FewNLU: Benchmarking State-of-the-Art Methods for Few-Shot Natural Language Understanding

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Abstract

The few-shot natural language understanding (NLU) task has attracted much recent attention. However, prior methods have been evaluated under a disparate set of protocols, which hinders fair comparison and measuring progress of the field. To address this issue, we introduce an evaluation framework that improves previous evaluation procedures in three key aspects, i.e., test performance, dev test correlation, and stability. Under this new evaluation framework, we re-evaluate several stateof-the-art few-shot methods for NLU tasks. Our framework reveals new insights: (1) both the absolute performance and relative gap of the methods were not accurately estimated in prior literature; (2) no single method dominates most tasks with consistent performance; (3) improvements of some methods diminish with a larger pretrained model; and (4) gains from different methods are often complementary and the best combined model performs close to a strong fully-supervised baseline. We open-source our toolkit, FewNLU, that implements our evaluation framework along with a number of state-of-the-art methods.¹

1 Introduction

Few-shot learning for natural language understanding (NLU) has been significantly advanced by pretrained language models (PLMs; Brown et al., 2020; Schick and Schütze, 2021a,b). With the goal of learning a new task with very few (usually less than a hundred) samples, few-shot learning benefits from the prior knowledge stored in pretrained models. Various few-shot methods based on PLMs and prompting have been proposed (Liu et al., 2021b; Menon et al., 2021; Gao et al., 2020).

Although the research of few-shot NLU is developing rapidly, the lack of a standard evaluation protocol has become an obstacle hindering fair comparison between various methods on a common ground and measuring progress of the field. While some work (Schick and Schütze, 2021b; Menon et al., 2021) experimented with a fixed set of hyper-parameters, it was pointed out that such a setting might be exposed to the risk of overestimation (Perez et al., 2021; Zhang et al., 2020).² Other research (Liu et al., 2021b; Gao et al., 2020; Perez et al., 2021) proposed to use a small development set to select hyper-parameters, but their evaluation protocols vary in a few key aspects (e.g., how to construct data splits), which in fact lead to large differences as we will show. The above phenomena highlight the need for a common protocol for the evaluation of few-shot NLU methods. However, the fact that few-shot learning is extremely sensitive to subtle variations of many factors (Dodge et al., 2020; Gao et al., 2020) poses challenges for designing a solid evaluation protocol.

In this work, aiming at addressing the aforementioned challenge, we propose an evaluation framework for few-shot NLU. The evaluation framework consists of a repeated procedure—selecting a hyperparameter, selecting a data split, training and evaluating the model. To set up a solid evaluation framework, it is crucial to specify two design choices: (1) how to construct data splits for model selection and (2) which hyper-parameters are critical in the search space. We conduct a comprehensive set of experiments to answer these two questions.

For the first question, we propose a "Multi-Splits" strategy, which randomly splits the available labeled data into training and development sets multiple times, followed by aggregating the results from each data split. We show that this simple strategy

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¹Our code repository is released at https://github.com/THUDM/FewNLU and a leaderboard is available at https://fewnlu.github.io.

²This is because the fixed hyper-parameters are selected according to practical considerations, which are informed by the test set performance from previous evaluations.

outperforms *K*-fold cross validation and minimum description length (Perez et al., 2021) in three dimensions: (1) the test set performance of the selected hyper-parameters; (2) correlation between development set and true test set performance; and (3) robustness to hyper-parameter settings.

For the second question, we conducted comprehensive experiments to study the effects of various hyper-parameters. Experiments show that prompt patterns and verbalizers (Schick and Schütze, 2021b) are critical hyper-parameters that largely affect performance. Moreover, factors concerning randomness like sample order during training are also important in determining the performance.

We then take a step further to re-evaluate recent state-of-the-art few-shot NLU methods under this common evaluation framework. Our re-evaluation leads to several findings summarized in Section 2.

To aid reproducing our results and benchmarking few-shot NLU methods, we open-source FewNLU, a toolkit that contains implementations of a number of state-of-the-art methods, data processing utilities, as well as our proposed evaluation framework.

To sum up, our contributions are as follows.

- We introduce a new evaluation framework of few-shot NLU. We propose three desiderata of few-shot evaluation and show that our framework outperforms previous ones in these aspects. Our framework makes it possible to compare methods and to measure progress of few-shot NLU in a justified manner.
- 2. Under the new evaluation framework, we benchmark the performance of recent methods individually as well as the best performance with a combined approach. These benchmarks reflect the current state of the art and will serve as important baselines for future research.
- 3. Throughout our exploration, we arrive at several key findings summarized in Section 2.
- 4. We open-source a toolkit, FewNLU, to facilitate future research with our framework.

2 Summary of Findings

For reference, we collect our key findings here and discuss each of them throughout the paper.

Finding 1. Multi-Splits is a better data-split strategy than K-fold cross validation and minimum description length in terms of (1) test performance, (2) correlation between development and test sets, and (3) stability w.r.t. the number of runs.

Finding 2. We recommend to at least search over

prompt patterns during hyper-parameter tuning, and it is also beneficial to search others. All comparison methods should be searched and compared under the same set of hyper-parameters.

Finding 3. The absolute performance and the relative gap of few-shot methods were in general not accurately estimated in prior literature. In addition, the benefits of some few-shot methods (e.g., ADAPET (Menon et al., 2021)) decrease on larger models like DeBERTa. The gains of semi-supervised few-shot methods (e.g., iPET (Schick and Schütze, 2021b) and Noisy Student (Xie et al., 2020)) are consistent even on larger models.

Finding 4. Gains from different methods are largely complementary. A combination of recent state-of-the-art methods largely outperforms individual methods and achieves the best performance, close to a strong fully-supervised baseline on RoBERTa (Liu et al., 2019). However, there is still a sizeable gap between the best few-shot and the fully-supervised system on DeBERTa (He et al., 2020).

Finding 5. No single few-shot method dominates most NLU tasks. This highlights the need for the development of few-shot methods with more consistent and robust performance across tasks.

3 Related Work

The "pretraining and fine-tuning" paradigm (Howard and Ruder, 2018) shows tremendous success in few-shot NLU tasks. Various methods have been developed such as the [CLS] classification fine-tuning (Devlin et al., 2018), prompting-based methods with discrete prompts (Schick and Schütze, 2021b; Gao et al., 2020) or continuous prompts (Liu et al., 2021b; Shin et al., 2020; Li and Liang, 2021; Lester et al., 2021), and methods that calibrate the output distribution (Yang et al., 2021; Zhao et al., 2021).

The fact that few-shot learning is sensitive to many factors and thus is extremely unstable (Liu et al., 2021a; Lu et al., 2021; Zhang et al., 2020; Dodge et al., 2020) increases the difficulty of few-shot evaluation. Several works address evaluation protocols to mitigate the effects of instability: Gao et al. (2020) and Liu et al. (2021b) adopt a held-out set to select models. Perez et al. (2021) proposed K-fold cross validation and minimum description length evaluation strategies. Bragg et al. (2021) and Ye et al. (2021) proposed few-shot NLP benchmarks FLEX and CrossFit respectively, which fo-

cus mainly on datasets and metrics for few-shot learning. In contrast, our work addresses inherent problems of the evaluation procedure. It additionally differs from other work on few-shot evaluation in several aspects: (1) we propose three metrics to evaluate data split strategies; (2) while most prior work proposed evaluation protocols without justification, we conduct comprehensive experiments to support our two key design choices; and (3) we formulate a general evaluation framework.

4 Evaluation Framework

We first formally define the few-shot NLU problem. For each NLU task, we have a small labeled dataset $D_{label} = \{(x_i, y_i)\}_{i=1}^N$ and a large test set $D_{test} = \{x_i^{test}, y_i^{test}\}_i$ where N is the number of labeled data, x_i is a text input (consisting of one or multiple pieces of text), and $y_i \in \mathcal{Y}$ is a label. The goal is to fine-tune a pretrained model with D_{label} to obtain the best performance on D_{test} . An unlabeled dataset $D_{unlab} = \{x_i^{unlab}\}_i$ may additionally be used by semi-supervised few-shot methods (§5.1).

4.1 Fixed Hyper-Parameters are not Optimal

Some prior works (Schick and Schütze, 2021a,b; Menon et al., 2021) perform few-shot learning with a fixed set of hyper-parameters (determined by practical considerations and experiences) without early stopping and any model selection. We term this evaluation strategy as *fixed hyper-params*.

		Hyper-l	Parame	ters	Test Acc.	Avg.
	P	LR	Step	WR	Test Acc.	Avg.
	0				69.31 ±4.39	
	1				61.13 ±0.91	
Fixed	2	1e-5	250	0	63.06 ± 1.50	67.36
	3				63.06 ±1.82	
	4				80.26 ±1.85	
	0	1e-5	300	0.05	72.44 ±1.85	
	1	5e-6	300	0.05	63.78 ±1.37	
Optimal	2	5e-6	300	0	69.07 ±5.55	70.42
1	3	5e-6	300	0	65.70 ± 1.25	
	4	5e-6	300	0	81.11 ±1.37	

Table 1: The performance of PET on the RTE task with different hyper-parameters. The patterns and fixed hyper-parameters are provided by (Schick and Schütze, 2021b). Base model: DeBERTa-xxlarge-v2, "P": pattern ID, "LR": learning rate, "Step": number of training steps, "WR": warm-up ratio.

We would like to know how well fixed hyperparameters transfer to a new scenario, e.g. switching to another base pretrained model. We perform preliminary experiments on few-shot Super-GLUE with a 64-sample labeled set based on De-BERTa. Firstly, we experiment with the fixed hyper-parameters used for ALBERT in (Schick and Schütze, 2021b). Secondly, we manually try other hyper-parameters to find out whether there are better configurations. From Table 1, we observe:

- 1. Certain factors, especially the patterns, impact the performance a lot (best 80.26%, and worst 61.13%). However, we cannot differentiate between them without a development set.
- 2. There exists a hyper-parameter (the Optimal in Table 1) that performs much better than the fixed one. A mechanism to identify the best hyper-parameter setting is thus necessary.
- 3. Results show a good hyper-parameter on AL-BERT does not work well on DeBERTa. Fixed hyper-parameters are not optimal and we need to re-select them given new conditions.

4.2 Formulation of Evaluation Framework

The observations in Section 4.1 motivate us to study a more robust evaluation framework for few-shot NLU. The goal of an evaluation framework is twofold: (1) benchmarking few-shot methods for NLU tasks such that they can be fairly compared and evaluated; and (2) obtaining the best few-shot performance such that it could be used in practice. In light of these two aspects, we propose the few-shot evaluation framework shown in Algorithm 1.

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Algorithm 1: A Few-Shot Evaluation Framework
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Data: the labeled and test sets (D_{label} and D_{test}), a few-shot method M, a hyper-parameter space \mathcal{H}, the number of data splits K.
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Result: test performance; best hyper-parameter h^* .

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\begin{array}{c|c} \textbf{1} & \textbf{for} \ \underline{k} \leftarrow 1 \cdots \underline{K} \ \textbf{do} \\ \textbf{2} & \boxed{ \  \  \, \text{Divide} \ D_{tabel} \ \text{into} \ D_{train}^k \ \text{and} \ D_{dev}^k \ \text{according} \\ \textbf{to certain data-split strategy;}} \\ \textbf{3} & \textbf{end} \\ \textbf{4} & \textbf{for} \ \underline{h} \in \mathcal{H} \ \textbf{do} \\ \textbf{5} & \boxed{ \  \  \, \text{for} \ \underline{k} \leftarrow 1 \cdots \underline{K} \ \textbf{do} \\ \textbf{6} & \boxed{ \  \  \, \text{Run the method} \ M \ \text{by training on} \ D_{train}^k \\ \textbf{and evaluating on} \ D_{dev}^k;} \\ \textbf{7} & \boxed{ \  \  \, \text{Report the dev-set performance} \ \mathcal{P}_{dev}^{h,k}.} \\ \textbf{8} & \boxed{ \  \  \, \textbf{end} } \\ \textbf{9} & \boxed{ \  \  \, \text{Compute the mean and standard deviation over} \\ K \ \text{dev-set results}, \ \mathcal{P}_{dev}^h \pm \mathcal{S}_{dev}^h;} \\ \textbf{10} & \boxed{ \  \  \, \textbf{end} } \\ \end{array}
```

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11 Select h^{\star} with the best P_{dev}^{h}.;
12 if the goal is to evaluate a method then
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Evaluate on the test set D_{test} with the K checkpoints that correspond to h*;
Report the mean and standard deviation over the K test results P_{test}^{h*} + S_{test}^{h*}.

15 **else if** the goal is to obtain the best performance **then**16 Re-run on the entire labeled set D_{label} by fixing h^* with L different random seeds:

Evaluate on the test set with the L checkpoints; Report the mean and standard deviation results over L test results.

19 end

The framework searches over a hyper-parameter space \mathcal{H} to evaluate a given few-shot method M, obtaining its test set results and the best hyperparameter setting h^* . The measurement for each h is estimated by performing training and evaluation on multiple data splits (obtained by randomly splitting the labeled data according to a strategy) and reporting their average dev set results. Finally, the method is evaluated on the test set using the checkpoints corresponding to h^* . For benchmarking, we report the average and standard deviation over multiple test set results. Otherwise, we re-run on the entire labeled data with h^* . Since this work focuses on benchmarking, the experiments in later sections report the mean and standard deviation results without re-running on the entire labeled set.

The framework requires specifying two design choices: how to construct the data splits and which hyper-parameters are critical for searching, which we discuss in Sections 4.3 and 4.4.³

4.3 How to Construct Data Splits

4.3.1 Desiderata: Performance, Correlation, and Stability

We first propose the following three key desiderata for the evaluation of different data split strategies.

- 1. **Performance of selected hyper-parameter.** An effective data split strategy should select a hyper-parameter that obtains a good test-set performance. We report the same metrics as (Schick and Schütze, 2021b), along with corresponding standard deviations.
- 2. Correlation between the development and test sets (over a hyper-parameter distribution). Since a small development set is used for model selection, it is important for a good strategy to obtain a high correlation between the performances on the small development set and test set over a distribution of hyper-parameters. We report the Spearman's rank correlation coefficient for measurement.
- 3. **Stability w.r.t. the number of runs** *K***.** The choice of the hyper-parameter *K* should not become another significant impacting factor to the above two metrics (i.e., performance and correlation). Besides, it is desirable to have reduced variance when *K* increases. Thus we

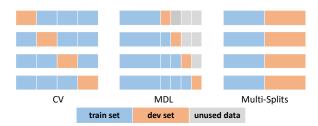


Figure 1: Illustration of how different data split strategies partition the labelled data, with K=4 and r=0.5.

report the above two metrics with different values of K as well as the standard deviation of test scores over K runs.

4.3.2 Data Split Strategies

This section considers three data split strategies, including K-fold cross validation (CV), minimum description length (MDL), and our Multi-Splits. The first two are introduced by Perez et al. (2021), while we introduce Multi-Splits as an adaptation of previous work (Gao et al., 2020; Liu et al., 2021b).⁴ All three strategies fit into the pipeline of the proposed framework in Section 4.2:

- 1. K-fold Cross Validation equally partitions the labeled data into K folds. For each hyperparameter, it performs training K times, each time using the k^{th} (k=1,2,...,K) fold as the development set and the other K-1 folds as the training set.
- 2. **Minimum Description Length** assigns half of the labeled data as joint training data and equally partitions the other half into K folds. Each time, it uses the k^{th} fold as development set, and uses the joint fold and all previous k-1 folds for training.
- 3. **Multi-Splits** performs training K times, each time using a different data split obtained by randomly splitting the labeled data into training and development sets by a fixed ratio r.

Figure 1 illustrates how each data split strategy works. Essentially, they differ in several aspects.

- 1. For CV and MDL, K controls the number of runs over multiple data splits as well as the split ratio. For Multi-Splits, the split ratio is decoupled from K and is controlled by another hyper-parameter r.5
- 2. They use a different amount of data for training and development sets as Table 2 shows.

 $^{^3}$ For simplicity and ease of use, we use grid search for searching the hyper-parameter space \mathcal{H} and identify critical hyper-parameters to limit its size. More complex search methods such as Bayesian Optimization (Snoek et al., 2012) could be used to search over larger hyper-parameter spaces.

⁴MDL has also been used to evaluate the generalization ability of pre-trained models (Yogatama et al., 2019) and for probing (Voita and Titov, 2020).

⁵Though Multi-Splits uses an additional hyper-parameter, r, we will show in Section 4.3.4 that performance is robust with regard to different values of r.

	CV	MDL	Multi-Splits
# train	(K-1)*N/K	N/2+N*(k-1)/(2K)	N*r
# dev	N/K	N/(2K)	N*(1-r)

Table 2: Number of examples of training and development sets for different data split strategies. N is the total number of labeled data, K is the number of runs, k is the k^{th} split for MDL, and r is the pre-specified split ratio for Multi-Splits.

3. There are cases when CV and Multi-Splits share the same data-split ratio. The difference is that Multi-Splits allows overlap between different data splits while CV does not.

In the limit, Multi-Splits is similar to leave-P-out cross-validation (LPOCV; Celisse, 2014)⁶ where LPOCV runs $\binom{N}{P}$ times (P is the number of dev set examples) while Multi-Splits runs K times. As K increases, Multi-Splits gradually approaches LPOCV. Since it is impossible to traverse the large number of possible splits in practice, Multi-Splits can be viewed as a practical version of LPOCV. Compared with the strategy of (Gao et al., 2020) that uses multiple datasets, our proposed Multi-Splits strategy uses multiple data splits for a single dataset. It is thus more practical as in realworld scenarios, it is hard to obtain multiple labeled datasets for a true few-shot problem; otherwise, it becomes a fully supervised learning problem. The strategy in (Liu et al., 2021b) is a special case of Multi-Splits when K = 1, which samples a single data split and suffers from higher variance.

4.3.3 Experimental Setup

We experiment with the few-shot SuperGLUE benchmark (Wang et al., 2019a). We consider settings using 32 labeled samples—the same as prior work (Schick and Schütze, 2021b; Menon et al., 2021)—as well as 64 labeled samples for each task. We evaluate strategies based on the widely used prompt-based few-shot method PET (Schick and Schütze, 2021b) with DeBERTa-xxlarge as base model. We run experiments on the same tasks with the same hyper-parameter space to ensure a fair comparison; in this experiment we searched learning rate, evaluation ratio, prompt pattern and maximum training step. More details about datasets and hyper-parameters are in Appendix A.1.

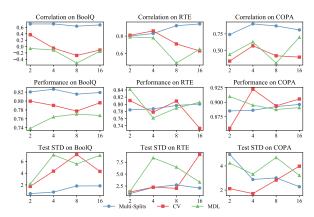


Figure 2: Few-shot performance, Spearman's rank correlation and standard deviation results along with selection of K on BoolQ, RTE, and COPA tasks under different strategies. A smooth and stable dot-line indicates the setting is insensitive to the choice of K.

4.3.4 Main Results and Analysis

Figure 2 and Table 3 show results under the data setting with 64 labeled data. Results with 32 labeled examples are given in Appendix A.1.

Test Performance Results. From Table 3a, we observe both the Multi-Splits and CV strategies obtain the best overall average test set performance. Multi-Splits uses fewer labeled examples for training (128) while CV and MDL use more (192 and 176 respectively). Despite using more training data, both CV and MDL do not substantially perform better. This indicates few-shot performance is limited by not being able to select the best model rather than not having sufficient training data.

Correlation Results. In Table 3b, Multi-Splits significantly outperforms both CV and MDL with an advantage of around 0.2 points on average. For 5/7 tasks, Multi-Splits shows the best correlation results. A potential reason is that both CV and MDL assign fewer labeled data examples to the development set (64 and 32 respectively) than Multi-Splits (128), which leads to poor correlation, and as a result, poor model selection.

Stability w.r.t. the number of runs K. Figure 2 shows the results w.r.t. different K. We observe the following: (1) Multi-Splits (blue lines) is the most stable in correlation and performance, while CV and MDL are more sensitive to the choice of K. (2) Multi-Splits shows the smallest variance over multiple runs on both BoolQ and RTE. For COPA, though Multi-Splits shows high variance when K=2, the variance becomes smaller with larger K, while CV and MDL suffer from increasing or unstable variance.

A possible explanation is that increasing K does not affect the number of training and development

 $^{^{6}}$ Leave-P-out cross-validation uses P data examples as the development set and the remaining data examples as the training set. This is repeated on all ways to cut the labeled dataset in a development set and a training set.

⁷We fixed the parameters of DeBERTa's bottom third layers due to GPU memory limitations, which did not affect the performance much in our preliminary experiments.

Table 3: Results of different data-split strategies with PET on FewGLUE (K=4). Larger scores indicate that the strategy effectively selects a model that achieves better test set performance. The best results are denoted in bold.

	(:	a)	The test	performance	under th	e data	setting	with	64	labeled	data exampl	les.
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	BoolQ	RTE	WiC	C	B	Mul	tiRC	WSC	COPA	Avg.
	Acc.	Acc.	Acc.	Acc.	F1	F1a	EM.	Acc.	Acc	
CV	79.01	77.8	65.3	90.18	87.52	80.08	45.02	82.69	92.25	78.35
CV	±4.35	± 2.25	± 1.71	± 2.31	± 2.2	± 1.15	± 1.46	± 1.76	± 1.71	16.55
MDL	76.43	76.17	64.64	86.01	83.03	77.63	43.81	80.05	89.5	76.00
MDL	±7.12	± 8.42	± 2.93	± 4.09	± 4.79	± 1.2	± 1.32	± 1.21	± 3.32	70.00
Multi-Splits	82.67	78.73	67.2	91.96	88.63	78.18	42.79	80.53	88.62	78.36
(r = 1:1)	±0.78	± 2.2	± 1.34	± 3.72	± 4.91	± 1.59	± 2.42	± 1.82	± 2.88	76.50
Multi-Splits	81.92	79.18	64.86	91.96	87.92	80.82	45.93	82.45	90.13	78.84
(r = 3:1)	±0.90	± 5.23	± 1.41	± 3.09	± 5.20	± 0.60	± 1.06	± 2.87	± 3.68	70.04

(b) The correlation results under the data setting with 64 labeled data examples.

	BoolQ	RTE	WiC	СВ	MultiRC	WSC	COPA	Avg.
CV	-0.0497	0.8561	0.8184	0.5286	0.1493	0.5398	0.5668	0.4870
MDL	-0.1143	0.7806	0.6326	0.3274	0.2652	0.4327	0.6342	0.4226
Multi-Splits $(r = 1:1)$	0.7079	0.8266	0.9464	0.7558	0.4530	0.1590	0.8997	0.6783
Multi-Splits $(r = 3:1)$	0.6220	0.8163	0.8007	0.0432	0.4470	0.2662	0.5049	0.5001

examples for Multi-Splits; instead, it increases the confidence of results. An important practical benefit of Multi-Splits is that one can always choose to increase K for lower variance. However, for CV and MDL, the sizes of training and development sets are affected by K, where extremely large K values lead to a failure mode and extremely small K lead to unstable results. In practice, it is hard to know which value of K to use a priori.

We experiment with two values for the r hyperparameter in Multi-Splits, 1:1 and 3:1. The former equally splits labeled data. The latter constructs the same size of training and development splits as CV. Results in Table 3b show that both values share similar test performance, while r=1:1 has better correlation. The results of both ratios outperform CV and MDL. For few-shot NLU with less than a hundred labeled examples, r=1:1 is empirically recommended. We adopt r=1:1 throughout the experiments.

To sum up, based on the aforementioned results and analysis, we arrive at the following finding.

Finding 1. Multi-Splits is a better data-split strategy than K-fold cross validation and minimum description length in terms of (1) test performance, (2) correlation between development and test sets, and (3) stability w.r.t. the number of runs.

4.4 Which Hyper-Parameters are Crucial

4.4.1 Should We Search Random Seeds?

In this work, we focus on two types of factors that affect few-shot evaluation, hyper-parameters and randomness. Randomness could cause different weight initialization, data splits, and data order during training. Empirically, how randomness is dealt with differs depending on the use case. In order to obtain the best possible performance, one could search over sensitive random factors such as random seeds. However, as we are focused on benchmarking few-shot NLU methods, we report mean results (along with the standard deviation) in our experiments in order to rule out the effects of randomness and reflect the average performance of a method for fair comparison and measurement.

4.4.2 Experiments

Experimental Setup To examine to which degree a certain factor affects few-shot performance, we conduct experiments by assigning different values to the target factor and fixing all other hyperparameters. We report the standard deviation (SD) over multiple performance results. Larger values indicate that the target factor influences the few-shot performance, and thus is crucial for searching. We experiment with four tasks including BoolQ, RTE, CB, and COPA. We consider the following factors: sample order during training, prompt pattern, training batch size, learning rate, evaluation frequency, and maximum train steps. More experimental details are given in Appendix A.2.

Results and Analysis Results are in Table 4. We mark values larger than a threshold of 2.0 in bold. We can see that the prompt pattern is the most influential factor among all, indicating the design or selection of prompt patterns is crucial. Training

Table 4: Sensitivity analysis of different factors on BoolQ, RTE, CB and COPA based on PET and DeBERTa. The metric is standard deviation. We set hyper-parameters to be the best-performing ones obtained in Section 5 while assigning different values to the target factor. For CB, A/B means Acc./F1. "Train Order": training sample order; "Train Batch": total train batch size; "Eval Freq": evaluation frequency.

	Hyper-params	BoolQ	RTE	COPA	СВ
	Train Order	3.64	4.01	2.17	2.21/6.09
Dev	Prompt Pattern	3.44	10.28	5.80	3.18/4.07
Set	Train Batch	3.34	1.33	2.64	1.01/ 5.87
SCI	Learning Rate	0.00	1.63	1.97	1.56/ 4.56
	Eval Freq	2.39	2.96	2.73	0.45/0.82
	Train Order	0.87	1.87	2.17	3.01/4.73
Test	Prompt Pattern	2.85	10.03	2.65	6.45/7.08
Set	Train Batch	2.44	1.09	0.72	0.89/1.32
SCI	Learning Rate	0.17	0.65	0.52	4.82/7.25
	Eval Freq	0.84	0.53	1.18	0.77/ 2.07

example order also significantly affects the performance. The evaluation frequency affects the score on the small development but not on the test set. We speculate that a lower frequency selects a model with better performance on the small development set, but the gains do not transfer to the test set because of partial overfitting. To conclude:

Finding 2. We recommend to at least search over prompt patterns during hyper-parameter tuning, and it is also beneficial to search others. All comparison methods should be searched and compared under the same set of hyper-parameters.

5 Re-Evaluation of State-of-the-Art Methods

5.1 Few-Shot Methods

We now proceed to re-evaluate state-of-the-art few-shot methods under our new evaluation frame-work with the Multi-Splits strategy. We consider two types of few-shot methods: *Minimal few-shot methods*, which only assume access to a small labeled dataset, including Classification (CLS; Devlin et al., 2018), PET (Schick and Schütze, 2021b), ADAPET (Menon et al., 2021), and P-tuning (Liu et al., 2021b); and *semi-supervised few-shot methods*, which allow accessing an additional unlabeled dataset, including PET+MLM (Schick and Schütze, 2021a), iPET (Schick and Schütze, 2021b) and Noisy Student (Xie et al., 2020).

5.2 Experimental Setup

We use the same benchmark datasets, metrics, and hyper-parameter space as Section 4.3.3. Experiments are conducted based on ALBERT-xxlarge and DeBERTa-xxlarge under the data setting with 64 labeled examples. For semi-supervised methods

(i.e., iPET and Noisy Student), they require pseudolabels on unlabeled data for self-training. We consider two labeling strategies, including *single-split labeling* and *cross-split labeling*. In the single-split setting (Schick and Schütze, 2021b), pseudo-labels are generated by the models trained on the same data split. In the cross-split setting in our evaluation framework, the pseudo-labels are generated by the models trained on multiple different data splits. Details about configurations are in Appendix A.3.

5.3 Main Results and Analysis

Re-Evaluation Results Our re-evaluation results are shown in Table 5. The results suggest that the prompt-based fine-tuning paradigm significantly outperforms the classification-based fine-tuning on all tasks and on both pretrained models (with an advantage of more than 15 points on average). De-BERTa outperforms ALBERT consistently. We observe significant differences in performance between different prompt-based minimal few-shot methods on ALBERT (e.g., PET and ADAPET differ by more than 4 points on average) while differences with DeBERTa are slight (e.g., PET, ADAPET and P-tuning have a performance gap of less than 1.0 points on average). In contrast, semisupervised few-shot methods (including iPET and Noisy) generally show 1-2 points improvement on average compared to minimal few-shot methods on both models.

Comparison to Prior Evaluations In Table 7, we list the absolute performance as well as the relative performance gap (to baseline PET) respectively from previous evaluations as well as our evaluation. Results show that the absolute performance of few-shot methods in previouss evaluation were generally overestimated on BoolQ, RTE and COPA. Similar findings have also been highlighted in prior works (Perez et al., 2021; Zhang et al., 2020), and our evaluation framework confirms these observations under a more reliable setup. In addition, prior evaluations inaccurately estimated the relative performance gap. For example, according to previous evaluations, the relative performance of several methods (i.e., ADAPET, P-tuning, and PET+MLM) compared to PET is lower by more than 6.0 points on COPA due to an overestimation of PET's performance in previous work. However, when comparing them with PET on a common ground, these methods generally show improvements. More broadly, we observe that the perfor-

Table 5: Re-evaluation of few-shot methods on ALBERT and DeBERTa under our evaluation framework with the Multi-Splits strategy on SuperGLUE test set of our setup. The data setting is 64 labeled examples. For iPET and Noisy Student, (cross) and (single) respectively means cross-split labeling and single-split labeling strategies as introduced in Section 5.2. "Our Best (few-shot)" is the results achieved by a combination method as introduced in Section 5.4. The **globally best results** for each task are denoted in bold. The <u>best results for minimal few-shot methods</u> are underlined. The <u>best results for semi-supervised</u> few-shot methods are marked with wavelines.

Base	Few-Shot	BoolQ	RTE	WiC	C	В	Mult	tiRC	WSC	COPA	Avg.
Models	Methods	Acc.	Acc.	Acc.	Acc.	F1	F1a	EM.	Acc.	Acc	
	CLS	55.01	53.97	50.82	67.97	52.18	59.95	18.86	51.44	64.25	53.57
		± 2.95	± 5.49	± 3.02	± 18.29	± 10.30	± 10.69	± 9.80	± 4.87	± 9.36	
	PET	76.70	72.83	53.87	84.38	62.56	76.51	36.46	75.72	81.75	70.12
		±1.85	±1.30	± 4.47	± 4.47	± 7.66	±1.52	±2.13	±6.40	±4.03	
	ADAPET	79.24	74.28	58.07	92.86	89.99	77.24	37.17	78.13	81.75	74.30
	D	±1.42	±3.57	±2.96	±1.46	±3.91	±1.99	±2.64	±3.46	±3.95	71.06
	P-tuning	76.55	63.27	55.49	88.39	84.24	75.91	38.01	73.56	85.25	71.06
		±2.68	±3.63	±1.21	±3.72	±5.15	±1.74	±0.78	±2.78	±3.30	
ALBERT	PET+MLM ³	76.83	71.48	52.39	83.93	67.37	75.15	35.68	76.20	85.75	70.53
	0.4	± 1.18	± 1.64	± 1.44	± 5.05	± 8.31	± 0.34	± 1.10	± 5.52	± 3.40	
	iPET(single) ^{3,4}	74.29	72.35	54.78	84.67	76.92	76.33	37.72	71.39	84.00	70.66
	9.4	± 4.10	± 3.71	± 3.93	± 3.18	± 5.44	± 1.18	± 2.58	± 5.59	± 6.02	
	Noisy(single) ^{3,4}	76.11	72.62	54.11	84.38	72.57	76.59	37.00	73.16	83.50	70.68
		± 2.16	± 2.80	± 1.98	± 5.60	± 11.84	± 1.40	± 2.34	± 3.72	± 3.34	
	iPET(cross) ^{3,4}	76.83	74.28	58.35	83.48	73.86	75.71	37.30	76.20	83.25	72.01
	2.4	± 1.39	± 4.31	± 2.42	± 2.68	± 2.48	± 2.14	± 2.71	± 4.33	± 4.19	
	Noisy(cross) ^{3,4}	75.64	75.27	56.43	84.82	77.79	77.11	38.25	78.61	83.00	72.56
		±1.82	± 1.97	± 2.67	±4.49	± 8.46	±1.49	± 0.92	±2.76	±4.76	
	CLS	59.49	49.55	54.08	68.30	60.10	75.42	34.23	60.82	85.25	61.17
		± 1.74	± 2.23	± 2.15	± 3.96	± 10.14	± 2.39	± 5.02	± 14.23	± 2.22	
	PET	82.67	79.42	<u>67.20</u>	91.96	88.63	78.18	42.79	80.53	<u>89.00</u>	78.51
		±0.78	±2.41	±1.34	±3.72	±4.91	±1.59	± 2.42	±1.82	±2.94	
	ADAPET	81.28	82.58	66.50	89.73	86.63	77.88	43.05	83.41	88.75	78.74
		±1.26	±2.44	±2.11	±6.08	±7.29	±2.55	±3.60	±3.46	±4.43	5 0.42
	P-tuning	82.25	82.22	66.22	94.20	91.76	<u>78.45</u>	43.78	84.62	86.50	<u>79.42</u>
		±0.85	±1.23	±1.18	±2.25	±3.30	±1.46	±3.93	±4.64	±3.70	
	PET+MLM ³	82.80	83.30	58.23	90.18	87.18	77.05	40.63	79.81	85.75	76.77
DeBERTa	0.4	± 0.97	± 2.40	± 4.98	± 3.09	± 6.17	± 1.80	± 1.64	± 4.08	± 3.40	
	iPET(single) ^{3,4}	81.27	81.11	64.75	89.88	87.70	79.99	45.23	82.61	90.83	78.85
		± 1.61	± 1.89	± 4.27	± 5.01	± 6.52	± 1.94	± 2.19	± 3.68	± 2.79	
	Noisy(single) ^{3,4}	81.60	81.95	65.97	$\underbrace{91.67}$	89.17	79.85	45.10	82.61	90.67	79.38
		± 1.54	± 2.01	± 2.44	± 2.33	± 2.95	± 1.22	± 2.58	± 3.83	± 2.53	
	iPET(cross) ^{3,4}	83.45	83.12	<i>6</i> 9. <i>6</i> 3	91.52	90.72	79.92	44.96	<u>85.58</u>	93.75	81.30
		± 0.90	± 1.04	± 2.15	± 3.05	± 2.68	± 1.11	± 3.13	±1.76	± 2.99	
	Noisy(cross) ^{3,4}	82.19	81.95	68.26	90.18	86.74	79.48	44.20	85.10	93.75	80.22
		± 0.65	± 0.51	± 1.12	± 2.31	± 3.00	± 2.53	± 4.14	± 3.28	± 3.30	
	Our Best ^{3,4}	84.0	85.7	69.6	94.6	92.9	81.5	48.0	87.0	93.8	85.17 ¹
DeBERTa	(few-shot)	±0.55	± 0.63	±2.15	±1.46	±1.85	± 0.76	± 0.99	±2.29	±2.99	
RoBERTa	RoBERTa ⁵ (fully sup.)	86.9	86.6	75.6	98.2	-	85.7	-	91.3	94.0	88.33
DeBERTa	DeBERTa ² (fully sup.)	88.3	93.5	-	-	-	87.8	63.6	-	97.0	-

¹ For comparison with RoBERTa (fully sup.), the average of Our Best (few-shot) 85.17 excludes MultiRC-EM and CB-F1.

Table 6: Combination of methods that achieves the best few-shot performance for each task. We consider three minimal few-shot methods including PET, ADAPET, and P-tuning, and five training paradigms including single-run, iPET (single/cross), and Noisy (single/cross). "+MLM" denotes whether we include the MLM as the additional regularization loss.

	BoolQ	RTE	WiC	СВ	MultiRC	WSC	COPA
Minimal Few-Shot Methods	PET	ADAPET	PET	PET	ADAPET	ADAPET	PET
Training Paradigm	iPET(cross)	Noisy(cross)	iPET(cross)	iPET(cross)	Noisy(cross)	Noisy(cross)	iPET(cross)
+ MLM	✓	-	-	\checkmark	-	-	-

² The fully-supervised results on DeBERTa are reported in https://github.com/THUDM/GLM.

³ Unlabeled data are used.

⁴ The ensemble technique is used.

⁵ The RoBERTa (fully-sup.) results by (Liu et al., 2019). RoBERTa-large has less parameters than DeBERTa-xxlarge-v2.

Table 7: Comparison of prior evaluations and our evaluation. We report the absolute performance (Abs.) and the relative performance gap to PET (Schick and Schütze, 2021b) (Rel.) of different methods respectively from previous evaluation (Prev.) and our evaluation framework (Ours.) on BoolQ, RTE, WiC and COPA tasks. The results are based on ALBERT. Results of previous evaluation are taken from the original papers, including ADAPET (Menon et al., 2021), P-tuning (Liu et al., 2021b), PET+MLM (Schick and Schütze, 2021a) and iPET (Schick and Schütze, 2021b). Since (Schick and Schütze, 2021a) reported the effectiveness of PET+MLM on different tasks, we reexperimented on the same tasks under the original setting reported in (Schick and Schütze, 2021a).

Methods		Boo	olQ	R	ГЕ	W	ïС	CC)PA
Methods		Prev.	Ours	Prev.	Ours	Prev.	Ours	Prev.	Ours
PET (baseline)	Abs.	79.40	76.70	69.80	72.83	52.40	53.87	95.00	81.75
ADAPET	Abs. Rel.	80.30 +0.90	79.24 +2.54	76.50 +6.70	74.28 +1.45	54.40 +2.00	58.07 +4.20	89.0	81.75 0.00
P-tuning	Abs. Rel.	77.80 -1.60	76.55 -0.15	76.50 +6.70	63.27 -9.56	56.30 +3.90	55.49 +1.62	87.00	85.25 +3.50
PET+MLM	Abs. Rel.	76.00 -3.40	76.83 +0.13	62.20 -7.60	71.48 -1.35	51.30 -1.10	52.39 -1.48	86.70	85.75 +4.00
iPET	Abs. Rel.	80.60 +1.20	74.29 -2.41	74.0 +4.20	72.35 -0.48	52.20 -0.20	54.78 +0.91	95.0	84.00 +2.25

mance differences between many pairs of methods were not accurately estimated by previous evaluation methods. For example, it was estimated that ADAPET outperforms P-Tuning on COPA and P-Tuning beats ADAPET on WiC, while our evaluation reveals the opposite.

Finally, our re-evaluation first compares all methods on a common ground, revealing the following:

Finding 3. The absolute performance and the relative gap of few-shot methods were generally not accurately estimated in the literature. The benefits of some minimal few-shot methods (i.e., ADAPET (Menon et al., 2021)) decrease on larger models like DeBERTa. The gains of semi-supervised few-shot methods (i.e., iPET (Schick and Schütze, 2021b) and Noisy Student (Xie et al., 2020)) are consistent even on larger models.

A possible reason for the lower performance of ADAPET on DeBERTa is that larger pretrained models have learned more prior knowledge. Therefore, gains obtained by either adding additional regularization terms (e.g. ADAPET) are not significant anymore. We also conjecture that larger models could have a higher capacity to adapt and may thus benefit from more training examples. Thus, the semi-supervised few-shot methods (i.e., iPET and Noisy Student) that augment data demonstrate consistent improvements compared to baselines.

5.4 What is the Best Performance Few-Shot Learning can Achieve?

We explore the best performance few-shot learning can achieve by combining various methods

and techniques using our evaluation framework with the Multi-Splits strategy and DeBERTa as base model. We consider three minimal few-shot methods including PET, ADAPET, and P-tuning, five training paradigms including single-run, iPET (single/cross), and Noisy Student (single/cross), as well as the addition of a regularization loss (+MLM). We experiment with all possible combinations among them and report the best performance for each task.

The "Best (few-shot)" results are shown in Table 5, achieving the best results on all tasks among all methods. This demonstrates that existing few-shot methods can be practically used in combination. Comparing our best few-shot results with the results of RoBERTa-large (fully-sup) (Liu et al., 2019), we observe the performance gap has been further narrowed to 3.16 points on average⁸. Compared to DeBERTa (fully-sup), there is still a size-able gap between few-shot and fully-supervised systems.

We list the best-performing method combination for each task in Table 6. We observe that different combinations perform best across tasks, and that there is no single method that dominates all tasks. PET and ADAPET as well as iPET and Noisy Student are about equally preferred while cross-split labeling and no regularization term perform better. We thus recommend future work to focus on the development of methods that achieve consistent and

⁸Note that the gap could be larger since RoBERTa-large has a smaller number of parameters than DeBERTa-xxlarge-v2, and RoBERTa (fully-sup) does not incorporate additional beneficial techniques such as ensembling or self-training.

robust performance across tasks. We summarize the following findings:

Finding 4. Gains from different methods are largely complementary. A combination of recent state-of-the-art methods largely outperforms individual methods and achieves the best performance, close to a strong fully-supervised baseline on RoBERTa (Liu et al., 2019). However, there is still a sizeable gap between the best few-shot and the fully-supervised system on DeBERTa (He et al., 2020).

Finding 5. No single few-shot method dominates most NLU tasks. This highlights the need for the development of few-shot methods with more consistent and robust performance across tasks.

6 FewNLU Toolkit

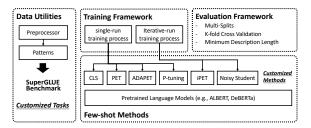


Figure 3: Architecture of FewNLU. It contains implementation of several state-of-the-art methods, data processing utilities, a standardized few-shot training framework, and most importantly, the proposed evaluation framework.

We open-source FewNLU, an integrated toolkit designed for few-shot NLU. It contains implementations of several state-of-the-art methods, data processing utilities, a standardized few-shot training framework, and most importantly, the proposed evaluation framework. FewNLU also allows customizing new tasks/methods, and performing training and evaluation over them. Figure 3 shows the relationships between the four blocks. The goal of FewNLU is to facilitate benchmarking few-shot learning methods for NLU tasks. For more detailed features of FewNLU, please refer to the source codes and documents.

7 Conclusions

We introduce an evaluation framework, re-evaluate a number of few-shot learning methods under the evaluation framework with a novel Multi-Splits strategy, and release a few-shot toolkit. Apart from this, we also aim at advancing the development of few-shot learning by sharing several new experimental findings. We identify several new directions for future work: (1) Our work revealed that the prompt patterns and training sample order are crucial hyper-parameters, but in practice how to define the hyper-parameter search space a priori is still a challenge. (2) It is critical for the community to iterate and converge on a common evaluation framework. (3) Few-shot natural language generation might also be studied in a similar framework.

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A Appendix

A.1 Details of Data-Split Strategy Experiments

A.1.1 Datasets

To justify the proposed evaluation framework, we perform experiments on the few-shot SuperGLUE benchmark, which was constructed to include some of the most difficult language understanding tasks for current NLP approaches (Wang et al., 2019a). Unlike other NLU benchmarks (e.g., GLUE (Wang et al., 2019b)) that contain single-sentence tasks, SuperGLUE consists of complicated ones that are sentence-pair or sentence-triple tasks, which demand advanced understanding capabilities. Seven SuperGLUE tasks are considered, including question answering (BoolQ (Clark et al., 2019) & MultiRC (Khashabi et al., 2018)), textual entailment (CB (De Marneffe et al., 2019) & RTE (Dagan et al., 2005)), word sense disambiguation (WiC (Pilehvar and Camacho-Collados, 2018)), causal reasoning (COPA (Roemmele et al., 2011)), and co-reference resolution (WSC (Levesque et al., 2012)).

A.1.2 Hyper-parameters of Data-Split Strategy Evaluation

To quantitatively evaluate different data-split strategies, we perform extensive experiments with the following hyper-parameter search space. Data-split experiments are based on DeBERTa (xxlarge). The hyper-parameter search space is shown in Table 8. We use the same prompt patterns as in (Schick and Schütze, 2021b). To observe the changes of performance and correlation metrics w.r.t different K values, we also experimented with $K = \{2,4,8,16\}$ over three tasks (i.e., BoolQ, RTE and COPA).

Table 8: Hyper-parameter Search Space for Data-Split Strategy Evaluation

Hyper-parameter	Value
Learning Rate	$\{5e-6, 1e-5\}$
Maximum Training Step	$\{250, 500\}$
Evaluation Frequency	$\{0.02, 0.04\}$
Number of Runs K	4
Split Ratio r for Multi-Splits	1:1

A.1.3 32-Data-Setting Results for Data-Split Strategy Evaluation

In data-split strategy evaluation, in addition to the 64-data-setting results in the main texts, we also experimented with 32 labeled data as (Schick and Schütze, 2021b,a; Menon et al., 2021). The 32-data-setting results are also provided in Table 9.

A.2 Details of Crucial Factor Evaluation

To study whether a certain factor is crucial for the searching procedure, we conduct multiple-time experiments by assigning a certain factor with multiple values and keeping all the other hyperparameters fixed. The standard deviation (STD) over the multiple experimental results is reported, where a larger STD indicates the few-shot performance is sensitive to this targeted factor. It is worth noting that we assign values under a small disturbance to the target factor, without considering the extreme values, which will definitely make the model fail, so it doesn't make much sense in fact.

For a given task and a target factor, we fixed the hyper-parameters to be the best-performing ones obtained in Section 4.3, and assigned multiple values for the target factor. For the prompt pattern, we assigned it with the same values as (Schick and Schütze, 2021b). Possible values for other hyper-parameters are in Table 11.

A.3 Details of Few-Shot Method Re-Evaluation

A.3.1 Details of Re-Evaluated Methods

The four considered minimal few-shot methods are introduced as follows.

- 1. **Classification** is a conventional finetuning algorithm, which uses the hidden states of a special [CLS] token for classification.
- 2. **PET** is a prompt-based finetuning algorithm. It transforms NLU problems into cloze problems with prompts, and then converts the cloze outputs into the predicted class.
- 3. **ADAPET** is based on PET and decouples the losses for the label tokens. It proposes a label-conditioned masked language modeling (MLM) objective as a regularization term.
- 4. **P-tuning** is also based on PET and automatically learns continuous vectors as prompts via gradient update.

The three semi-supervised few-shot methods are introduced as follows.

- PET+MLM is based on PET and additionally adds an auxiliary language modeling task performed on unlabeled dataset. It was first proposed by (Schick and Schütze, 2021a) to resolve catastrophic forgetting.
- 2. **iPET** is a self-training method. It iteratively performs PET for multiple generations. At the end of each generation, unlabeled data are assigned with pseudo-labels by the fully-

Table 9: Evaluation results of different few-shot data-split strategies with PET on FewGLUE (*K*=4) under the same data setting as (Schick and Schütze, 2021b,a; Menon et al., 2021) with 32 labeled data. Larger scores indicate that a data-split strategy effectively selects a model that achieves better test-set performance. The best results for each task are denoted in bold.

(a) Results of test performance of the selected hyper-parameters	neter
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	BoolQ	RTE	WiC	C	CB	Mul	tiRC	WSC	COPA	Avg.
	Acc.	Acc.	Acc.	Acc.	F1	F1a	EM.	Acc.	Acc	
CV	77.29	75.63	55.56	89.29	80.66	78.61	42.26	78.37	90.00	74.61
CV	±3.32	± 4.26	± 1.06	± 3.86	± 14.87	± 0.84	± 2.07	± 4.26	± 2.45	74.01
MDL	79.29	75.87	53.53	79.61	59.25	75.77	37.30	77.82	76.25	69.82
WIDL	±6.01	± 5.19	± 0.58	± 5.42	± 11.27	± 4.72	± 6.27	± 4.19	± 12.50	09.02
Multi-Splits	78.11	79.42	61.72	83.04	70.93	78.23	41.45	74.52	84.75	73.62
(r = 1:1)	±2.63	± 1.79	± 3.10	± 6.66	± 13.40	± 1.24	± 1.74	± 3.96	± 2.12	73.02
Multi-Splits	79.18	75.00	52.90	87.05	81.06	76.70	41.13	78.37	84.50	73.27
(r = 3:1)	±1.96	± 3.84	± 2.40	± 4.22	± 8.14	± 1.06	± 1.95	± 1.24	± 5.80	13.21

(b) Results of correlation between the development and training sets

	BoolQ	RTE	WiC	CB	MultiRC	WSC	COPA	Avg.
CV	0.4134	0.6759	0.4189	0.0938	0.1061	-0.1683	0.6567	0.3138
MDL	0.6394	0.5687	-0.0732	0.2127	0.1690	0.0741	0.1100	0.2429
Multi-Splits $(r = 1:1)$	0.5347	0.6911	0.8448	0.7232	0.6280	0.0853	0.4531	0.5657
Multi-Splits $(r = 3:1)$	0.3003	0.7601	0.4938	0.6867	0.3310	-0.1595	0.7024	0.4450

Table 10: The best hyper-parameters searched for PET. We search each task with a learning rate of $\{1e-5,5e-6\}$, max steps of $\{250,500\}$, evaluation frequency ratio of $\{0.02,0.04\}$, and all the available prompt patterns. Therefore, each task has 8N hyper-parameter combinations, where N is the number of available prompt patterns, i.e., 6 for BoolQ and RTE, 3 for WiC, and 2 for COPA.

	BoolQ	RTE	WiC	CB	MultiRC	WSC	COPA
Learning Rate	1e-5	5e-6	5e-6	1e-5	1e-5	5e-6	1e-5
Maximum Training Step	250	250	250	250	500	250	500
Evaluation Frequency	0.02	0.02	0.02	0.02	0.02	0.02	0.02
Prompt Pattern	1	5	2	5	0	2	0

Table 11: Hyper-parameter Search Space for Crucial Factor Evaluation

Hyper-parameter	Value			
Learning Rate	$\{6e-6, 8e-6, 1e-5\}$			
Evaluation Frequency	{0.02, 0.04, 0.08}			
Training Batch Size	{8, 16, 32, 64}			
Sample Order Seed	$ \left\{ 10, 20, 30, 40, 50, 60, 70, 80 \right\} $			

trained model, and will be used for training along with train data in the next generation.

3. **Noisy Student** is similar to iPET with the difference that Noisy Student injects noises into the input embeddings of the model.

A.3.2 Hyper-parameters for Re-Evaluation

For minimal few-shot methods on DeBERTa, such as PET, ADAPET, and P-tuning, we search in the same hyper-parameter space as introduced in Section A.1.2. The hyper-parameter search space for other few-shot methods are shown in Table 14.

A.3.3 The Searched Best Hyper-parameters

We list the searched best hyper-parameter configuration for different tasks and methods in Table 10, Table 12, and Table 13.

A.3.4 More Discussion on ADAPET

Since it is observed that ADAPET shows less improvements on DeBERTa than it has achieved on ALBERT, we further discuss the phenomena by raising the question what other differences it has made. We respectively visualize the fewshot performance distribution over the same hyperparameter space of PET and ADAPET in Figure 4. We observe that PET is more likely to obtain extremely bad results on BoolQ and RTE, while ADAPET shows stable results. It suggests that ADAPET appears to be more robust to the hyperparameters, and overall achieves good performance regardless of hyper-parameter selection. However, ADAPET is less inclined to produce better peak results. To sum up, we can conclude: Loss regularization (e.g., ADAPET (Menon et al., 2021)) enhances stability w.r.t. hyper-parameters.

A.3.5 More Discussion on Semi-supervised Few-shot Methods

We focus on semi-supervised methods that iteratively augment data (i.e., iPET and Noisy Student),

Table 12: The best hyper-parameters searched for ADAPET. We search each task with a learning rate of $\{1e-5,5e-6\}$, max steps of $\{250,500\}$, evaluation frequency ratio of $\{0.02,0.04\}$, and all the available prompt patterns. Therefore, each task has 8N hyper-parameter combinations, where N is the number of available prompt patterns, i.e., 6 for BoolQ and RTE, 3 for WiC, and 2 for COPA.

	BoolQ	RTE	WiC	CB	MultiRC	WSC	COPA
Learning Rate	1e-5	5e-6	5e-6	1e-5	5e-6	1e-5	5e-6
Maximum Training Step	250	500	500	500	500	500	500
Evaluation Frequency	0.04	0.04	0.02	0.02	0.02	0.02	0.04
Prompt Pattern	1	5	2	5	0	1	0

Table 13: The best hyper-parameters searched for P-tuning. We search each task with a learning rate of $\{1e-5,5e-6\}$, max steps of $\{250,500\}$, warmup ratio of $\{0.0,0.1\}$, evaluation frequency ratio of $\{0.02,0.04\}$, and prompt encoder impelmented with $\{\text{"mlp"}, \text{"lstm"}\}$.

	BoolQ	RTE	WiC	CB	MultiRC	WSC	COPA
Learning Rate	5e-6	5e-6	5e-6	1e-5	1e-5	1e-5	1e-5
Maximum Training Step	500	250	500	250	500	250	500
Warmup Ratio	0.0	0.0	0.0	0.1	0.1	0.0	0.1
Evaluation Frequency	0.02	0.02	0.02	0.04	0.02	0.04	0.04
Prompt Encoder Type	mlp	lstm	lstm	lstm	lstm	mlp	mlp

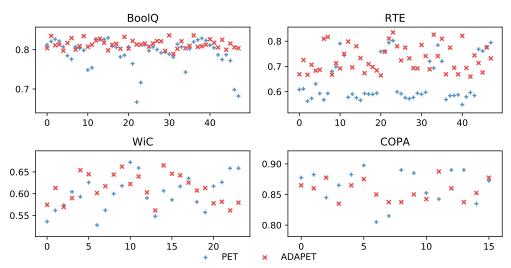


Figure 4: Visualization of few-shot performance over the same hyper-parameter space of ADAPET and PET based on DeBERTa and Multi-Splits. The x-axis is the index of the hyper-parameter combination. We search each task with a learning rate of 1e-5 or 5e-6, max steps of 250 or 500, evaluation ratio of 0.02 or 0.04, and all the available prompt patterns. Therefore, each task has 8N hyper-parameter combinations, where N is the number of available prompt patterns, i.e., 6 for BoolQ and RTE, 3 for WiC, and 2 for COPA. The y-axis is the score of each task given a certain hyper-parameter combination.

which have demonstrate promising results on both models in Table 5. Several key points for their success are especially discussed.

- 1. For semi-supervised methods such as iPET and Noisy Student, it is time-consuming when searching over a large hyper-parameter space for each generation. We directly use the searched best hyper-parameters for PET in each generation. From Table 5, we can see that their results show advantages over PET (by more than 1 points). It suggests that best hyper-parameters can be transferred to such
- methods, to reduce the cost of time and computational resources. If we search for each generation, results might be even better.
- 2. Comparing the single-split labeling strategy, the cross-split labeling strategy works better. As the results show, both iPET (cross) and Noisy (cross) outperform iPET (single) and Noisy (single) in most tasks on both models.
- 3. Another simple and effective technique is our proposed ensemble labeling strategies. (Schick and Schütze, 2021b) utilizes the ensemble results over all patterns to label unla-

Table 14: Hyper-parameter Space for Re-Evaluation

Method	Hyper-Parameter	Value
CLS	Learning Rate (DeBERTa) Learning Rate (ALBERT) Maximum Training Step	
PET/ ADAPET	Learning Rate (DeBERTa) Learning Rate (ALBERT) Maximum Training Step Evaluation Frequency	
P-tuning	Learning Rate (DeBERTa) Learning Rate (ALBERT) Maximum Training Step Evaluation Frequency Warmup Ratio Prompt Encoder Type	$ \begin{cases} 5e-6, 1e-5 \\ \{1e-5, 2e-5 \} \\ \{250, 500 \} \\ \{0.02, 0.04 \} \\ \{0.0, 0.1 \} \\ \{\text{mlp, lstm} \} \end{cases} $
iPET/ Noisy	Unlabeled Data Number Increasing Factor Sample Ratio (single-split) Sample Ratio (cross-split) Dropout Rate for Noisy	500 3.0 1.0 2/3 0.05

Table 15: The performance results of iPET on both WiC and RTE at every generation (g1, g2, and g3). Each experiment uses either ensemble over all patterns (Multi-Patterns) or ensemble over the only best pattern (Best-Pattern).

task	method	g1	g2	g3
WiC	Multi-Patterns Best-Pattern	60.11 ±5.64 64.21 ±2.58	60.19 ±4.12 64.18 ±4.61	59.66 ±4.27 63.37 ±6.29
RTE	Multi-Patterns Best-Pattern	$ \begin{array}{c} 65.08 \pm 10.07 \\ 79.39 \pm 2.75 \end{array} $	69.20 ±7.13 81.95 ±1.04	71.46 ±5.59 83.12 ±1.42

beled data, since it is hard to select patterns. Under the Multi-Splits strategy, self-training methods can recognize the best pattern, and only ensemble trained models for the best pattern when labeling unlabeled data. Table 15 shows the results of iPET on WiC and RTE tasks, respectively ensemble over multiple patterns or ensemble over the only best pattern. We can see that results of ensemble with the best pattern significantly outperform results of ensemble with all patterns at every generation.