Language Branch Gated Multilingual Neural Machine Translation

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Abstract

Knowledge transfer across languages is crucial for multilingual neural machine translation. In this paper, we propose language branch (LB) gated multilingual neural machine translation that encourages knowledge transfer within the same language branch with a LB-gated module that is integrated into both the encoder and decoder. The LB-gated module distinguishes LB-specific parameters from global parameters shared by all languages and routes languages from the same LB to the corresponding LB-specific network. Comprehensive experiments on the OPUS-100 dataset show that the proposed approach substantially improves translation quality on both middle- and low-resource languages over previous methods. Further analysis demonstrates its ability in learning similarities between language branches.

1 Introduction

Recent years have witnessed a growing interest in multilingual neural machine translation (NMT), which supports translation among multiple languages with one single model (Dong et al., 2015; Luong et al., 2016; Firat et al., 2016; Johnson et al., 2017; Aharoni et al., 2019; Arivazhagan et al., 2019; Xu et al., 2021). As the parameters of multilingual NMT are fully or partially shared by multiple languages, knowledge transfer across languages improves translation quality of low-resource languages.

Despite these advantages, there still exist challenges in multilingual NMT. As previous studies have found, multilingual NMT usually underperforms its bilingual counterparts on high-resource languages (Johnson et al., 2017; Arivazhagan et al., 2019). A way to alleviate this issue is to use language-aware modules, which could be more computationally efficient than simply enlarging model capacity with deeper/wider models (Zhang et al., 2020, 2021; Lin et al., 2021). As for low-resource languages, positive transfer is more pronounced among related languages than distant languages (Sachan and Neubig, 2018). Additionally, explicit language clustering benefits multilingual NMT (Tan et al., 2019) although itself can learn linguistic typology during training (Lu et al., 2018).

Inspired by these, we propose language branch (subfamily) gated multilingual neural machine translation, which fuses language branch information into multilingual NMT by a Language Branch Gated Module (LBGM). A language branch is a subfamily of a language family. Take the Indo-European language family as an example. It can be further divided into subfamilies like Germanic, Slavic, Celtic, etc. The reason why we use language branches rather than language families is that the latter are relatively coarse-grained. Languages within a language branch are more closely related to each other than those in a language family.

A token that indicates the language branch for the current sentence is fed into LBGM, in addition to the input from other layers in multilingual NMT. With the language branch token, LBGM distinguishes language-branch-specific parameters from global parameters shared by all languages and uses a gate to aggregate these two parts as the output of the module.

We conduct experiments on the OPUS-100 dataset (Zhang et al., 2020) with a large number of different languages. Our main findings can be summarized as follows:

• The proposed LBGM can significantly improve translation quality, achieving more substantial gains for middle- and low-resource languages than its counterparts.
• LBGM performs better for language branches that contain plentiful languages, including

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not only high-resource languages, but also middle/low-resource languages.

- LBGM is capable of capturing similarities between language branches.

2 Related Work

Research of multilingual NMT mainly focuses on partial or full parameter sharing in NMT modules (Dong et al., 2015; Luong et al., 2016; Firat et al., 2016). Johnson et al. (2017) propose prefixing sentences with a language token in a joint set of parallel corpora, using a single NMT model to enable multilingual translation. There is a trade-off between boosting the performance of low-resource languages and sacrificing the performance of high-resource languages (Arivazhagan et al., 2019).

Language-Specific Parameters  Previous works have been trying to use language-specific parameters to alleviate the trade-off issue in multilingual NMT, such as adding adaptation layers into pre-trained models for each language (Bapna and Firat, 2019; Philip et al., 2020; Zhu et al., 2021). Zhang et al. (2020) propose language-aware layer normalization to relax normalization constraint for target languages. Lin et al. (2021) produce masks for different language pairs and use them to select sub-networks for language pairs, in order to counter parameter interference. The closest work to ours is done by Zhang et al. (2021), who introduce a module called CLSR into the Transformer model. The CLSR module adopts a gating function, which is trained with injected zero-mean Gaussian noise and discretized at inference time, to choose whether to share the parameters for all languages or not. However, the CLSR does not take the relationship between languages into account, since it uses language identity as the router.

Language Clustering  Sachan and Neubig (2018) have found that full parameter sharing improves translation quality mainly for related languages that are from the same language group. Tan et al. (2019) attempt to cluster languages into different groups using two methods: prior knowledge and language embedding. They build a multilingual NMT model for each group and observe that both clustering approaches are able to improve model performance. Fan et al. (2021) propose adding a language-specific layer for each language group. They cluster languages according to the amount of training data and vocabulary. Different from them, we use a linguistically-motivated and fine-grained method to group languages (i.e., language subfamily).

3 Methodology

We adopt the Transformer model as the backbone network (Vaswani et al., 2017). Following Johnson et al. (2017), we extend the Transformer to multilingual Transformer by prefixing a language token to the source and target side respectively.

We cluster languages into their language branches. More specifically, for Indo-European languages, we cluster them into 10 branches, including Baltic, Celtic, East Slavic, Germanic, Hellenic, Indo-Aryan, Iranian, Romance, South Slavic and West Slavic. But for Afro-Asiatic languages, as there are only five languages in the dataset we use, we just group them into one language branch. For isolated languages, e.g., Esperanto, Japanese, we keep them in the isolated language group, expecting them to benefit from the positive transfer from all languages.

We adapt the multilingual Transformer to integrate language branch information with the proposed LBGM, which is illustrated in Figure 1. Particularly, we use an additional token, i.e., LB token, to indicate the language branch for each corresponding sentence. LBGM contains a gating function and two feedforward networks, namely, LB-specific FFN and global FFN. The LB-specific FFN is exclusively used for sentences from the corresponding language branch while the global FFN is fully shared across all languages. The purpose of the fully-shared global FFN is to capture global linguistic information from all language pairs, so as to enable knowledge transfer across all languages, especially for the isolated language branch which only contains one or a few languages. The LB-specific FFN is to capture linguistic features for languages from the same language branch and hence
enabling intra-language-branch knowledge transfer. LBGM can be formulated as follows:

\[
\text{Gate}(a^l) = \text{ReLU}(a^l W + b) \tag{1}
\]

\[
g^l = \sigma(\text{Gate}(a^l)) \tag{2}
\]

\[
\text{LBGM}(a^l) = g^l \cdot \text{FFN}^{\text{LB-specific}}(a^l)
+ (1 - g^l) \cdot \text{FFN}^{\text{global}}(a^l) \tag{3}
\]

where \(W\) and \(b\) are trainable parameters, \(a^l\) is the output from the preceding layer \(l\). FFNs are calculated as follows:

\[
\text{FFN}^{\text{LB-specific}} = a^l W^{\text{LB-specific}} + b^{\text{LB-specific}} \tag{4}
\]

\[
\text{FFN}^{\text{global}} = a^l W^{\text{global}} + b^{\text{global}} \tag{5}
\]

The LB token is used to route information from previous layer into the corresponding LB-specific FFN, which is acting as an “expert” for that language branch.

In contrast to the previous CLSR method Zhang et al. (2021), we do not use the discrete gating function and additional loss component. In our preliminary experiments, we have found that these two components could not bring improvements to our LBGM module and the discretized gating function is even harmful to the LBGM. Instead, we use an individual gating function per LBGM sub-module (not shared by the whole model like CLSR). This is because, at different positions, the importance of the two types of FFN may be different, which is to be determined by the corresponding gating function in our model.

4 Experiments

We conducted experiments with a massive number of languages to examine the effectiveness of the proposed LBGM.

4.1 Settings

We used the OPUS-100 dataset (Zhang et al., 2020) for our experiments. OPUS-100\(^1\) is an English-centric dataset covering 99 language pairs. As 5 language pairs do not have their test and dev sets, we conducted experiments using the rest 94 language pairs. We roughly divided the languages into three categories according to the training data size: high-resource languages (more than 1M training samples, 44 languages), low-resource languages (fewer than 0.1M training samples, 21 languages) and middle-resource languages (others, 29 languages) following Zhang et al. (2020). This division is only for experiments while in our model, we linguistically grouped these languages into 26 language branches, shown in Table 5 in Appendix A.

We applied Byte Pair Encoding (BPE) (Sennrich et al., 2016) to preprocess the data with a joint vocabulary size of 64K, using the SentencePiece Toolkit (Kudo and Richardson, 2018)\(^2\). We adopted the temperature-based oversampling method with a temperature of \(T = 5\).

Translation quality was evaluated by BLEU (Papineni et al., 2002) using SacreBleu (Post, 2018)\(^3\).

We adopted the Transformer-base model (Vaswani et al., 2017) as our baseline. The dimensions of our LB-specific FFNs and global FFN are 512. As we have 26 language branches, so the total number of LB-specific FFNs is 26. We also compared with CLSR (Zhang et al., 2021), which uses a language-specific module and conditional routing function to learn the representation of each language. All models were implemented with fairseq (Ott et al., 2019)\(^4\).

Other details about experiments and model settings are in Appendix A.

4.2 Main Results of One-to-Many and Many-to-One Translation

We first conducted experiments for one-to-many and many-to-one translation (i.e., English→X and X→English). Although there is only one language on the source side for one-to-many translation and on the target side for many-to-one translation, we use the proposed LBGM in both the encoder and decoder, as shown in Figure 1, to keep both LB-informed.

As shown in Table 1, our LBGM outperforms the baseline and CLSR on the OPUS-100 dataset. Particularly, we achieve an overall improvement of 1.32/0.70 BLEU points on English→X, 1.31/0.30 BLEU points on X→English over the baseline/CLSR. In terms of the amount of training data available, we observe that the proposed LBGM gains larger improvements on low-resource languages than those on high/middle-resource languages over the baseline and CLSR.

\(^1\)http://opus.nlpl.eu/opus-100.php
\(^2\)https://github.com/google/sentencepiece
\(^3\)https://github.com/mjpost/sacrebleu
\(^4\)https://github.com/facebookresearch/fairseq
Table 1: Results on the OPUS-100 dataset. We report the average BLEU of English→X and X→English translation on 94 language pairs.

| Model          | #Params | English→X               | High | Mid | Low | All |
|----------------|---------|-------------------------|------|-----|-----|-----|
| Baseline       | 99M     | 15.01                   | 22.26| 25.99| 19.70|     |
| Baseline-592dim| 117M    | 15.44                   | 22.72| 26.41| 20.14|     |
| CLSR           | 154M    | 15.81                   | 22.73| 26.43| 20.32|     |
| LBGM-LS        | 154M    | **16.01**               | **23.13**| **26.87**| **20.63**|     |
| LBGM           | 117M    | **15.95**               | **23.77**| **27.85**| **21.02**|     |

4.3 Ablation Study

In order to eliminate the difference in the number of parameters of the LBGM and baseline, we scaled the hidden size of the baseline from 512 to 592 dimensions, denoted in Table 1 as Baseline-592dim. The results still demonstrate that our LBGM is more efficient than the vanilla Transformer. This ablation study confirms that the improvement obtained by the LBGM is not due to the capacity advantage.

We conducted another group of experiments to investigate whether language branches are helpful in comparison to the original CLSR architecture, which could tell us whether the modified LBGM architecture would be better adapted to the use of language branches. We used the same settings as the previous experiments. Differently, language identities, instead of language branches, were used as the router. The results are shown in Table 1 denoted as LBGM-LS. From the comparison between the LBGM-LS and LBGM, we can find that language branches are indeed important. Although the LBGM-LS obtains a slightly higher improvement than the LBGM on high-resource languages (0.06 BLEU), it’s acceptable for our LBGM approach. That is because the LBGM-LS allocates an individual FFN module for each language, rather than one for each language branch, and it alleviates the capacity constraints of the model on high-resource languages. LBGM-LS still outperforms the CLSR approach, suggesting that our modifications to the original CLSR module are not harmful to the model but more appropriate in the context of using language branches.

Table 2: Results on the English→X translation for the Germanic language branch, which includes high/middle/low-resource language pairs. ∆-B and ∆-C denote the improvements over Baseline and CLSR respectively.

| Lang | Data Size | Baseline | CLSR | LBGM | ∆-B | ∆-C |
|------|-----------|----------|------|------|-----|-----|
| da   | 1000000   | 20.74    | 22.45| 22.64| 1.90| 0.19|
| de   | 1000000   | 16.90    | 17.79| 18.03| 1.13| 0.24|
| is   | 1000000   | 10.83    | 11.86| 12.01| 1.18| 0.15|
| nl   | 1000000   | 16.58    | 17.34| 17.86| 1.28| 0.52|
| no   | 1000000   | 17.81    | 18.92| 19.34| 1.53| 0.42|
| sv   | 1000000   | 18.37    | 19.27| 19.82| 1.45| 0.55|
| nn   | 486055    | 23.55    | 24.88| **25.40**| 1.85| 0.52|
| af   | 275512    | 30.02    | 31.14| 32.15| 2.13| 1.01|
| nb   | 142906    | 23.16    | 24.39| 25.48| 2.32| 1.09|
| fy   | 54342     | 25.03    | 27.02| 27.63| 2.60| 0.61|
| li   | 25535     | 27.42    | 29.27| **30.59**| 3.17| 1.32|
| yi   | 15010     | 25.29    | 27.31| **30.73**| 5.44| 3.42|

Table 3: Results on the West Slavic (WS) language branch and Baltic (BA) language branch on English→X translation. Bilingual is the bilingual model trained with the same architecture.

| LB | Lang | Data Size | Bilingual | Baseline | CLSR | LBGM |
|----|------|-----------|------------|----------|------|------|
| ws | cs   | 1000000   | **18.03**  | 14.92    | 15.46| 16.11|
| pl | cs   | 1000000   | **18.57**  | 11.37    | 11.83| 12.55|
| sk | cs   | 1000000   | **18.66**  | 15.89    | 16.71| 17.44|
| ba | lt   | 1000000   | **17.63**  | 18.55    | **19.82**| **19.61**|
| lv | lv   | 1000000   | 21.10    | 22.57    | 22.09|      |

4.4 Effect on the Different Types of Language Branches

To further investigate how the proposed LBGM improves translation quality, we categorize language branches into three types: (I) language branch containing high/middle/low-resource languages. (II) language branch with only high-resource languages. (III) language branch with one or two languages, which are usually isolated languages. We analyzed the effects of our LBGM on these three types of language branches.

Table 2 shows the results of the West Slavic (WS) language branch and Baltic (BA) language branch on English→X translation. Bilingual is the bilingual model trained with the same architecture.
Table 4: Results on the isolated language branch of English→X translation.

| Lang | Data Size | Baseline | CLSR | LBGM |
|------|-----------|----------|------|------|
| ja   | 1000000   | 4.73     | 5.27 | 4.46 |
| ko   | 1000000   | 3.03     | 2.91 | 2.84 |
| ka   | 377306    | 14.39    | 14.91| 14.57|

Finally, Table 4 shows results on the isolated language branch. It can be seen that LBGM achieves results comparable to CLSR. And the effect on isolated languages depends more on the characteristics of the language itself.

All these results suggest that our LBGM can significantly improve performance on both middle- and low-resource languages and achieve comparable results to CLSR on high-resource languages but with fewer parameters. The gains on middle- and low-resource languages are more substantial when the language branch contains mixed languages in terms of the amount of available training data.

6 Conclusions

In this paper, we have presented LBGM that uses a LB-specific FFN and a global FFN shared across all languages to enhance knowledge transfer within the same language branch for multilingual neural machine translation. Experiments on the OPUS-100 dataset have shown that LBGM can significantly improve translation quality on both middle- and low-resource languages, over the baseline and CLSR (Zhang et al., 2021). Further analysis on LB-specific FFN discloses that the proposed LBGM is able to capture language branch relations.

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| ISO | Name          | Family           | Branch | Code |
|-----|---------------|------------------|--------|------|
| am  | Amharic       | Afro-Asiatic     | Semitic| SE   |
| ar  | Arabic        | Afro-Asiatic     | Semitic| SE   |
| ha  | Hausa         | Afro-Asiatic     | Chadic | SE   |
| he  | Hebrew        | Afro-Asiatic     | Semitic| SE   |
| mh  | Maltese       | Austroasiatic    | Austroasiatic| AU |
| vi  | Vietnamese    | Austroasiatic    | Austroasiatic| AU |
| id  | Indonesian    | Austronesian     | Malayo-Polynesian| MP |
| mg  | Malagasy      | Austronesian     | Malayo-Polynesian| MP |
| ms  | Malay         | Austronesian     | Malayo-Polynesian| MP |
| eo  | Esperanto     | Constructed      | Constructed| CON |
| kn  | Kannada       | Dravidian        | Dravidian | DR |
| ml  | Malayalam     | Dravidian        | Dravidian | DR |
| ta  | Tamil         | Dravidian        | Dravidian | DR |
| te  | Telugu        | Dravidian        | Dravidian | DR |
| lt  | Lithuanian    | Indo-European    | Baltic | BA   |
| lv  | Latvian       | Indo-European    | Baltic | BA   |
| br  | Breton        | Indo-European    | Celtic | CE   |
| cy  | Welsh         | Indo-European    | Celtic | CE   |
| ga  | Irish         | Indo-European    | Celtic | CE   |
| gd  | Scots Gaelic  | Indo-European    | Celtic | CE   |
| be  | Byelorussian  | Indo-European    | East Slavic | ES |
| ru  | Russian       | Indo-European    | East Slavic | ES |
| uk  | Ukrainian     | Indo-European    | East Slavic | ES |
| af  | Afrikaans     | Indo-European    | Germanic| GE   |
| da  | Danish        | Indo-European    | Germanic| GE   |
| de  | German        | Indo-European    | Germanic| GE   |
| fr  | Friesian      | Indo-European    | Germanic| GE   |
| is  | Icelandic     | Indo-European    | Germanic| GE   |
| li  | Limburgian    | Indo-European    | Germanic| GE   |
| nb  | Bokmal        | Indo-European    | Germanic| GE   |
| nl  | Dutch         | Indo-European    | Germanic| GE   |
| nn  | Norwegian     | Indo-European    | Germanic| GE   |
| sv  | Swedish       | Indo-European    | Germanic| GE   |
| yi  | Yiddish       | Indo-European    | Germanic| GE   |
| as  | Assamese      | Indo-European    | Indo-Aryan | IA  |
| bn  | Bengali       | Indo-European    | Indo-Aryan | IA  |
| gu  | Gujarati      | Indo-European    | Indo-Aryan | IA  |
| hi  | Hindi         | Indo-European    | Indo-Aryan | IA  |
| ma  | Marathi       | Indo-European    | Indo-Aryan | IA  |
| ne  | Nepali        | Indo-European    | Indo-Aryan | IA  |
| or  | Oriya         | Indo-European    | Indo-Aryan | IA  |
| pa  | Punjabi       | Indo-European    | Indo-Aryan | IA  |
| si  | Singhalese    | Indo-European    | Indo-Aryan | IA  |
| ur  | Urdu          | Indo-European    | Indo-Aryan | IA  |
| el  | Greek         | Indo-European    | Hellenic| HE   |
| sq  | Albanian      | Indo-European    | Albanian| HE   |

| ISO | Name          | Family           | Branch | Code |
|-----|---------------|------------------|--------|------|
| fa  | Persian       | Indo-European    | Iranian | IR  |
| ku  | Kurdish       | Indo-European    | Iranian | IR  |
| ps  | Pashto        | Indo-European    | Iranian | IR  |
| tg  | Tajik         | Indo-European    | Iranian | IR  |
| ca  | Catalan       | Indo-European    | Romance | RO  |
| es  | Spanish       | Indo-European    | Romance | RO  |
| fr  | French        | Indo-European    | Romance | RO  |
| gl  | Galician      | Indo-European    | Romance | RO  |
| it  | Italian       | Indo-European    | Romance | RO  |
| oc  | Occitan       | Indo-European    | Romance | RO  |
| pt  | Portuguese    | Indo-European    | Romance | RO  |
| ro  | Romanian      | Indo-European    | Romance | RO  |
| wa  | Wolof         | Indo-European    | Romance | RO  |
| bg  | Bulgarian     | Indo-European    | South Slavic | SS |
| bs  | Bosanski      | Indo-European    | South Slavic | SS |
| hr  | Croatian      | Indo-European    | South Slavic | SS |
| mk  | Macedonian    | Indo-European    | South Slavic | SS |
| sh  | Serbo-Croatian| Indo-European    | South Slavic | SS |
| sl  | Slovenian     | Indo-European    | South Slavic | SS |
| sr  | Serbian       | Indo-European    | South Slavic | SS |
| cs  | Czech         | Indo-European    | West Slavic | WS |
| pl  | Polish        | Indo-European    | West Slavic | WS |
| sk  | Slovak        | Indo-European    | West Slavic | WS |
| ja  | Japanese      | Japanese         | Japonic | JA  |
| ka  | Georgian      | Kartvelian        | Kartvelian | KA |
| ko  | Korean        | Korean            | Korean | KO  |
| es  | Basque        | Language isolate  | Language isolate | LI |
| ig  | Igbo          | Niger-Congo       | Niger-Congo | NC |
| rw  | Kinyarwanda   | Niger-Congo       | Niger-Congo | NC |
| zh  | Xhosa         | Niger-Congo       | Niger-Congo | NC |
| zu  | Zulu          | Niger-Congo       | Niger-Congo | NC |
| my  | Burmese       | Sino-Tibetan      | Sino-Tibetan | ST |
| zh  | Chinese       | Sino-Tibetan      | Sino-Tibetan | ST |
| th  | Thai          | Thai-Kadai        | Thai-Kadai | TK |
| ug  | Ugur          | Turkic            | Turkic | KAL |
| uz  | Uzbek         | Turkic            | Turkic | KAL |
| kk  | Kazakh        | Turkic            | Turkic | KI  |
| ky  | Kirghiz       | Turkic            | Turkic | KI  |
| tt  | Tatar         | Turkic            | Turkic | KI  |
| az  | Azerbaijani   | Turkic            | Oghuz  | OG  |
| tk  | Turkmen       | Turkic            | Oghuz  | OG  |
| tr  | Turkish       | Turkic            | Oghuz  | OG  |
| et  | Estonian      | Uralic            | Uralic | UR  |
| fi  | Finnish       | Uralic            | Uralic | UR  |
| hu  | Hungarian     | Uralic            | Uralic | UR  |
| se  | Northern Sami | Uralic            | Uralic | UR  |

Table 5: ISO-639-1 language code, language name, language family, language branch and language branch code in the OPUS-100 dataset.

A Appendix

A.1 Languages in the OPUS-100 Dataset

We list the languages used in our experiments in Table 5. The language branches are most based on linguistic characteristics, but some of them are based on geopolitical locations, e.g., Greek and Albanian.

A.2 Experiment Settings

We optimized parameters using Adam optimizer (Kingma and Ba, 2015) with a label smoothing rate of 0.1. The learning rate was scheduled according to the inverse square root of running steps with a warmup step of 4K and the weight decay rate was set to 0.0001. We set the maximum number of steps to 500K. For inference, we used beam search with a beam size of 4 and a length penalty of 0.6.