MTet: Multi-domain Translation for English and Vietnamese

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Abstract
We introduce MTet, the largest publicly available parallel corpus for English-Vietnamese translation. MTet consists of 4.2M high-quality training sentence pairs and a multi-domain test set refined by the Vietnamese research community. Combining with previous works on English-Vietnamese translation, we grow the existing parallel dataset to 6.2M sentence pairs. We also release the first pre-trained model EnViT5 for English and Vietnamese languages. Combining both resources, our model significantly outperforms previous state-of-the-art results by up to 2 points in translation BLEU score, while being 1.6 times smaller.

1 Introduction
Machine Translation is an impactful subdomain of Natural Language Processing that directly benefits the world’s interconnected regions and nations, especially so for fast-developing economies such as Vietnam (Baum, 2020). Neural machine translation, however, is hindered for many pairs of languages due to their scarce availability. The literature tackling this problem consists mainly of regularization and data augmentation methods (Provilkov et al., 2019; Nguyen and Salazar, 2019a; Clark et al., 2018). Recently a more data-centric view with more successful results arises: directly growing the small existing datasets (Fan et al., 2020; Ngo and Trinh, 2021; Cruz and Cheng, 2021) and better pretraining methodologies to extract value from large corpora (Liu et al., 2020; Lample and Conneau, 2019; Song et al., 2019).

In this work, we introduce EnViT5, the first pre-trained Transformer-based encoder-decoder model for English-Vietnamese, and MTet - Multi-domain Translation for English-Vietnamese, the largest high-quality multi-domain corpus for English-Vietnamese translation of size 4.2M. Notably, MTet also focuses on highly technical, impactful yet mostly neglected domains due to their expensive-to-obtain nature such as law and biomedical bitexts. We also introduce a test set of four distinctively different domains, refined and cross-checked by human experts through a data crowdsourcing platform. Our final model, pretrained on EnViT5 and finetuned on MTet + phoMT (Doan et al., 2021a) outperforms previous results by a significant margin of up to 2 points in BLEU score. Finally, we perform experiments to confirm that with the same amount of training data, a multi-domain training set results in a better test performance as shown in Section 6, further supporting the multi-domain nature of MTet.

2 Related Works
In recent years, research works focusing on improving Machine Translation Systems for Low-Resource Languages have received a lot of attention from both academia and the industry (Chen et al., 2019; Shen et al., 2019; Gu et al., 2018; Nasir and Mchechesi, 2022). Prior works include collecting more parallel translation data (Thu et al., 2016; Bañón et al., 2020; Sánchez-Cartagena et al.), training large multilingual models (Fan et al., 2020; Liu et al., 2020), and utilizing data augmentation or regularization techniques (He et al., 2019; Edunov et al., 2018; Provilkov et al., 2019). Previous works from ParaCrawl (Bañón et al., 2020) and BiCleaner (Sánchez-Cartagena et al.) focused on mass crawling parallel translation data for many low-resource language pairs. Yet, previous work (Doan et al., 2021b) shows that crawling at scale still has limitation and affect downstream translation performance. We also compare our high-quality MTet with other crawling at-scale datasets in Section 3.

Encouraging results have also been achieved in low-resource English-Vietnamese translation. The most popular and well-adopted translation dataset for English-Vietnamese is IWSLT15 (Cettolo et al.,
which consists of 133K text pairs collected from TED talk transcripts. Some studies (Provilkov et al., 2020; Xu et al., 2019; Nguyen and Salazar, 2019b) show decent improvements through different regularization techniques. Recently, PhoMT (Doan et al., 2021b) and VLSP2020 (Ha et al., 2020) released larger parallel datasets of size 3M and 4M text pairs, extracted from publicly available resources for the English-Vietnamese translation. mBART model trained on PhoMT sets the current state-of-the-art results.

3 MTet: a Machine Translation dataset in English and Vietnamese

In this section, we describe in details our MTet - Multidomain Translation for English-Vietnamese dataset. We curated a total of 4.2M training examples. Based on the curation methodology, we divide this data into four types.

Combining existing sources This includes sources from the Open Parallel corpus (Tiedemann, 2012), spanning across different domains such as educational videos (Abdelali et al., 2014), software user interface (GNOME, KDE4, Ubuntu), COVID-related news articles (ELRC), religious texts (Christodouloupoulos and Steedman, 2015), subtitles (Tatoeba), Wikipedia (Wolk and Marasek, 2014), TED Talks (Reimers and Gurevych, 2020). Together with the original IWSLT’15 (Cettolo et al., 2015a) training set, the total dataset reaches 1.2M training examples. We train a base Transformer on this data, denoted \( bT_A \), to aid the collection of other data sources described below.

Scoring and filtering Another large source from OPUS is OpenSubtitles (Lison and Tiedemann, 2016) and CCAAlign-envi (El-Kishky et al., 2020) of sizes 3.5M and 9.3M respectively. For OpenSubtitles, manual inspection showed inaccurate translations similar to the previous observations in Doan et al. (2021b). Including CCAAlign-envi as-is will significantly reduce the model test performance in test set (Appendix C). For this reason, we make use of \( bT_A \) to score each bitext by computing the loss of all text pairs and select the best 700K training examples using cross-validation on the tst2013 test set\(^2\). CCAAlign-envi, on the other hand, is entirely discarded through the same process.

Dynamic Programming style alignment Another large source of parallel data but trickier to extract comes from weakly-aligned books and articles (Ladhak et al., 2020). This includes many mismatches at sentence and paragraph levels due to versioning, translator formatting, extra headers and page footer information. We propose a dynamic-programming style alignment algorithm detailed in Algorithm 1, a simplified version of BleuAlign (Sennrich and Volk, 2011), to filter and align sentences between each pair of documents, maximizing the total BLEU score after alignment. In total, we collected 900K training examples from 300 bilingual books and news articles.

Manual crawl and clean For this source, we focus on more technical and high-impact domains, this include law documents and biomedical scientific articles. We manually crawl and clean across 20 different websites of public biomedical journals and law document libraries, treating them individually due to their significantly different formatting. We also manually crawl and clean some other available websites that are more straightforward to process, as detailed in Appendix D. Overall, this source contributed another 1.2M training examples.

Data crowdsourcing for MTet multi-domain test set We utilize dataset.vn to distribute 4K test examples held out from the collected data to 13 human experts to further refine its content. These domains include biomedical, religion, law, and news.

Overall, we collected 4.2M training examples across all sources. After combining MTet with PhoMT and IWSLT’15, we grew the existing training set from 3M to 6M training examples. Compared to the existing data sources, this dataset is both larger and much more diverse, with the inclusion of technical, impactful, yet so far mostly neglected domains such as law and biomedical data.

4 EnViT5

4.1 Model

EnViT5 is a Text-to-Text Transfer Transformer model follows the encoder-decoder architecture proposed by (Vaswani et al., 2017) and the T5 framework proposed by (Raffel et al., 2019). The original works of T5 proposed five different configurations in model size: small, base, large, 3B, and 11B. For the practical purpose of the study, we...
Table 1: Results on PhoMT English-Vietnamese Translation Test Set

| Model          | # Params | Pretrained | Finetuned Dataset | # pairs | En-Vi | Vi-En |
|----------------|----------|------------|-------------------|---------|-------|-------|
| M2M100         | 1.2B     | -          | CCMatrix + CCAligned | 7.5B    | 35.83 | 31.15 |
| Google Translate | -        | -          | -                 | -       | 39.86 | 35.76 |
| Bing Translator | -        | -          | -                 | -       | 40.37 | 35.74 |
| Transformer-base | 65M      | -          | PhoMT             | 3M      | 42.12 | 37.19 |
| Transformer-big | 213M     | -          | PhoMT             | 3M      | 42.94 | 37.83 |
| mBART†         | 448M     | CC25       | PhoMT             | 3M      | 43.46 | 39.78 |
| EnViT5-base    | 275M     | CC100      | MTet              | 4.2M    | 43.87 | 39.57 |
|                |          |            | MTet + PhoMT      | 6.2M    | **45.47** | **40.57** |

Notes: The best scores are in bold and second best scores are underlined. (†) mBART trained on PhoMT train set are published work (Doan et al., 2021b) that previously achieved state-of-the-art results on English-Vietnamese translation.

adapt the base architecture for EnViT5 and save the bigger models for future works.

We train EnViT5 models from scratch with the input and output length of 1024 tokens and batch size of 256. For the self-supervised learning objectives, we use the span-corruption objective with a corruption rate of 15%.

4.2 Pretraining data

We use the CC100 Dataset (Monolingual Datasets from Web Crawl Data) (Wenzek et al., 2020) for pre-training the model. The corpus contains monolingual data for over 100 languages. The corpus was constructed using the pipeline provided by (Wenzek et al., 2020) through processing January-December 2018 Commoncrawl snapshots. Following the discussion regarding the importance of long context sequences during pretraining for T5 models from previous works (Phan et al., 2022), we process and filter for 80GB of long sequence (fit in 1024-length embedding) for each language.

5 Benchmarking EnViT5 and MTet

5.1 Experimental settings

To develop our analysis, we conduct experiments to verify the quality of our MTet dataset and our pretrained bilingual model EnViT5 on both English-to-Vietnamese and Vietnamese-to-English translation. We are interested in the final performance of EnViT5 trained on MTet and PhoMT and aim to demonstrate the best results for both research communities and industry applications.

We compare EnViT5 against well-known engines and baseline models: Google Translate, Bing Translator, Transformer-base, Transformer-large (Vaswani et al., 2017), and mBART (Doan et al., 2021b). All our models are trained for 30 epochs with a batch size of 256. We use SacreBLEU (Post, 2018) to compute the case-sensitive BLEU score on the PhoMT test set (Doan et al., 2021b).

5.2 Results

Table 1 presents BLEU scores of our models on both translation directions. A first takeaway is that the large finetuned English-Vietnamese translation dataset accounts for the significant improvement of both En-Vi and Vi-En translations. Both Transformer models (Vaswani et al., 2017) and EnViT5 models (Raffel et al., 2019) without self-supervised learning steps still achieve notable results on translations compared to current famous translation models from Google Translate and Bing Translator.

Our EnViT5-base model when training on a combination of MTet and the released PhoMT achieves state-of-the-art results on low-resource English-Vietnamese translation (45.47 and 40.57 for En-Vi and Vi-En respectively). EnViT5 models outperform current existing multilingual models mBART and M2M100 while being significantly smaller in parameter size (275M parameters compared to 448M and 1.2B). This allows our models not only be able to scale in academia but also very promising for industry and community applications.

6 Evaluating multi-domain training data

In this section, we investigate the importance of multi-domain in training data for a Machine Translation. Since each domain tends to be different in textual structure and style, the ability to generalize across domains will makes translation models more practical in real-world applications.

For fair comparison between different do-
mains, pretraining is not used. We start from Transformer$_\text{base}$ (Vaswani et al., 2017) and compare the following three training data on our multi-domain test set described in Section 3: (1) 300k Multi-Domain sentence pairs, (2) 300K Ted-talk sentence pairs, and (3) 300K Law sentence pairs.

Besides TED Talk and Law, other domains do not have enough data to fairly take part in our comparison. The result of this experiment is shown in Table 2. There is a significant increase in BLEU scores across all domains when the model is trained on a Multi-domain training set. Surprisingly, training on Multi-domain data gives better performance on the Law domain than training on the pure Law parallel training dataset itself. This result indicates that multi-domain data during supervised training does indeed lead to better test set performance.

### 7 A time budget comparison of self-supervised and supervised data

In this experiment, we first start with IWSLT’15 of 133k training examples and follow two separate processes to improve test performance on top of this initial data point: (1) we pretrain the model on an amount of non-aligned bilingual texts described in section 4.2 before further fine-tuning it on the IWSLT’15 training set for one epoch; (2) we simply grow the IWSLT’15 training set by an amount of high-quality parallel text before training for one epoch from random weights.

In both methods, we measure the improvement in BLEU score at various amounts of additional data. Following this, we are able to measure the amount of training wall time needed to achieve the target BLEU score. This time is also directly proportional to the added amount of data.

As reported in Figure 1, we first confirmed that BLEU score on the test set steadily improved as both types of data grows, albeit at vastly different rates. BLEU scores improvement from pretraining quickly diminishes, eventually hitting a wall. After this point, it becomes infeasible to reach further target BLEU scores by pure pretraining, a 1.5X increase in pretraining data does not lead to any meaningful improvement. At a target BLEU score of 34, we found that it took close to 1000X the amount of data and 2000X training wall time for pretraining to reach the same performance as supervised training.

### 8 Conclusion

In this work, we released a state-of-the-art pre-trained Transformer model and the largest multi-domain parallel dataset for English-Vietnamese translation. Namely, MTet consists of 4.2M high-quality training sentence pairs collected using various methods across multiple domains of data. Combining with phoMT, the total training data grow to 6.2M sentence pairs, currently the largest publicly available dataset. Further, we released EnviT5, the first pretrained model for English and Vietnamese languages. Fine-tuning EnviT5 on MTet, we obtained state-of-the-art results with improvements up to 2 points in BLEU score for English-Vietnamese Translation and 1 BLEU score in Vietnamese-English translation. With much better test results, our model is also 1.6 times smaller than previous translation models with much faster inference time.
9 Limitations

Although we conjecture that behaviors observed in our work will exhibit similarly in other low-resource language pairs, there are legitimate reasons to believe different languages might behave differently due to their own unique morphology. Generalizing our work to other pairs requires non-trivial effort and we leave this for future investigation.

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A Dataset Statistics

The data distribution of our MTet dataset is described in Figure 2.

B Data collection time

We record human time as the time spent developing different code bases for crawlers, inspecting manually, cleaning of different data sources, aggregating website sources, and converting files to appropriate text format. Machine time is execution time for long-running jobs such as crawling and rendering millions of websites, batch downloading files, preprocessing large volumes of texts, running inference for millions of sentences on Transformer models, and computing BLEU scores between billions of pairs of sentences. The recorded time is shown in Figure 3.

C Quality of existing BiText Mining Datasets

MultiCCAligned (El-Kishky et al., 2020) massively crawled the Web and aligned bilingual texts using the auto-metric of embedding-based document similarity. This results in 9.3M English-Vietnamese text pairs - the largest collection available to the public at the moment3. However, auto-metric-based alignment produces data of lower quality than our carefully hand-curated collection, many pairs in MultiCCAligned are themselves low-quality machine translated. Training on MultiCCAligned, therefore, gives a much lower BLEU score, while incorporating MultiCCAligned into our own data slightly decreases our result.

D Data sources for Manual Crawl and Clean

Medical

- https://yhoctphcm.ump.edu.vn
- http://jmp.huemed-univ.edu.vn
- http://tonghoiyhoc.vn
- http://hoinhikhoavn.com
- http://hoiyoctphcm.org.vn

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3The MultiCCAligned paper reported 12.4M pairs, we detected and removed duplicates, which accounted for nearly one quarter of their released data.
Figure 2: Training data distribution across multiple domains

Figure 3: Time required to 4.2M bitexts, color-coded for four tiers of data sources (1) combine existing open-sourced corpora, (2) score and filter noisy sources, (3) DP alignment from weakly-aligned documents, and (4) manual crawl and clean. With comparable outputs, the time invested is vastly different between them. The most expensive approach is manual crawl and clean, while the most scalable is DP alignment.

- https://jns.vn
- https://jprp.vn
- http://hocvienquany.edu.vn
- https://sinhlyhoc.com.vn
- https://tapchinghiencuuyhoc.vn
- http://tapchi.vienbongquocgia.vn
- http://vienduoclieu.org.vn
- https://vjpm.vn/index.php
- http://vjfc.nifc.gov.vn
- https://vjs.ac.vn
- http://vutm.edu.vn
- https://jcmhch.com
Figure 4: Performance comparison between parallel datasets

- http://www.yhth.vn
- https://sj.ctu.edu.vn
- https://radiology.com.vn
- https://vjol.info.vn
- http://www.vjph.vn

Others websites
- https://vietanhsongngu.com
- https://baosongngu.com
- https://sachsongngu.top
- https://tvpl.vn
- http://vbpl.vn
- http://automation.net
- http://tapchixaydungbxd.vn
- https://duytan.edu.vn
- https://tapchikhcn.hau.edu.vn
- https://tapchivatuyentap.tlu.edu.vn
- http://tapchimoitruong.vn
- https://translations.launchpad.net
- https://translationproject.org
- https://issuu.com/
- https://lyricstranslate.com
- https://www.wikihow.com
- https://d2l.aivivn.com

Youtube Channels
- Khan Academy
- Ted Ed
- Asap Science
- Crash courses
- GCP Grey
- Veritasium
- Vsauce