Towards Multilingual Transitivity and Bidirectional Multilingual Agreement for Multilingual Document-level Machine Translation

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Abstract
Multilingual machine translation has been proved an effective strategy to support translation between multiple languages with a single model. However, most studies focus on multilingual sentence translation without considering generating long documents across different languages, which requires an understanding of multilingual context dependency and is typically harder. In this paper, we first spot that naively incorporating auxiliary multilingual data either auxiliary-target or source-auxiliary brings no improvement to the source-target language pair in our interest. Motivated by this observation, we propose a novel framework called Multilingual Transitivity (MTrans) to find an implicit optimal route via source-auxiliary-target within the multilingual model. To encourage MTrans, we propose a novel method called Triplet Parallel Data (TPD), which uses parallel triplets that contain (source-auxiliary, auxiliary-target, and source-target) for training. The auxiliary language then serves as a pivot and automatically facilitates the implicit information transition flow which is easier to translate. We further propose a novel framework called Bidirectional Multilingual Agreement (Bi-M Agree) that encourages the bidirectional agreement between different languages. To encourage Bi-M Agree, we propose a novel method called Multilingual Kullback-Leibler Divergence (MKL) that forces the output distribution of the inputs with the same meaning but in different languages to be consistent with each other. The experimental results indicate that our methods bring consistent improvements over strong baselines on three document translation tasks: IWSLT2015 Zh-En, De-En, and Vi-En. Our analysis validates the usefulness and existence of MTrans and Bi-M Agree, and our frameworks and methods are effective on synthetic auxiliary data.

Introduction
Multilingual training has been a promising research direction in the community. One direction involves either multilingual pre-training with automatically mined sentence pairs, translation pairs and document-level data (Schwenk et al. 2019; El-Kishky et al. 2019; Chi et al. 2021). The other direction involves downstream fine-tuning with multilingual input that either assumes the existence of authentic

1Here, source and auxiliary are parallel inputs with the same meaning in different languages. Target refers to the desired output.

2Combining source-auxiliary and auxiliary-target forms an implicit transition route source-auxiliary-target, i.e., source-target.

Figure 1: An illustrated document translation example that can be better learned by the effect of MTrans that finds an implicit optimal route from path ② to path ③ that could be easier than directly from path ①. All the highlighted words refer to the wife of the speaker, though they are expressed in gender-neutral pronoun in Traditional Chinese (this is common in certain areas), gender pronoun in German, and specific noun in English. Such a difference induces the difference in translation difficulty. Best viewed in colour.

multisource auxiliary data during inference or uses synthetic auxiliary data (Zoph and Knight 2016; Xu et al. 2021).

The above introduced works have mostly focused on sentence-level tasks. Document-level translation is also an important direction. According to the literature, neural document translation is a naturally harder problem than sentence-level translation tasks with neural models. Bao et al. (2021) has reported that the direct training of document-level machine translation is hampered by the sparse input problem (Pouget-Abadie et al. 2014; Koehn and Knowles 2017), i.e., the long sentences problem. This is also validated from the linguistic aspect that contextual inconsistency problems such as deixis, ellipsis and lexical cohesion commonly exist for context-aware document-level machine translation (Voita, Sennrich, and Titov 2019a;b; Jiang et al. 2022).

Possibly due to the nature of the difficulties for the task, we found that including parallel data tuples across multiple languages (Xu et al. 2021), either auxiliary-target or source-auxiliary data.
In other words, we follow the fact that using the auxiliary language can be beneficial to improve the source-target language pair in our interest, and we hypothesise that go through the path ② and then ③ can be easier to translate than directly via path ①. TPD thus falls into the stream of work that exploits auxiliary language. Previous works either undesirably double the inference cost for pseudo auxiliary language (Kauers et al. 2002; Gispert and Marínó 2006; Xu et al. 2021) or uses English as a pivot to improve non-English-centric translation under low-resource settings (Kim et al. 2019; Zhang, Li, and Liu 2022), which requires authentic auxiliary data. In contrast, TPD (MTrans) can be used to leverage arbitrary auxiliary language to improve the translation performance with neither the additional inference cost, assertion on low-resource settings, nor the requirements on the authentic auxiliary data. This paper is the first work to establish MTrans as a novel framework as well as analyse its existence and usefulness within multilingual models.

To further enhance the relationship between the source language and the auxiliary language introduced with TPD (MTrans), we follow the fact that it is beneficial to exploit Multilingual Agreement (MA), i.e., specifically optimizing the agreement between parallel inputs with the same meaning but in different languages (Yang et al. 2021b). We hypothesise that it is beneficial to optimize it in a bidirectional manner, and we establish a novel framework called Bi-directional Multilingual Agreement (Bi-MAgree). One of our novelties here is the bidirectionality of it. Unidirectional MA is quite sensible especially when the auxiliary language and the target language are in the same language family, but the source language does not. For example, Fan et al. (2020) has sorted German and English as the same language family – Germanic, while Chinese has its own family. It is also a commonly accepted fact by the community that the machine translation model usually reports a higher quality on German-English than on Chinese-English. This means that it is intuitive to have the unidirectional multilingual agreement to minimize the gap from Chinese to German to gain improvement in the direction of Chinese-English. However, we hypothesise that the reverse direction, minimizing the gap from German to Chinese, should be incorporated as well.

The motivation is that there are still cases where Chinese can outperform German when being translated to English. One of the cases can be the shared subword units in multilingual models (Conneau and Lample 2019; Huang et al. 2019). Although such a sharing mechanism mitigates the data sparsity problem for low-resource language, this can bring negative effects. We demonstrate a case in Figure 2. In this case, Chinese is incorrectly translated due to its gender-neutral pronoun, while the translation from German to English is also problematic. Here, the word ‘glance’ shares common subwords units with ‘Glanz’, while they have different meanings. This means that optimizing using unidirectional MA can introduce errors to the model. Hence, we propose to use Multilingual Kullback–Leibler Divergence (MKL) to encourage BMA, where the MKL loss is calculated in a bidirectional manner. This paper also serves as the first attempt to explicitly optimize for MA/Bi-MAgree with a similarity metric (KL Divergence).
Overall, this paper makes four contributions:

• This is the first attempt for multilingual document-level machine translation without large-scale bilingual document pairs for pre-training.
• We establish a novel framework called Multilingual Transitivity (MTrans) to implicitly find the optimal transition route source-auxiliary-target. We propose a technique called Triplet Parallel Data (TPD) with the auxiliary languages as a pivot in the route.
• We establish a novel framework called Bidirectional Multilingual Agreement (Bi-MAgree). We propose a novel loss called Multilingual Kullback–Leibler Divergence (MKL) to force the inputs with the same meaning in different languages to have the same output.
• Combining TPD and MKL reports obvious improvements over strong multilingual pre-trained machine translation model on three document translation tasks: IWSLT2015 Zh-En, De-En, and Vi-En, validating the usefulness of MTrans and Bi-MAgree. We also validate the existence of MTrans and Bi-MAgree, and their effectiveness with synthetic auxiliary data. We conclude their promise as a future research direction.

Our proposed TPD (MTrans) and MKL (Bi-MAgree) can be adapted to other cross-lingual tasks with some modification. They can be adapted to any dataset with no hard requirement on the authentic auxiliary data.

Related Work
Multilingual Training via Auxiliary Language
Multilingual NLP is an active research area in the community. It has been proved that training language data with different languages boosts performance on low-resource or mid-resource languages (Liu et al. 2020; Fan et al. 2020). Despite the potential improvements on the performance, it is also tempting to have a single strong model that can deal with different languages. Current researches on multilingual NLP can be roughly divided into two categories: multilingual pre-training and multilingual fine-tuning. The former refers to a set of techniques to improve multilingual model during pre-training (Liu et al. 2020; Xue et al. 2021; Huang et al. 2019; Lewis et al. 2020; Fan et al. 2020). The latter refers to the counterpart that improves the model during fine-tuning with auxiliary languages.

Our methods fall into the category of the latter one, multilingual fine-tuning. The earliest works used an auxiliary language as an intermediate decoding stop to decode twice (Kauers et al. 2002; Gispert and Mariño 2006). Xu et al. (2021) has also employed multi-source encoders to leverage information from inputs with the same meaning but in different languages. These works typically double the inference costs, while ours does not induce additional inference costs.

Another relevant stream of work uses English as an auxiliary language to improve non-English-centric translation via transfer learning (Kim et al. 2019; Zhang, Li, and Liu 2022). This typically assumes the low-resource setting with the lack of data pairs between non-English languages. Also, the previous experimental results are based on non-pre-trained models. Some works also assume the existence of authentic auxiliary data. In contrast, our work is more general and useful in English-centric circumstances on strong pre-trained models. Furthermore, we assert neither the lack of data pairs in interest nor the hard requirement on the authentic auxiliary data.

Agreement-based Learning
Agreement-based learning has been proved as a useful framework in the language community (Liang, Taskar, and Klein 2006; Liang, Klein, and Jordan 2007; Cheng et al. 2016). Zhang et al. (2019) has used an agreement on the output with left-to-right and right-to-left inputs on recurrent neural networks for machine translation. Yang et al. (2020) has used phrase-level agreement for machine translation.

Perhaps the closest work to ours is Yang et al. (2021b), which employed simple code-switching for fine-tuning on a non-pre-trained model for Multilingual Agreement (MA). In contrast, we propose to have it optimized in a bidirectional manner and we establish a novel framework called Bidirectional Multilingual Agreement (Bi-MAgree), which is encouraged via MKL. This is also the first attempt to encourage MA/Bi-MAgree via MKL loss that explicitly optimizes for divergence loss rather than simple code-switching.

Document-level Machine Translation
Document-level machine translation is a typical hard task that we found hard to optimize with a multilingual pre-trained model in our primary study. It can be roughly divided into two categories: Window2Window and Doc2Doc. Window2Window refers to the set of techniques that models sliding windows on the source and target ends (Miculicich et al. 2018; Zheng et al. 2020; Chen et al. 2020). Doc2Doc refers to the technique that directly translates blocks of longer chunks from the documents with no more than 512 or 1,000 subwords (Junczys-Dowmunt 2019; Lee et al. 2022). Previous works spotted failure case when directly trains on Doc2Doc (Bao et al. 2021; Liu et al. 2020) possibly due to the long input length problem (Pouget-Abadie et al. 2014; Koehn and Knowles 2017). Our setting falls into the category of Doc2Doc, which is a hard setting (Liu et al. 2020; Bao et al. 2021). We propose to use TPD and MKL to encourage MTrans and Bi-MAgree to ease its training.

Our Method
Multilingual Machine Translation Model
We conduct our experiments on the large-scale pre-trained multilingual translation model (Yang et al. 2021a; Ma et al. 2021) that shares a universal subword dictionary among all of the languages. For both training and inference, given $I$ languages $\{L_1, \ldots, L_I\}$, we append a special target language token $L_t$ to the source input to signal the multilingual model that we are translating from arbitrary source language to the target language $L_t$.

Document-level Machine Translation
To facilitate document-level neural machine translation, we adopt the setting to split long documents that contain thou-
sands of tokens into smaller chunks before being translated (Lee et al. 2022). Given a bilingual document dataset consists of \(M\) documents \(\{B_1, ..., B_M\}\), we split them into \(N\) paragraph-level smaller chunks \(\{P_1, ..., P_N\}\). Each of the bilingual paragraph pair \(P_i\) in the source bilingual corpora \(D_S\) contains a source input \(x\) and the corresponding translation target \(y\). Given a Seq2Seq generation model (Sutskever, Vinyals, and Le 2014) with parameters \(\theta\), the model is trained to optimize the following likelihood:

\[
L_{\text{main}} = \sum_{n=1}^{N} \mathbb{E}_{x_n, y_n \in D_S} [-\log P_\theta(y \mid x)]
\]  

(1)

For inference, translated paragraphs are concatenated together to form the final translation output.

The above setting can be extended to multilingual to handle multiple language pairs which is a difficult direction to study, partially due to the lack of parallel document data.

**Multilingual Transitivity (MTrans)**

Traditional fine-tuning optimizes for the bilingual setting as we described in Equation 1. As depicted in Figure 1, such a translation direction could be a sub-optimal choice for a multilingual pre-trained model. To leverage the effect of Multilingual Transitivity (MTrans) and find the optimal path from the source language to the target language, we augment the original dataset with parallel auxiliary language. We use a triplet of TPD (source-auxiliary, auxiliary-target, and source-target). Here, we add the auxiliary-target as the auxiliary dataset \(D_A\) and we include the auxiliary dataset and optimizes for the auxiliary loss:

\[
L_{\text{auxiliary}} = \sum_{n=1}^{N} \mathbb{E}_{x_n, y_n \in D_A} [-\log P_\theta(y \mid x)]
\]

(2)

We add the source-auxiliary dataset as the transitivity dataset \(D_T\) and optimize for the transitivity loss:

\[
L_{\text{transitivity}} = \sum_{n=1}^{N} \mathbb{E}_{x_n, y_n \in D_T} [-\log P_\theta(y \mid x)]
\]

(3)

Overall, we optimize the multilingual translation model for the combinatorial multilingual translation loss:

\[
L_{\text{translation}} = L_{\text{main}} + L_{\text{auxiliary}} + L_{\text{transitivity}}
\]

(4)

Here, the main loss refers to the path ① in Figure 1. The auxiliary loss refers to the path ③, and the transitivity loss refers to the path ②. We expect to see such a supportive multilingual loss can help the translation model to learn the document-level translation more efficiently via MTrans. Indeed, we have found that removing either \(L_{\text{auxiliary}}\) or \(L_{\text{transitivity}}\) obviously deteriorates the results. Such a finding validates our proposed framework of MTrans.

**Bidirectional Multilingual Agreement (Bi-MAgree)**

To further enhance the relationship between the source language and the auxiliary language, we propose a new framework called Bidirectional Multilingual Agreement (Bi-MAgree). We propose Multilingual Kullback–Leibler Divergence (MKL) to force our multilingual model to have the output distribution with regards to inputs with the same meaning but in different languages to be consistent with each other in a bidirectional manner. The underlying motivation for Bi-MAgree is that we hypothesise different languages might have different cues which could be useful to the translation. For example, Figure 2 depicts an example which can be even advantageous for Chinese to be translated to a Germanic language, English, over another Germanic language, German. The reason is the shared multilingual vocabulary among different languages which can induce the same sub-word unit to have vastly different meanings in different languages. Therefore, we propose to optimize the loss in a bidirectional manner to achieve Bi-MAgree.

MKL optimizes for a code-switching corpora \(D_C\) with \(N\) bilingual translation pairs that have the same number of training samples as \(D_S\). For the \(i\)-th sample in each dataset, \((x_i, y_i)\) in \(D_S\) aligns with \((\bar{x}_i, y_i)\) in \(D_C\), and they share the same target. \(\bar{x}_i\) is the code-switched version of \(x_i\), meaning some sentences in \(\bar{x}_i\) are in the source language as in \(x_i\) while some are in some arbitrary auxiliary language that the multilingual pre-trained model can handle with. By feeding both \(x\) and \(\bar{x}\) into a shared multilingual translation model, we first measure the KL divergence in the first direction from the source language to the target language \(L_{\text{MKL}}^1\):

\[
\sum_{n=1}^{N} \mathbb{E}_{x_n, y_n \in D_S, \bar{x}_n, y_n \in D_C} [KL(P_\theta(y \mid x) \mid\mid P_\theta(y \mid \bar{x})] ]
\]

(5)

We calculate the reverse direction of the KL loss \(L_{\text{MKL}}^2\):

\[
\sum_{n=1}^{N} \mathbb{E}_{x_n, y_n \in D_S, \bar{x}_n, y_n \in D_C} [KL(P_\theta(y \mid \bar{x}) \mid\mid P_\theta(y \mid x)] ]
\]

(6)

To encourage Bi-MAgree, we then calculate the overall bidirectional MKL loss by adding up \(L_{\text{MKL}}^1\) and \(L_{\text{MKL}}^2\):

\[
L_{\text{MKL}} = \frac{1}{2} (L_{\text{MKL}}^1 + L_{\text{MKL}}^2)
\]

(7)

We optimize our machine translation model with the combinatorial final loss \(L\):

\[
L = L_{\text{translation}} + L_{\text{MKL}}
\]

(8)

With MTrans and Bi-MAgree, we expect to see that it can help downstream fine-tuning in effectively exploiting the multilingual information buried in the pre-trained model.

**Constructing Training Samples**

To facilitate Bi-MAgree with Multilingual KL, we need to construct inputs that consist of the source language that interleaves with auxiliary language. Here, we denote the source language tag as \(L_{\text{src}}\) and the auxiliary language tag as \(L_{\text{aux}}\). Given an original input paragraph \(x\) with \(n\) sentences, we denote the input as \((s_{1}^{L_{\text{src}}}, s_{2}^{L_{\text{src}}}, s_{3}^{L_{\text{src}}}, ..., s_{n}^{L_{\text{src}}})\) where \(s_{i}^{L_{\text{src}}}\) represents the \(i\)-th sentence in the paragraph expressed in the source language. We randomly replace some sentences in \(x\) with their counterpart expressed in the auxiliary language to get \(\bar{x}\), which is the code-switching training sample that expresses the same meaning as \(x\):

\[
(s_{1}^{L_{\text{aux}}}, s_{2}^{L_{\text{aux}}}, s_{3}^{L_{\text{aux}}}, ..., s_{n}^{L_{\text{aux}}})
\]

(9)
For MKL, we use parallel sentences in different languages to create multiple $\bar{x}$ that interleaves the source language with auxiliary languages. The number of auxiliary languages to be mixed in a single example $\bar{x}$ can be limited to $|\mathcal{W}|$. Theoretically, $|\mathcal{W}|$ could be upper-bounded by the minimum of the number of language supported by the pre-trained multilingual model and the number of available parallel languages.

### Experimental Setup

#### Datasets, Preprocess, and Evaluation Metrics

Table 1 depicts the dataset statistics for IWSLT2015 datasets we employ for our experiments. The datasets are composed of TED talks on many topics from animals to education, which can be useful to evaluate the robustness of our frameworks. Following previous works (Miculicich et al. 2018; Lee et al. 2022), we use dev.2010 as the dev set and tst.2010-tst.2013 as the test set for the direction Zh-En. We use the same setting for the remaining two directions De-En and Vi-En. The statistics are partially taken from the IWSLT official report (Cettolo et al. 2014). For the statistics with no official report, for example, Zh-En, we follow Cettolo et al. (2014) to tokenize the data using the standard tokenization script from Europarl corpus (Koehn 2005). Note that we use this tokenization only for dataset statistics. For training and inference with the multilingual model, we use the trained SentencePiece model (Kudo and Richardson 2018) released by previous work (Yang et al. 2021a). Following previous work (Lee et al. 2022), we limit each bilingual pair to have 512 tokens at maximum for both source and target.

In addition, to prevent information leakage, we have carefully ensured that there is no mixing between train, dev, and test sets when we augment with parallel documents. Also, we create the dataset for MKL by replacing the source dataset. Hence, there is no information leakage.

For all the experiments in our paper, we calculate the numbers using sacreBLEU\(^3\) in the document level.

#### Baselines

**HAN** This is a classic Window2Window document machine translation model that uses a hierarchical attention mechanism that models attention with different granularities between both words and sentences (Miculicich et al. 2018).

**mBART** This is a baseline fine-tuned on mBART (Liu et al. 2020), which is pre-trained on large-scale monolingual datasets in different languages with pre-training objectives such as sentence permutation and phrase masking.

**MARGE** This is a baseline fine-tuned on MARGE, which employs a retrieve-generator mechanism to pre-train on unsupervised translation objective (Lewis et al. 2020).

**mT5** This is a baseline fine-tuned on mT5 (Xue et al. 2021) with the reconstruction of span corruption as the pre-training objective on monolingual corpus across many languages. We adopt two variants mT5-cont-5langs and mT5-Dr (Lee et al. 2022) that use additional data and sentence shuffling as the pre-training objective based on mT5.

**DeltaLM-WMT21** This is a strong machine translation model that ranked first place in three tracks in the WMT21 shared task. It is initialized with DeltaLM and adopts progressive learning for further training (Yang et al. 2021a). Since this is a translation model, we report its performance both with and without fine-tuning.

#### Implementation Details

We use the Adam optimizer (Kingma and Ba 2014) with $\beta_1 = 0.9$ and $\beta_2 = 0.98$ for our multilingual model training. The learning rate is set as $1e-4$ with a warm-up step of 4000. We use the label smoothing cross-entropy for our translation loss and we set label smoothing with a ratio of 0.1 for model training. All of our experiments are conducted on 4 NVIDIA V100 GPUs. We use DeltaLM-WMT21, a strong machine translation model that supports 102 languages to initialize the model parameters in which we employ our proposed TPD and MKL to conduct our downstream fine-tuning.

### Experimental Results

#### Main Results

Table 3 reports the comparisons of our proposed methods with previous baselines on IWSLT2015 Zh-En. Among all of the baselines we report, DeltaLM-WMT21 (Yang et al. 2021a) achieves a competitive score, which is on par with mBART (Liu et al. 2020). This is reasonable as mBART employs document-level objectives and DeltaLM-WMT21 is pre-trained with more languages in translation tasks, and they have their own advantages. Our proposed methods obviously improves the results by +0.56 d-BLEU compared to DeltaLM-WMT21. Our proposed method also surpasses

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\(^3\)https://github.com/mjpost/sacrebleu
Table 2: Our results on IWSLT2015 Zh-En, De-En and Vi-En. We report the d-BLEU scores on all the results on tst.2010-2013.

| models                      | Zh-En | De-En | Vi-En |
|-----------------------------|-------|-------|-------|
|                             | 2010  | 2011  | 2012  | 2013  | 2010  | 2011  | 2012  | 2013  | 2010  | 2011  | 2012  | 2013  |
| DeltaLM-WMT21 w/ fine-tune |       |       |       |       |       |       |       |       |       |       |       |       |
| 26.67                       | 30.99 | 29.62 | 30.58 |       | 44.38 | 49.20 | 44.12 | 45.03 | 39.89 | 34.98 | 36.78 | 42.48 |
| Ours w/ TPD & MKL           | 27.26 | 31.39 | 29.82 | 31.57 | 45.17 | 49.93 | 44.33 | 45.56 | 40.59 | 35.21 | 36.97 | 42.73 |

Table 3: Our results on IWSLT2015 Zh-En. We report the overall results on tst.2010-2013. The score attached with * represents the system that uses bilingual document pairs for pre-training, thus is not directly comparable with ours.

| models                              | d-BLEU |
|-------------------------------------|--------|
| Baselines w/o Bilingual Document Pairs for Pre-training |        |
| HAN (Miculich et al. 2018)          | 24.00  |
| mBART (Liu et al. 2020)             | 29.60  |
| MARGE (Lewis et al. 2020)           | 28.40  |
| mT5-cont-5langs (Xue et al. 2021)   | 24.22  |
| mT5-Dr (Xue et al. 2021)            | 23.75  |
| DeltaLM-WMT21 (Yang et al. 2021a) w/ fine-tune | 23.69 |
| DeltaLM-WMT21 (Yang et al. 2021a) w/ fine-tune | 29.34 |
| Ours w/ TPD & MKL                   | 31.40* |
| Ours w/ TPD                         | 29.90  |

Table 4: Results of various studies that we conduct on TPD (MTrans) and MKL (Bi-MAgree). TD1 refers to using (auxiliary, target) only as the additional data, i.e., the path ② in Figure 1. TD2 refers to using (source, auxiliary) only as the additional data, i.e., the path ③ in Figure 1. CSW refers to the Multilingual Agreement (MA) where only code-switching is used (Yang et al. 2021b) instead of MKL. KL1 and KL2 refer to the scene when unidirectional MKL is used, i.e., the direction as in Equation 5 and Equation 6.

| models                              | 2010  | 2011  | 2012  | 2013  | 2010  | 2011  | 2012  | 2013  |
|-------------------------------------|-------|-------|-------|-------|-------|-------|-------|-------|
| Part A: Study on the existence of TPD (MTrans) |       |       |       |       |       |       |       |       |
| Ours w/ TPD & MKL                   | 27.26 | 31.39 | 29.82 | 31.57 |       |       |       |       |
| Ours w/ TD1 & MKL                   | 26.78 | 30.40 | 29.33 | 30.72 |       |       |       |       |
| Ours w/ TD2 & MKL                   | 26.43 | 30.80 | 29.26 | 30.11 |       |       |       |       |
| Part B: Study on the comparison between MA and Bi-MAgree |       |       |       |       |       |       |       |       |
| Ours w/ TPD                         | 27.26 | 31.39 | 29.82 | 31.57 |       |       |       |       |
| Ours w/ TPD & CSW                   | 26.75 | 31.04 | 29.55 | 30.98 |       |       |       |       |
| Ours w/ CSW                         | 26.63 | 31.38 | 29.45 | 30.95 |       |       |       |       |
| Part C: Ablation study for TPD and MKL |       |       |       |       |       |       |       |       |
| Ours w/ TPD & MKL                   | 27.26 | 31.39 | 29.82 | 31.57 |       |       |       |       |
| Ours w/ TPD                         | 27.00 | 31.14 | 29.31 | 30.80 |       |       |       |       |
| Ours w/ MKL                         | 26.59 | 30.97 | 29.23 | 31.00 |       |       |       |       |

RQ1: Is TPD helpful? Whether Multilingual Transitivity (MTrans) exists or not?
First of all, our primary experiments indicate that using either additional data tuples auxiliary-target or source-

RQ2: Whether Bidirectional Multilingual Agreement (Bi-MAgree) is useful? Should it be bidirectional?
Although previous work has attempted to use code-switching (CSW) to encourage MA (Yang et al. 2021b), they are trying to encourage MA in a weak manner through the cross-entropy loss computed with the target output. To our

4https://github.com/EleanorJiang/BlonDe
...we know that engineering processes are complicated don’t work very well. So we’re starting to rely on computers to do a process that’s very different from engineering. It allows us to produce things that are much more complicated than normal engineering can produce. ...In fact, we know that engineering processes are complicated and don’t work very well. And so we’re starting to rely on computers to do a process that’s very different from engineering. It allows us to produce things that are more complicated than normal engineering can produce. ...

**Table 5:** Results for our analysis on whether synthetic auxiliary datasets also work for MTrans and Bi-MAgree.

| data set | models | d-BLEU       |
|----------|--------|-------------|
| tst.2010 | DeltaLM-WMT21 w/ fine-tuning | 26.67 (+0%) |
|         | Ours w/ synthetic auxiliary data | 27.41 (+125%) |
|         | Ours w/ authentic auxiliary data | 27.26 (+100%) |
| tst.2011 | DeltaLM-WMT21 w/ fine-tuning | 30.99 (+0%) |
|         | Ours w/ synthetic auxiliary data | 31.27 (+70%) |
|         | Ours w/ authentic auxiliary data | 31.39 (+100%) |
| tst.2012 | DeltaLM-WMT21 w/ fine-tuning | 29.62 (+0%) |
|         | Ours w/ synthetic auxiliary data | 29.63 (+5%) |
|         | Ours w/ authentic auxiliary data | 29.82 (+100%) |
| tst.2013 | DeltaLM-WMT21 w/ fine-tuning | 30.58 (+0%) |
|         | Ours w/ synthetic auxiliary data | 31.50 (+93%) |
|         | Ours w/ authentic auxiliary data | 31.57 (+100%) |

Table 5: Results for our analysis on whether synthetic auxiliary datasets also work for MTrans and Bi-MAgree.

knowledge, this paper is the first attempt to truly encourage MA that explicitly enforces the inputs with the same meaning in different languages to be close to each other. Our results in Part B in Table 4 indicate that our proposed MKL (Bi-MAgree) is more effective than CSW (MA). Further, as in Part D, removing MKL vastly hurts the performance. Such results indicate that our proposed novel framework Bi-MAgree is useful for multilingual training, and it brings better improvement than the previously proposed CSW (MA).

Here, we have used Chinese and German as the auxiliary language for each other. The effectiveness with Bi-MAgree validates the motivation we demonstrate in Figure 2. Further, as in Part C in Table 4, the bidirectionality in the MKL loss is necessary, and removing either loss in Equation 5 or Equation 6 vastly hurts the performance. This validates the necessity to have the bidirectionality for Bi-MAgree.

**RQ3: Whether the effects of MTrans and Bi-MAgree are complementary to each other?**

Part D in Table 4 reports our ablation study. Here, TPD (MTrans) is individually effective most of the time. However, using MKL (Bi-MAgree) solely deteriorates the baseline performance. This derives to a conclusion that Bi-MAgree should be used with MTrans, which highlights the importance of MTrans. For all of the test sets we use, we observe an obvious improvement when we combine TPD (MTrans) and MKL (Bi-MAgree) together. We conclude that both effects are complementary to each other. The result is beneficial for the understanding of multilingual models and we plan to further investigate the interaction between MTrans and Bi-MAgree in the future.

**RQ4: Whether synthetic auxiliary datasets also work for MTrans and Bi-MAgree?**

Table 5 reports the results when we use high-quality machine translation model DeltaLM-WMT21 to obtain synthetic auxiliary data using the training target. The results are calculated when we use these synthetic data for MTrans and Bi-MAgree instead of the authentic auxiliary data. As expected, the synthetic data has overall less improvements than the authentic data. However, the result is positive. The synthetic data can achieve by up to 125% of the improvement (+0.74 in d-BLEU) on tst.2010 compared to the authentic data, and 93% improvement (+0.92 in d-BLEU) on tst.2013.

This highlights the fact that our method is quite empirically useful with no hard requirement on the authentic auxiliary data. One promising direction that we will continue is to study the use of MTrans and Bi-MAgree in various pre-training scenarios with authentic auxiliary data, automatically mined parallel data, and synthetic auxiliary data.

**Conclusions**

In this paper, we establish two novel frameworks for multilingual models, namely Multilingual Transitivity (MTrans) and Bidirectional Multilingual Agreement (Bi-MAgree). We propose Triplet Parallel Data (TPD) to find the optimal multilingual route to encourage MTrans, and we propose Multilingual Kullback–Leibler Divergence (MKL) to encourage Bi-MAgree. Our experimental results indicate that leveraging MTrans and Bi-MAgree brings significant improvements to a strong pre-trained baseline on three document-level translation datasets: IWSLT2015 Zh-En, De-En, and Vi-En. Furthermore, our analysis shows the existence and usefulness of MTrans and Bi-MAgree. The results also show that MTrans and Bi-MAgree are two complementary effects that enhance each other. Finally, the results show that using synthetic data instead of the authentic auxiliary data effectively exploits the use of MTrans and Bi-MAgree. We conclude that MTrans and Bi-MAgree are empirically useful frameworks to be further studied and exploited in the future for multilingual research.
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