by leveraging information from a related task (Weiss et al., 2016). An example is seen in MMT, where training models on multiple language pairs benefits resource-poor languages by leveraging shared linguistic information and parameters from other languages (Zoph et al., 2016; Murthy et al., 2019).

However, for one-to-many machine translation, gains are much more pronounced for many-to-one than for one-to-many translation. This performance discrepancy is caused by the complexities of target-side transfer. Aharoni et al. (2019) empirically measure the difficulty of target-side transfer by showing the marginal benefits, even for low-resource language pairs, for large-scale one-to-many translation. Dabre et al. (2020) suggest that the reason behind this challenge is mainly due to its characteristics of representations on the decoder side, where each target language has an independent output distribution and the decoder representations are more sensitive to the target languages (Kudugunta et al., 2019). Wang et al. (2018) further supports this claim by keeping target language-specific parameters to improve one-to-many translation. This increases uncertainties on the effectiveness of transfer learning on the target-side, which in turn prefers language-invariant representations.

Despite prior work (Gao et al., 2020; Shaham et al., 2022) indicating that linguistic similarity matters for encouraging positive target-side transfer, their findings are limited to scenarios where knowledge is transferred from high-resource to low-resource. Fernandes et al. (2023) conversely shows that no impact of linguistic similarity on the translation performance for translating into two high-resource target languages, with an example of translating English into {French, Chinese} and English into {French, German}.

In summary, these studies show an inconsistent view towards target-side transfer, particularly concerning the issue whether target-side transfer exists and what factors influence it. This disagreement indicates the importance of exploring target-side transfer in one-to-many MT and the impact of different factors, e.g., linguistic similarity and target data size.

2.2 Regularization

The multilingual training regime is known as a source of regularization, improving the generalization abilities of the models (Neubig and Hu, 2018; Aharoni et al., 2019; Dabre et al., 2020). Aharoni et al. (2019) support this claim by showing that adding out-of-English translation tasks can lead to better results, as it prevents the model to overfit on the target side.

However, the effects of language regularization induced by multiple target tasks are underexplored, compared to other regularization techniques, such as dropout (Srivastava et al., 2014) and label smoothing (Szegedy et al., 2015). Dropout randomly selects activations to be set to zero during training. This randomness introduced by dropout encourages the network to learn robust and generalized representations (Liang et al., 2021). Another common regularization technique, label smoothing, regularizes the model by penalizing the output confidence. It has also been shown that these changes in output confidence introduced by label smoothing could implicitly enhance machine translation model calibration (Müller et al., 2019), thereby improving translation performance. In line with this, we aim to investigate language regularization in one-to-many translation to understand when and why it is effective.

3 Experimental Setting

Model. We follow the setup of the Transformer base model (Vaswani et al., 2017). More details on model hyperparameters can be found in Appendix B.

Data. We choose three main language pairs (LPs) in different language families and written scripts: English-into-German (En→De), English-into-Russian (En→Ru), and English-into-Spanish (En→Es). The training data for the main language pairs En→De, En→Ru, and En→Es are from WMT13, WMT14, and WMT22, respectively. We randomly sample 100K and 1M sentence pairs from each language pair respectively to mimic low- and medium-resource settings[1]. We also choose two real world low- and medium-resource language pairs: English-into-Belarusian (En→Be) and English-into-Sinhala (En→Si) from the OPUS repository.[2] For different controlled experiments, we cover 20 auxiliary target language pairs to train together with the main translation tasks. We randomly sample the auxiliary covered language pairs from CCMatrix. The detailed statistics of the main and auxiliary language pairs can be found in Appendix C.

ISO	Lang.	Family	Script
De	**German**	**Germanic**	**Latin**
Nl	Dutch	Germanic	Latin
Et	Estonia	Uralic	Latin
Ru	Russian	Slavic	Cyrillic
Zh	Mandarin	Chinese	Chinese
Es	**Spanish**	**Romance**	**Latin**
Pt	Portuguese	Romance	Latin
Nl	Dutch	Germanic	Latin
Ru	Russian	Slavic	Cyrillic
Zh	Mandarin	Chinese	Chinese
Ru	**Russian**	**Slavic**	**Cyrillic**
Uk	Ukrainian	Slavic	Cyrillic
Cs	Czech	Slavic	Latin
De	German	Germanic	Latin
Zh	Mandarin	Chinese	Chinese
Si	**Sinhala**	**Indo-Aryan**	**Sinhala**
Hi	Hindi	Indo-Aryan	Devanagari
Ur	Urdu	Indo-Aryan	Arabic
De	German	Germanic	Latin
Zh	Mandarin	Chinese	Chinese
Be	**Belarusian**	**Slavic**	**Cyrillic**
Ru	Russian	Slavic	Cyrillic
Pl	Polish	Slavic	Latin
De	German	Germanic	Latin
Zh	Mandarin	Chinese	Chinese

Table 1: Linguistic information for the main and auxiliary target languages. **Bold** designates the main target languages: De, Es, Ru, Si, and Be.

Training and Evaluation. We use the Fairseq (Ott et al., 2019) toolkit to train transformer models. All models are trained with the Adam optimizer (Kingma and Ba, 2017) for up to 100K steps, with a learning rate of 5e-4 and an inverse square root scheduler. A dropout rate of 0.3 and label smoothing of 0.2 are used. Each model is trained on one NVIDIA A6000 GPU with a batch size of 25K tokens. We choose the best checkpoint according to the average validation loss of all language pairs. The data

[1]Using high-resource LPs to mimic low/med-resource LPs helps compare the transfer and regularization levels induced from the same and other target languages.

[2]https://opus.nlpl.eu

En→De (Baseline: 7.4)						**En→De (Baseline: 20.0)**					
$\alpha\%$	en→de	en→nl	en→et	en→ru	en→zh	$\alpha\%$	en→de	en→nl	en→et	en→ru	en→zh
10%	$8.5_{0.4}$	$7.9_{0.7}$	$8.2_{0.6}$	$8.6_{0.5}$	$8.9_{0.8}$	1%	$20.0_{0.4}$	$20.2_{0.4}$	$20.5_{0.2}$	$20.7_{0.3}$	$20.8_{0.5}$
50%	$10.2_{0.3}$	$10.3_{0.6}$	$10.5_{0.6}$	$10.9_{0.3}$	$11.5_{0.4}$	10%	$20.3_{0.2}$	$21.0_{0.3}$	$20.7_{0.4}$	$21.2_{0.6}$	$21.8_{0.6}$
100%	$11.6_{0.4}$	$11.3_{0.4}$	$10.9_{0.2}$	$11.0_{0.4}$	$12.1_{0.2}$	50%	$22.1_{0.4}$	$21.6_{0.5}$	$21.3_{0.1}$	$21.2_{0.2}$	$21.6_{0.2}$
500%	$15.9_{0.3}$	$14.0_{0.2}$	$13.7_{0.3}$	$13.4_{0.2}$	$13.5_{0.3}$	100%	$23.4_{0.2}$	$22.2_{0.2}$	$21.2_{0.2}$	$21.0_{0.2}$	$21.2_{0.2}$
1000%	$19.9_{0.1}$	$16.2_{0.2}$	$15.3_{0.1}$	$14.1_{0.2}$	$14.2_{0.1}$	200%	$24.5_{0.1}$	$22.2_{0.0}$	$20.2_{0.0}$	$20.0_{0.0}$	$20.7_{0.0}$

En→Ru (Baseline: 11.9)						**En→Ru (Baseline: 18.4)**					
$\alpha\%$	en→ru	en→uk	en→cs	en→de	en→zh	$\alpha\%$	en→ru	en→uk	en→cs	en→de	en→zh
10%	$12.0_{0.4}$	$11.8_{0.6}$	$11.6_{0.6}$	$11.7_{0.2}$	$12.0_{0.4}$	1%	$18.1_{0.3}$	$18.6_{0.5}$	$18.7_{0.8}$	$18.7_{0.5}$	$18.9_{0.2}$
50%	$12.8_{0.3}$	$13.0_{0.5}$	$12.2_{0.2}$	$12.4_{0.3}$	$12.6_{0.1}$	10%	$18.6_{0.5}$	$18.9_{0.2}$	$19.1_{0.1}$	$18.9_{0.2}$	$19.1_{0.3}$
100%	$14.0_{0.2}$	$13.3_{0.3}$	$12.6_{0.1}$	$12.7_{0.2}$	$12.8_{0.4}$	50%	$19.5_{0.2}$	$19.3_{0.3}$	$18.8_{0.1}$	$18.4_{0.2}$	$18.7_{0.1}$
500%	$15.7_{0.2}$	$14.7_{0.2}$	$14.2_{0.1}$	$14.4_{0.2}$	$14.6_{0.1}$	100%	$20.1_{0.1}$	$19.5_{0.2}$	$19.1_{0.1}$	$18.6_{0.2}$	$18.2_{0.1}$
1000%	$18.6_{0.3}$	$15.4_{0.1}$	$14.7_{0.2}$	$14.6_{0.2}$	$14.3_{0.2}$	200%	$22.4_{0.1}$	$20.5_{0.0}$	$18.5_{0.0}$	$17.2_{0.0}$	$17.1_{0.0}$

En→Es (Baseline: 16.9)						**En→Es (Baseline: 28.6)**					
$\alpha\%$	en→es	en→pt	en→nl	en→ru	en→zh	$\alpha\%$	en→es	en→pt	en→nl	en→ru	en→zh
10%	$17.1_{0.2}$	$17.0_{0.4}$	$17.3_{0.6}$	$17.2_{0.3}$	$17.6_{0.8}$	1%	$28.6_{0.3}$	$28.6_{0.1}$	$28.7_{0.2}$	$28.8_{0.2}$	$28.7_{0.5}$
50%	$19.0_{0.2}$	$18.1_{0.3}$	$18.5_{0.6}$	$19.0_{0.2}$	$19.5_{0.3}$	10%	$29.4_{0.2}$	$29.0_{0.3}$	$29.1_{0.2}$	$29.3_{0.4}$	$29.2_{0.3}$
100%	$20.9_{0.4}$	$19.1_{0.3}$	$19.4_{0.3}$	$19.1_{0.3}$	$21.0_{0.2}$	50%	$29.9_{0.4}$	$29.2_{0.5}$	$29.4_{0.2}$	$29.4_{0.2}$	$29.4_{0.1}$
500%	$27.1_{0.3}$	$23.2_{0.2}$	$21.5_{0.3}$	$22.8_{0.3}$	$23.0_{0.2}$	100%	$30.5_{0.3}$	$29.5_{0.3}$	$29.2_{0.1}$	$29.0_{0.3}$	$29.2_{0.4}$
1000%	$29.4_{0.2}$	$25.2_{0.4}$	$23.2_{0.1}$	$22.4_{0.3}$	$22.2_{0.1}$	200%	$31.8_{0.2}$	$29.6_{0.0}$	$28.9_{0.0}$	$28.3_{0.0}$	$28.0_{0.0}$

Table 2: BLEU scores (variance in subscript) for the three main tasks: En→De, En→Es, and En→Ru in low-resource 100K (left) and medium-resource 1M (right) settings when training with different auxiliary language pairs. $\alpha\%$ represents the auxiliary training data size. For low-resource setting, $\alpha\%$ ranges from 10% to 1000% of the proportion of the low-resource setting size. For the medium-resource setting, $\alpha\%$ ranges from 1% to 200% of the proportion of the medium-resource setting size. The color block represents the extent of positive transfer, with darker shades indicating a stronger positive transfer effect.

is tokenized with the SentencePiece tool (Kudo and Richardson, 2018) and we build a shared vocabulary of 32K tokens. We add language ID tokens to the vocabulary and prepend the language ID token to each source and target sequence to indicate the target language (Johnson et al., 2017). For evaluation, we employ beam search decoding with a beam size of 5. BLEU scores are computed using detokenized case-sensitive SacreBLEU[3] (Post, 2018).

4 Target-Side Transfer

In this section, we aim to estimate empirically whether target-side transfer occurs in MMT. To achieve this, we select three main language pairs, mimicking a low-resource direction: En→De, En→Es, En→Ru and two main real-world low-resource pairs: En→Be and En→Si. We train each main language pair with different auxiliary target languages to investigate the target-side transfer in multilingual machine translation for influencing main language pairs. We include variations in the auxiliary target language pairs, with changes in linguistic similarity, data size, and the total number of target tasks.

4.1 Changes in Target Language

Here, we introduce different auxiliary target languages with variations in linguistic similarity and data size. The varying auxiliary target data size represents the true distribution of varied data in multilingual machine translation.

4.1.1 Setup

For each main language pair (En→X), we train it with an auxiliary language pair (En→Y) that differs in language family and written script. Table 1 presents the linguistic information about the main and auxiliary target languages. For the auxiliary target data, which is trained jointly with the main low-resource language pair, we vary its data size with a proportion from 10% to 1000% of the main low-resource language pair. For the auxiliary target data, trained jointly with the medium-resource setting, we vary its data size with a proportion from 1% to 200% of the main language pair. To mitigate the variance in the quality of sampled auxiliary target language pairs, we run the experiment

[3] nrefs:1|case:mixed|eff:no|tok:13a|smooth:exp|version:2.3.1

α%	en→ru	en→pl	en→de	en→zh
En→Be (Baseline: 5.0)				
10%	$5.3_{0.2}$	$5.1_{0.1}$	$4.2_{0.3}$	$4.3_{0.3}$
50%	$6.6_{0.1}$	$4.7_{0.3}$	$5.4_{0.3}$	$5.8_{0.2}$
100%	$8.3_{0.1}$	$5.4_{0.1}$	$6.2_{0.2}$	$7.0_{0.2}$
500%	$13.0_{0.3}$	$9.9_{0.3}$	$10.0_{0.4}$	$11.0_{0.2}$
1000%	$13.0_{0.1}$	$9.4_{0.3}$	$9.3_{0.2}$	$10.0_{0.3}$
En→Si (Baseline: 22.6)				
α%	en→hi	en→ur	en→de	en→zh
1%	$22.8_{0.2}$	$23.2_{0.1}$	$22.4_{0.3}$	$22.9_{0.4}$
10%	$23.2_{0.2}$	$22.4_{0.1}$	$23.9_{0.3}$	$24.0_{0.3}$
50%	$23.3_{0.2}$	$21.8_{0.1}$	$23.5_{0.4}$	$23.7_{0.3}$
100%	$23.9_{0.3}$	$21.6_{0.2}$	$23.1_{0.2}$	$23.4_{0.1}$
200%	$23.6_{0.0}$	$21.0_{0.0}$	$22.5_{0.0}$	$22.4_{0.0}$

Table 3: BLEU scores for the real-world low-resource English→Belarusian (67K) and medium-resource English→Sinhala (970K) from OPUS dataset.

with three different randomly sampled sets.[4] Table 2 and Table 3 show the averaged results of main mimic and real-world low- and medium-resource translation tasks when training with different target languages, along with the corresponding variance.

4.1.2 Discussion

First, we show positive knowledge transfer occurs on the target-side, which benefits low- and medium-resource language pairs. This positive target-side transfer is highly correlated with translation task relatedness, i.e., linguistic similarity. Specifically, for low- and medium-resource settings, see Table 2, increasing the amounts of similar target languages improves positive knowledge transfer for the main language pairs, i.e., 9 BLEU points boost for the low-resource En→De task when training with 1000% En→Nl. However, training with the same amounts of a distant target task cannot achieve similar improvements, such as En→Zh. This also holds for the real-world low-resource En→Be task, shown in Table 3. Increasing the size of a similar translation task, En→Ru induces more positive knowledge transfer than other language pairs. Furthermore, the varying performance for the main tasks when training with different target-side languages shows that increasing the amount of English source data (Arivazhagan et al., 2019) cannot be entirely confirmed as the sole reason for the improvements.

Second, we demonstrate that negative transfer also exists with increasing amounts of target data. For medium-resource settings, increasing the size of distant auxiliary languages gradually shows the negative transfer for medium-resource main language pairs. Training with 200% of English to Chinese data leads to approximately 1.5 BLEU points drop for medium-resource English to Russian. This still correlates with linguistic similarity where distant data results in more performance drops than similar ones. In line with Wang et al. (2019), the divergence between joint distributions of tasks is the root of the negative transfer.

Third, we find that the gains for low- or medium-resource tasks in one-to-many translation cannot be fully attributed to transfer learning. Distant target languages which exhibit minimal positive transfer ability can also greatly improve the translation performance of the main language pairs. This becomes more evident when using small amounts of distant auxiliary languages. In Table 2 (right), joint training with 10% distant language pairs can even lead to better translation performance for all main language tasks than using 10% of similar data. 10% of En→Zh data can even lead to an improvement of about 2 BLEU points for the En→De task in a medium-resource setting. In the real-world medium-resource En→Si task, training with 10% of distant data En→De or En→Zh can outperform the maximum positive transfer induced by 200% of similar language En→Hi. The gains resulting from the small size of distant auxiliary data show the role of language regularization, discussed in Section 5. By joint training with auxiliary low-resource target tasks, uncertainties are increased for the model to prevent over-fitting on the main tasks. Moreover, the unexpected benefits from distant auxiliary data on multilingual machine translation also encourages future work to exploit the role of distant data in other cross-lingual tasks.

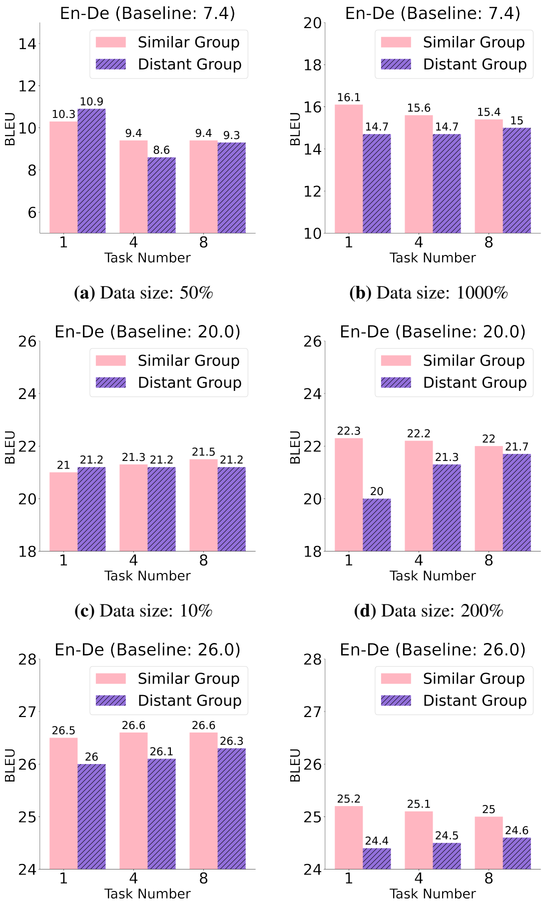
4.2 Changes in Task Number

To further validate the previous findings, we expand the scenario from training with a single target task to incorporating multiple tasks. We control the total amount of auxiliary training data to ensure a fair comparison.

4.2.1 Setup

We train the main translation task En→De for different resource levels with an increasing number of auxiliary target language pairs from two groups (Table 5 in Appendix A): (1) Similar group: the

[4] We use one random sample set for high-resource (2M) auxiliary data due to computational constraints.



(a) Data size: 50% **(b)** Data size: 1000%

(c) Data size: 10% **(d)** Data size: 200%

(e) Data size: 10% **(f)** Data size: 200%

Figure 2: Translation quality for En→De for a low-resource 100K (above), medium-resource 1M (middle) and high-resource 4.5M (below) language pair when training with different auxiliary task numbers and different linguistic groups. Data size represents the total amount of auxiliary target training data.

Germanic[5] language family with Latin scripts; (2) Distant group: the Slavic language family with Cyrillic scripts. The number of target language pairs is set as 1, 4, 8. The auxiliary target data size is evenly distributed among all target languages and controlled at 50% and 1000% for low-resource, and 10% and 200% for medium- and high-resource. Figure 2 shows the impact of task number when training with auxiliary tasks from different linguistic groups.

4.2.2 Discussion

We show that increasing the task number has little impact on target-side knowledge transfer, since our findings are similar for two tasks, see Section 4.1: (1) Positive transfer highly correlates with linguistic similarity when the auxiliary data size is large; (2) small distant auxiliary target data can also benefit the low- and medium-resource main tasks, which is attributed to regularization. Interestingly, for the medium-resource settings, increasing the auxiliary target task number from the large-size distant linguistic group (200%) can mitigate negative transfer to some extent. One possible explanation for this is that the negative training signal from one distant language pair becomes weaker when increasing the task number in controlled data size setting. This result also corroborates similar findings, where Shaham et al. (2022) find more than one unrelated language helps the translation task with less data.

In summary, Section 4 shows how target-side transfer occurs in one-to-many translation. Based on the empirical findings on main language pairs, we show that target-side transfer can transfer positive knowledge. Linguistic similarity and target data size mutually play a role in it. Meanwhile, we show that the increase in source data cannot be the sole reason for improving one-to-many translation due to the close correlation between translation performance and target data. Furthermore, we find that a small amount of distant auxiliary target languages can also improve translation performance. These gains cannot be fully attributed to target-side transfer, and we indicate another important factor, i.e., regularization, which is discussed in the next section.

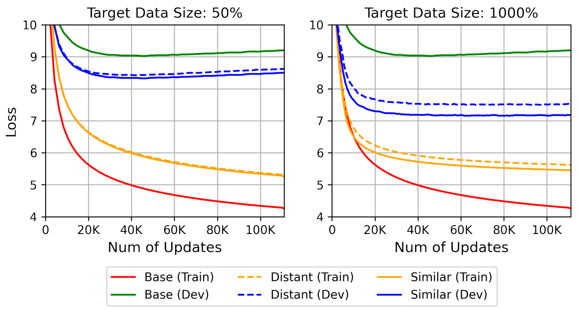
5 Language Regularization

The previous section shows low- and medium-resource translation tasks benefit from language regularization. In this section, we aim to further investigate the effectiveness of language regularization in one-to-many MT from two angles: generalization ability (Section 5.1) and model calibration (Section 5.2). In the end, we provide a simple but effective way to improve machine translation performance with the help of language regularization (Section 5.3).

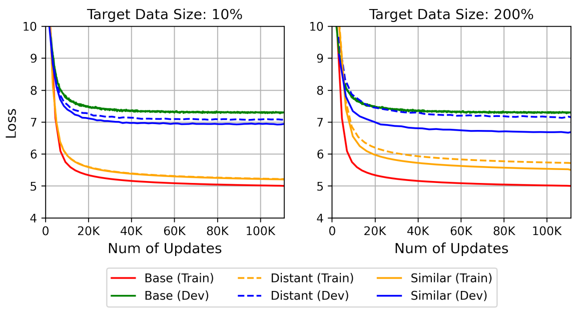
5.1 Reducing Generalization Errors

Reducing generalization errors is one of the benefits of regularization, which can be reflected by measuring the inconsistency between training and validation performance. Here, we show the regularization effects for one-to-many translation by comparing their learning curves for the training and validation losses.

[5]Due to data scarcity, we pick two target languages from the Romance language family, Galician, and Spanish. Romance and Germanic language families are close.

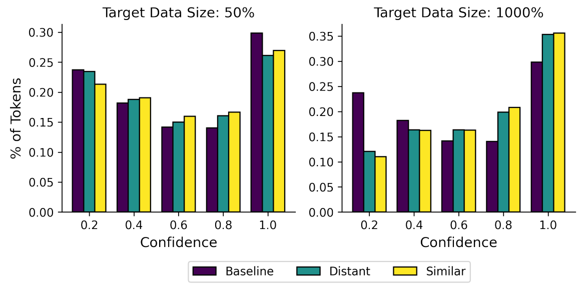


(a) En→De in Low-resource (100K)

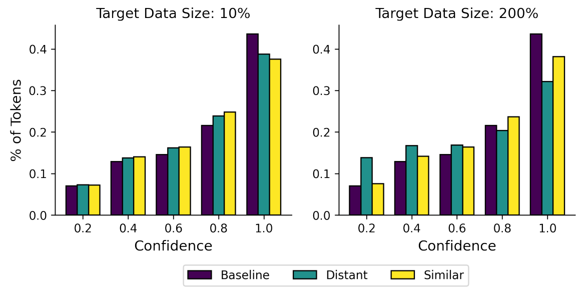


(b) En→De in Medium-resource (1M)

Figure 3: Loss curves for En→De translation tasks under low-resource 100K (a) and medium-resource 1M settings (b), with varying target linguistic groups (similar and distant) and varying auxiliary target data sizes.



(a) En→De in Low-resource (100K)



(b) En→De in Medium-resource (1M)

Figure 4: Confidence histograms for En→De translation tasks under low-resource (100K) (a) and mid-resource (1M) settings (b), with varying target linguistic groups (similar and distant) and total target data sizes.

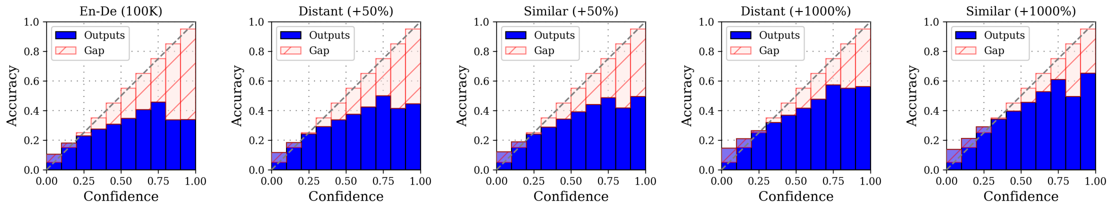
5.1.1 Setup

Different target languages have various levels of regularization effects. We vary the target data linguistic similarity and data size to investigate its impact on generalization ability. As we have shown in Section 4.1, low- and medium-resource main language pairs benefit from regularization. Thus, we choose the multilingual models trained on low- and medium-resource En→De tasks with two linguistic groups shown in Section 4.2. For the low-resource En→De setting (100K), we select the auxiliary target data size to be 50% and 1000% of the low-resource size. For the medium-resource En→De setting (1M), we select the target data size to be 10% and 200% of the medium-resource size. Figure 3 shows the learning curves En→De under different multilingual training settings.

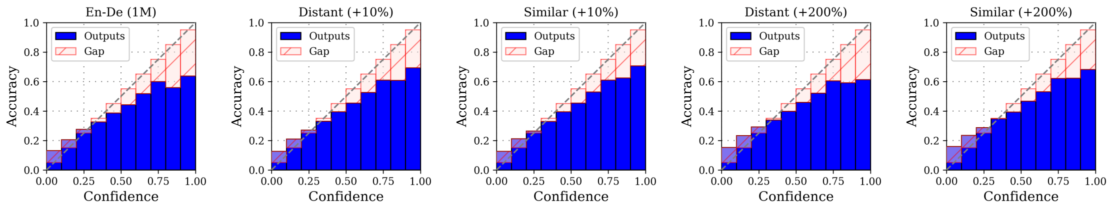
5.1.2 Discussion

First, regularization induced by the small size of auxiliary target tasks can reduce the generalization errors in one-to-many translation. Figure 3a shows that the baseline bilingual low-resource En→De model has a large gap between training and validation loss during training. This indicates that low-resource models can easily overfit and cannot generalize well to unseen data. When training with other target data, the generalization ability for the En→De task is improved at different levels. Surprisingly, 50% of distant auxiliary data can reduce the validation loss for the main low-resource En→De task. This observation aligns with our finding in Section 4.2 that distant auxiliary target languages benefit the main task performance. It confirms our hypothesis that regularization plays a crucial role by improving generalization ability.

Second, regularization effects from the large size of auxiliary target tasks can only reduce generalization errors for low-resource language pairs. Increasing the auxiliary target data size (+1000%) leads to better generalization ability for low-resource En→De, and the linguistically similar group shows slightly better effectiveness than the distant ones. This difference shows that positive target-side transfer also helps for better generalization ability since they exhibit a strong and transferable training signal for the main low-resource task. The same holds for the medium-resource En→De setting, see Figure 3b. However, when training with a large target data size (+200%), a distant linguistic group cannot further reduce generalization errors. This reflects that the role of regularization is not always positive, heavily depending on the target linguistic similarity level and the data size.



(a) InfECE=22.6 **(b)** InfECE=19.7 **(c)** InfECE=19.4 **(d)** InfECE=18.1 **(e)** InfECE=16.5



(f) InfECE=15.6 **(g)** InfECE=14.5 **(h)** InfECE=14.3 **(i)** InfECE=17.0 **(j)** InfECE=14.7

Figure 5: Reliability diagrams with inference calibration errors (InfECE) on the En→De test set in the low-resource (above) and medium-resource setting (below).

5.2 Improving Inference Calibration

Another benefit of regularization is to increase the model's uncertainty by penalizing output confidence, e.g., label smoothing. This regularization technique improves model calibration by making the confidence of its predictions more accurate for true accuracy (Müller et al., 2019). Wang et al. (2020) emphasizes the importance of calibrating confidence during inference for MT and regularization is a key factor. Motivated by these findings, we aim to investigate whether regularization induced by different target tasks has a similar impact on both output confidence and inference calibration.

In general, model calibration is measured by the expected calibration error (ECE) which calculates the difference in expectation between confidence and accuracy. As shown in Equation 5.2, ECE divides predictions into M bins $\{B_1, ..., B_M\}$ based on their confidence and calculates a weighted average of the bin's accuracy/confidence difference.[6]

$$ECE = \sum_{m=1}^{M} \frac{|B_m|}{N} |acc(B_m) - conf(B_m)| \quad (1)$$

In MT, the prediction target token is $\hat{y} = argmax_{y \in V} P(y)$ and the confidence is $P(\hat{y})$. The accuracy denotes whether the prediction $\hat{y}$ is correct. However, calculating the prediction accuracy during inference is challenging because it requires building complex alignments between generated tokens and the ground truth. Wang et al. (2020) propose using the Translation Error Rate metric (Snover et al., 2006) to determine the accuracy by measuring the number of edits to change a model output into the ground truth. We use their method to analyze inference calibration.

5.2.1 Setup

We examine the impact of regularization effects induced by different target data on the model's output confidence and inference calibration for the main En→De tasks. We calculate the output confidence histograms and inference calibration errors for the En→De test set with the same settings as for the multilingual models in Section 5.1.1. We plot the output confidence histograms in Figure 4 where the x-axis represents the output confidence scores and the y-axis represents the percentage of the number of tokens with those scores. In addition, we plot the reliability diagrams in Figure 5 to visualize the representations of model calibration where the x-axis is the average weighted confidence and the y-axis is the average weighted accuracy.

5.2.2 Discussion

First, regularization from the small size of auxiliary target tasks improves inference calibration by penalizing output confidence. For example, the main low-resource En→De translation task shows an over-confidence issue for its bilingual baseline model, see Figure 5a. The model seriously suffers from miscalibration, where the average gaps between confidence and accuracy are large (confidence > accuracy). Training with different target tasks could alleviate this issue at various lev-

[6] N is the number of prediction samples and $|B_m|$ is the number of samples in the m-th bin

Main Task	Auxiliary Task	BLEU	△
	En→De	28.4	-0.2
En→De	En→Nl	28.3	-0.3
	En→Zh	29.0	+0.6

Table 4: The main task of En→De BLEU scores with using larger model by adding 10% auxiliary tasks; △ represents the BLEU changes with the En→De baseline.

els. The small size of distant auxiliary target tasks can lead to better inference calibration. This regularization effect is achieved by penalizing over-confidence output (> 0.9) to enhance the model inference calibration, as shown in Figure 4a. These findings also align well with the medium-resource setting (1M). The relatively small size of auxiliary target tasks (10%) benefits inference calibration from penalizing over-confident output, as shown in Figure 4b.

Second, regularization in the large-size auxiliary target tasks improves inference calibration by improving translation accuracy. Unlike in the small data (50%) scenario, which penalizes over-confident output probabilities to benefit the task, training with a large size of auxiliary target language pairs mainly helps the low-resource En→De task improve translation accuracy to benefit inference calibration. Since similar language pairs share similar lexical and word order knowledge with the low-resource En→De task, they improve accuracy more effectively.

5.3 Regularization Effect in Larger Models

Sections 5.1 and 5.2 show that utilizing small distant auxiliary data can prevent overfitting translation models by regularization, particularly for low- and medium-resource language pairs. To further verify the impact of language regularization at a larger scale, we increase the model size from Transformer-Base (93M parameters) to Big (274M parameters) and utilize 10% of different auxiliary data to train with a high-resource En→De (4.5M) translation task[7]. Table 4 shows that 10% of distant auxiliary data En→Zh can help improve the bilingual baseline while adding the same target languages or similar ones cannot. This finding further shows the effectiveness of language regularization for optimizing machine translation performance.

[7]https://www.statmt.org/wmt14

6 Conclusion

In this work, we disentangle the roles of knowledge transfer and language regularization in one-to-many MMT. In contrast to previously held assumptions, we show that target-side knowledge transfer *does* play an important role in one-to-many MMT, influenced by several dominant factors: auxiliary target data size, linguistic similarity, and the number of auxiliary target tasks. This finding also shows that the increased amount of source data *does not* explain all transfer. Future work can leverage this information to encourage different language pairs to have similar word representations to achieve maximum positive transfer. Surprisingly, we find that using a small amount of linguistically distant auxiliary target data acts as an effective regularizer resulting in translation performance gains. This form of language regularization shows its effectiveness by benefiting generalization ability and inference calibration. Our findings on language regularization provide a simple but effective way to boost the translation performance of real-world low- and medium-resource language pairs, especially when similar target languages are not available. Future work can further explore the optimization of multilingual training by leveraging distant auxiliary data.

Limitations

We acknowledge several limitations in our work. To directly understand the impact of knowledge transfer, source data, and regularization in one-to-many translation, we only observe the performance changes for one selected main language pair. Although translation results for auxiliary language pairs are provided in Appendix D, further analysis of the dynamic performance trade-off between main and auxiliary language pairs is worthwhile to explore. Another limitation of our work is about the MMT setting, where we only work in one-to-many MT, while future work should extend it to many-to-many settings and explore the impact of adding multiple source languages.

Acknowledgments

This research was funded in part by the Netherlands Organization for Scientific Research (NWO) under project number VI.C.192.080. We would like to thank Di Wu, Shaomu Tan, David Stap, Wafaa Mohammed and Baohao Liao for their useful feedback and discussion. We would also like to thank the reviewers for their feedback. Yan Meng also thanks Yuheng Huo for encouragement and inspiration.

References

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, Dmitry Lepikhin, Melvin Johnson, Maxim Krikun, Mia Xu Chen, Yuan Cao, George F. Foster, Colin Cherry, Wolfgang Macherey, Zhifeng Chen, and Yonghui Wu. 2019. Massively multilingual neural machine translation in the wild: Findings and challenges. *CoRR*, abs/1907.05019.

Ting-Rui Chiang, Yi-Pei Chen, Yi-Ting Yeh, and Graham Neubig. 2021. Breaking down multilingual machine translation. In *Findings*.

Aakanksha Chowdhery, Sharan Narang, Jacob Devlin, Maarten Bosma, Gaurav Mishra, Adam Roberts, Paul Barham, Hyung Won Chung, Charles Sutton, Sebastian Gehrmann, Parker Schuh, Kensen Shi, Sasha Tsvyashchenko, Joshua Maynez, Abhishek Rao, Parker Barnes, Yi Tay, Noam M. Shazeer, Vinodkumar Prabhakaran, Emily Reif, Nan Du, Benton C. Hutchinson, Reiner Pope, James Bradbury, Jacob Austin, Michael Isard, Guy Gur-Ari, Pengcheng Yin, Toju Duke, Anselm Levskaya, Sanjay Ghemawat, Sunipa Dev, Henryk Michalewski, Xavier García, Vedant Misra, Kevin Robinson, Liam Fedus, Denny Zhou, Daphne Ippolito, David Luan, Hyeontaek Lim, Barret Zoph, Alexander Spiridonov, Ryan Sepassi, David Dohan, Shivani Agrawal, Mark Omernick, Andrew M. Dai, Thanumalayan Sankaranarayana Pillai, Marie Pellat, Aitor Lewkowycz, Erica Moreira, Rewon Child, Oleksandr Polozov, Katherine Lee, Zongwei Zhou, Xuezhi Wang, Brennan Saeta, Mark Díaz, Orhan Firat, Michele Catasta, Jason Wei, Kathleen S. Meier-Hellstern, Douglas Eck, Jeff Dean, Slav Petrov, and Noah Fiedel. 2022. Palm: Scaling language modeling with pathways. *ArXiv*, abs/2204.02311.

Raj Dabre, Chenhui Chu, and Anoop Kunchukuttan. 2020. A comprehensive survey of multilingual neural machine translation. *ArXiv*, abs/2001.01115.

Daxiang Dong, Hua Wu, Wei He, Dianhai Yu, and Haifeng Wang. 2015. Multi-task learning for multiple language translation. In *Proceedings of the 53rd Annual Meeting of the Association for Computational Linguistics and the 7th International Joint Conference on Natural Language Processing (Volume 1: Long Papers)*, pages 1723–1732, Beijing, China. Association for Computational Linguistics.

Patrick Fernandes, B. Ghorbani, Xavier García, Markus Freitag, and Orhan Firat. 2023. Scaling laws for multilingual neural machine translation. *ArXiv*, abs/2302.09650.

Luyu Gao, Xinyi Wang, and Graham Neubig. 2020. Improving target-side lexical transfer in multilingual neural machine translation. In *Findings of the Association for Computational Linguistics: EMNLP 2020*, pages 3560–3566, Online. Association for Computational Linguistics.

Melvin Johnson, Mike Schuster, Quoc V. Le, Maxim Krikun, Yonghui Wu, Zhifeng Chen, Nikhil Thorat, Fernanda Viégas, Martin Wattenberg, Greg Corrado, Macduff Hughes, and Jeffrey Dean. 2017. Google's multilingual neural machine translation system: Enabling zero-shot translation. *Transactions of the Association for Computational Linguistics*, 5:339–351.

Diederik P. Kingma and Jimmy Ba. 2017. Adam: A method for stochastic optimization.

Tom Kocmi and Ondřej Bojar. 2018. Trivial transfer learning for low-resource neural machine translation. In *Proceedings of the Third Conference on Machine Translation: Research Papers*, pages 244–252, Brussels, Belgium. Association for Computational Linguistics.

Taku Kudo and John Richardson. 2018. Sentencepiece: A simple and language independent subword tokenizer and detokenizer for neural text processing.

Sneha Kudugunta, Ankur Bapna, Isaac Caswell, and Orhan Firat. 2019. Investigating multilingual NMT representations at scale. 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 1565–1575, Hong Kong, China. Association for Computational Linguistics.

Surafel Melaku Lakew, Aliia Erofeeva, Matteo Negri, Marcello Federico, and Marco Turchi. 2018. Transfer learning in multilingual neural machine translation with dynamic vocabulary. In *International Workshop on Spoken Language Translation*.

Xiaobo Liang, Lijun Wu, Juntao Li, Yue Wang, Qi Meng, Tao Qin, Wei Chen, M. Zhang, and Tie-Yan Liu. 2021. R-drop: Regularized dropout for neural networks. *ArXiv*, abs/2106.14448.

Rafael Müller, Simon Kornblith, and Geoffrey E. Hinton. 2019. When does label smoothing help? In *Neural Information Processing Systems*.

Rudra Murthy, Anoop Kunchukuttan, and Pushpak Bhattacharyya. 2019. Addressing word-order divergence in multilingual neural machine translation for extremely low resource languages. 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 3868–3873, Minneapolis, Minnesota. Association for Computational Linguistics.

Graham Neubig and Junjie Hu. 2018. Rapid adaptation of neural machine translation to new languages. In *Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing*, pages 875–880, Brussels, Belgium. Association for Computational Linguistics.

Myle Ott, Sergey Edunov, Alexei Baevski, Angela Fan, Sam Gross, Nathan Ng, David Grangier, and Michael Auli. 2019. fairseq: A fast, extensible toolkit for sequence modeling. In *Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics (Demonstrations)*, pages 48–53, Minneapolis, Minnesota. Association for Computational Linguistics.

Matt Post. 2018. A call for clarity in reporting BLEU scores. In *Proceedings of the Third Conference on Machine Translation: Research Papers*, pages 186–191, Brussels, Belgium. Association for Computational Linguistics.

Uri Shaham, Maha Elbayad, Vedanuj Goswami, Omer Levy, and Shruti Bhosale. 2022. Causes and cures for interference in multilingual translation. *ArXiv*, abs/2212.07530.

Matthew Snover, Bonnie Dorr, Rich Schwartz, Linnea Micciulla, and John Makhoul. 2006. A study of translation edit rate with targeted human annotation. In *Proceedings of the 7th Conference of the Association for Machine Translation in the Americas: Technical Papers*, pages 223–231, Cambridge, Massachusetts, USA. Association for Machine Translation in the Americas.

Nitish Srivastava, Geoffrey Hinton, Alex Krizhevsky, Ilya Sutskever, and Ruslan Salakhutdinov. 2014. Dropout: A simple way to prevent neural networks from overfitting. *J. Mach. Learn. Res.*, 15(1):1929–1958.

David Stap, Vlad Niculae, and Christof Monz. 2023. Viewing knowledge transfer in multilingual machine translation through a representational lens. *ArXiv*, abs/2305.11550.

Christian Szegedy, Vincent Vanhoucke, Sergey Ioffe, Jonathon Shlens, and Zbigniew Wojna. 2015. Rethinking the inception architecture for computer vision. *2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, pages 2818–2826.

Y. Tang, C. Tran, Xian Li, Peng-Jen Chen, Naman Goyal, Vishrav Chaudhary, Jiatao Gu, and Angela Fan. 2020. Multilingual translation with extensible multilingual pretraining and finetuning. *ArXiv*, abs/2008.00401.

Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N Gomez, Ł ukasz Kaiser, and Illia Polosukhin. 2017. Attention is all you need. In *Advances in Neural Information Processing Systems*, volume 30. Curran Associates, Inc.

Shuo Wang, Zhaopeng Tu, Shuming Shi, and Yang Liu. 2020. On the inference calibration of neural machine translation. In *Annual Meeting of the Association for Computational Linguistics*.

Yining Wang, Jiajun Zhang, Feifei Zhai, Jingfang Xu, and Chengqing Zong. 2018. Three strategies to improve one-to-many multilingual translation. In *Conference on Empirical Methods in Natural Language Processing*.

Zirui Wang, Zihang Dai, Barnabás Póczos, and Jaime Carbonell. 2019. Characterizing and avoiding negative transfer. In *2019 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, pages 11285–11294.

Karl Weiss, Taghi M. Khoshgoftaar, and DingDing Wang. 2016. A survey of transfer learning. *Journal of Big Data*, 3(1):9.

Yilin Yang, Akiko Eriguchi, Alexandre Muzio, Prasad Tadepalli, Stefan Lee, and Hany Hassan. 2021. Improving multilingual translation by representation and gradient regularization. *ArXiv*, abs/2109.04778.

Barret Zoph, Deniz Yuret, Jonathan May, and Kevin Knight. 2016. Transfer learning for low-resource neural machine translation. In *Proceedings of the 2016 Conference on Empirical Methods in Natural Language Processing*, pages 1568–1575, Austin, Texas. Association for Computational Linguistics.

A Language Choices

Table 5 shows two linguistic groups trained with the main language pair.

ISO	Lang.	Family	Script	ISO	Lang.	Family	Script
Af	Afrikaans	Germanic	Latin	Bg	Bulgarian	Slavic	Cyrillic
Da	Danish	Germanic	Latin	Cs	Czech	Slavic	Cyrillic
Nl	Dutch	Germanic	Latin	Mk	Macedonian	Slavic	Cyrillic
Is	Icelandic	Germanic	Latin	Pl	Polish	Slavic	Cyrillic
No	Norwegian	Germanic	Latin	Sr	Serbian	Slavic	Cyrillic
Sv	Swedish	Germanic	Latin	Sk	Slovak	Slavic	Cyrillic
Gl	Galician	Romance	Latin	Sl	Slovenian	Slavic	Cyrillic
Es	Spanish	Romance	Latin	Uk	Ukrainia	Slavic	Cyrillic

Table 5: Two groups of auxiliary target languages.

B Model Parameters

We follow the setup of the Transformer-base and Transformer-big models (Vaswani et al., 2017). For each model, the number of layers in the encoder and in the decoder is $N = 6$. For Transformer-base, we employ $h = 8$ parallel attention layers or heads. The dimensionality of input and output is $d_model = 512$, and the inner layer of feed-forward networks has dimensionality $d_{ff} = 2048$. For Transformer-big, we employ $h = 16$ parallel attention layers or heads. The dimensionality of input and output is $d_model = 1024$, and the inner layer of feed-forward networks has dimensionality $d_{ff} = 4096$.

C Dataset Statistics

The data statistics of mimic and real-world main language pairs are shown in Table 6 and Table 7. The data statistics of joint training target language pairs are shown in Table 8.

Language	ISO	Dataset Source	Validation Set	Test Set
German	De	WMT14	WMT14	WMT14
Spanish	Es	WMT13	WMT13	WMT13
Russian	Ru	WMT22	WMT22	WMT22

Table 6: The data statistics of main low- and medium-resource language pairs. For each language, we display the ISO code, language name, sampled training dataset source, validation set, and test set. Sampled training low-resource dataset size: 100K, sampled training medium-resource dataset size: 1M.

D Additional Results

Here, we show all auxiliary language BLEU scores in Table 9 and 10.

Language	ISO	Dataset Source	Validation Set	Test Set
Sinhala	Si	OPUS	OPUS	OPUS
Belarusian	Be	OPUS	OPUS	OPUS

Table 7: The data statistics of real-world main low- and medium-resource language pairs. For each language, we display the ISO code, language name, sampled training dataset source, validation set, and test set. Training size for En-Si: 979109, for En-Be: 67312.

Language	ISO	Dataset Source	Validation/Test Set
Estonia	Et	CCMatrix	CCMatrix
Chinese	Zh	CCMatrix	CCMatrix
Portuguese	Pt	CCMatrix	CCMatrix
Ukrainian	Uk	CCMatrix	CCMatrix
Czech	Cs	CCMatrix	CCMatrix
Dutch	Nl	CCMatrix	CCMatrix
Afrikaans	Af	CCMatrix	CCMatrix
Danish	Da	CCMatrix	CCMatrix
Icelandic	Is	CCMatrix	CCMatrix
Norwegian	No	CCMatrix	CCMatrix
Swedish	Sw	CCMatrix	CCMatrix
Galician	Gl	CCMatrix	CCMatrix
Bulgarian	Bg	CCMatrix	CCMatrix
Macedonian	Mk	CCMatrix	CCMatrix
Polish	Pl	CCMatrix	CCMatrix
Serbian	Sr	CCMatrix	CCMatrix
Slovak	Sk	CCMatrix	CCMatrix
Slovenian	Sl	CCMatrix	CCMatrix

Table 8: The data statistics of auxiliary training target language pairs. For each language, we display the ISO code, language name, sampled training dataset source, and validation set. The validation and test sets from CCMatrix, are randomly sampled from the CCMatrix corpus, each containing 2000 samples.

En→De				
$\alpha\%$	en→nl	en→et	en→ru	en→zh
10%	$8.9_{0.2}$	$6.2_{0.7}$	$6.0_{0.6}$	$5.5_{0.5}$
50%	$11.9_{0.2}$	$11.2_{0.3}$	$10.2_{0.3}$	$9.8_{0.3}$
100%	$20.3_{0.2}$	$11.9_{0.4}$	$13.7_{0.2}$	$12.3_{0.4}$
500%	$23.7_{0.3}$	$14.3_{0.1}$	$17.6_{0.3}$	$15.6_{0.2}$
1000%	$26.4_{0.2}$	$15.3_{0.5}$	$18.5_{0.1}$	$16.7_{0.3}$
En→Ru				
$\alpha\%$	en→uk	en→cs	en→de	en→zh
10%	$8.8_{0.6}$	$7.6_{0.6}$	$7.8_{0.2}$	$5.0_{0.2}$
50%	$15.0_{0.5}$	$12.2_{0.2}$	$10.2_{0.3}$	$9.3_{0.1}$
100%	$18.3_{0.3}$	$12.6_{0.1}$	$11.0_{0.2}$	$12.5_{0.4}$
500%	$22.7_{0.2}$	$14.2_{0.1}$	$16.8_{0.2}$	$15.1_{0.1}$
1000%	$23.4_{0.1}$	$14.7_{0.2}$	$18.9_{0.2}$	$16.2_{0.2}$
En→Es				
$\alpha\%$	en→pt	en→nl	en→ru	en→zh
10%	$9.2_{0.4}$	$8.6_{0.6}$	$6.2_{0.3}$	$5.1_{0.8}$
50%	$12.3_{0.3}$	$11.3_{0.6}$	$10.0_{0.2}$	$9.2_{0.3}$
100%	$20.5_{0.3}$	$15.2_{0.3}$	$11.5_{0.3}$	$12.5_{0.2}$
500%	$23.2_{0.2}$	$18.2_{0.3}$	$16.5_{0.3}$	$15.6_{0.2}$
1000%	$26.2_{0.4}$	$19.6_{0.1}$	$18.6_{0.3}$	$16.4_{0.1}$

Table 9: BLEU scores for the auxiliary language pairs in a low-resource setting (100K) when training with main language pairs: En→De, En→Es, and En→Ru. $\alpha\% = 10, 50, 100, 500, 1000$ represents the proportion of the low-resource setting size.

En→De				
$\alpha\%$	en→nl	en→et	en→ru	en→zh
1%	$12.6_{0.2}$	$7.0_{0.7}$	$7.0_{0.6}$	$6.7_{0.5}$
10%	$22.7_{0.2}$	$12.3_{0.3}$	$12.7_{0.3}$	$13.5_{0.3}$
50%	$25.5_{0.2}$	$16.0_{0.4}$	$17.8_{0.2}$	$16.7_{0.4}$
100%	$28.4_{0.3}$	$16.5_{0.1}$	$18.2_{0.3}$	$16.5_{0.2}$
200%	$29.4_{0.0}$	$15.0_{0.0}$	$18.1_{0.0}$	$16.4_{0.0}$
En→Ru				
$\alpha\%$	en→uk	en→cs	en→de	en→zh
1%	$13.8_{0.6}$	$8.2_{0.6}$	$7.0_{0.2}$	$5.8_{0.2}$
10%	$18.0_{0.5}$	$11.2_{0.2}$	$12.5_{0.3}$	$12.3_{0.1}$
50%	$20.3_{0.3}$	$12.6_{0.1}$	$16.0_{0.2}$	$16.5_{0.4}$
100%	$23.7_{0.2}$	$15.2_{0.1}$	$17.8_{0.2}$	$16.1_{0.1}$
200%	$26.4_{0.0}$	$16.7_{0.0}$	$19.9_{0.0}$	$16.2_{0.0}$
En→Es				
$\alpha\%$	en→pt	en→nl	en→ru	en→zh
1%	$12.2_{0.4}$	$10.6_{0.6}$	$7.2_{0.3}$	$6.1_{0.8}$
10%	$19.3_{0.3}$	$12.3_{0.6}$	$13.0_{0.2}$	$14.2_{0.3}$
50%	$22.5_{0.3}$	$19.2_{0.3}$	$17.5_{0.3}$	$16.5_{0.2}$
100%	$27.2_{0.2}$	$20.2_{0.3}$	$18.5_{0.3}$	$16.6_{0.2}$
200%	$28.2_{0.0}$	$20.2_{0.0}$	$18.6_{0.0}$	$16.0_{0.0}$

Table 10: BLEU scores for the auxiliary language pairs in a mid-resource setting (1M) when training with main language pairs: En→De, En→Es, and En→Ru. $\alpha\% = 1, 10, 50, 100, 200$ represents the proportion of the medium-resource setting size.