ParaZh-22M: a Large-Scale Chinese Parabank via Machine Translation

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Abstract

Paraphrasing, i.e., restating the same meaning in different ways, is an important data augmentation approach for natural language processing (NLP). Zhang et al. (2019b) propose to extract sentence-level paraphrases from multiple Chinese translations of the same source texts, and construct the PKU Paraphrase Bank of 0.5M sentence pairs. However, despite being the largest Chinese parabank to date, the size of PKU parabank is limited by the availability of one-to-many sentence translation data, and cannot well support the training of large Chinese paraphrasers. In this paper, we relieve the restriction with one-to-many sentence translation data, and construct ParaZh-22M, a larger Chinese parabank that is composed of 22M sentence pairs, based on one-to-one bilingual sentence translation data and machine translation (MT). In our data augmentation experiments, we show that paraphrasing based on ParaZh-22M can bring about consistent and significant improvements over several strong baselines on a wide range of Chinese NLP tasks, including a number of Chinese natural language understanding benchmarks (CLUE) and low-resource machine translation.

1 Introduction

A paraphrase is a restatement of meaning with different expressions (Bhagat and Hovy, 2013). Paraphrasing has been proven to be an effective data augmentation approach for many NLP tasks, ranging from linguistically controlled paraphrase generation (Iyyer et al., 2018; Chen et al., 2019; Li et al., 2019; Sun et al., 2021), style transfer (Krishna et al., 2020), to applications like low-resource machine translation (Khayrallah et al., 2020) and automatic MT evaluation (Thompson and Post, 2020; Bawden et al., 2020).

Zhang et al. (2019b) extract sentence-level paraphrases from multiple Chinese translations of the same source texts, and create the largest Chinese paraphrase bank (PKU Parabank) to date, which contains 509,832 pairs of paraphrased sentences. However, the amount of one-to-many sentence translation data constrains the size of PKU parabank, and it cannot meet the requirement to train large Chinese paraphrasers.

Inspired by Wieting and Gimpel (2018) and Hu et al. (2019a,b), we propose to relax the restriction that requires one-to-many translation data on the construction of large-scale Chinese parabanks, by utilizing bilingual one-to-one translation data of larger scales and MT, and construct ParaZh-22M. Specifically, we leverage the huge Chinese-English machine translation data from WMT 2021 (Akhbardeh et al., 2021) of 30.4M sentence pairs, apply strict rules to ensure the data quality, and translate the English side of the parallel corpus to Chinese with the cutting-edge deep Transformers and several approaches to ensure the translation quality. We pick the machine translated Chinese sentences considering both diversity and semantic consistency, and pair with the corresponding original Chinese references to form paraphrase pairs. Compared to the PKU parabank, ParaZh-22M is ~40 times as large, involves a broader range of paraphrase phenomena and domains, and can support the training of large Chinese paraphrasers.

Our main contributions are as follows:

• We propose to relieve the need of one-to-many translation data for the construction of Chinese parabank, and construct a Chinese parabank of 22M sentence pairs based on one-to-one sentence translation data and advanced MT models, which involves many domains and is ~40 times as large as the previous largest PKU Chinese parabank;

• We test the effects of data augmentation via

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¹We opensource our dataset at https://github.com/haowj9977/parazh-22M.
paraphrasing based on our parabank on a wide range of Chinese NLP tasks, including short/long text classification, natural language inference, keyword recognition, and low-resource machine translation, and show that paraphrasing based on our parabank is able to achieve consistent and significant improvements over several baselines.

2 Construction of ParaZh-22M

Zhang et al. (2019b) extract sentence-level paraphrases from multiple Chinese translations of the same source texts. Their approach requires one-to-many translation data, which is hard to collect. Instead, we try to relieve this restriction in Chinese parabank construction, and build the parabank based on one-to-one sentence-level translation data. Specifically, we translate the translation of Chinese sentences in the parallel data back to Chinese with the cutting-edge Neural Machine Translation (NMT) technology, and construct the parabank by pairing the machine translated Chinese sentences with the corresponding original Chinese sentences. We suggest that the semantic consistency and quality of the parallel bank is ensured by the cutting-edge NMT algorithm, as the translation quality of advanced NMT methods is already close to that of translation agencies in high resource scenarios (Akhbardeh et al., 2021).

The construction of ParaZh-22M can be divided into 4 steps: 1) data collection, 2) data processing and cleaning, 3) training of NMT models, and 4) paraphrase generation.

2.1 Data Collection

We leverage bilingual parallel sentence data for the construction of the Chinese parabank and the training of NMT models, and monolingual data to further boost the performance of NMT via back-translation (Sennrich et al., 2016a). We select several datasets from WMT 2021 Chinese-English news translation task (Akhbardeh et al., 2021), and statistics are shown in Table 1. Even though the data is collected for the news translation task in WMT, they indeed involve many domains, e.g., the ParaCrawl corpus is the extraction of parallel sentences from the web regardless of their domains.

| Dataset                      | Size  |
|------------------------------|-------|
| bilingual United Nations Parallel Corpus | 15.9M |
|                              | ParaCrawl | 14.2M |
|                              | News Commentary v16 | 0.3M |
| total                        | 30.4M |
| monolingual                  | News Crawl | 10.6M |

Table 1: Statistics of the bilingual and monolingual data. Size: the number of sentence pairs (for bilingual data) / sentences (for monolingual data). The monolingual data contain 10.6M sentences per language.

The United Nations Parallel Corpus (Ziemska et al., 2016) contains over 15.9M English-Chinese sentence pairs, which is composed of official records and other parliamentary documents of the United Nations that are in the public domain. The current version of the corpus contains content that was produced and manually translated between 1990 and 2014.

The News Commentary dataset is a collection of news about general politics, economics and science. Its English-Chinese section has about 0.3M sentence pairs.

The ParaCrawl dataset (Bañón et al., 2020) contains about 14.2M English-Chinese parallel sentences, constructed through web crawling software. Although its quality is slightly worse than the other two datasets in our manual evaluation, the ParaCrawl dataset involves many domains and provides a large number of training samples. In our experiments on the Zh→En task with base Transformers, using ParaCrawl dataset can bring about +5.4 and +3.8 BLEU improvements on the newstest 2020 and newstest 2021 test sets respectively.

2.2 Monolingual corpus

Back translation is a simple and effective approach to improve the performance of MT with monolingual data (Sennrich et al., 2016a; Fadaee and Monz, 2018; Eduvov et al., 2018; Wang et al., 2019b; Dou et al., 2020; Wei et al., 2020a; Marie et al., 2020). To further boost the performance of our NMT models (§ 2.3), and to obtain more accurate probability estimation in dual scoring (§ 2.4), we collect monolingual data of both languages, and augment the parallel data with the back translated monolingual data for the training of NMT models. Using back-translation data for NMT models’ training also helps improve
2.3 Training of NMT models

To construct the parabank, we only need to translate the English sentences into Chinese with NMT, but we have trained two NMT models for the forward and reverse translation directions for back translation (Sennrich et al., 2016a) and dual scoring (§ 2.4).

We employ the Transformer translation model (Vaswani et al., 2017) for NMT, as it has achieved the state-of-the-art performance in MT evaluations (Akhbardeh et al., 2021). We first use the parallel data to train 2 NMT models. Then we use greedy decoding to construct synthetic parallel data by back-translating the monolingual data (Sennrich et al., 2016a; Edunov et al., 2018). The back-translation data is then mixed with the original parallel data (the monolingual sentences at the target side and the greedy decoding texts at the source side). We fine-tune the NMT models trained in the first step on the mixed data for another 300k steps for improved performance.

To obtain good translation quality, we adopted the Transformer Big setting with 1024 and 4096 as the embedding dimension and the number of hidden units of the feed-forward layer respectively, together with a 12-layer deep encoder (Bapna et al., 2018; Wang et al., 2019a; Wu et al., 2019; Wei et al., 2020; Zhang et al., 2019a; Li et al., 2020; Hu et al., 2019; Xu et al., 2021). Parameters were initialized under the Lipschitz constraint (Xu et al., 2020a) to ensure the convergence of deep encoders. Since these NMT models are used to translate tens of millions of sentences (monolingual data for back-translation and the MT training set for the construction of the parabank), we used a 6-layer decoder instead of a deeper one to preserve the decoding efficiency (Kasai et al., 2021; Xu et al., 2021a). The number of warm-up steps was set to 8k. We used a batch size of around 25k target tokens achieved by gradient accumulation (Xu et al., 2020b), and trained the models for 300k steps, which takes about 50 hours to train a model on 4 Nvidia A100 GPUs.

We averaged the last 20 checkpoints saved with an interval of 1, 500 training steps.

The newstest 2019 was used as the development set, and newstest 2020 and newstest 2021 as the test set. The beam size of the decoder was set to 4, and translation quality was evaluated by case-sensitive BLEU (Papineni et al., 2002) with the SacreBLEU
Table 2: BLEU scores of our NMT models on the WMT 20 and WMT 21 news translation test sets.

| Model  | Zh→En |    | En→Zh |    |
|--------|--------|----|--------|----|
|        | newstest20 |    | newstest21 |    |
| NMT    | 30.53 | 24.74 | 42.38 | 32.85 |
| BT-NMT | 30.97 | 25.18 | 52.42 | 42.99 |

toolkit (Post, 2018; Bawden et al., 2020). Results are shown in Table 2.

Table 2 shows that our BT-NMT models can obtain comparably strong translation performance.

2.4 Paraphrase Generation

Language filtering We find that there are some English words in the Chinese part of the parallel data, which may affect the quality of the constructed parabank. To address this issue, we remove sentence pairs where a large percentage of English words appear in its Chinese sentence. Specifically, we check the percentage of English characters in Chinese sentences, and sentence pairs will be dropped if the proportion is larger than 60%.

Generating paraphrase candidates The English sentences are semantically consistent with the corresponding Chinese sentences in the parallel data. So we can obtain paraphrases of the original Chinese sentences by translating the English sentences into Chinese with MT.

We use the En→Zh BT-NMT model for the translation. For each English sentence, we use a beam size of 15 and collect all Chinese beam search candidates. Then, we pair each MT candidate with the corresponding original Chinese sentence to get a candidate Chinese paraphrase pair.

We find that En→Zh translation is more challenging than that for the construction of English parabanks although the NMT model obtains a high BLEU score for character-level evaluation (used for Chinese translations), and approaches like sampling/constrained-decoding (Post and Vilar, 2018) further drop the performance (by ~5 BLEU), causing semantic changes. Hence, we put a higher priority on translation quality to ensure the semantic consistency without using diversity-oriented approaches, such as sampling and constrained decoding. We suggest that our work provides a valuable reference for the construction of many other languages’ parabanks with MT when ensuring MT quality is a problem.

Edit-distance ratio filtering To effectively ensure the diversity of the parabank, we compute the edit-distance ratio (the edit distance divided by the length) between the beam search candidate and the corresponding original Chinese sentence, and use a minimum edit-distance ratio of 12% to filter the paraphrase pairs. We note that, as the parallel data are large, it is easy to further filter out a large subset with an edit-distance threshold larger than ours.

Dual scoring filtering The En→Zh model may leave some source tokens untranslated, leading to the under-translation issue (Tu et al., 2016). Measuring the round-trip translation consistency has been proven to be an effective way to address this and to improve the translation quality (Goto and Tanaka, 2017). Instead of selecting the beam search candidate with the highest decoding probability (Pforward), we also take the force decoding probability of the reverse model (Zh→En) Preverse into consideration. We re-rank the beam search candidates by summing the forward and reverse probabilities.

\[ p_{dual} = p_{forward} + p_{reverse} \] (1)

During filtering, we first select the candidate with the highest \( p_{dual} \) from beam search results for each remaining Chinese sentence. Then we derive the per-token probability of all instances of the dataset based on \( p_{dual} \), and only retain \( \sim 22M \) sentence pairs with the highest per-token probability to further ensure the quality, obtaining the final Chinese parabank, ParaZh-22M.

3 Evaluation of ParaZh-22M

We compare the constructed ParaZh-22M with two existing Chinese paraphrase datasets: PKU Paraphrase Bank (Zhang et al., 2019b) and Chinese Paraphrase from Quora (Wang et al., 2021).

PKU Paraphrase Bank Zhang et al. (2019b) construct the PKU parabank by extracting multiple...
Chinese translations of the same source texts (written in English as well as other European languages). The sentence pairs are from literary work.

**Chinese Paraphrase from Quora** Wang et al. (2021) transfer English retelling corpus, Quora, to Chinese with machine translation engines.

### 3.1 Statistics

We provide the basic information of Chinese paraphranks on source materials, domain, size (the number of sentence pairs), and the average sentence length (the number of Chinese words segmented by jieba) in Table 3.

Table 3 shows that: 1) ParaZh-22M is two orders of magnitude larger than the others, in terms of the number of paraphrases, it is 84 times as large as the Chinese Paraphrase from Quora (Wang et al., 2021) and 43 times as large as the PKU Paraphrase Bank (Zhang et al., 2019b). 2) the average number of words of ParaZh-22M is similar to that of the PKU Paraphrase Bank, and ParaZh-22M has more words than the Chinese Paraphrase from Quora on average. And 3) as ParaZh-22M is constructed upon bilingual data which involve many domains and rich styles (for the use of 14.2M ParaCrawl data), it is more general than the other two paraphrase corpora (PKU Paraphrase Bank is constructed based on literature work while Chinese Paraphrase from Quora are translations of English Quora), and can be easily adapted to different domains.

We suggest that: 1) the large size of ParaZh-22M is crucial to support the training of large neural paraphraser models, 2) it is easy to filter out a large subset for the use of a special task given an edit-distance threshold, and 3) covering a wide range of domains makes the application of ParaZh-22M domain-agnostic, leading to robust performance.

### 3.2 Manual Evaluation

There lacks an ideal evaluation metric that takes both semantic consistency and diversity into account for paraphrasing. Semantic consistency, fluency, and diversity are all important, while the diversity evaluation is normally against the consistency evaluation, e.g., a lower BLEU indicating higher diversity but lower semantic consistency (in MT). So we manually evaluate ParaZh-22M and PKU Paraphrase Bank (Zhang et al., 2019b) in terms of semantic consistency, literal fluency, and sentential diversity to measure their quality. We design our evaluation criteria following Wieting and Gimpel (2018); Wang et al. (2021), and specifics are shown in Table 4. For each evaluation criterion, we design 5 levels to distinguish the quality of sentence pairs.

We randomly sampled 800 sentence pairs from each dataset, and employed 8 native Chinese linguistic experts to rate them. Each sample is rated by 2 experts, and the final score is the average of their ratings. Results are shown in Table 5.

For the evaluation of ParaZh-22M, Table 5 shows that: 1) 93.9% of ParaZh-22M samples are strongly semantically consistent (with a score no less than 4, indicating that the semantic meaning of the sentence pair is nearly equivalent, or only may differ in some unimportant details). 2) 97.9% of ParaZh-22M samples are fluent (with at most one grammatical error), and 3) 97.9% of ParaZh-22M samples have at least one lexical variation.

Compared to the PKU Paraphrase Bank, ParaZh-22M achieves much higher scores in semantic consistency and literal fluency evaluation, while obtaining a slightly lower score in sentential diversity. We conjecture this might be because: 1) we pay more attention to optimizing the translation quality when constructing the parabank (§ 2), which gives the correctness (semantic consistency and fluency) a higher priority than the diversity, and 2) Zhang et al. (2019b) use one-to-many parallel data for the construction of the parabank, while we only use one-to-one translation data.

We evaluated the inter-annotator agreement with kappa (Artstein and Poesio, 2008), and obtained a kappa value of 0.87, suggesting that a high agreement is achieved with our evaluation criteria and our evaluation is reliable.
Table 4: Manual evaluation criteria of semantic consistency, literal fluency, and sentential diversity.

| Score | Semantic Consistency | Literal Fluency | Sentential Diversity |
|-------|----------------------|-----------------|----------------------|
| 5     | Sentences have exactly the same meaning with all the same details. | The sentence pair has no grammatical error. | The sentences have more than one grammatical variation or more than two lexical variations. |
| 4     | Sentences are mostly equivalent, but some unimportant details can differ. | The sentence pair has one grammatical error. | The sentences have grammatical variation slightly. |
| 3     | Sentences are roughly equivalent, with some important information missing or that differs slightly. | The sentence pair has two grammatical errors. | The sentences have unchanged grammatical structure but two lexical variations. |
| 2     | Sentences are not equivalent, even if they share slight details. | The sentence pair has three grammatical errors. | The sentences have unchanged grammatical structure but one lexical variation. |
| 1     | The sentences are totally different. | The sentence pair has more than three grammatical errors. | The sentence pair has basically unchanged grammatical structure and lexical variation. |

Table 5: Manual evaluation results of our corpus and PKU Paraphrase Bank on semantic consistency, literal fluency, and sentential diversity. **Medium**: the cumulative percentages of samples with the scores. **Bottom**: the average score and the standard deviation of each criterion.

| Score | Semantic Consistency | Literal Fluency | Sentential Diversity |
|-------|----------------------|-----------------|----------------------|
|       | Ours | PKU | Ours | PKU | Ours | PKU |
| ≥ 5.0 | 69.1 | 34.3 | 82.4 | 72.0 | 56.9 | 65.3 |
| ≥ 4.0 | 93.9 | 66.5 | 97.9 | 97.3 | 70.8 | 74.9 |
| ≥ 3.0 | 98.4 | 87.8 | 99.9 | 99.5 | 84.0 | 87.3 |
| ≥ 2.0 | 99.6 | 94.8 | 100.0 | 100.0 | 97.9 | 98.5 |

AVG score | **4.64±0.64** | **3.89±1.11** | **4.82±0.41** | **4.72±0.50** | **4.11±1.19** | **4.28±1.10**

4 Using ParaZh-22M in Chinese NLP

We examine the effectiveness of data augmentation based on ParaZh-22M on a number of Chinese NLP tasks, including long/short text classification, natural language inference, keyword recognition from CLUE (a Chinese Language Understanding Evaluation benchmark) (Xu et al., 2020c) and the CCMT 2022 low-resource Chinese → Thai machine translation task, by paraphrasing the original training set.

4.1 Chinese Paraphraser

ParaZh-22M contains a large number of Chinese paraphrase examples, but cannot be directly used to augment the training sets of NLP tasks. To paraphrase arbitrary Chinese sentences, we train a Chinese paraphrase model, i.e., a Chinese paraphraser, on ParaZh-22M.

Like back translation, we use the machine translated Chinese sentences as the source input of the model, and the original Chinese sentences from the parallel data as the target when training the paraphraser on ParaZh-22M.

We used the same vocabulary and BPE as the Chinese part of NMT data (§ 2.2). We employed a base Transformer as the paraphraser. Specifically, we used 6 encoder and decoder layers, an embedding size of 512, 8 attention heads, a feed-forward layer of 2048 hidden units, and shared the encoder-decoder embeddings. The model was trained for 100k steps. The average of the last 5 checkpoints saved with an interval of 1,500 training steps is served as the paraphraser.
Table 6: Results (accuracy) on the validation sets of TNEWS and IFLYTEK tasks. "Δ" indicates the improvements over the baseline. "avg" is the average improvement of data augmentation over three baselines.

| Model             | TNEWS          | IFLYTEK        |
|-------------------|----------------|----------------|
|                   | Baseline | PKU | Ours | Δ | Baseline | PKU | Ours | Δ |
| ALBERT-tiny       | 53.55    | 53.52 | -0.03 | | 53.74 | +0.19 | 48.76 | 52.59 | +3.83 |
| BERT-base         | 56.09    | 57.11 | +1.02 | | 57.19 | +1.10 | 60.37 | 60.52 | +0.15 |
| BERT-wwm-ext-base | 56.77    | 57.55 | +0.78 | | 57.69 | +0.92 | 59.88 | 59.75 | -0.13 |
| avg               | /        | /   | +0.59 | / | +0.74 | /   | +1.28 | / | +2.94 |

4.2 Text Classification

We conducted experiments on two text classification tasks of the CLUE benchmark (Xu et al., 2020c): TNEWS for short texts, and IFLYTEK for long texts.

The TNEWS task has 15 categories (finance, technology, sports, etc.), including 53.3k training instances and 10k validation data. The IFLYTEK task has 119 classes (food, car rental, education, etc.), with 12.1k training samples and 2.6k validation data.

We augmented the training data of these 2 tasks by paraphrasing the input sentences with our paraphraser, and constructed the synthetic data $D_p$ by pairing paraphrases with the tag of the corresponding original sentence. We concatenated $D_p$ with the original training set $D_o$ as the augmented training set $D_{aug}$, and trained the same baseline model on the augmented training set.

We used ALBERT-tiny, BERT-base, BERT-wwm-ext-base as our baselines. ALBERT-tiny is a tiny version of ALBERT with only 4 layers and a hidden size of 312. BERT-base has 12 layers and uses a hidden size of 768. BERT-wwm-ext-base has the same configuration as BERT-base, but is pre-trained with whole word masking. We evaluated these models on the validation sets (as the test sets are not publicly available). Results are shown in Table 6.

Table 6 shows that: 1) paraphrasing based on both the PKU parabank and ParaZh-22M can lead to improvements on average, and 2) data augmentation based on ParaZh-22M leads to consistent and significant improvements over all baselines on both datasets, and brings about more accuracy improvements than based on the PKU parabank, showing the advantages of ParaZh-22M for both short and long text classification.

4.3 Natural Language Inference

We also examined the effects of paraphrasing based on ParaZh-22M on the natural language inference (NLI) task, and conducted experiments on CMNLI dataset. NLI aims to predict the relation (neutral, entailment, and contradiction) between sentence pairs. The CMNLI contains 391k training samples, and 12k validation instances.

We used the same baseline models described in § 4.2. For data augmentation, as each CMNLI training instance has a sentence pair, we investigate 4 cases: 1) augmentation by paraphrasing the first sentence ($S_1$), 2) augmentation by paraphrasing the second sentence ($S_2$), 3) augmentation by paraphrasing both sentences ($S_1+S_2$), and 4) the combination of case 1 and case 2 ($S_1+S_2$). We concatenated the paraphrased training set with the original training set. Results are shown in Table 7.

Table 7 shows that: even though paraphrasing based on the PKU parabank brings about more improvements in the $S_1+S_2$ and $S_2$ settings with the ALBERT-tiny model than based on ParaZh-22M, data augmentation with ParaZh-22M leads to consistent and significant improvements over all baselines, and works better with larger models and stronger baselines (BERT-base and BERT-wwm-ext-base) than with the PKU parabank.

4.4 Keyword Recognition

The keyword recognition task requires the model to distinguish real keywords of paper abstracts from fake keywords. Chinese Scientific Literature (CSL) dataset (Xu et al., 2020c) contains Chinese paper abstracts and their real keywords from core journals of China, covering multiple fields of natural sciences and social sciences, with fake keywords generated through TF-IDF. CSL datasets provide 20k samples for training and 3k samples for validation.

We used the same baselines as in § 4.2. When paraphrasing the abstract, we performed beam de-
| Model          | Baseline | $D_{aug}$ | S1+S2 | $\Delta$ | S12 | $\Delta$ | S1/S2 | $\Delta$ |
|----------------|----------|-----------|-------|----------|-----|----------|-------|----------|
| ALBERT-tiny    | PKU      | 73.67     | +3.41 | 72.01    | +1.75 | 71.88/73.27 | +1.62/+3.01 |
|                | Ours     | 73.07     | 2.81  | 72.88    | +2.62 | 72.56/72.45 | +2.30/+2.19 |
| BERT-base      | PKU      | 79.55     | +0.08 | 79.95    | +0.48 | 79.90/79.81 | +0.43/+0.34 |
|                | Ours     | 80.27     | 0.80  | 80.80    | +1.33 | 80.57/80.30 | +1.10/+0.83 |
| BERT-wwm-ext-base | PKU   | 79.98     | -0.94 | 80.50    | -0.42 | 80.04/80.08 | -0.88/-0.84 |
|                | Ours     | 81.23     | 0.31  | 81.21    | +0.29 | 81.28/81.16 | +0.36/+0.24 |

Table 7: Results (accuracy) on the validation set of CMNLI task.

| Model          | Baseline | PKU | $\Delta$ | Ours | $\Delta$ |
|----------------|----------|-----|----------|------|----------|
| ALBERT-tiny    | 74.34    | 76.66 | +2.32   | 77.20 | +2.86   |
| BERT-base      | 79.63    | 79.03 | -0.60   | 80.90 | +1.27   |
| BERT-wwm-ext-base | 80.60 | 79.30 | -1.30   | 81.00 | +0.40   |

Table 8: Results (accuracy) on the validation set of CSL task.

coding with a beam size of 15 with the paraphraser, and selected the beam search candidate that contains all corresponding keywords and has the highest decoding probability. We did not augment training instances when no beam search candidate contains the keywords. The synthetic training set $D_p$ was then combined with the original training set $D_o$. Results are shown in Table 8.

Table 8 shows that: 1) data augmentation based on both the PKU parabank and ParaZh-22M can bring about improvements on average, 2) the accuracy improvements with ParaZh-22M are consistent and significant with all baselines, including in challenging cases (with BERT-base and BERT-wwm-ext-base), and are larger than with the PKU parabank, demonstrating the effectiveness of ParaZh-22M in challenging settings.

4.5 Low-Resource Machine Translation

We conducted experiments on the CCMT 2022 Chinese→Thai low-resource translation task. Its training set has 200k sentence pairs. As the evaluation does not release both the development set and the test set, we held out the last 2000 sentence pairs of the training set, and equally divided them into 2 parts for validation and test respectively. We paraphrased the Chinese sentences of the training data and paired with the corresponding Thai sentences.

We employed a 6-layer and a 12-layer Transformer as our baselines. Following Sennrich and Zhang (2019), we used an embedding dimension of 256, 4 attention heads, 1024 as the hidden dimension of the feed-forward layer, a dropout probability of 0.1, and applied 16k BPE operations enforced by sentence piece (Kudo and Richardson, 2018).

We set the a beam size to 4, and evaluated translation quality via BLEU with the average of the last 5 checkpoints saved in an interval of 1,500 training steps. Results are shown in Table 9.

Table 9 shows that: 1) paraphrasing based on ParaZh-22M can lead to consistent and significant improvements in the low-resource translation task with both settings, and 2) the improvements with the 12-layer model (+4.09 BLEU) in the MT task without using pre-trained models are much larger than in CLUE tasks with pre-trained models and than with the 6-layer model with fewer parameters.

5 Related Work

Data augmentation via paraphrasing is beneficial for many NLP tasks, such as question answering (Dong et al., 2017), semantic parsing (Berant and Liang, 2014; Su and Yan, 2017) and machine translation (Cho et al., 2014; Khayrallah et al., 2020), especially in low-resource scenarios. Paraphrasing relies heavily on large scale paraphrase datasets.

Construction of English paraphrase data Most paraphrase corpus construction studies are for English (Suzuki et al., 2017; Mallinson et al., 2017). Given the development of NMT, Wieting and Gim-
pel (2018) leverage large amounts of bilingual parallel data to generate paraphrases via MT. Hu et al. (2019a) add lexical constraints during NMT decoding to enrich the diversity. Hu et al. (2019b) cluster over constrained sampling decoding candidates to generate diverse paraphrases. Compared to Wieting and Gimpel (2018) and Hu et al. (2019a,b), we assign a higher priority to the quality of machine translation than the diversity to ensure the translation correctness and the semantic consistency, without using constrained decoding or sampling that hampers the translation quality.

**Chinese paraphrase corpus** To our knowledge, existing Chinese parabanks are much smaller than large scale English parabanks. Zhang et al. (2019b) extract sentence-level paraphrases from multiple Chinese translations of the same source text, obtaining the PKU Paraphrase Bank of 509,832 paraphrase pairs. Wang et al. (2021) translate the question retelling Quora corpus into Chinese with multiple MT engines, and construct a Chinese parabank of 263,729 sentence pairs. Compared to their work, ParaZh-22M is much larger and involves many domains.

### 6 Conclusion

In this paper, we relieve the requirement of one-to-many translation data for the construction of Chinese parabank, and construct a Chinese parabank of 22M sentence pairs, ParaZh-22M, utilizing one-to-one sentence-level parallel data and MT technology. ParaZh-22M involves many domains and is over 40 times as large as the previous largest PKU Chinese Paraphrase Bank. Human evaluation on semantic consistency, fluency and sentential diversity shows the good quality of ParaZh-22M.

We test the effects of data augmentation via paraphrasing based on ParaZh-22M on a wide range of Chinese NLP tasks, including short/long text classification, natural language inference, keyword recognition, and low-resource machine translation. Our experiment results show that paraphrasing based on ParaZh-22M is able to achieve consistent and significant improvements over several baselines in all evaluations, demonstrating the contribution of ParaZh-22M to Chinese NLP tasks.

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