An Empirical Investigation of Multi-bridge Multilingual NMT models

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Abstract
In this paper, we present an extensive investigation of multi-bridge, many-to-many multilingual NMT models (MB-M2M) i.e., models trained on non-English language pairs in addition to English-centric language pairs. In addition to validating previous work which shows that MB-MNMT models can overcome zeroshot translation problems, our analysis reveals the following results about multibridge models: (1) it is possible to extract a reasonable amount of parallel corpora between non-English languages for low-resource languages (2) with limited non-English centric data, MB-M2M models are competitive with or outperform pivot models, (3) MB-M2M models can outperform English-Any models and perform at par with Any-English models, so a single multilingual NMT system can serve all translation directions.

Introduction
Neural Machine Translation has led to significant advances in MT quality in recent times (Bahdanau, Cho, and Bengio 2015; Wu et al. 2016; Sennrich, Haddow, and Birch 2016). MT research has seen significant efforts in translation between English and other languages, driven in significant measure by availability of English-centric parallel corpora. Particularly, multilingual NMT models using English-centric parallel corpora have shown significant improvements for translation between English and low-resource languages (Firat, Cho, and Bengio 2016; Johnson et al. 2017). Translation between non-English languages has received lesser attention, with the default approach being pivot translation (Lakew et al. 2017). Pivot translation is a strong baseline, but needs multiple decoding steps resulting in increased latency and cascading errors.

Zeroshot translation using English-centric many-to-many multilingual models (EC-M2M) (Johnson et al. 2017) is promising, but is plagued by problems of spurious correlations between input and output language (Gu et al. 2019; Arivazhagan et al. 2019). Hence, vanilla zeroshot translation quality significantly lags behind pivot translation. Various methods have been proposed to address these limitations by aligning encoder representations (Arivazhagan et al. 2019).

Recently, there has been interest in multi-bridge many-to-many multilingual models (MB-M2M, referred to as multi-bridge models henceforth). These models are trained on direct parallel corpora between non-English languages in addition to English-centric corpora (Rios, Müller, and Sennrich 2020; Freitag and Firat 2020; Fan et al. 2020). Such corpora can either be mined from monolingual corpora (Fan et al. 2020) using bitext mining approaches like LASER (Artetxe and Schwenk 2019) and LABSE (Feng et al. 2020) or extracted from English-centric parallel corpora (Rios, Müller, and Sennrich 2020; Freitag and Firat 2020). These works show that multi-bridge models can overcome zeroshot translation problems and perform at par/better than pivot approaches. In addition, models using separate encoders and decoders for one or more language(s) are feasible with such parallel corpora helping build modular multilingual NMT systems with modest model capacity that can be incrementally trained (Escolano et al. 2021; Lyu et al. 2020).

In this paper, we undertake an extensive analysis of MB-M2M models to understand design choices for building improved multilingual NMT models. We focus on models trained using non-English corpora mined from English-centric corpora. The following are the major contributions of our work:

• An investigation of various sampling strategies reveals that only a limited amount of non-English parallel training data is required for improving upon pivot translation with increased non-English parallel data yielding limited gains.

• We observe that under the proposed data sampling strategy, the MB-M2M models can outperform English-centric many-to-one and one-to-many models in any-English and English-any directions respectively. Particularly, we observe significant gains for the challenging problem of multilingual translation from English into other languages (Dabre, Chu, and Kunchukuttan 2020). Finetuning the multi-bridge models for particular directions does not result in a significant improvement.

• While MB-M2M models show improved translation between non-English languages, we observe that there
| en | bn | gu | hi | kn | ml | mr | or | pa | ta | te |
|---|---|---|---|---|---|---|---|---|---|---|
| 960 | 0 | 264 | 819 | 221 | 1,396 | 264 | 58 | 274 | 500 | 218 |
| 500 | 264 | 0 | 390 | 289 | 297 | 303 | 58 | 326 | 320 | 218 |
| 2,553 | 819 | 390 | 0 | 345 | 925 | 407 | 153 | 432 | 789 | 314 |
| 382 | 221 | 289 | 345 | 0 | 319 | 297 | 45 | 268 | 277 | 232 |
| 1,018 | 1,396 | 297 | 925 | 319 | 0 | 310 | 45 | 288 | 300 | 243 |
| 479 | 264 | 303 | 407 | 297 | 310 | 0 | 71 | 288 | 300 | 243 |
| 180 | 58 | 58 | 153 | 26 | 45 | 71 | 0 | 76 | 79 | 39 |
| 496 | 274 | 326 | 432 | 268 | 295 | 288 | 76 | 0 | 356 | 208 |
| 1,207 | 500 | 320 | 789 | 277 | 588 | 300 | 79 | 356 | 0 | 231 |
| 352 | 218 | 219 | 314 | 232 | 277 | 243 | 39 | 208 | 231 | 0 |

SUM 8,127 4,014 2,466 4,574 2,274 4,452 2,483 605 2,523 3,440 1,981 28,812

**Table 1:** Statistics of the WAT 2021 dataset used in the experiments: English-centric and extracted non-English centric. All figures in 1000s of sentences

| Model | bn | gu | hi | kn | ml | mr | or | pa | ta | te | AVG |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Zeroshot | 0.4 | 0.3 | 0.3 | 0.5 | 0.6 | 0.3 | 0.2 | 0.6 | 0.4 | 0.4 | 0.4 |
| Pivot | 12.7 | 18.7 | 27.0 | 13.8 | 10.7 | 15.1 | 14.4 | 24.3 | 10.2 | 12.5 | 15.9 |
| SamplePairs | 13.0 | 19.9 | 29.5 | 13.9 | 10.4 | 15.5 | 15.1 | 26.7 | 10.7 | 12.6 | 16.7 |
| SampleFraction | 12.8 | 20.3 | 30.5 | 13.9 | 10.4 | 15.8 | 15.7 | 27.1 | 10.8 | 12.8 | 17.0 |
| TrainAll | 12.5 | 20.2 | 30.2 | 14.1 | 10.5 | 15.5 | 15.6 | 26.9 | 10.7 | 12.7 | 16.9 |

**Table 2:** Results for translation between non-English languages. Each cell shows the average BLEU score for translating into corresponding language. The last column shows the micro-averaged BLEU score for the model.

is a significant quality gap compared to translation in English-centric directions - pointing to the need for further research to address the gap.

- **Our experiments involve English and 10 Indian languages, unlike previous work which focussed on high-resource European languages. We show that it is possible to extract a significant amount of non-English parallel corpora from the English-centric corpora even for these low-resource languages - indicating the feasibility of this extraction approach for low-resource languages as well.**

The rest of the paper is organized as follows. Section describes our experimental settings. Section describes the research questions we explore. discusses the results of our experiments. concludes the paper.

**Experiment Design**

**Extracting non-English centric corpora**

The parallel corpora between non-English languages is extracted from the English-centric parallel corpus using English as a pivot language. For languages $l_1$, $l_2$ and $e$ ($e$ being English and $l_1$, $l_2$ being non-English languages), given the sentence pairs $(s_{l_1}, s_e)$ and $(s_{l_2}, s_e)$, we mine all sentence pairs $(s_{l_1}, s_{l_2})$ which are parallel to the English sentence $s_e$.

In this work, we used the WAT 2021 MultiIndicMT shared task dataset[1] (Nakazawa et al. 2021) containing parallel corpora from various sources between English and 10 Indian languages. From around 8.1m English-centric parallel corpora, we extract 14.3m sentence pairs between Indic languages. The statistics of the English-centric training set and extracted Indic parallel corpora are shown in Table 1. This shows that a reasonable amount of parallel corpus can be mined between low-resources languages too from English-centric parallel corpora.

**Multi-bridge Model**

We train a single multilingual model using data from English-X, X-English and X-Y language pairs using the multilingual model proposed by Johnson et al. (2017). The input sequence contains a special token indicating the target language. We also include a special token to indicate the source language (Tan et al. 2019; Tang et al. 2020), allowing the model to utilize the source language tag as well as the similarity of encoder representations for transfer learning. We use a subword vocabulary size of 32K. We use transformer_vaswani_vmt_en_de_big architecture as defined

[1]http://lotus.kuee.kyoto-u.ac.jp/WAT/indic-multilingual
Table 3: Results for translation between some non-English languages (BLEU score).

| Model | bn-mr | bn-or | bn-pa | gu-kn | gu-te | kn-pa | ml-hi | ml-te | mr-te | ta-mt | AVG |
|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-----|
| bilingual | 4.5   | 4.6   | 9.0   | 3.2   | 4.2   | 8.8   | 10.8  | 4.3   | 3.9   | 2.4   | 5.6 |
| pivot | 13.0   | 12.4   | 20.6  | 14.8  | 13.5  | 23.3  | 24.8  | 12.0  | 11.8  | 9.8   | 15.6 |
| SampleFraction | 13.6 | 13.4 | 22.2 | 15.2 | 13.8 | 24.5 | 26.3 | 12.3 | 11.9 | 9.2 | 16.3 |

Table 4: Comparing English-centric and non-English translation quality

| src | labse | chrF2 | bleu | tset_sim |
|-----|-------|-------|------|----------|
| bn  | 81.2  | 45.8  | 14.6 | 78.1     |
| gu  | 84.4  | 51.1  | 19.0 | 83.2     |
| hi  | 86.0  | 52.9  | 19.7 | 83.8     |
| kn  | 82.8  | 47.9  | 16.4 | 81.7     |
| ml  | 83.1  | 47.3  | 16.0 | 80.1     |
| mr  | 82.6  | 47.9  | 16.2 | 81.6     |
| or  | 82.2  | 48.3  | 17.0 | 79.6     |
| pa  | 85.1  | 52.3  | 19.5 | 82.6     |
| ta  | 82.1  | 46.2  | 15.4 | 80.3     |
| te  | 83.9  | 48.2  | 16.3 | 74.5     |
| AVG | 83.3  | 48.8  | 17.0 | 80.6     |
| en  | 86.9  | 53.8  | 20.9 | 80.1     |

Preprocessing  We convert all the Indic data to the Devanagari script. This allows better lexical sharing between languages for transfer learning, prevents fragmentation of the subword vocabulary between Indic languages and allows using a smaller subword vocabulary. When the target language is Indic, the output in Devanagari script is converted back to the corresponding Indic script. Other standard preprocessing done on the data are Unicode normalization and tokenization. All Indic language text processing uses the Indic NLP library* (Kunchukuttan 2020) and English text processing uses the sacremoses package.

We learn a BPE subword vocabulary using *subword_nmt* (Sennrich, Haddow, and Birch 2016b) with 32K merge operations. We consider only those vocabulary items that have occurred at least 5 times in the training corpus.

Training and decoding  The models were trained using fairseq (Ott et al. 2019) on 8 V-100 GPUs. We optimized the cross entropy loss using the Adam optimizer with a label-smoothing of 0.1 and gradient clipping of 1.0. We use mixed precision training with Nvidia Apex®. We use an initial learning rate of 5e-4, 4000 warmup steps and the same learning rate annealing schedule as proposed in Vaswani et al. (2017). We use a global batch size of 262K tokens. We use early stopping with the patience set to 5 epochs. For decoding, we use a beam size of 5.

Validation and Evaluation  We use the n-way parallel validation and testset provided by the above mentioned WAT2021 shared task. The dev and test sets contain 1000 and 2390 sentences per language respectively. Since there are multiple translation directions we sample 10% of the data for each translation direction following Aharoni, Johnson, and Firat (2019). The n-way testset enables evaluation in all translation directions. We use BLEU as the evaluation metric computed using the sacrebleu package* (Post 2018). For Indic-English, we use the in-built, default mteval-v13a tokenizer. For En-Indic, we first tokenize using the IndicNLP tokenizer before running sacreBleu.

Research Questions  This work explores the following research questions

- How do multi-bridge models perform under different data sampling strategies?
- Does fine-tuning the multi-bridge models for certain translation directions improve translation quality?
- How does translation between non-English languages compare with English-centric translation?

Data Sampling Strategies  We studied MB-M2M models trained under different data sampling conditions for non-English pairs. In all the cases mentioned below, all English-centric data is used during training:

- **SamplePairs**: Use all data from some non-English centric language pairs. We randomly select the language pairs while ensuring that all the languages involved are spanned. In our experiments, we used 22 language pairs (out of the possible 90). The language pairs used (in both directions) are: bn-hi, bn-mr, bn-or, gu-pa, gu-te, hi-ta, kn-pa, kn-ta, ml-or, ml-te, mr-te.

- **SampleFraction**: Sample from all non-English language pairs. We sample around 100k sentence pairs from each non-English pair so that the total non-English parallel corpora is roughly equal to the SamplePairs method.

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*We used a gradient update of 16 and per GPU batch size of 2048 tokens.

*BLEU+case.mixed+numrefs.1+smooth.exp+tok.13a+version.1.5.1

*BLEU+case.mixed+numrefs.1+smooth.exp+tok.none+version.1.5.1
• TrainAll: All parallel data from all the non-English pairs are used.

Baselines
We also train many-to-one (M2O), one-to-many (O2M) and English-centric many-to-many (EC-M2M) (transformer-eswami-swami-en-de-big architecture). We use the M2O and O2M models for pivot baselines and EC-M2M for zero-shot baselines for evaluating translation between Indic languages. We also train bilingual baselines for all English-Indian, Indian-English directions using the small transformer-jwsl-aben architecture and for 10 Indian language pairs using the base transformer architecture.

Results and Analysis
In this section, we discuss the results of our experiments.

Translation between non-English languages
Table 2 shows the results of translation between non-English languages.

Comparison with zeroshot and pivot translation
The English-centric M2M translation model performs very poorly for zeroshot translation between Indian languages. The model always generates English output which is consistent with previous observations in literature. Zeroshot translation is particularly pathological for Indian languages since their scripts are totally different from the Latin English script - hence there is very little vocabulary sharing and the model exclusively generates English for translation between Indian languages. All the multi-bridge models perform better than the pivot model. We also find that the multilingual and pivot models are substantially better than bilingual models. To illustrate that, we show results for some non-English pairs in Table 3.

Data Sampling conditions
All three data sampling methods show roughly the same translation quality, suggesting that all the data is not needed for training non-English directions. Particularly, SampleFraction performs is slightly better than SamplePairs and is equivalent to TrainAll.

Indic-data only models
They are inferior to the models using English-centric data pointing to the need for the original English-centric data as well.

Comparison with English-centric models
We compare translations from English to Indian languages with translations between Indian languages. The n-way nature of the WAT2021 testset make such a study possible. It is desirable that translation between Indian languages achieve the same quality as English-Indic languages since multilingual model enable transfer learning and the Indic training corpus is extracted from the English-centric corpus. We compare the average translation quality metrics of: (1) English to Indian language directions, and (2) Indian-Indian language directions. We use multiple evaluations metrics to obtain a holistic comparison: BLEU (token-based) (Papineni et al. 2002), chrF2 (character-based) (Popović 2015) and LABSE cosine similarity (semantic similarity) (Feng et al. 2020). Table 4 shows that the English to Indian language translation shows a higher quality than Indic-Indic translation on all these metrics.

A possible explanation for this gap is the nature of the testsets - most likely the English source sentence has been independently translated into all Indic languages. This might cause a semantic drift in the reference translations between the Indic languages and is a potential issue in n-way testsets. To check this hypothesis, we compute the semantic similarity between the source and target languages in the testset using cosine similarity between LABSE representations of the sentences. We see that semantic similarity between Indic languages is roughly similar to that between English and Indian languages. Hence, We can discount any semantic drift in the testsets.

Translation to English
Table 5 show the results. We observe that all the multilingual models are significantly better than the bilingual models. The multi-bridge models perform better than the English-centric many to one model. The SampledFraction and SamplePairs strategies outperform the TrainAll model. The TrainAll model sees more non-English language data training and hence its performance on English target might be degrading.

Translation from English
Table 6 show the results. We observe that all the multilingual models are significantly better than the bilingual models. Further, it is important to note that the multi-bridge models significantly outperform the English-centric one to many model (about 1.5 BLEU points average across languages). Improving multilingual models when multiple target languages are involved has been a challenge and these results indicate that multibrige models can provide significant improvement in this scenario. The SampledFraction and SamplePairs strategies outperform the TrainAll strategy.

Finetuning of multi-bridge models
We finetune the multibrige models by continuing training on the finetuning dataset. We experiment with 3 finetuning scenarios: (1) non-English parallel data, (2) English-Any parallel data, (3) Any language to English parallel data. We stop finetuning when we see no improvement on the validation set for 5 epochs. The results of finetuning of multibrige models are shown in Table 7. Finetuning these models on non-English data alone does not yield any major gains. Fine-tuning the model on X to English data only also does not result in any significant change. Finetuning the model on English to language data improves the TrainAll model by a BLEU point.

Conclusion
We conduct a systematic analysis of multibrige multilingual NMT models. Our results show that only a small amount of translation data from non-English pairs is sufficient to achieve best results with standard multilingual training. It is possible to train a single multilingual model to serve
multiple translation directions. Further advances in multilingual learning are needed to achieve better transfer from English-centric directions to non-English directions. Particularly, when the non-English languages are related, better methods to utilize relatedness of these languages are required.

References

Aharoni, R.; Johnson, M.; and Firat, O. 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), 3874–3884. Minneapolis, Minnesota: Association for Computational Linguistics.

Arivazhagan, N.; Bapna, A.; Firat, O.; Aharoni, R.; Johnson, M.; and Macherey, W. 2019. The Missing Ingredient in Zero-Shot Neural Machine Translation. CoRR, abs/1903.07091.

Artetxe, M.; and Schwenk, H. 2019. Massively Multilingual Sentence Embeddings for Zero-Shot Cross-Lingual Transfer and Beyond. Transactions of the Association for Computational Linguistics, 7: 597–610.

Bahdanau, D.; Cho, K.; and Bengio, Y. 2015. Neural Machine Translation by Jointly Learning to Align and Translate. In 3rd International Conference on Learning Representations, ICLR 2015, San Diego, CA, USA, May 7-9, 2015, Conference Track Proceedings.

Dabre, R.; Chu, C.; and Kunchukuttan, A. 2020. A Survey of Multilingual Neural Machine Translation. ACM Comput. Surv., 53(5).

Escolano, C.; Costa-jussà, M. R.; Fonollosa, J. A. R.; and Artetxe, M. 2021. Multilingual Machine Translation: Closing the Gap between Shared and Language-specific Encoder-Decoders. In Proceedings of the 16th Conference of the European Chapter of the Association for Computational Linguistics: Main Volume, 944–948. Online: Association for Computational Linguistics.

Fan, A.; Bhosale, S.; Schwenk, H.; Ma, Z.; El-Kishky, A.; Goyal, S.; Baines, M.; Celebi, O.; Wenzek, G.; Chaudhary, V.; Goyal, N.; Birch, T.; Liptchinsky, V.; Edunov, S.; Grave, E.; Auli, M.; and Joulin, A. 2020. Beyond English-Centric Multilingual Machine Translation. arXiv:2010.11125.

Feng, F.; Yang, Y.; Cer, D.; Arivazhagan, N.; and Wang, W. 2020. Language-agnostic BERT Sentence Embedding. arXiv:2007.01852.

Firat, O.; Cho, K.; and Bengio, Y. 2016. Multi-Way, Multilingual Neural Machine Translation with a Shared Attention Mechanism. In Proceedings of the 2016 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, 866–875. San Diego, California: Association for Computational Linguistics.

Freitag, M.; and Firat, O. 2020. Complete Multilingual Neural Machine Translation. In Proceedings of the Fifth Conference on Machine Translation, 550–560. Online: Association for Computational Linguistics.

Gu, J.; Wang, Y.; Cho, K.; and Li, V. O. 2019. Improved Zero-shot Neural Machine Translation via Ignoring Spurious Correlations. In Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics, 1258–1268. Florence, Italy: Association for Computational Linguistics.

Johnson, M.; Schuster, M.; Le, Q. V.; Krikun, M.; Wu, Y.; Chen, Z.; Thorat, N.; Viégas, F.; Wattenberg, M.; Corrado, G.; Hughes, M.; and Dean, J. 2017. Google’s Multilingual Neural Machine Translation System: Enabling Zero-
Table 7: Results for finetuning of multibridge models. For translation between Indic languages, each cell shows the average BLEU score for translating into corresponding language. The last column shows the average BLEU score for the model.
Rudnick, A.; Vinyals, O.; Corrado, G.; Hughes, M.; and Dean, J. 2016. Google’s Neural Machine Translation System: Bridging the Gap between Human and Machine Translation. *CoRR*, abs/1609.08144.