

FewCLUE: A Chinese Few-shot Learning Evaluation Benchmark

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Abstract

Pretrained Language Models (PLMs) have achieved tremendous success in natural language understanding tasks. While different learning schemes—fine-tuning, zero-shot and few-shot learning—have been widely explored and compared for languages such as English, there is comparatively little work in Chinese to fairly and comprehensively evaluate and compare these methods. This work first introduces Chinese Few-shot Learning Evaluation Benchmark (Few-CLUE), the first comprehensive small sample evaluation benchmark in Chinese. It includes nine tasks, ranging from single-sentence and sentence-pair classification tasks to machine reading comprehension tasks. Given the high variance of the few-shot learning performance, we provide multiple training/validation sets to facilitate a more accurate and stable evaluation of few-shot modeling. An unlabeled training set with up to 20,000 additional samples per task is provided, allowing researchers to explore better ways of using unlabeled samples. Next, we implement a set of state-of-the-art (SOTA) few-shot learning methods (including PET, ADAPET, LM-BFF, P-tuning and EFL), and compare their performance with fine-tuning and zero-shot learning schemes on the newly constructed FewCLUE benchmark. Our results show that: 1) all five few-shot learning methods exhibit better performance than fine-tuning or zero-shot learning; 2) among the five methods, PET is the best performing few-shot method; 3) few-shot learning performance is highly dependent on the specific task. Our benchmark and code are available at <https://github.com/CLUEbenchmark/FewCLUE>

1 Introduction

Pretrained Language Models (PLMs) such as BERT (Devlin et al., 2019) and RoBERTa (Liu et al., 2019) have achieved impressive performance on general language understanding benchmarks in several languages, e.g., GLUE (Wang et al., 2018) and SuperGLUE (Wang et al., 2019) in English, CLUE (Xu et al., 2020) in Chinese, KLUE (Park et al., 2021) in Korean, among others. However, most natural language understanding (NLU) benchmarks assume a data-rich situation, where thousands or even more hand-labeled data are available (for instance, MNLI has more than 390k training data). In the real world, high-quality human annotation can be costly and time-consuming. Thus, there has been growing interest in the few-shot or even zero-shot learning scheme, where only a handful of hand-annotated, task-specific training examples are fed to PLMs in the training stage (Brown et al., 2020; Gao et al., 2021; Schick and Schütze, 2021a; Schick and Schütze, 2021b; Liu et al., 2021).

However, there are two issues in current few-shot learning studies. First, mostly studies focus primarily on English (Brown et al., 2020; Gao et al., 2021; Schick and Schütze, 2021a); it is unclear how few-shot learning will perform in languages that are typologically very different from English or have much less pretraining data than English. Second, there is no systematic and comprehensive comparison of the different few-shot learning methods proposed in recent years, e.g., PET (Schick and Schütze, 2021a), LM-BFF (Gao et al., 2021), ADAPET (Tam et al., 2021), EFL (Wang et al., 2021), Ptuning (Liu et al., 2021), among others.

To address these issues, we first introduce the few-shot Chinese Language Understanding Evaluation (FewCLUE) benchmark, which consists of 9 NLU tasks in Chinese, where 3/9 are new tasks,

and test sets of some other tasks were re-labeled. Next, taking into consideration the feedback we received from the research community, and the need to maximally reduce the instability of few shot learning (Dodge et al., 2020; Zhang et al., 2021), we adopt a reasonable and comprehensive evaluation method. Finally, we compare 5 popular few-shot learning mechanisms on the newly constructed Few-CLUE. Our results show that template-based methods, represented by PET, works better than traditional fine-tuning (FT) on pre-trained models.

Our contributions are:

- We construct the first systematic and comprehensive Few-shot Chinese Language Understanding Evaluation benchmark, and provide strong baselines and human evaluation. We believe the benchmark will facilitate the research on few-shot learning for Chinese NLU.
- To accommodate different few-shot learning scenarios, we adopt unified few shot learning evaluation methods including various training/validation split for accurate and stable evaluation, and with additional unlabeled data. We believe this is of critical importance in the evaluation of different few-shot learning paradigms.
- Based on our benchmark, we found that template-based method (Schick and Schütze, 2021a; Schick and Schütze, 2021b) can achieve better performance than fine-tuned-based method (Liu et al., 2021), which can provide some guidance and promising research directions for researchers and practitioners in NLP. Furthermore, although there are many methods to generate templates automatically, our experiments show that the template created manually is the best.

2 Related Work

2.1 Few Shot Learning Benchmarks

In computer vision, few-shot benchmarks have been proposed to measure the few-shot learning ability of pretrained computer vision models and the related few-shot learning methods (Chen et al., 2019). In NLP, there are also some methods considering the few shot learning process and achieved some good performance in standard benchmark (Floridi and Chiriatti, 2020). FewGLUE (Schick and Schütze, 2021b), is a few-shot learning dataset, consisting of a random selection of 32 training examples from the SuperGLUE (Wang et al., 2019) training sets and up to 20,000 unlabeled examples for each SuperGLUE task. We observe that recent research generates their datasets from GLUE (Wang et al., 2018) or SuperGLUE (Wang et al., 2019), in a different way.

2.2 Few Shot Learning Methods

In this section, we briefly review current few-shot learning strategies for PLMs. We explain the implementation details in section 5.1 and section 5.2.

PET converts a task into a template-based cloze task (Schick and Schütze, 2021a; Schick and Schütze, 2021b). Compared with the direct fine-tuning of downstream tasks through BERT-based PLMs, PET produces considerable performance improvement in the few-shot scenario; for some tasks the performance increase can be as large as 10 points. While the templates in PET are manually constructed, researchers have also explored various ways of automated template-construction. For example, LM-BFF (Gao et al., 2021) uses the generative model T5 (Raffel et al., 2020) to generate templates. Ptuning (Liu et al., 2021) builds continuous end-to-end templates which are not in the form of natural language. Furthermore, there are other works transforming tasks into natural language inference (EFL, Wang et al. (2021)). One of our goals in this paper is to systematically compare the performance of these methods.

2.3 Few Shot Evaluation Methods

In computer vision, few-shot evaluation can be classified into matched-based, fine-tuned-based, and meta-based. In the matched-based setting, the few-shot samples will not be used but only for matching

(Chen et al., 2019; Chen et al., 2020). In the fine-tuning-based and meta-based settings, the few-shot samples will be used to learn the model. Considering the few-shot learning property, we add unlabeled data for a more practical and comprehensive evaluation. We also adopt the multi-split evaluation, which alleviates the instability of few-shot learning.

3 Dataset Construction

3.1 Task Selection

The goal of FewCLUE is to provide a reliable evaluation for few-shot learning, discover the challenges, and provide a basis for further research in Chinese by creating such a systematic and comprehensive benchmark. The benchmark aims to investigate the NLU capabilities using a variety of tasks, e.g., text classification, natural language inference, text similarity, reading comprehension, etc. These tasks can be generalized into single-sentence, sentence-pair, and general reading comprehension tasks. To ensure the quality and coverage of the language understanding tasks, we select tasks using the following criteria:

Representative Tasks should reflect real-world settings, e.g., classification with many labels, samples from real text data.

Challenging and discriminative We expect the tasks to be challenging, showing the gap between human and machines. Moreover, the benchmark ought to better discriminate the performance of different models, resulting in more discrete results on the leaderboard.

Consistent We expect that the results of the same model on different train/dev splits to be consistent.

3.2 Building the Benchmark

In order for our FewCLUE benchmark to maximally satisfy the needs of the NLP community, we first sent out a public survey to collect opinions and suggestions on the benchmark.

Public survey The feedback we received include: 1) tasks should be diverse, including single-sentence, sentence-pair classification, and machine comprehension tasks; 2) Each dataset typically contains 16 or 32 samples per class; 3) Each task include enough unlabelled samples for research in zero-shot and semi-supervised learning; etc. The benchmark is built to satisfy these features.

Next, we picked 6 tasks from the CLUE (Xu et al., 2020) benchmark, and then added 3 new tasks. See Table 1 and section 4 for detailed descriptions.

Data sampling: we adopt multiple sampling strategies to generate samples from original datasets to reflect real scenarios. Specifically, we collect 32 samples for tasks with $n_label \leq 3$. Five tasks fall into this category: EPRSTMT, OCNLI, BUSTM, CSL and CLUEWSC. For tasks where $3 < n_label \leq 20$, we sample 16 samples per class; TNEWS falls into this category. For tasks where $n_label > 20$ we sample 8 samples per class; CSLDCP and IFLYTEK fall into this category. For CHID, since each sample has 7 candidate idiom and the correct answer can appear at any position (1st to 7th), we collect 6 samples for each position where the correct answer locates (7 positions, $6 * 7 = 42$ samples in total).

Multiple training/validation splits: since training on small datasets might lead to fluctuating results, we provide multiple training/validation splits to alleviate the issue and make our benchmark more robust. Participants should train and evaluate each split and submit their results on the unique private test set.

Public test set: each task comes with a public test set, on which people can conduct experiments and publish results for research purposes.

Unlabeled data: up to 20k unlabeled samples are also provided in each task for potential research in unsupervised and semi-supervised learning.

Overall, we create a comprehensive Chinese few-shot benchmark containing nine tasks, including single-sentence, sentence-pair, and machine reading comprehension tasks. We adopt different sampling methods to reflect the real-world setting while maintaining the few-shot characteristic. Also, we provide multiple training and validation sets for each task to ensure the benchmark’s robustness and release an

Corpus	Train	Dev	Test Pub	Test Priv	N Labels	Unlabeled	Task	Metric	Source
Single Sentence Tasks									
EPRSTMT	32	32	610	753	2	19565	SntmntAnalysis	Acc	E-CommrcceReview
CSLDCP	536	536	1784	2999	67	18111	LongTextClassify	Acc	AcademicCNKI
TNEWS	240	240	2010	1500	15	20000	ShortTextClassify	Acc	NewsTitle
IFLYTEK	928	690	1749	2279	119	7558	LongTextClassify	Acc	AppDesc
Sentence Pair Tasks									
OCNLI	32	32	2520	3000	3	20000	NLI	Acc	5Genres
BUSTM	32	32	1772	2000	2	4251	SemanticSmlarty	Acc	AIVirtualAssistant
Reading Comprehension									
CHID	42	42	2002	2000	7	7585	MultipleChoice,idiom	Acc	Novel,EssayNews
CSL	32	32	2828	3000	2	19841	KeywordRecognntn	Acc	AcademicCNKI
CLUEWSC	32	32	976	290	2	0	CorefResolution	Acc	ChineseFictionBooks

Table 1: Task descriptions and statistics.

additional public test set for further research. Finally, we release a large number of unlabeled samples for unsupervised and semi-supervised learning. The details of each task in FewCLUE are shown in Table 1

4 Tasks

The following sections will briefly introduce the nine tasks in FewCLUE. Six tasks are originally proposed in CLUE: TNEWS, IFLYTEK (IFLYTEK CO., 2019), OCNLI (Hu et al., 2020), CHID (Zheng et al., 2019), CSL (Xu et al., 2020) and CLUEWSC (Xu et al., 2020). They are sampled to fit the few-shot learning scenario. Please refer to (Xu et al., 2020) for details of the tasks. Furthermore, three new tasks are proposed in FewCLUE, which we describe in this section.

EPRSTMT (E-commerce Product Review Dataset for Sentiment Analysis), also known as EPR-sentiment, is a binary sentiment analysis dataset based on product reviews on e-commerce platform. Each sample is labelled as Positive or Negative. It collect by ICIP Lab of Beijing Normal University. We filter, test and re-organized it.

CSLDCP (Chinese Science Literature discipline Classification) is a text classification dataset including abstracts from a variety of Chinese scientific papers, with 13 scientific disciplines(field), and each discipline contains multiple categories. These papers belong to domains ranging from social science to natural science, including 67 categories, e.g., “口腔医学” (Oral medicine), “社会学” (Sociology) and “机械工程” (Mechanical engineering).

BUSTM (XiaoBu Dialogue Short Text Matching) (of OPPO XiaoBu, 2021) is a dataset provided by XiaoBu Assistant (Breeno), voice assistance produced by OPPO for its smartphones and IoT devices. The dataset comes from the data used to train XiaoBu on intent recognition through short text matching and mainly consists of colloquial sentence pairs.

For examples of each task, see Table 3 in the Appendix.

5 Experiments

5.1 Baseline models

- BERT/RobERTa fine-tuning:** fine-tuning pre-trained models with downstream tasks is a commonly used paradigm in NLU (Devlin et al., 2019; Liu et al., 2019). This baseline takes pre-trained BERT/RobERTa and fine-tunes it on each FewCLUE task.
- Exploiting cloze questions:** Since most BERT-style PLMs are pre-trained with a cloze-test (also referred to as ‘masked language modeling’, Taylor (1953)) objective, several methods have been proposed to exploit the cloze question format, where the task of the model is to correctly predict the [MASK]. We experiment with two such methods.

- (a) **PET (Pattern Exploiting Training)** is a semi-supervised training scheme that reformulates the downstream task into cloze questions (Schick and Schütze, 2021b; Schick and Schütze, 2021a). Such a method includes two steps. The first step reformulates the input sentence into a cloze-style phrase containing a portion of masked tokens. For example, in text classification the input can be “这个手机壳很不错” (“This is a nice phone case”), and it’ll be reformulated into “这个手机壳很不错。我觉得[MASK]好” (“This is a nice phone case. I think it’s [MASK] good”). Here “[MASK]” is the position where the model needs to fill in to complete the classification; the second step maps the label into a single token. E.g., for sentiment classification, labels POSITIVE and NEGATIVE can be mapped to the word “very”(“很”) and “not”(“不”). It is not unique to map a label to a word. Many choices exist. Finally, supervised training is performed on the dataset by using cross-entropy loss.
- (b) **ADAPET** is an improved PET model which involves more supervised signals (Tam et al., 2021). It proposes two improvements over the original PET method:
 - (1) Decoupling Label Losses: when predicting labels in the “[MASK]” position, the model calculates the probabilities of all tokens in the vocabulary (not only the token that is the candidate label) and chooses the highest-probability token as the predicted label. For example, we use the former example, “这个手机壳很不错。我觉得[MASK]好” (“This is a nice phone case. I think it’s [MASK] good”). It will not only calculate the probabilities of “very”(“很”) and “not”(“不”) in the “[MASK]” position, but also for all other vocabulary words.
 - (2) Label Conditioning: original tokens in the sentence are randomly masked, and the model tries to predict the original token based on the label. In other words, in PET the model predicts the correct label based on the input; but reversely, ADAPET predicts the correct input having the label. More specifically, given a constructed pattern with the correct label, the model is asked to predict the original token and calculate the loss; if the label is wrong, it will not calculate loss. Sentence 1: Oil prices rise (“石油价格上涨”); Sentence: Oil prices fall back (“石油价格回落”); correct label: no; incorrect label: yes. If our randomly masked token is “oil” (“石油”), for the correct label, we get pattern: [mask] price rise, no, oil price fall (“模板: [mask]价格上涨,不,价格回落”). In this case, as the label is correct, let the model predict that the token corresponding to [mask] is oil (“石油”). For incorrect label, we get pattern: [mask] price, rise, yes, oil price fall (“模板: [mask]价格上涨,是的,价格回落”). At this time, the model is incorrect, because the label is not correct, the model will not predict this [mask], and no loss will be calculated.

3. Automatic Template Construction

- (a) **LM-BFF (Gao et al., 2021)** is a method that explores automatic prompt generation. It utilizes a generative model T5 (Raffel et al., 2020) to automatically generate prompts for cloze questions, including template generation and label word generation, and evaluate the generated candidates based on the validation set. In addition, LM-BFF incorporates demonstrations during training to help the model better distinguish samples.
 - (b) **P-tuning (Liu et al., 2021)** The above methods all restrict the generated templates to be natural language. P-tuning discards this assumption and proposes to learn the optimal templates by using the unused tokens in a model’s vocabulary. Only embeddings corresponding to the template tokens will be updated during training, further speeding up the training process. Models of the GPT family can also achieve good results using P-tuning.
4. **EFL (Wang et al., 2021)** Unlike cloze-question-based models like PET and LM-BFF, Entailment as Few-shot Learners (EFL) reformulates the fine-tuning task into textual entailment and designs fine-grained textual descriptions for the labels. A basic model is obtained through training on a textual entailment dataset before fine-tuning on downstream tasks. For English, MNLI (Williams et al., 2018) can be used to train the model. For us, we use the machine translated version of MNLI—CMNLI (Xu et al., 2020).

5. **Zero-shot learning** We also adopt a standard scheme for zero-shot learning with RoBERTa and GPT3 (Brown et al., 2020). Similar to PET, a prompt with masked tokens is constructed, then the model is required to predict label words at the masked position and choose the label with the highest probabilities. The difference between RoBERTa and GPT in such a scheme is that RoBERTa’s prompt can be masked in any position, while GPT can only be masked in the last position.

5.2 Implementation Details

Our BERT and RoBERTa models are implemented using RoBERTa-wwm-ext and BERT-wwm-ext (Cui et al., 2020)¹. They have outstanding performance on CLUE benchmark, wide usage, and moderate size, which can be trained using around 11 GB of GPU memory. GPT model is implemented using NEZHA-Gen (Wei et al., 2019)².

PET For PET, we use RoBERTa and design specific templates for each task (see our Github repository for the templates). It is noteworthy that since the input format of CHID is already cloze-style, its training using PET becomes equivalent to zero-shot learning.

P-tuning For P-tuning, our model is based on this implementation³, with random masks on original tokens, nine prompt tokens and LSTM layers removed. We implement P-tuning and zero-shot method with both RoBERTa and GPT.

EFL For EFL, we first fine-tune the model on Chinese textual entailment task CMNLI to obtain the base model. Then, different templates are used to reformulate each task into a textual entailment task and perform downstream fine-tuning.

LM-BFF In LM-BFF, auto-T strategy is used for prompt generation, i.e., automatic template generation combined with predefined label word mapping, as described in the original paper. A smaller beam width (30) and Chinese T5 models provided by UER⁴ (Zhao et al., 2019) are used to shorten the time for template generation and evaluation due to resource limit. BERT is used for fine-tuning and other hyper-parameters are the same as the original implementation. Demonstrations are not adopted since preliminary experiment shows a worse result.

ADAPET For ADAPET, we also design different Chinese templates to adapt to each task. Model is trained for 1k steps, with batch size 16, learning rate 1e-5. Other hyper-parameters follow the original paper.

For more details of our implementation such as the hyper-parameters for each method, please refer to our Github repository.⁵

6 Benchmark Results

6.1 Human Performance

We take human performance for those tasks available in CLUE benchmark. And for the three new tasks, human evaluation is performed in the same way as CLUE: We follow procedures in SuperGLUE (Wang et al., 2019) to train the annotators before asking them to work on the test data. Specifically, each annotator is asked to annotate 30 to 50 pieces of data from the development set, and then compare their answers with the ground truth label. Then they are encouraged to discuss their answers with other annotators until they are confident with the task. Finally each annotator annotate 100 pieces of test data, which is used to compute the final human performance.

According to the experiment result, human achieves a final score of 82.40%, and over 80% in 6 out of 9 tasks. Human performance is especially high for CLUEWSC, reaching nearly 98% of accuracy.

¹<https://github.com/ymcui/Chinese-BERT-wwm>

²<https://github.com/huawei-noah/Pretrained-Language-Model/tree/master/NEZHA-Gen-TensorFlow>

³<https://github.com/bojone/P-tuning>

⁴<https://huggingface.co/uer/t5-base-chinese-cluecorpussmall>

⁵<https://github.com/CLUEbenchmark/FewCLUE>

Method	Score	Single Sentence				Sentence Pair			MRC		
		EPRSTMT	CSLDCP	TNEWS	IFLYTEK	OCNLI	BUSTM	CSL	CHID	WSC	
Human	82.5	90.0	68.0	71.0	66.0	90.3	88.0	84.0	87.1	98.0	
FineTuningB	39.6	61.9	25.6	40.5	22.6	33.6	54.1	50.5	15.0	50.3	
FineTuningR	42.8	63.2	35.7	49.3	32.8	33.5	55.5	50.0	15.7	49.6	
Zero-shotR	44.6	85.2	12.6	25.3	27.7	40.3	50.6	52.2	57.6	50.0	
Zero-shotG	43.4	57.5	26.2	37.0	19.0	34.4	50.0	50.1	65.6	50.3	
PET	57.37	87.2	56.9	53.7	35.1	43.9	64.0	55.0	61.3	59.2	
P-tuningR	52.46	88.5	44.4	48.2	32.0	35.0	65.4	50.0	57.6	51.0	
P-tuningG	42.83	75.7	33.7	45.3	24.0	35.8	54.9	53.5	13.7	49.0	
EFL	56.54	85.6	46.7	53.5	44.0	67.5	67.6	61.6	28.2	54.2	
LM-BFF	55.8	84.6	53.6	56.3	46.1	43.1	54.1	51.2	61.3	51.8	
ADAPET	50.9	89.0	43.3	54.8	36.3	37.0	69.7	52.1	22.2	53.9	

Table 2: Main results of different learning mechanisms on FewCLUE. Single sentence task: EPRSTMT, CSLDCP, TNEWS and IFLYTEK. Sentence-pair task: BUSTM, OCNLI. MRC task: CHID, WSC, CSL. B, R and G stands for BERT, RoBERTa and GPT series models respectively. MRC: Machine reading comprehension requires a machine to answer questions based on a given context. As these tasks all have context, so that can be regarded as MRC tasks. We get the result by train on train_0 for each task and test on test_public. We plan to conduct more experiments within a month and update results, such as initialize the embedding of the unused token using additional steps (instead of randomly initialize it) for P-tuning.

However, humans are not satisfying in tasks containing numerous classes, e.g., about 60% accuracy in IFLYTEK (119 classes) and CSLDCP (67 classes).

6.2 Model Performance and Analysis

The overall results are shown in Table 2. Our discoveries are summarized as follows.

Model potentials: The best model with the highest overall score (57.36) is far lower than human performance (82.49), nearly 15 points lower, which shows that few-shot learning still have huge potentials.

New learning paradigm: recently proposed few-shot learning methods show a remarkable improvement compared to traditional fine-tuning. For example, with the same pre-trained model, PET is about 18 points higher than fine-tuning. Especially in EPSTMT, PET is 24% higher, while zero-shot learning is also 21% higher than fine-tuning. The reason might be the insufficient training on significant trainable parameters during fine-tuning using very limited samples. Besides, PET, P-tuning and the zero-shot method are also substantially better than fine-tuning on CHID. It might because CHID is natively suitable for cloze-style learning methods.

Comparing few-shot learning methods: We have implemented five few-shot learning methods, including PET, ADAPET, LM-BFF, Ptuning, EFL. The first four methods transformed the task to Cloze task, the last one transforming the task to natural language inference. Among the first four methods, ADAPET and Ptuning, try to find template automatically, but in a differnt way. PET achieves better results than other methods. P-tuningG, stands for P-tuning using a generated-based model, it performs the worst in our experiment. EFF achieves quite good results for natural language inference tasks, OCNLI and BUSTM, but performs poorly on CHID, a machine learning comprehension task.

Zero-shot learning capability: zero-shot learning methods have obtained good results in some tasks without any training data. For example, in IFLYTEK, zero-shot models achieve an accuracy of 27.7%, which is only 5% lower than the fine-tuning model, while random guessing has only 1% accuracy. Similar discoveries also show up in CSLDCP. The improvement on single-sentence tasks is more significant than sentence-pair tasks. It might be because most of the models' knowledge still comes from pre-training phase, and the input of single-sentence tasks is more similar to what they have seen in the pre-training

corpus. However, for sentence-pair and reading comprehension tasks, the input’s consistency is likely to be damaged whether using manual or auto-generated templates, which leads to less improvement.

Learning instability for single train/dev set: we discover that there is a severe fluctuation among the results produced by different training sets. Also, models that achieve the best validation result do not necessarily lead to the best test result. We assume that this is because the training and validation splits are too small to represent the overall distribution of the whole dataset. To show this phenomenon, we perform three comparison experiments based on PET and TNEWS datasets. For each experiment, training and validation sets are randomly sampled again from the full dataset, while test set is the same as above.

1. 20 samples/class, training/validation ratio 1:1.
2. 20 samples/class, training/validation ratio 1:3.
3. 7 samples/class, training/validation ratio 1:1.

Three experiments obtain the accuracy of 50.8%, 51.2%, 50.0% using the best validation model, which are sub-optimal compared with 53.7%. We also discover that validation results for exp. 2 have higher variance than exp. 1 and 3. It shows that accuracies are quite unstable using a single validation set, and it is also hard to obtain the best testing accuracy. Therefore, how to improve the stability of few-shot learning is a valuable research topic in the future.

6.3 Task Analysis

We have found that in few-shot learning, the difficulties of tasks for humans and models are substantially different. On the one hand, tasks like coreference resolution WSC are extremely easy for humans (98%), but it is hard for models to perform, which is no different from random guessing (~50%); However, in some other tasks, the gap is much smaller. For CSLDCP, a task with 67 labels, humans only archive an accuracy of 68%, which is relatively low compared to other tasks, while PET’s results are only 16 points lower. Thus, we can anticipate that few-shot models still have space to progress.

7 Conclusion

In this paper, we introduce FewCLUE, the first systematic and comprehensive few-shot learning benchmark in Chinese. It has three different types of NLU tasks, totally including nine tasks. We also provide multiple training and validation sets to handle instability problems in few-shot learning, public. Besides private testing sets for the leaderboard, we also provide a public test set that can be used for research purposes. Furthermore, a large amount of unlabeled data is available for unsupervised and semi-supervised learning. Different learning methods are evaluated on the benchmark, including fine-tuning, few-shot learning, and zero-shot learning using pre-trained language models. We also report human performance to better understanding the native of tasks and the potential of models. Experiment results of FewCLUE show that our tasks are challenging for models and leave a big room for future research.

We plan to update the experiment results on 2021-08-17 using five splits and get the average score. Meanwhile, we will also conduct more experiments, such as initialize the embedding of the unused token using additional steps (instead of randomly initialize it) for P-tuning.

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A Examples in the 9 tasks in FewCLUE

EPRSTMT	<p>sentence: 外包装上有点磨损，试听后感觉不错</p> <p>sentence (en): <i>The packaging is showing some wear, but after listening it feels good.</i></p> <p>label: positive</p>
CSLDCP	<p>sentence: 通过几年的观察和实践，初步掌握了盆栽菊花的栽培技术及方法，并进行了总结，以满足人们对花卉消费的需求，提高观赏植物的商品价值，为企业化生产的盆菊提供技术指导。</p> <p>sentence (en): <i>After years of observation and practice, to learn and summarize the basic techniques and methods for planting the Chrysanthemum, in order to satisfy people's needs for the flowers, to increase the value of ornamental plants, and to provide technical guidance to companies on growing the Chrysanthemum.</i></p> <p>label: horticulture</p>
INEWS	<p>sentence: 如果我的世界下架了，你会玩迷你世界吗？</p> <p>sentence (en): <i>If Minecraft is gone, will you play miniworld?</i></p> <p>label: 116(news_game)</p>
IFLYTEK	<p>sentence: 《钢铁英雄》是一款角色扮演类游戏。游戏拥有 带领他们逃出去。修复部分小错误，提升整体稳定性。</p> <p>sentence (en): <i>"Heroes of Steel" is a role-playing game. The game has all four heroes are imprisoned and you will lead them out. repair part small Errors to improve overall stability.</i></p> <p>label: 22(Strategy)</p>
CSL CLUEWSC	<p>text: 这时候放在床上枕头旁边的手机响了，我感到奇怪，因为欠费已被停机两个月，现在它突然响了。</p> <p>text (en): <i>At this moment, the <u>cellphone</u> on the bed next to the pillow rang. I feel this is quite strange because the cellphone plan was terminated two months ago since I did not pay the bill. Now <u>it</u> was ringing all of a sudden.</i></p> <p>label: true</p>
CSL	<p>abst: 不同阶段电子数据的操作都会留下表现各异的轨迹.从操作系统、计算机应用系统 分析审计电子数据轨迹在计算机系统中表现形式,可以为审计人员提供有效的审计方法</p> <p>keyword: ["计算机审计", "数据轨迹", "日志文件"]</p> <p>abst (en): <i>The operation of electronic data in different stages will leave different traces. From operating system, computer application system provide effective audit methods for auditors by analyzing the expression of audit electronic data trace in computer system.</i></p> <p>keyword (en): ["computer audit", "data trace", "log file"]</p> <p>label: 0(false)</p>
BUSTMT	<p>sentence1: 女孩子到底是不是你 sentence2: 你不是女孩子吗</p> <p>sentence1 (en): <i>Are you a girl or not?</i> sentence2 (en): <i>Aren't you a girl?</i></p> <p>label: paraphrase</p>
OCNLI	<p>premise: 但是不光是中国,日本,整个东亚文化都有这个特点就是被权力影响很深 hypothesis: 有超过两个东亚国家有这个特点</p> <p>premise (en): <i>But not only China and Japan, the entire East Asian culture has this feature, that is it is deeply influenced by the power.</i> hypothesis (en): <i>More than two East Asian countries have this feature.</i></p> <p>label: entailment</p>
ChID	<p>content: 中国青年报: 篮协改革联赛切莫#idiom#.....</p> <p>candidates: ["急功近利", "画蛇添足", "本末倒置"(answer)]</p> <p>content (en): <i>China Youth Daily: Chinese Basketball Association should not #idiom# when reforming the league</i></p> <p>candidates (en): ["seeking instant benefit", "to overdo it", "<u>take the branch for the root</u>"(answer)]</p>

Table 3: Development set examples from the tasks in FewCLUE. **Bold** text represents part of the example format for each task. Chinese text is part of the model input, and the corresponding text in *italics* is the English version translated from that. Underlined text is specially marked in the input. Text in a monospaced font represents the expected model output.