
Don't Stop Pretraining? Make Prompt-based Fine-tuning Powerful Learner

Zhengxiang Shi

University College London
London, United Kingdom
zhengxiang.shi.19@ucl.ac.uk

Aldo Lipani

University College London
London, United Kingdom
aldo.lipani@ucl.ac.uk

Abstract

Language models (LMs) trained on vast quantities of unlabelled data have greatly advanced the field of natural language processing (NLP). In this study, we re-visit the widely accepted notion in NLP that continued pre-training LMs on task-related texts improves the performance of fine-tuning (FT) in downstream tasks. Through experiments on eight single-sentence tasks and eight sentence-pair tasks in both semi-supervised and fully-supervised settings, we find that conventional continued pre-training does not consistently provide benefits and can even be detrimental for sentence-pair tasks or when prompt-based FT is used. To tackle these issues, we propose Prompt-based Continued Pre-training (PCP), which combines the idea of instruction tuning with conventional continued pre-training. Our approach aims to improve the performance of prompt-based FT by presenting both task-related texts and prompt templates to LMs through unsupervised pre-training objectives before fine-tuning for the target task. Our empirical evaluations on 21 benchmarks demonstrate that the PCP consistently improves the performance of state-of-the-art prompt-based FT approaches (up to 20.1% absolute) in both semi-supervised and fully-supervised settings, even with only hundreds of unlabelled examples. Additionally, prompt-based FT with the PCP outperforms state-of-the-art semi-supervised approaches with greater simplicity, eliminating the need for an iterative process and extra data augmentation. Our further analysis explores the performance lower bound of the PCP and reveals that the advantages of PCP persist across different sizes of models and datasets. Code is available at <https://github.com/ZhengxiangShi/PowerfulPromptFT>.

1 Introduction

Pre-training language models (LMs) [26, 55, 70] over massive unlabelled data and then fine-tuning on task-specific labelled data for the specific downstream task offer large performance gains across NLP tasks. In this study, we re-visit the commonly held belief in NLP [40, 83, 36] that continued pre-training LMs on either task-specific data [1, 58] or in-domain data [56, 97] is generally beneficial for improving the performance of fine-tuning (FT) on downstream tasks. As shown in Figure 1, our experiments on eight single-sentence tasks and eight sentence-pair tasks in both semi- and fully-supervised settings reveal that conventional continued pre-training on task-specific data [36], known as task

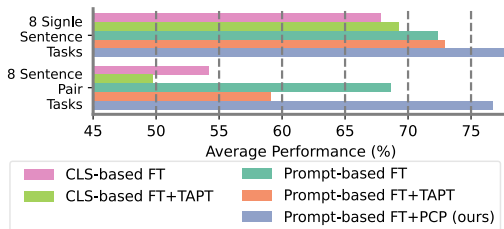


Figure 1: Mean performance of CLS- and prompt-based FT across 16 NLP tasks when trained by *themselves* or in combination with either TAPT or our proposed PCP in the semi-supervised setting. Please refer to Table 1 for details.

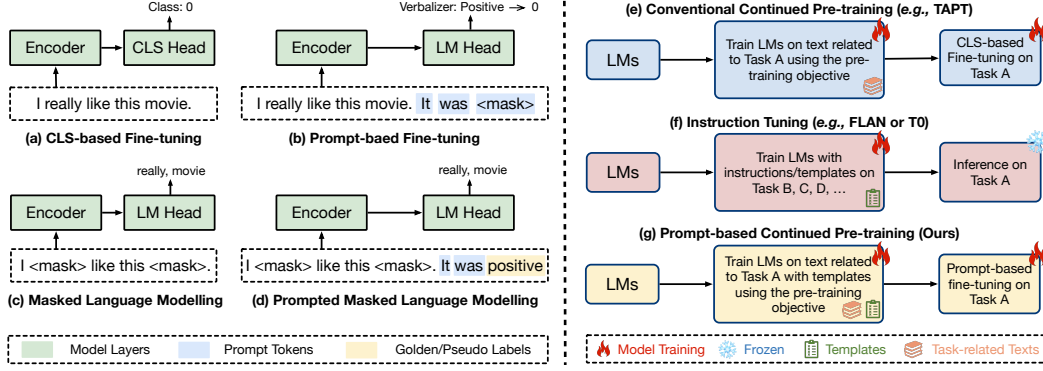


Figure 2: The overview of **Prompt-based Continued Pre-training** (g), in comparison to conventional continued pre-training (e) and instruction tuning (f), along with fine-tuning methods (a,b) and continued pre-training techniques (c,d). The verbalizer functions as a mapping from the task label space to individual words. We use masked language modelling for illustrative purposes, where <mask> represents a masked token in the LM vocabulary.

adaptive pre-training (TAPT) (see Figure 2e): (1) can lead to a substantial drop in performance of CLS-based FT (see Figure 2a) on sentence-pair tasks; and (2) can be highly unstable across different tasks for prompt-based FT (see Figure 2b), which is typically considered a better alternative to CLS-based FT by previous studies [74, 47] (§4.2). These findings suggest that exclusively **presenting task-related texts to LMs** through continued pre-training may not be the most effective approach for improving the performance of FT in the aforementioned situations.

Recent research [44, 3, 66, 91, 63, 73, 89, 61] on cross-task generalization has demonstrated the impressive improvement on zero-shot or few-shot learning capabilities of LMs (see Figure 2f). These studies suggest that **presenting appropriate instructions/prompt templates to LMs** through training on a range of NLP tasks improves their downstream performance on held-out tasks. Although these works train LMs with different objectives from pre-training phases, we interpret “fine-tuning LMs on a range of NLP tasks” as a special type of continued pre-training. Therefore, we hypothesize that **presenting both task-related texts and instructions/prompt templates to LMs** can relieve the above-mentioned issues for conventional continued pre-training and be beneficial for the target task performance. Rather than improve the generalizability of the LMs with supervised objectives, our work places a greater emphasis on enhancing specific target task performance with unsupervised pre-training objectives.

In this work, we propose Prompt-based Continued Pre-training (PCP) (§3), which integrates instructions/prompt templates into task-related texts with golden or pseudo labels (see Figure 2g). Our experiments demonstrate that PCP consistently improves the performance of state-of-the-art prompt-based FT approaches [29, 100] in both semi- and fully-supervised settings, covering both single sentence tasks and sentence pair tasks, and that the performance gains from PCP exceed those from conventional continued pre-training (TAPT) by a substantial margin (§4.2). In the most favourable case, PCP boosts the performance of prompt-based FT by more than 20% absolute where TAPT results in a 9.2% performance decline. Furthermore, our evaluations show that PCP outperforms state-of-the-art semi-supervised approaches [81, 94, 96, 99, 13] with greater simplicity, eliminating the need for an iterative process and extra data augmentation (§4.3). Additionally, our analysis suggests that the PCP can efficiently improve the performance of prompt-based FT with only hundreds of unlabelled examples, while previous work [34] pursuing a similar goal with ours requires a 10GB English corpus for continued pre-training. Finally, our analysis explores the performance lower bound of the PCP and reveals that the advantages of PCP persist across different sizes of models and datasets (§4.4).

In summary, the main contributions of this paper are as follows:

- Our study empirically demonstrates that conventional continued pre-training might not be as effective as initially thought and can even negatively impact fine-tuning performance, particularly in sentence pair tasks or when utilising prompt-based FT;

- Our evaluation on 21 classification and regression NLP tasks shows that our proposed method PCP provides a superior option to conventional continue pre-training for prompt-based FT. This approach consistently yields performance improvements in diverse model and dataset settings, even with only a few hundred unlabelled examples. Moreover, it can outperform state-of-the-art semi-supervised approaches with greater simplification;
- Our result shows the effectiveness of presenting both task-related texts and templates/instructions to the LMs through unsupervised pre-training objectives on improving the performance of prompt-based FT on downstream tasks.

2 Background

Suppose that we focus on the LMs trained with the masked language modelling (MLM) objective [26, 55]. Let $X = \{x_1, x_2, \dots, x_N\}$ be a sequence of tokens, where N represents the total number of tokens. LMs are designed to encode the input text X into a corresponding sequence of hidden vectors $\{\mathbf{h}_i \in \mathbb{R}^d\}$. As shown in Figure 2a, the conventional CLS-based FT [26, 36, 76] trains the output vector \mathbf{h} corresponding to the [CLS] token with an additional head layer (*e.g.*, an MLP layer). However, there is a discrepancy between the pre-training objective (see Figure 2c) and the CLS-based FT objective, which has led to research on prompt-based techniques for better LM performance.

The prompt-based FT is formulated as a MLM problem where the objective is to predict the masked token [74, 75]. Specifically, the input text X is conditioned with a specific prompt template $\tilde{X} = \mathcal{T}(X)$, which includes one special token [MASK]. The prompt-based FT then maps the output vector associated with the [MASK] token to a label word. The probability of predicting class $y \in \mathcal{Y}$ is computed as:

$$p(y|X) = p([\text{MASK}] = \mathcal{M}(y)|\tilde{X}), \quad (1)$$

where the verbalizer $\mathcal{M} : \mathcal{Y} \rightarrow \mathcal{V}$ is a mapping from the task label space to individual words in the vocabulary \mathcal{V} .

Prompt-based FT can use either hard or soft prompt templates \mathcal{T} , with label words potentially being a part of the prompt templates as well [37, 100]. Hard prompt template [74, 29, 79] requires careful designs of prompts and label words for each task. The use of hard prompts, however, was found to be sub-optimal and sensitive to the choice of the prompt [102, 54]. Soft prompt [54, 100] was then proposed to use unused tokens from the vocabulary \mathcal{V} or additional tokens as tuneable embeddings for prompt template and can be directly trained with the task-specific supervision. This design allows the token embeddings in the prompt template to be updated independently of specific word embeddings after initialization, thus reducing the effort of searching for prompt templates and label words.

3 Our Approach: Prompt-based Continued Pre-training (PCP)

In this section, we introduce the proposed method, Prompt-based Continued Pre-training (PCP), which aims to improve the performance of LMs on downstream tasks through continued pre-training with prompt templates, as shown in Figure 2g. Let $L \triangleq \{(X_1, y_1), \dots, (X_n, y_n)\}$ denote n labelled examples and $U \triangleq \{X'_1, \dots, X'_m\}$ denote m unlabelled examples. Our approach consists of two main steps, as described below.

Step 1: Construct Continued Pre-training Corpus. Initially, we select a model F , pre-trained with the MLM objective and parameterized by Θ . We then train this model using the prompt-based FT, minimizing the target loss function ℓ on the labelled examples L , as illustrated in Figure 2b:

$$\mathcal{L}(L) = \sum_{X_i, y_i \in L} \ell(y_i, F(\mathcal{T}(X_i), \Theta)), \quad (2)$$

Next, we use the trained model F with the learned parameters Θ' to generate predictions (termed "pseudo-labels") on the unlabelled samples U :

$$y'_i = F(\mathcal{T}(X'_i), \Theta'), \quad (3)$$

For each text example X and its associated (golden or pseudo) label y , we create an example for our proposed PCP as $X^{pcp} = \mathcal{T}(X, \mathcal{M}(y))$, where the original [MASK] position is substituted with $\mathcal{M}(y)$. This results in a new corpus, $\mathcal{C} = \{X_i^{pcp}\}_{i=1}^{n+m}$. In the fully-supervised setting, $m = 0$ and all examples use the golden labels.

Step 2: Perform continued pre-training and prompt-based FT. We then proceed to further pre-train another model G , parameterized by Θ , using the MLM objective on the newly generated corpus \mathcal{C} , to obtain the PCP checkpoint Φ (see Figure 2d). Finally, we train model G , initialised by Φ , using Equation 2 with prompt-based FT for downstream tasks.

In comparison to conventional continued pre-training, PCP does not require any modification for the model architecture or training process. The sole difference is the addition of a few extra tokens to the input text during continued pre-training. This modification does not hinder the efficiency of the method, *i.e.*, both conventional continued pre-training and PCP maintain equal levels of efficiency. Prompt-based approaches [54, 49, 53, 34] can be readily adapted for different model architectures and pre-training objectives [26, 71, 78, 15, 66]. Consequently, PCP can be seamlessly extended to accommodate diverse architectures and objectives, in line with these adaptable prompt-based techniques. In this study, we primarily focus on LMs pre-trained with the MLM objective [55].

4 Experiments and Results

In this section, we evaluate the proposed method PCP by comparing it with conventional continued pre-training and four state-of-the-art semi-supervised approaches. We assess their relative performance across 21 different classification and regression NLP tasks, including single-sentence and sentence-pair tasks. We conduct additional analysis concerning the performance lower bound of PCP and the effectiveness of the PCP across varying datasets and model sizes.

4.1 Experimental Setup

Datasets. Our study conducts a comprehensive analysis of 21 NLP datasets, including classification and regression tasks. Following previous studies [29, 37, 100] on prompt-based FT, we derive 8 single-sentence tasks and 8 sentence-pair English tasks from the GLUE benchmark [87], SNLI [14], and 6 other widely used sentence classification tasks (*i.e.*, SST-5, MR, CR, MPQA, Subj, TREC). Additionally, we use 5 popular benchmarks for semi-supervised learning from previous research [35, 22, 94, 50, 30, 77], including IMDB [57], AG NEWS [101], YELP REVIEW¹, YAHOO! ANSWER [19], and AMAZON REVIEW [59]. See dataset details in Appendix §A. We train the model with two different settings: (1) fully-supervised setting, where we train the model with the full training set; and (2) semi-supervised setting, where we sample the same amount of labelled data per class from the full training set. We re-sample the labelled data using the same five seeds for all comparison approaches and report the average performance with an error bar.

All Comparison Approaches. We utilise the conventional CLS-based FT and two state-of-the-art prompt-based FT approaches: (1) “CLS-based FT”: fine-tuning with the [CLS] token representation with an extra MLP layer; (2) “Prompt-based FT (hard)”: fine-tuning with high-quality manual or auto-generated prompts and label words [74, 29]; and (3) “Prompt-based FT (soft)”: fine-tuning with soft prompts using additional tokens for both templates and label words [100]. Since the objective of soft prompt FT is to minimize the reliance on human-designed templates, we unify the template for all tasks here. See the template specifics used for each dataset in Appendix §B. We train these three types of FT approaches from three different types of checkpoints to evaluate their relative effectiveness: (i) the off-the-shelf ROBERTA-LARGE checkpoint; (ii) the task-adaptive pre-training (TAPT) checkpoint [36] (represents the conventional continued pre-training). For sentence pair tasks, we concatenate the two sentences as an input example; and (iii) the proposed PCP checkpoint, obtained in §3. For both (ii) and (iii), we perform MLM on all full training sets except MNLI, MNLI-mm, SNLI, QNLI, and QQP, where we select up to 10k unlabelled examples from the full training sets (see supplementary experiments on the full training sets in Appendix §D). Additionally, we compare the proposed PCP with four state-of-the-art semi-supervised approaches, including FixMatch [81], Dash [96], FlexMatch [99], and AdaMatch [13] (see descriptions of these approaches in Appendix §C), where back-translation [65] is used for data augmentation as previous works [94, 77] and prompt-based FT (hard) is used as the backbone. See hyperparameter and implementation details in Appendix §E.

¹<https://www.yelp.com/dataset>

Single Sentence Tasks								
	SST-2 (acc)	SST-5 (acc)	MR (acc)	CR (acc)	MPQA (acc)	Subj (acc)	TREC (acc)	CoLA (Matt.)
Majority (full)	50.9	23.1	50.0	50.0	50.0	50.0	18.8	0.0
Prompt-based zero-shot [†]	83.6	35.0	80.8	79.5	67.6	51.4	32.0	2.0
in-context learning	84.8 _{1.3}	30.6 _{0.9}	80.5 _{1.7}	87.4 _{0.8}	63.8 _{2.1}	53.6 _{1.0}	26.2 _{2.4}	-1.5 _{2.4}
Fully Supervised Learning								
CLS-based FT	95.1	59.4	90.8	90.8	89.1	96.9	96.8	54.3
+ TAPT	96.0 \uparrow _{0.9}	60.6 \uparrow _{1.2}	91.4 \uparrow _{0.6}	91.0 \uparrow _{0.2}	89.9 \uparrow _{0.8}	96.9 \uparrow _{0.0}	97.6 \uparrow _{0.8}	43.6 \downarrow _{10.7}
Prompt-based FT (hard)	95.2	60.0	90.8	92.4	89.4	95.9	97.8	54.7
+ TAPT	93.5 \downarrow _{1.7}	60.4 \uparrow _{0.4}	90.3 \downarrow _{0.5}	90.8 \downarrow _{1.6}	89.5 \uparrow _{0.1}	95.9 \uparrow _{0.0}	97.6 \downarrow _{0.2}	44.0 \downarrow _{10.7}
+ PCP (ours)	95.5 \uparrow _{0.3}	60.5 \uparrow _{0.5}	91.7 \uparrow _{0.9}	92.8 \uparrow _{0.4}	89.6 \uparrow _{0.2}	96.8 \uparrow _{0.9}	97.8 \uparrow _{0.0}	56.0 \uparrow _{1.3}
Prompt-based FT (soft)	94.2	59.8	90.4	92.7	87.8	96.4	97.4	61.3
+ TAPT	92.7 \downarrow _{1.5}	59.5 \downarrow _{0.3}	91.8 \uparrow _{1.4}	92.5 \downarrow _{0.2}	89.5 \uparrow _{1.7}	96.8 \uparrow _{0.4}	97.8 \uparrow _{0.4}	52.6 \downarrow _{8.7}
+ PCP (ours)	94.3 \uparrow _{0.1}	60.7 \uparrow _{0.9}	91.8 \uparrow _{1.4}	92.8 \uparrow _{0.1}	90.4 \uparrow _{2.6}	97.1 \uparrow _{0.7}	98.0 \uparrow _{0.6}	62.0 \uparrow _{0.7}
Semi Supervised Learning								
CLS-based FT	81.2 _{2.7}	41.7 _{1.3}	76.3 _{3.2}	79.5 _{3.8}	65.1 _{12.6}	91.7 _{0.4}	80.3 _{5.8}	26.7 _{7.8}
+ TAPT	88.2 _{1.5} \uparrow _{7.0}	43.4 _{2.6} \uparrow _{1.7}	86.1 _{0.7} \uparrow _{9.8}	86.2 _{2.4} \uparrow _{6.7}	73.7 _{4.4} \uparrow _{8.6}	94.2 _{1.5} \uparrow _{2.5}	80.4 _{6.4} \uparrow _{0.1}	1.9 _{2.4} \downarrow _{24.8}
Prompt-based FT (hard)	92.7 _{1.3}	46.7 _{1.5}	86.2 _{1.2}	90.7 _{0.8}	80.8 _{6.9}	91.0 _{1.1}	84.7 _{4.4}	7.2 _{5.5}
+ TAPT	92.9 _{1.0} \uparrow _{0.2}	48.9 _{1.1} \uparrow _{2.2}	88.4 _{0.5} \uparrow _{2.2}	89.8 _{2.3} \downarrow _{0.9}	84.6 _{4.9} \uparrow _{3.8}	93.5 _{1.1} \uparrow _{2.5}	85.2 _{2.9} \uparrow _{0.5}	1.4 _{3.5} \downarrow _{5.8}
+ PCP (ours)	93.0 _{0.3} \uparrow _{0.9}	50.9 _{1.3} \uparrow _{4.2}	89.0 _{0.6} \uparrow _{2.8}	92.3 _{0.4} \uparrow _{1.6}	87.9 _{0.5} \uparrow _{7.1}	95.7 _{0.4} \uparrow _{4.7}	90.6 _{3.5} \uparrow _{9.9}	25.0 _{2.9} \uparrow _{17.8}
Prompt-based FT (soft)	92.5 _{1.2}	48.0 _{0.7}	86.8 _{1.4}	90.8 _{1.3}	81.2 _{6.8}	90.3 _{3.0}	83.0 _{3.0}	4.9 _{3.7}
+ TAPT	93.4 _{0.5} \uparrow _{0.9}	47.0 _{1.2} \downarrow _{1.0}	88.5 _{0.8} \uparrow _{1.7}	89.6 _{3.4} \downarrow _{1.2}	83.4 _{5.1} \uparrow _{2.2}	93.3 _{0.7} \uparrow _{3.0}	84.5 _{2.4} \uparrow _{1.5}	2.1 _{1.8} \downarrow _{2.8}
+ PCP (ours)	93.9 _{0.3} \uparrow _{1.4}	50.7 _{1.3} \uparrow _{2.7}	89.8 _{0.6} \uparrow _{3.0}	92.0 _{0.5} \uparrow _{1.2}	88.3 _{0.5} \uparrow _{7.1}	94.9 _{0.9} \uparrow _{4.6}	88.6 _{5.4} \uparrow _{5.6}	21.5 _{2.5} \uparrow _{16.6}
Sentence Pair Tasks								
	MNLI (acc)	MNLI-mm (acc)	SNLI (acc)	QNLI (acc)	RTE (acc)	MRPC (F1)	QQP (F1)	STS-B (Pear.)
Majority (full)	32.7	33.0	33.8	49.5	52.7	81.2	0.0	-
Prompt-based zero-shot [†]	50.8	51.7	49.5	50.8	51.3	61.9	49.7	-3.2
in-context learning	52.0 _{0.7}	53.4 _{0.6}	47.1 _{0.6}	53.8 _{0.4}	60.4 _{1.4}	45.7 _{6.0}	36.1 _{5.2}	14.3 _{2.8}
Fully Supervised Learning								
CLS-based FT	82.1	82.7	88.1	90.2	83.4	91.9	79.7	91.2
+ TAPT	81.0 \downarrow _{1.1}	82.0 \downarrow _{0.7}	86.7 \downarrow _{1.4}	85.6 \downarrow _{4.6}	83.4 \uparrow _{0.0}	91.6 \downarrow _{0.3}	80.2 \uparrow _{0.5}	90.4 \downarrow _{0.8}
Prompt-based FT (hard)	85.4	85.8	89.0	89.6	88.1	93.1	73.8	91.5
+ TAPT	82.8 \downarrow _{2.6}	83.2 \downarrow _{2.6}	88.3 \downarrow _{0.7}	90.9 \uparrow _{1.3}	83.8 \downarrow _{4.3}	92.7 \downarrow _{0.4}	78.2 \uparrow _{4.4}	91.2 \downarrow _{0.3}
+ PCP (ours)	86.5 \uparrow _{1.1}	86.2 \uparrow _{0.4}	89.5 \uparrow _{0.5}	91.5 \uparrow _{1.9}	88.5 \uparrow _{0.4}	93.3 \uparrow _{0.2}	79.6 \uparrow _{5.8}	91.9 \uparrow _{0.4}
Prompt-based FT (soft)	84.6	85.4	89.0	89.5	84.5	92.4	73.9	91.6
+ TAPT	83.5 \downarrow _{1.1}	84.1 \downarrow _{1.3}	88.3 \downarrow _{0.7}	90.9 \uparrow _{1.4}	82.7 \downarrow _{1.8}	92.6 \uparrow _{0.2}	79.9 \uparrow _{6.0}	90.9 \downarrow _{0.7}
+ PCP (ours)	85.7 \uparrow _{1.1}	86.0 \uparrow _{0.6}	89.5 \uparrow _{0.5}	91.0 \uparrow _{1.5}	85.5 \uparrow _{1.0}	92.6 \uparrow _{0.2}	79.6 \uparrow _{5.7}	91.7 \uparrow _{0.1}
Semi Supervised Learning								
CLS-based FT	46.2 _{0.6}	48.5 _{1.0}	45.6 _{5.4}	61.4 _{8.2}	54.2 _{4.3}	73.2 _{8.7}	58.5 _{3.8}	46.0 _{16.3}
+ TAPT	36.0 _{1.0} \downarrow _{10.2}	36.3 _{1.1} \downarrow _{12.2}	45.7 _{3.6} \uparrow _{0.1}	55.6 _{2.7} \downarrow _{5.8}	53.4 _{1.0} \downarrow _{0.8}	67.7 _{8.5} \downarrow _{5.5}	55.0 _{4.1} \downarrow _{3.5}	48.1 _{19.6} \uparrow _{2.1}
Prompt-based FT (hard)	67.3 _{1.3}	68.9 _{1.2}	76.7 _{1.6}	66.5 _{4.3}	68.3 _{3.1}	75.9 _{1.6}	66.8 _{1.9}	67.7 _{8.1}
+ TAPT	50.7 _{3.9} \downarrow _{16.6}	52.2 _{4.6} \downarrow _{16.7}	74.5 _{3.1} \downarrow _{2.2}	55.3 _{1.1} \downarrow _{11.2}	59.9 _{2.7} \downarrow _{8.4}	63.2 _{6.3} \downarrow _{12.7}	58.2 _{2.6} \downarrow _{8.6}	63.1 _{8.0} \downarrow _{4.6}
+ PCP (ours)	75.6 _{1.4} \uparrow _{8.3}	76.8 _{0.9} \uparrow _{7.9}	82.4 _{1.3} \uparrow _{5.7}	85.1 _{0.8} \uparrow _{18.6}	70.2 _{2.7} \uparrow _{1.9}	80.7 _{3.3} \uparrow _{4.8}	71.8 _{1.3} \uparrow _{5.0}	71.5 _{8.4} \uparrow _{3.8}
Prompt-based FT (soft)	62.7 _{2.2}	65.9 _{1.2}	75.4 _{0.8}	64.2 _{4.7}	68.2 _{3.7}	73.0 _{10.6}	66.5 _{1.8}	63.7 _{6.8}
+ TAPT	46.6 _{3.9} \downarrow _{16.1}	49.5 _{6.8} \downarrow _{16.4}	72.1 _{2.0} \downarrow _{3.3}	55.0 _{2.3} \downarrow _{9.2}	58.4 _{2.4} \downarrow _{9.8}	63.3 _{5.8} \downarrow _{9.7}	58.3 _{1.9} \downarrow _{8.2}	65.3 _{6.3} \uparrow _{1.6}
+ PCP (ours)	75.4 _{0.7} \uparrow _{12.7}	76.8 _{0.3} \uparrow _{10.9}	82.6 _{1.2} \uparrow _{7.2}	84.3 _{2.0} \uparrow _{20.1}	70.4 _{3.2} \uparrow _{2.2}	80.0 _{2.4} \uparrow _{7.0}	72.3 _{1.2} \uparrow _{5.8}	71.4 _{7.8} \uparrow _{7.7}
Summary of results: the probability of improving the performance for TAPT and PCP								
Checkpoint	Single Sentence Tasks				Sentence Pair Tasks			
	TAPT(full)	PCP(full)	TAPT(semi)	PCP(semi)	TAPT(full)	PCP(full)	TAPT(semi)	PCP(semi)
CLS-based FT	87.5 (7/8)	-	87.5 (7/8)	-	25.0 (2/8)	-	25.0 (2/8)	-
Prompt-based FT (hard)	37.5 (3/8)	100 (8/8)	75.0 (6/8)	100 (8/8)	25.0 (2/8)	100 (8/8)	0.0 (0/8)	100 (8/8)
Prompt-based FT (soft)	50.0 (4/8)	100 (8/8)	62.5 (5/8)	100 (8/8)	37.5 (3/8)	100 (8/8)	12.5 (1/8)	100 (8/8)

Table 1: Comparison between the PCP and conventional continued pre-training (TAPT) using ROBERTA-LARGE. The summary highlights the percentage of positive impact brought by the PCP and TAPT. The mean and standard deviation on test sets are reported over 5 different seeds. In semi-supervised learning, 16 examples per class are used for training, in line with previous studies [29, 54, 100]. Green and red arrows indicate changes with respect to the FT baselines that do not use TAPT or PCP. \uparrow represents that no training examples are used. Three extra baselines sourced from [29] are included, where “Majority” refers to the majority class, and “in-context learning” indicates the usage of in-context learning [15] with ROBERTA-LARGE, without updating any parameters.

4.2 Comparison of the PCP and conventional continued pre-training

Table 1 presents and summarises our experimental results on 8 single-sentence tasks and 8 sentence-pair tasks. Below we delve deeper into our two major findings.

#1. TAPT is not consistently beneficial for sentence pair tasks, nor when prompt-based FT is employed. Initially, we re-visit the impact of TAPT (representing the conventional continued pre-training) on the CLS-based FT, as shown in Table 1. Our experimental results align with earlier

Method	IMDB		AG NEWS		YELP REVIEW		YAHOO! ANSWER		AMAZON REVIEW		Mean
	20	100	40	200	40	200	40	200	40	200	
DASH [96]	93.34 _{0.7}	93.30 _{0.6}	85.00 _{2.9}	87.90 _{0.3}	47.44 _{2.2}	58.85 _{1.0}	60.07 _{4.7}	66.46 _{0.9}	44.09 _{2.6}	53.95 _{1.0}	69.04
FIXMATCH [81]	95.26 _{0.4}	94.28 _{0.5}	85.44 _{1.1}	88.21 _{0.4}	47.26 _{1.2}	58.51 _{0.3}	61.56 _{6.9}	68.37 _{0.7}	44.26 _{2.0}	52.33 _{1.7}	69.55
FLEXMATCH [99]	95.22 _{0.3}	94.84 _{0.4}	85.33 _{1.4}	88.57 _{0.6}	50.60 _{2.5}	58.34 _{1.9}	58.09 _{3.7}	66.43 _{1.3}	45.48 _{3.1}	54.19 _{1.1}	69.71
ADAMATCH [13]	95.20 _{0.5}	94.94 _{0.1}	85.79 _{2.1}	88.72 _{0.8}	50.42 _{2.7}	58.95 _{1.9}	63.68 _{0.7}	68.09 _{0.8}	44.66 _{3.4}	53.05 _{0.6}	70.35
Prompt-based FT (hard)	86.78 _{2.1}	89.52 _{1.6}	84.87 _{1.1}	86.99 _{0.3}	46.69 _{4.2}	58.27 _{0.7}	60.63 _{1.5}	66.94 _{1.1}	44.34 _{1.5}	57.01 _{0.4}	68.20
+ PCP (ours)	92.49 _{1.2}	94.24 _{0.9}	87.06 _{1.0}	88.94 _{0.4}	52.92 _{4.5}	63.15 _{1.3}	65.58 _{1.8}	70.22 _{0.9}	53.44 _{3.0}	59.64 _{1.6}	72.77
Prompt-based FT (soft)	88.14 _{2.9}	90.80 _{1.5}	85.65 _{1.3}	87.66 _{0.3}	45.43 _{3.4}	57.12 _{1.0}	61.18 _{1.5}	67.85 _{0.8}	44.52 _{3.6}	55.03 _{1.5}	68.34
+ PCP (ours)	93.53 _{1.5}	94.36 _{0.7}	87.26 _{0.8}	88.96 _{0.6}	50.66 _{3.3}	62.92 _{1.0}	65.26 _{1.5}	70.03 _{0.9}	52.78 _{3.2}	59.16 _{0.8}	72.49
Prompt-based FT (hard)†	95.60		91.06		68.71		74.30		63.85		78.70
Prompt-based FT (soft)†	95.50		91.10		69.63		75.66		63.32		79.04

Table 2: Comparison between the PCP and four semi-supervised approaches using ROBERTA-LARGE. Each dataset is evaluated with two different labelled data sizes and full training set is used as unlabelled data. † indicates that full training set is used as the labelled data. We report the average Macro- F_1 score on the test set across five seeds, with standard deviations as subscripts. For each column, blue represents the best performance and orange stands for the second-best performance.

studies [40, 36, 77], showing that TAPT generally improves the performance of the CLS-based FT on 7 out of 8 single sentence tasks in both semi-supervised and full-supervised setting. However, intriguingly, we observe that TAPT negatively affects the performance of CLS-based FT on 6 out of 8 sentence pair tasks, as summarised in Figure 1 and the at the bottom of Table 1. This finding implies that conventional continued pre-training (TAPT) may not be beneficial for sentence pair tasks.

Moreover, our investigation reveals that TAPT may negatively affect prompt-based FT. Specifically, in the fully supervised setting, TAPT results in reduced performance on 11 out of 16 tasks for prompt-based FT (hard) and on 9 out of 16 tasks for prompt-based FT (soft). In the most favourable scenario, TAPT enhances the performance of prompt-based FT (soft) from 73.9% to 79.9% on the QQP dataset. Conversely, in the least favourable situation, TAPT diminishes the performance of prompt-based FT (hard) from 54.7% to 44.0% on the CoLA dataset. In the semi-supervised setting, TAPT leads to a decline in performance on 12 out of 16 tasks for both prompt-based FT (hard) and prompt-based FT (soft) (see the summary of results in Figure 1 and the at the bottom of Table 1). Particularly, for sentence pair tasks, TAPT results in an average absolute decrease of 9.5% in performance for prompt-based FT. These results suggest that the effectiveness of TAPT varies across different tasks and cannot be universally applied. We conduct additional experiments to confirm the limitations of TAPT persist across different sizes of the pre-training corpus in Appendix D.

#2. PCP offers consistent and substantial improvements in both semi- and fully-supervised settings. As depicted in Table 1, our experiments covering 16 datasets in both semi- and fully-supervised settings, including single sentence tasks and sentence pair tasks, reveal that (1) PCP consistently boosts the performance of prompt-based FT; and that (2) the performance gains achieved by PCP consistently exceed those obtained by TAPT by a substantial margin. Specifically, compared to prompt-based FT, PCP leads to more than a 1.0% average absolute improvement in the fully-supervised setting and contributes to an average absolute performance boost of 6.8% in the semi-supervised setting across 16 tasks. Compared to TAPT, PCP yields over a 1.8% average absolute improvement in the fully-supervised setting and contributes to an average absolute performance increase of 11.2% in the semi-supervised setting across 16 tasks. Notably, PCP can produce considerable gains in certain datasets. For instance, it elevates the performance of prompt-based FT (hard) from 7.2% (Matthews Correlation Coefficient) to 25.0%, while TAPT even reduces the performance of the prompt-based FT. Additionally, PCP improves the performance of prompt-based FT (soft) on the QNLI dataset from 64.2% to 84.3% with 31% improvement, while TAPT leads to a 9.2% absolute performance decline. We attribute the improvements to presenting the prompt template to the LMs through the further pre-training phrase, which implies that merely showing task-related texts to the LMs may not be the optimal approach for prompt-based FT.

4.3 Comparison of the PCP and state-of-the-art semi-supervised approaches

Table 2 presents our experimental results on five datasets, comparing the proposed PCP with state-of-the-art semi-supervised approaches. Below we delve deeper into our main finding with a discussion.

#1. The proposed PCP outperforms state-of-the-art semi-supervised approaches on 4 out of 5 tasks. As shown in Table 2, our proposed PCP approach with either hard or soft variants of

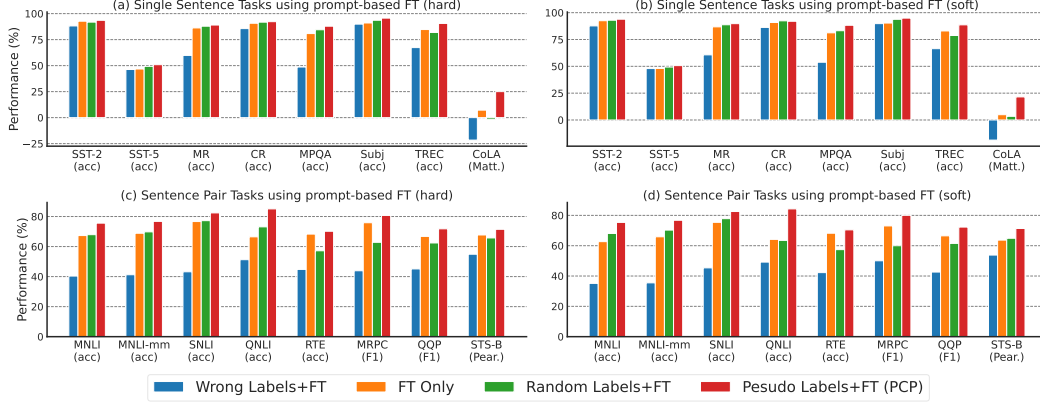


Figure 3: The performance lower bound of the PCP, where “wrong labels” indicates that all labels in the PCP are incorrect and “random labels” indicates that all labels in the PCP are randomly selected. For each dataset, 16 examples per class are used as labelled data and the full training set is used as unlabelled data. The mean performance on test sets is reported over 5 different seeds.

prompt-based FT outperforms the best-performing semi-supervised approaches on 4 out of 5 datasets. Notably, the prompt-based FT (hard) with the PCP outperforms the best performing semi-supervised approaches (FLEXMATCH) with an absolute 5.5% Macro- F_1 score on the AMAZON REVIEW dataset when 200 labelled training examples are used. While the best performing semi-supervised approach, FIXMATCH, outperforms PCP by 1.7% in absolute value on the IMDB dataset using 20 labelled examples, the performance discrepancy narrows as the number of labelled training examples increases. Overall, the prompt-based FT (hard) and (soft) with the PCP outperform all these semi-supervised approaches with an average absolute performance improvement of more than 2% across various datasets and labelled dataset sizes, demonstrating the effectiveness of our proposed approach.

Discussion. State-of-the-art semi-supervised approaches typically rely on generating pseudo labels for unlabelled examples in order to train student and teacher models iteratively [4, 16, 95, 28, 94, 30]. However, this iterative process is prone to *confirmation bias* [84, 2, 32], which can result in error accumulation if the pseudo label is incorrect at any iterative step [51, 88, 32, 21]. Various efforts have been made to mitigate *confirmation bias*, such as using only high-confidence pseudo labels [81, 99, 13] or relying heavily on data augmentation [94, 22, 12]. While these efforts make the training process more sophisticated, the issue remains difficult to fully address [21, 77]. Our proposed method offers an alternative way to utilise pseudo labels different from previous semi-supervised approaches [98, 60]. Instead of relying on an iteration process with direct supervision signals from pseudo labels, we incorporate pseudo labels through continued pre-training with an unsupervised objective (*i.e.*, MLM). While our proposed approach may not always outperform semi-supervised approaches across all benchmarks, it delivers highly competitive performance while significantly streamlining the process by removing the necessity for iteration and additional data augmentation. We will discuss the efficiency of the proposed PCP later (§4.4). Additionally, PCP is orthogonal to these semi-supervised approaches and can be combined easily by initialising their backbone from the PCP checkpoint. In future work, we plan to investigate the more specific use cases where our proposed PCP may be preferred over these semi-supervised approaches.

4.4 Further Analysis

#1. What is the lower bound of the model performance using the PCP? To understand the lower bound of PCP performance, we conduct additional analysis with two different configurations of pseudo labels in PCP: (1) all pseudo labels are incorrect; and (2) all labels are randomly selected. Figure 3 depicts the performance using different types of pseudo labels. We use the prompt-based FT without PCP (shown in yellow) and with PCP (shown in red) as baselines. Experimental results indicate that using incorrect pseudo labels (shown in blue) typically leads to inferior performance. In experiments using two prompt-based FT on 16 datasets, we find that using random labels leads to improved outcomes in 19 out of 32 scenarios. This suggests that PCP with random labels has over a 50% chance of improving the performance of prompt-based FT, indicating that the performance lower bound is satisfactory. Additionally, PCP with random labels improves the performance on sentence

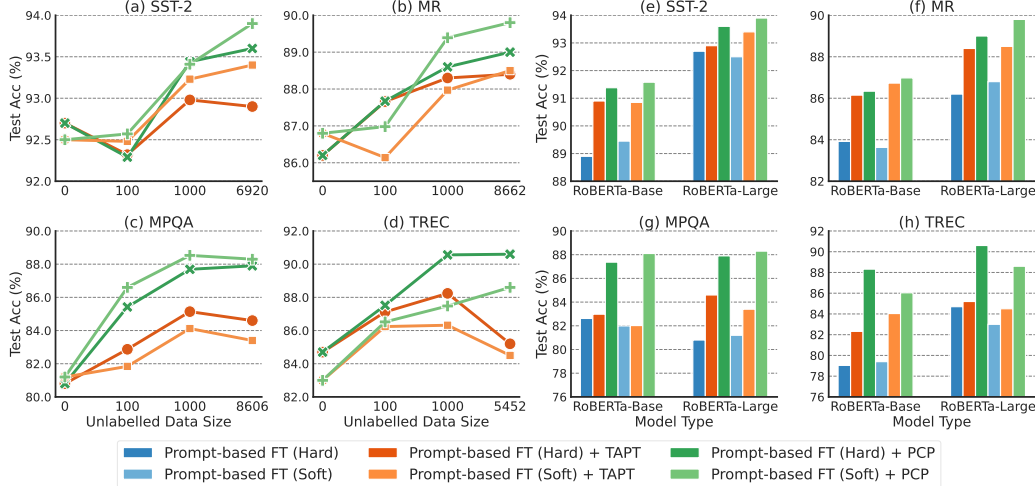


Figure 4: (Left) The effect of different unlabelled data sizes using ROBERTA-LARGE. (Right) The effect of Scaling Laws, where ROBERTA-BASE (123M) and ROBERTA-LARGE (354M). All comparison approaches are trained with 16 examples per class for each dataset.

pair tasks in 8 out of 16 cases, while TAPT leads to poorer results in 15 of 16 cases (refer to Table 1). This suggests that PCP can be advantageous even when using random labels, providing benefits in scenarios where TAPT falls short. Interestingly, unlike prior study [62] on in-context learning [15], where LMs using random labels in demonstrations perform close to those using ground-truth labels, our results show that using pseudo labels assigned by a trained model (shown in red) consistently leads to the better performance, highlighting the importance of accurate pseudo labels.

#2. What are the requirements of data size and computational resources for the PCP?

To gain a deeper understanding of the efficacy of our proposed PCP method, we conduct additional analysis to determine the number of data points necessary for the PCP. Figure 4 (left) presents the performance of prompt-based FT methods, including both hard and soft variants, across four datasets. The prompt-based FT performance generally improves when the PCP is implemented with more than 1000 unlabelled examples, and some enhancements can be observed even with just 100 unlabelled examples. This indicates that continued pre-training (both TAPT and PCP) is not necessarily computationally demanding and can be used efficiently even with only hundreds of training examples. In our experiments, performing the PCP on 1k unlabelled example takes less than 10 minutes using two 24GB NVIDIA 3090 GPUs, and all PCP performance achieved in §4.2 use fewer than 10k unlabelled examples. This is a stark contrast to the previous work [34] that pursued similar objectives to ours but utilised 10GB of English text data.

#3. Power of scale. Our empirical analysis investigates the impact of increasing the backbone LM size on the model performance using the PCP. Figure 4 (right) shows the results of prompt-based FT methods, including hard and soft variants, trained using either TAPT or PCP, on four datasets. The performance of the PCP method largely improves as the backbone LM size expands, which aligns with the scaling laws observed in LMs [43, 38]. Furthermore, the PCP method consistently surpasses other baseline approaches, highlighting the advantages of the PCP across different model sizes.

#4. The impact of a larger continued pre-training corpus on the model performance using PCP and TAPT. Here we expand our investigation to whether the advantage of the proposed PCP approach persists as the size of the continued pre-training corpus increases. Table 3 presents the performance of prompt-based FT (soft), trained using either TAPT or PCP, across five datasets

Dataset	Size	FT	+TAPT	+PCP
IMDB	23K	87.3 _{1.2}	88.9 _{1.3}	91.4 _{0.5}
AG NEWS	100K	86.4 _{0.9}	87.6 _{1.1}	88.0 _{0.4}
YELP REVIEW	250K	52.4 _{2.5}	60.3 _{1.9}	61.4 _{2.0}
AMAZON REVIEW	250K	51.2 _{1.8}	56.8 _{1.2}	57.0 _{1.5}
YAHOO! ANSWER	500K	64.9 _{0.8}	64.9 _{1.1}	69.0 _{1.4}

Table 3: Test Results for prompt-based FT (soft) using ROBERTA-BASE with varying continued pre-training corpus sizes. The average Macro- F_1 with standard deviations are reported across five seeds. The model is trained on the IMDB dataset using 100 labelled examples and uses 200 labelled examples for other datasets. The best performance for each dataset is highlighted in blue.

with varying sizes of unlabelled training examples. These experimental results are consistent with our findings in §4.2 and §4.3, showing that the proposed PCP approach consistently outperforms the model performance using the TAPT even when the larger corpus for continued pre-training is used.

5 Related Work

Prompt-based Approaches. In recent years, researchers have been exploring prompt-based approaches to improve the performance of fine-tuning. These approaches can be broadly divided into two research directions. The first direction, known as prompt-based FT, optimizes all parameters in LMs for better performance [74, 29, 54, 100], as discussed in §2. Adaprompt [23] improved the performance of hard prompt-based FT [74, 29] on single sentence tasks through conventional continued pre-training, which is generally consistent with our experimental results. The second direction is parameter-efficient fine-tuning (PEFT) [53, 69, 49, 82, 86, 5], which aims to achieve competitive results while maintaining low computational costs. PPT [34] strives to improve the performance of PEFT [49] by further pre-training the T5 model [71], which pursues a similar idea as ours. However, this method relies on a series of hand-crafted and task-dependent designs for further pre-training, making it less adaptable to novel downstream tasks [86]. Furthermore, it demands a much larger training corpus, as discussed in §4.4. In contrast, our work offers a uniform design across all tasks and focuses on prompt-based FT. In future work, we plan to explore the compatibility of continued pre-training (including both TAPT and our proposed PCP) and PEFT methods.

Train LMs with Instructions/Templates. Our work is related to training LMs with templates. Recent studies [44, 3, 66, 91, 63, 73, 89, 61] have explored the idea of LMs training on a variety of NLP tasks with natural language instructions/templates, with the goal of generalizing to unseen tasks. Similar ideas, prompt transfer, have also been explored in the context of PEFT [34, 82, 86, 5], which seeks to learn an effective representation of the soft prompt for the target task by training on other tasks. In our approach, we transfer knowledge from task-related texts with prompt templates that are tailored to a single target task to LMs.

Semi-supervised Learning. Our work is related to *semi-supervised learning* [33, 20, 45], with the goal of utilising unlabelled data effectively. Continued pre-training followed by fine-tuning [40, 83, 36] is one type of semi-supervised approaches. While the benefits of continued pre-training are well acknowledged [7, 1, 58], it is commonly assumed that large amounts of data are necessary for continued pre-training [e.g., 52, 39, 34]. Contrarily, our research demonstrates that continued pre-training can improve performance using only a few hundred unlabelled samples. *Self-training* [98, 60] is another powerful semi-supervised approach, which typically uses student-teacher models to assign pseudo-labels to the unlabelled data [48, 46, 84, 64, 4, 16, 28, 94, 81, 30]. Our work offers an alternative way to use pseudo-labels without resorting to an iterative process, as discussed in §4.3.

6 Epilogue

Conclusion. This study challenges the widely accepted notion in NLP, showing that conventional continued pre-training can be detrimental to model performance, especially for sentence pair tasks and prompt-based FT. As an alternative, we propose Prompt-based Continued Pre-training (PCP), which consistently improves the performance of state-of-the-art prompt-based FT approaches over conventional continued pre-training. Additionally, our proposed PCP outperforms state-of-the-art semi-supervised approaches with a more streamlined process. Further analysis reveals that the advantages of PCP remain consistent across different sizes of models and datasets. This study emphasizes the importance of presenting both task-related texts and templates/instructions to LMs during pre-training for better fine-tuning performance on downstream tasks, contributing to the growing body of research on the optimisation of pre-training and fine-tuning strategies in NLP.

Limitations and Broader Impact. Our work is based on pre-training and prompting methods for LMs. Previous works [9, 15, 8] have extensively discussed the risks and potential harms associated with LMs, including the amplification of undesirable biases learned from unlabelled training data [9, 6, 17]. The energy cost and carbon footprint for our work were approximately 125 kWh and 70 kg CO₂e, which are comparatively smaller than LM pre-training [26, 55, 15, 24]. Future endeavours will explore our proposed method in the parameter-efficient context [53, 49, 41] and investigate the potential of developing a unified method that efficiently serves multiple tasks.

References

- [1] Emily Alsentzer, John Murphy, William Boag, Wei-Hung Weng, Di Jindi, Tristan Naumann, and Matthew McDermott. Publicly available clinical BERT embeddings. In *Proceedings of the 2nd Clinical Natural Language Processing Workshop*, pages 72–78, Minneapolis, Minnesota, USA, June 2019. Association for Computational Linguistics.
- [2] Eric Arazo, Diego Ortego, Paul Albert, Noel E O’Connor, and Kevin McGuinness. Pseudo-labeling and confirmation bias in deep semi-supervised learning. In *2020 International Joint Conference on Neural Networks (IJCNN)*, pages 1–8. IEEE, 2020.
- [3] Vamsi Aribandi, Yi Tay, Tal Schuster, Jinfeng Rao, Huaixiu Steven Zheng, Sanket Vaibhav Mehta, Honglei Zhuang, Vinh Q. Tran, Dara Bahri, Jianmo Ni, Jai Gupta, Kai Hui, Sebastian Ruder, and Donald Metzler. Ext5: Towards extreme multi-task scaling for transfer learning. In *International Conference on Learning Representations*, 2022.
- [4] Mikel Artetxe, Gorka Labaka, and Eneko Agirre. A robust self-learning method for fully unsupervised cross-lingual mappings of word embeddings. In *Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 789–798, Melbourne, Australia, July 2018. Association for Computational Linguistics.
- [5] Akari Asai, Mohammadreza Salehi, Matthew E Peters, and Hannaneh Hajishirzi. Attempt: Parameter-efficient multi-task tuning via attentional mixtures of soft prompts. In *Proceedings of the 2022 Conference on Empirical Methods in Natural Language Processing*, pages 6655–6672, 2022.
- [6] Jacob Austin, Augustus Odena, Maxwell Nye, Maarten Bosma, Henryk Michalewski, David Dohan, Ellen Jiang, Carrie Cai, Michael Terry, Quoc Le, et al. Program synthesis with large language models. *arXiv preprint arXiv:2108.07732*, 2021.
- [7] Iz Beltagy, Kyle Lo, and Arman Cohan. SciBERT: A pretrained language model for scientific text. In *Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP)*, pages 3615–3620, Hong Kong, China, November 2019. Association for Computational Linguistics.
- [8] Emily M. Bender, Timnit Gebru, Angelina McMillan-Major, and Shmargaret Shmitchell. On the dangers of stochastic parrots: Can language models be too big? In *Proceedings of the 2021 ACM Conference on Fairness, Accountability, and Transparency, FAccT ’21*, page 610–623, New York, NY, USA, 2021. Association for Computing Machinery.
- [9] Emily M. Bender and Alexander Koller. Climbing towards NLU: On meaning, form, and understanding in the age of data. In *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics*, pages 5185–5198, Online, July 2020. Association for Computational Linguistics.
- [10] Yoshua Bengio, Jérôme Louradour, Ronan Collobert, and Jason Weston. Curriculum learning. In *Proceedings of the 26th Annual International Conference on Machine Learning, ICML ’09*, page 41–48, New York, NY, USA, 2009. Association for Computing Machinery.
- [11] Luisa Bentivogli, Peter Clark, Ido Dagan, and Danilo Giampiccolo. The fifth PASCAL recognizing textual entailment challenge. In *TAC*, 2009.
- [12] David Berthelot, Nicholas Carlini, Ekin D. Cubuk, Alex Kurakin, Kihyuk Sohn, Han Zhang, and Colin Raffel. Remixmatch: Semi-supervised learning with distribution matching and augmentation anchoring. In *International Conference on Learning Representations*, 2020.
- [13] David Berthelot, Rebecca Roelofs, Kihyuk Sohn, Nicholas Carlini, and Alexey Kurakin. Adamatch: A unified approach to semi-supervised learning and domain adaptation. In *International Conference on Learning Representations*, 2022.
- [14] Samuel R. Bowman, Gabor Angeli, Christopher Potts, and Christopher D. Manning. A large annotated corpus for learning natural language inference. In *Proceedings of the 2015 Conference on Empirical Methods in Natural Language Processing*, pages 632–642, Lisbon, Portugal, September 2015. Association for Computational Linguistics.

- [15] Tom B. Brown, Benjamin Mann, Nick Ryder, Melanie Subbiah, Jared Kaplan, Prafulla Dhariwal, Arvind Neelakantan, Pranav Shyam, Girish Sastry, Amanda Askell, Sandhini Agarwal, Ariel Herbert-Voss, Gretchen Krueger, Tom Henighan, Rewon Child, Aditya Ramesh, Daniel M. Ziegler, Jeffrey Wu, Clemens Winter, Christopher Hesse, Mark Chen, Eric Sigler, Mateusz Litwin, Scott Gray, Benjamin Chess, Jack Clark, Christopher Berner, Sam McCandlish, Alec Radford, Ilya Sutskever, and Dario Amodei. Language models are few-shot learners. In *Proceedings of the 34th International Conference on Neural Information Processing Systems*, NIPS’20, Red Hook, NY, USA, 2020. Curran Associates Inc.
- [16] Rui Cai and Mirella Lapata. Semi-supervised semantic role labeling with cross-view training. In *Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP)*, pages 1018–1027, Hong Kong, China, November 2019. Association for Computational Linguistics.
- [17] Nicholas Carlini, Florian Tramer, Eric Wallace, Matthew Jagielski, Ariel Herbert-Voss, Katherine Lee, Adam Roberts, Tom B Brown, Dawn Song, Ulfar Erlingsson, et al. Extracting training data from large language models. In *USENIX Security Symposium*, volume 6, 2021.
- [18] Daniel Cer, Mona Diab, Eneko Agirre, Iñigo Lopez-Gazpio, and Lucia Specia. SemEval-2017 task 1: Semantic textual similarity multilingual and crosslingual focused evaluation. In *the 11th International Workshop on Semantic Evaluation (SemEval-2017)*, 2017.
- [19] Ming-Wei Chang, Lev Ratinov, Dan Roth, and Vivek Srikumar. Importance of semantic representation: dataless classification. In *Proceedings of the 23rd national conference on Artificial intelligence-Volume 2*, pages 830–835, 2008.
- [20] Olivier Chapelle, Bernhard Scholkopf, and Alexander Zien. Semi-supervised learning (chapelle, o. et al., eds.; 2006)[book reviews]. *IEEE Transactions on Neural Networks*, 20(3):542–542, 2009.
- [21] Baixu Chen, Junguang Jiang, Ximei Wang, Pengfei Wan, Jianmin Wang, and Mingsheng Long. Debiased self-training for semi-supervised learning. In *Advances in Neural Information Processing Systems*, NIPS’22, 2022.
- [22] Jiaao Chen, Zichao Yang, and Diyi Yang. MixText: Linguistically-informed interpolation of hidden space for semi-supervised text classification. In *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics*, pages 2147–2157, Online, July 2020. Association for Computational Linguistics.
- [23] Yulong Chen, Yang Liu, Li Dong, Shuohang Wang, Chenguang Zhu, Michael Zeng, and Yue Zhang. AdaPrompt: Adaptive model training for prompt-based NLP. In *Findings of the Association for Computational Linguistics: EMNLP 2022*, pages 6057–6068, Abu Dhabi, United Arab Emirates, December 2022. Association for Computational Linguistics.
- [24] Aakanksha Chowdhery, Sharan Narang, Jacob Devlin, Maarten Bosma, Gaurav Mishra, Adam Roberts, Paul Barham, Hyung Won Chung, Charles Sutton, Sebastian Gehrmann, et al. Palm: Scaling language modeling with pathways. *arXiv preprint arXiv:2204.02311*, 2022.
- [25] Ido Dagan, Oren Glickman, and Bernardo Magnini. The PASCAL recognising textual entailment challenge. In *the First International Conference on Machine Learning Challenges: Evaluating Predictive Uncertainty Visual Object Classification, and Recognizing Textual Entailment*, 2005.
- [26] Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. BERT: Pre-training of deep bidirectional transformers for language understanding. In *Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers)*, Minneapolis, Minnesota, 2019. Association for Computational Linguistics.
- [27] William B. Dolan and Chris Brockett. Automatically constructing a corpus of sentential paraphrases. In *the Third International Workshop on Paraphrasing (IWP2005)*, 2005.

- [28] Xin Dong and Gerard de Melo. A robust self-learning framework for cross-lingual text classification. In *Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP)*, pages 6306–6310, Hong Kong, China, November 2019. Association for Computational Linguistics.
- [29] Tianyu Gao, Adam Fisch, and Danqi Chen. Making pre-trained language models better few-shot learners. In *Proceedings of the 59th Annual Meeting of the Association for Computational Linguistics and the 11th International Joint Conference on Natural Language Processing (Volume 1: Long Papers)*, pages 3816–3830, Online, August 2021. Association for Computational Linguistics.
- [30] Ariel Gera, Alon Halfon, Eyal Shnarch, Yotam Perlitz, Liat Ein-Dor, and Noam Slonim. Zero-shot text classification with self-training. In *Proceedings of the 2022 Conference on Empirical Methods in Natural Language Processing*. Association for Computational Linguistics, 2022.
- [31] Danilo Giampiccolo, Bernardo Magnini, Ido Dagan, and Bill Dolan. The third PASCAL recognizing textual entailment challenge. In *the ACL-PASCAL Workshop on Textual Entailment and Paraphrasing*, 2007.
- [32] Arushi Goel, Yunlong Jiao, and Jordan Massiah. Pars: Pseudo-label aware robust sample selection for learning with noisy labels. *arXiv preprint arXiv:2201.10836*, 2022.
- [33] Yves Grandvalet and Yoshua Bengio. Semi-supervised learning by entropy minimization. *Advances in neural information processing systems*, 17, 2004.
- [34] Yuxian Gu, Xu Han, Zhiyuan Liu, and Minlie Huang. PPT: Pre-trained prompt tuning for few-shot learning. In *Proceedings of the 60th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 8410–8423, Dublin, Ireland, May 2022. Association for Computational Linguistics.
- [35] Suchin Gururangan, Tam Dang, Dallas Card, and Noah A. Smith. Variational pretraining for semi-supervised text classification. In *Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics*, pages 5880–5894, Florence, Italy, July 2019. Association for Computational Linguistics.
- [36] Suchin Gururangan, Ana Marasović, Swabha Swayamdipta, Kyle Lo, Iz Beltagy, Doug Downey, and Noah A. Smith. Don’t stop pretraining: Adapt language models to domains and tasks. In *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics*, pages 8342–8360, Online, July 2020. Association for Computational Linguistics.
- [37] Karen Hambardzumyan, Hrant Khachatrian, and Jonathan May. WARP: Word-level Adversarial ReProgramming. In *Proceedings of the 59th Annual Meeting of the Association for Computational Linguistics and the 11th International Joint Conference on Natural Language Processing (Volume 1: Long Papers)*, pages 4921–4933, Online, August 2021. Association for Computational Linguistics.
- [38] Jordan Hoffmann, Sebastian Borgeaud, Arthur Mensch, Elena Buchatskaya, Trevor Cai, Eliza Rutherford, Diego de Las Casas, Lisa Anne Hendricks, Johannes Welbl, Aidan Clark, et al. Training compute-optimal large language models. *arXiv preprint arXiv:2203.15556*, 2022.
- [39] Zejiang Hou, Julian Salazar, and George Polovets. Meta-Learning the Difference: Preparing Large Language Models for Efficient Adaptation. *Transactions of the Association for Computational Linguistics*, 10:1249–1265, 11 2022.
- [40] Jeremy Howard and Sebastian Ruder. Universal language model fine-tuning for text classification. In *Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 328–339, Melbourne, Australia, July 2018. Association for Computational Linguistics.
- [41] Edward J Hu, yelong shen, Phillip Wallis, Zeyuan Allen-Zhu, Yanzhi Li, Shean Wang, Lu Wang, and Weizhu Chen. LoRA: Low-rank adaptation of large language models. In *International Conference on Learning Representations*, 2022.

- [42] Mingqing Hu and Bing Liu. Mining and summarizing customer reviews. In *ACM SIGKDD international conference on Knowledge discovery and data mining*, 2004.
- [43] Jared Kaplan, Sam McCandlish, Tom Henighan, Tom B Brown, Benjamin Chess, Rewon Child, Scott Gray, Alec Radford, Jeffrey Wu, and Dario Amodei. Scaling laws for neural language models. *arXiv preprint arXiv:2001.08361*, 2020.
- [44] Daniel Khashabi, Sewon Min, Tushar Khot, Ashish Sabharwal, Oyvind Tafjord, Peter Clark, and Hannaneh Hajishirzi. UNIFIEDQA: Crossing format boundaries with a single QA system. In *Findings of the Association for Computational Linguistics: EMNLP 2020*, pages 1896–1907, Online, November 2020. Association for Computational Linguistics.
- [45] Thomas N. Kipf and Max Welling. Semi-supervised classification with graph convolutional networks. In *International Conference on Learning Representations (ICLR)*, 2017.
- [46] Samuli Laine and Timo Aila. Temporal ensembling for semi-supervised learning. In *5th International Conference on Learning Representations, ICLR 2017, Toulon, France, April 24-26, 2017, Conference Track Proceedings*. OpenReview.net, 2017.
- [47] Teven Le Scao and Alexander Rush. How many data points is a prompt worth? In *Proceedings of the 2021 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*, pages 2627–2636, Online, June 2021. Association for Computational Linguistics.
- [48] Dong-Hyun Lee et al. Pseudo-label: The simple and efficient semi-supervised learning method for deep neural networks. In *Workshop on challenges in representation learning, ICML*, page 896, 2013.
- [49] Brian Lester, Rami Al-Rfou, and Noah Constant. The power of scale for parameter-efficient prompt tuning. In *Proceedings of the 2021 Conference on Empirical Methods in Natural Language Processing*, pages 3045–3059, Online and Punta Cana, Dominican Republic, November 2021. Association for Computational Linguistics.
- [50] Changchun Li, Ximing Li, and Jihong Ouyang. Semi-supervised text classification with balanced deep representation distributions. In *Proceedings of the 59th Annual Meeting of the Association for Computational Linguistics and the 11th International Joint Conference on Natural Language Processing (Volume 1: Long Papers)*, pages 5044–5053, Online, August 2021. Association for Computational Linguistics.
- [51] Junnan Li, Richard Socher, and Steven C H Hoi. DIVIDEMIX: LEARNING WITH NOISY LABELS AS SEMI-SUPERVISED LEARNING. In *ICLR 2020*, page 14. ICLR, 2020.
- [52] Shiyang Li, Semih Yavuz, Wenhui Chen, and Xifeng Yan. Task-adaptive pre-training and self-training are complementary for natural language understanding. In *Findings of the Association for Computational Linguistics: EMNLP 2021*, pages 1006–1015, Punta Cana, Dominican Republic, November 2021. Association for Computational Linguistics.
- [53] Xiang Lisa Li and Percy Liang. Prefix-tuning: Optimizing continuous prompts for generation. In *Proceedings of the 59th Annual Meeting of the Association for Computational Linguistics and the 11th International Joint Conference on Natural Language Processing (Volume 1: Long Papers)*, pages 4582–4597, Online, August 2021. Association for Computational Linguistics.
- [54] Xiao Liu, Yanan Zheng, Zhengxiao Du, Ming Ding, Yujie Qian, Zhilin Yang, and Jie Tang. Gpt understands, too. *arXiv:2103.10385*, 2021.
- [55] Yinhan Liu, Myle Ott, Naman Goyal, Jingfei Du, Mandar Joshi, Danqi Chen, Omer Levy, Mike Lewis, Luke Zettlemoyer, and Veselin Stoyanov. Roberta: A robustly optimized bert pretraining approach. *arXiv preprint arXiv:1907.11692*, 2019.
- [56] Lajanugen Logeswaran, Ming-Wei Chang, Kenton Lee, Kristina Toutanova, Jacob Devlin, and Honglak Lee. Zero-shot entity linking by reading entity descriptions. In *Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics*, pages 3449–3460, Florence, Italy, July 2019. Association for Computational Linguistics.

- [57] Andrew L. Maas, Raymond E. Daly, Peter T. Pham, Dan Huang, Andrew Y. Ng, and Christopher Potts. Learning word vectors for sentiment analysis. In *Proceedings of the 49th Annual Meeting of the Association for Computational Linguistics: Human Language Technologies*, pages 142–150, Portland, USA, June 2011. Association for Computational Linguistics.
- [58] Katerina Margatina, Loic Barrault, and Nikolaos Aletras. On the importance of effectively adapting pretrained language models for active learning. In *Proceedings of the 60th Annual Meeting of the Association for Computational Linguistics (Volume 2: Short Papers)*, pages 825–836, Dublin, Ireland, May 2022. Association for Computational Linguistics.
- [59] Julian McAuley and Jure Leskovec. Hidden factors and hidden topics: Understanding rating dimensions with review text. In *Proceedings of the 7th ACM Conference on Recommender Systems, RecSys '13*, page 165–172, New York, NY, USA, 2013. Association for Computing Machinery.
- [60] David McClosky, Eugene Charniak, and Mark Johnson. Effective self-training for parsing. In *Proceedings of the Human Language Technology Conference of the NAACL, Main Conference*, pages 152–159, New York City, USA, June 2006. Association for Computational Linguistics.
- [61] Sewon Min, Mike Lewis, Luke Zettlemoyer, and Hannaneh Hajishirzi. MetaICL: Learning to learn in context. In *Proceedings of the 2022 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*, pages 2791–2809, Seattle, United States, July 2022. Association for Computational Linguistics.
- [62] Sewon Min, Xinxu Lyu, Ari Holtzman, Mikel Artetxe, Mike Lewis, Hannaneh Hajishirzi, and Luke Zettlemoyer. Rethinking the role of demonstrations: What makes in-context learning work? In *Proceedings of the 2022 Conference on Empirical Methods in Natural Language Processing*, pages 11048–11064, Abu Dhabi, United Arab Emirates, December 2022. Association for Computational Linguistics.
- [63] Swaroop Mishra, Daniel Khashabi, Chitta Baral, and Hannaneh Hajishirzi. Cross-task generalization via natural language crowdsourcing instructions. In *Proceedings of the 60th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 3470–3487, Dublin, Ireland, May 2022. Association for Computational Linguistics.
- [64] Takeru Miyato, Shin-ichi Maeda, Masanori Koyama, and Shin Ishii. Virtual adversarial training: a regularization method for supervised and semi-supervised learning. *IEEE transactions on pattern analysis and machine intelligence*, 41:1979–1993, 2018.
- [65] Myle Ott, Sergey Edunov, Alexei Baevski, Angela Fan, Sam Gross, Nathan Ng, David Grangier, and Michael Auli. fairseq: A fast, extensible toolkit for sequence modeling. In *Proceedings of NAACL-HLT 2019: Demonstrations*, 2019.
- [66] Long Ouyang, Jeffrey Wu, Xu Jiang, Diogo Almeida, Carroll Wainwright, Pamela Mishkin, Chong Zhang, Sandhini Agarwal, Katarina Slama, Alex Gray, John Schulman, Jacob Hilton, Fraser Kelton, Luke Miller, Maddie Simens, Amanda Askell, Peter Welinder, Paul Christiano, Jan Leike, and Ryan Lowe. Training language models to follow instructions with human feedback. In Alice H. Oh, Alekh Agarwal, Danielle Belgrave, and Kyunghyun Cho, editors, *Advances in Neural Information Processing Systems*, 2022.
- [67] Bo Pang and Lillian Lee. A sentimental education: Sentiment analysis using subjectivity summarization based on minimum cuts. In *Association for Computational Linguistics (ACL)*, 2004.
- [68] Bo Pang and Lillian Lee. Seeing stars: Exploiting class relationships for sentiment categorization with respect to rating scales. In *Association for Computational Linguistics (ACL)*, 2005.
- [69] Guanghui Qin and Jason Eisner. Learning how to ask: Querying LMs with mixtures of soft prompts. In *Proceedings of the 2021 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*, pages 5203–5212, Online, June 2021. Association for Computational Linguistics.

- [70] Alec Radford, Jeffrey Wu, Rewon Child, David Luan, Dario Amodei, Ilya Sutskever, et al. Language models are unsupervised multitask learners. *OpenAI blog*, 1(8), 2019.
- [71] Colin Raffel, Noam Shazeer, Adam Roberts, Katherine Lee, Sharan Narang, Michael Matena, Yanqi Zhou, Wei Li, and Peter J. Liu. Exploring the limits of transfer learning with a unified text-to-text transformer. *J. Mach. Learn. Res.*, 21(1), jan 2020.
- [72] Pranav Rajpurkar, Jian Zhang, Konstantin Lopyrev, and Percy Liang. SQuAD: 100,000+ questions for machine comprehension of text. In *Empirical Methods in Natural Language Processing (EMNLP)*, 2016.
- [73] Victor Sanh, Albert Webson, Colin Raffel, Stephen Bach, Lintang Sutawika, Zaid Alyafeai, Antoine Chaffin, Arnaud Stiegler, Arun Raja, Manan Dey, et al. Multitask prompted training enables zero-shot task generalization. In *International Conference on Learning Representations*, 2022.
- [74] Timo Schick and Hinrich Schütze. Exploiting cloze-questions for few-shot text classification and natural language inference. In *Proceedings of the 16th Conference of the European Chapter of the Association for Computational Linguistics: Main Volume*, pages 255–269, Online, April 2021. Association for Computational Linguistics.
- [75] Timo Schick and Hinrich Schütze. It’s not just size that matters: Small language models are also few-shot learners. In *Proceedings of the 2021 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*, pages 2339–2352, Online, June 2021. Association for Computational Linguistics.
- [76] Zhengxiang Shi, Yue Feng, and Aldo Lipani. Learning to execute actions or ask clarification questions. In *Findings of the Association for Computational Linguistics: NAACL 2022*, pages 2060–2070, Seattle, United States, July 2022. Association for Computational Linguistics.
- [77] Zhengxiang Shi, Francesco Tonolini, Nikolaos Aletras, Emine Yilmaz, Gabriella Kazai, and Yunlong Jiao. Rethinking semi-supervised learning with language models. In *Findings of ACL 2023*, Toronto, Canada, 2023. Association for Computational Linguistics.
- [78] Zhengxiang Shi, Qiang Zhang, and Aldo Lipani. Stepgame: A new benchmark for robust multi-hop spatial reasoning in texts. In *Proceedings of the AAAI Conference on Artificial Intelligence*, volume 36, pages 11321–11329, Jun. 2022.
- [79] Taylor Shin, Yasaman Razeghi, Robert L. Logan IV, Eric Wallace, and Sameer Singh. Auto-Prompt: Eliciting Knowledge from Language Models with Automatically Generated Prompts. In *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP)*, pages 4222–4235, Online, November 2020. Association for Computational Linguistics.
- [80] Richard Socher, Alex Perelygin, Jean Wu, Jason Chuang, Christopher D. Manning, Andrew Ng, and Christopher Potts. Recursive deep models for semantic compositionality over a sentiment treebank. In *Empirical Methods in Natural Language Processing (EMNLP)*, 2013.
- [81] Kihyuk Sohn, David Berthelot, Chun-Liang Li, Zizhao Zhang, Nicholas Carlini, Ekin D. Cubuk, Alex Kurakin, Han Zhang, and Colin Raffel. Fixmatch: Simplifying semi-supervised learning with consistency and confidence. In *Proceedings of the 34th International Conference on Neural Information Processing Systems, NIPS’20*, Red Hook, NY, USA, 2020. Curran Associates Inc.
- [82] Yusheng Su, Xiaozhi Wang, Yujia Qin, Chi-Min Chan, Yankai Lin, Huadong Wang, Kaiyue Wen, Zhiyuan Liu, Peng Li, Juanzi Li, Lei Hou, Maosong Sun, and Jie Zhou. On transferability of prompt tuning for natural language processing. In *Proceedings of the 2022 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*. Association for Computational Linguistics, July 2022.
- [83] Chi Sun, Xipeng Qiu, Yige Xu, and Xuanjing Huang. How to fine-tune bert for text classification? In *China national conference on Chinese computational linguistics*, pages 194–206. Springer, 2019.

- [84] Antti Tarvainen and Harri Valpola. Mean teachers are better role models: Weight-averaged consistency targets improve semi-supervised deep learning results. In *Proceedings of the 31st International Conference on Neural Information Processing Systems, NIPS'17*, page 1195–1204, Red Hook, NY, USA, 2017. Curran Associates Inc.
- [85] Ellen M Voorhees and Dawn M Tice. Building a question answering test collection. In *the 23rd annual international ACM SIGIR conference on Research and development in information retrieval*, 2000.
- [86] Tu Vu, Brian Lester, Noah Constant, Rami Al-Rfou', and Daniel Cer. SPoT: Better frozen model adaptation through soft prompt transfer. In *Proceedings of the 60th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 5039–5059, Dublin, Ireland, May 2022. Association for Computational Linguistics.
- [87] Alex Wang, Amanpreet Singh, Julian Michael, Felix Hill, Omer Levy, and Samuel Bowman. GLUE: A multi-task benchmark and analysis platform for natural language understanding. In *Proceedings of the 2018 EMNLP Workshop BlackboxNLP: Analyzing and Interpreting Neural Networks for NLP*, pages 353–355, Brussels, Belgium, November 2018. Association for Computational Linguistics.
- [88] Ximei Wang, Jinghan Gao, Mingsheng Long, and Jianmin Wang. Self-tuning for data-efficient deep learning. In *International Conference on Machine Learning (ICML)*, 2021.
- [89] Yizhong Wang, Swaroop Mishra, Pegah Alipoormolabashi, Yeganeh Kordi, Amirreza Mirzaei, Atharva Naik, Arjun Ashok, Arut Selvan Dhanasekaran, Anjana Arunkumar, David Stap, Eshaan Pathak, Giannis Karamanolakis, Haizhi Lai, Ishan Purohit, Ishani Mondal, Jacob Anderson, Kirby Kuznia, Krma Doshi, Kuntal Kumar Pal, Maitreya Patel, Mehrad Moradshahi, Mihir Parmar, Mirali Purohit, Neeraj Varshney, Phani Rohitha Kaza, Pulkit Verma, Ravsehaj Singh Puri, Rushang Karia, Savan Doshi, Shailaja Keyur Sampat, Siddhartha Mishra, Sujan Reddy A, Sumanta Patro, Tanay Dixit, and Xudong Shen. Super-NaturalInstructions: Generalization via declarative instructions on 1600+ NLP tasks. In *Proceedings of the 2022 Conference on Empirical Methods in Natural Language Processing*, pages 5085–5109, Abu Dhabi, United Arab Emirates, December 2022. Association for Computational Linguistics.
- [90] Alex Warstadt, Amanpreet Singh, and Samuel R. Bowman. Neural network acceptability judgments. *Transactions of the Association of Computational Linguistics (TACL)*, 7, 2019.
- [91] Jason Wei, Maarten Bosma, Vincent Zhao, Kelvin Guu, Adams Wei Yu, Brian Lester, Nan Du, Andrew M. Dai, and Quoc V Le. Finetuned language models are zero-shot learners. In *International Conference on Learning Representations*, 2022.
- [92] Janyce Wiebe, Theresa Wilson, and Claire Cardie. Annotating expressions of opinions and emotions in language. *Language resources and evaluation*, 39(2-3), 2005.
- [93] Adina Williams, Nikita Nangia, and Samuel Bowman. A broad-coverage challenge corpus for sentence understanding through inference. In *North American Chapter of the Association for Computational Linguistics: Human Language Technologies (NAACL-HLT)*, 2018.
- [94] Qizhe Xie, Zihang Dai, Eduard Hovy, Minh-Thang Luong, and Quoc V. Le. Unsupervised data augmentation for consistency training. In *Proceedings of the 34th International Conference on Neural Information Processing Systems, NIPS'20*, Red Hook, NY, USA, 2020. Curran Associates Inc.
- [95] Qizhe Xie, Minh-Thang Luong, Eduard Hovy, and Quoc V Le. Self-training with noisy student improves imagenet classification. In *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition*, pages 10687–10698, 2020.
- [96] Yi Xu, Lei Shang, Jinxing Ye, Qi Qian, Yu-Feng Li, Baigui Sun, Hao Li, and Rong Jin. Dash: Semi-supervised learning with dynamic thresholding. In *International Conference on Machine Learning*, pages 11525–11536. PMLR, 2021.

- [97] Linting Xue, Noah Constant, Adam Roberts, Mihir Kale, Rami Al-Rfou, Aditya Siddhant, Aditya Barua, and Colin Raffel. mT5: A massively multilingual pre-trained text-to-text transformer. In *Proceedings of the 2021 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*, pages 483–498, Online, June 2021. Association for Computational Linguistics.
- [98] David Yarowsky. Unsupervised word sense disambiguation rivaling supervised methods. In *33rd Annual Meeting of the Association for Computational Linguistics*, pages 189–196, Cambridge, Massachusetts, USA, June 1995. Association for Computational Linguistics.
- [99] Bowen Zhang, Yidong Wang, Wenxin Hou, Hao Wu, Jindong Wang, Manabu Okumura, and Takahiro Shinozaki. Flexmatch: Boosting semi-supervised learning with curriculum pseudo labeling. In *Proceedings of the 35th International Conference on Neural Information Processing Systems*, volume 34, 2021.
- [100] Ningyu Zhang, Luoqi Li, Xiang Chen, Shumin Deng, Zhen Bi, Chuanqi Tan, Fei Huang, and Huajun Chen. Differentiable prompt makes pre-trained language models better few-shot learners. In *International Conference on Learning Representations*, 2022.
- [101] Xiang Zhang, Junbo Zhao, and Yann LeCun. Character-level convolutional networks for text classification. In *Proceedings of the 28th International Conference on Neural Information Processing Systems - Volume 1*, NIPS’15, page 649–657, Cambridge, MA, USA, 2015. MIT Press.
- [102] Zihao Zhao, Eric Wallace, Shi Feng, Dan Klein, and Sameer Singh. Calibrate before use: Improving few-shot performance of language models. In Marina Meila and Tong Zhang, editors, *Proceedings of the 38th International Conference on Machine Learning*, volume 139 of *Proceedings of Machine Learning Research*, pages 12697–12706. PMLR, 18–24 Jul 2021.

Appendix Overview

The appendix is structured as follows:

Appendix §A provides a brief description for each dataset.

Appendix §B provides details of templates and label words used for each dataset.

Appendix §C presents a brief description of state-of-the-art four semi-supervised (self-training) approaches.

Appendix §D provides the supplementary experimental results.

Appendix §E provides implementation details and hyperparameters for all comparison methods used in our experiments.

A Dataset

In this work, we use 21 popular datasets from previous few-shot learning and semi-supervised learning research.

For experiments in §4.2, we adhere to the approach in [29] and utilise 16 different datasets², including SST-2 [80], SST-5 [80], MR [68], CR [42], MPQA [92], Subj [67], TREC [85], CoLA [90], MNLI [93], SNLI [14], QNLI [72], RTE [25, 31, 11], MRPC [27], QQP³, and STS-B [18]. Consistent with prior research [29], our validation set comprises 16 examples per class from the aforementioned datasets. Additionally, we use 16 examples per class for the training set and the entire training set as the unlabeled set in the semi-supervised setting. We also utilise the full training set for training purposes in the fully supervised setting. For sentence pair tasks, we select at most 10k examples for continued pre-training to reduce the computational costs.

For experiments in §4.3, we follow the setup in [77] and utilise 5 different datasets, including IMDB [57], AG NEWS [101], YELP REVIEW⁴, YAHOO! ANSWER [19], and AMAZON REVIEW [59]. Refer to the dataset statistics in Table 4. Our validation set comprises 1,000 examples for each dataset.

B Templates for Prompt-based FT

Here we introduce the templates used in two state-of-the-art prompt-based FT approaches for each dataset. For “Prompt-based FT (hard)”, we use high-quality manual or auto-generated prompts and label words for each task from previous works [74, 29]. For “Prompt-based FT (soft)”, we use the STS-2 template for all single sentence tasks and STS-B template for all sentence pair tasks, while the label words for each task follow the description in Table 5.

C ST Frameworks

FIXMATCH. FIXMATCH [81] generates artificial labels using both consistency regularization and pseudo-labelling, where the artificial labels are produced based on weakly-augmented unlabelled data. These artificial labels are then used as targets to train the model on strongly-augmented unlabelled data. FIXMATCH only retains an artificial label if the model assigns a high probability to one of the possible classes.

DASH. DASH [96] extends FIXMATCH by introducing a mechanism with a dynamically adjusted threshold of loss to select a subset of training examples from the unlabelled data for performing SSL.

²https://github.com/princeton-nlp/LM-BFF/blob/main/data/download_dataset.sh

³<https://www.quora.com/q/quoradata/>

⁴<https://www.yelp.com/dataset>

<i>Single Sentence Tasks</i>						
Dataset	$ \mathcal{Y} $	L	#Train	#Test	Type	Labels (classification tasks)
SST-2	2	19	6,920	872	Sentiment	positive, negative
SST-5	5	18	8,544	2,210	Sentiment	v. pos., positive, neutral, negative, v. neg.
MR	2	20	8,662	2,000	Sentiment	positive, negative
CR	2	19	1,775	2,000	Sentiment	positive, negative
MPQA	2	3	8,606	2,000	Opinion Polarity	positive, negative
Subj	2	23	8,000	2,000	Subjectivity	subjective, objective
TREC	6	10	5,452	500	Question cls.	abbr., entity, description, human, loc., num.
CoLA	2	8	8,551	1,042	Acceptability	grammatical, not_grammatical
IMDB	2	149	8,000	1,000	Movie Review	positive, negative
AG NEWS	2	37	8,000	1,000	News Topic	world, sports, business, sci/tech
YELP REVIEW	2	134	8,000	1,000	Review Sentiment	1, 2, 3, 4, 5
AMAZON REVIEW	2	79	8,000	1,000	Review Sentiment	1, 2, 3, 4, 5
YAHOO! ANSWER	2	32	8,000	1,000	Topic Classification	culture, science, health, education, computer, sports, business, music, family, politics
<i>Sentence Pair Tasks</i>						
Dataset	$ \mathcal{Y} $	L	#Train	#Test	Type	Labels (classification tasks)
MNLI	3	22/11	392,702	9,815	NLI	entailment, neutral, contradiction
SNLI	3	14/8	549,367	9,842	NLI	entailment, neutral, contradiction
QNLI	2	11/30	104,743	5,463	NLI	entailment, not_entailment
RTE	2	49/10	2,490	277	NLI	entailment, not_entailment
MRPC	2	22/21	3,668	408	Paraphrase	equivalent, not_equivalent
QQP	2	12/12	363,846	40,431	Paraphrase	equivalent, not_equivalent
STS-B	\mathcal{R}	11/11	5,749	1,500	Sent. Similarity	-

Table 4: The datasets evaluated in this work. $|\mathcal{Y}|$: # of classes for classification tasks (with one exception: STS-B is a real-valued regression task over the interval $[0, 5]$). L : average # of words in input sentence(s). Note that we only sample examples from the original training set in our few-shot experiments.

<i>Single Sentence Tasks</i>		
Task	Template	Label words
SST-2	$\langle S_1 \rangle$ It was [MASK] .	positive: great, negative: terrible
SST-5	$\langle S_1 \rangle$ It was [MASK] .	v.positive: great, positive: good, neutral: okay, negative: bad, v.negative: terrible
MR	$\langle S_1 \rangle$ It was [MASK] .	positive: great, negative: terrible
CR	$\langle S_1 \rangle$ It was [MASK] .	positive: great, negative: terrible
MPQA	$\langle S_1 \rangle$ is [MASK] .	positive: positive, negative: negative
Subj	$\langle S_1 \rangle$ This is [MASK] .	subjective: subjective, objective: objective
TREC	[MASK] : $\langle S_1 \rangle$	abbreviation: Expression, entity: Entity, description: Description human: Human, location: Location, numeric: Number
COLA	$\langle S_1 \rangle$ This is [MASK] .	grammatical: correct, not_grammatical: incorrect
IMDB	$\langle S_1 \rangle$ It was [MASK] .	positive: great, negative: terrible
AG NEWS	$\langle S_1 \rangle$ It was [MASK] .	World: world, Sports:sports, Business: business, Sci/Tech: tech
YELP REVIEW	$\langle S_1 \rangle$ It was [MASK] .	0: 0, 1: 1, 2: 2, 3: 3, 4: 4
AMAZON REVIEW	$\langle S_1 \rangle$ It was [MASK] .	0: 0, 1: 1, 2: 2, 3: 3, 4: 4
YAHOO! ANSWER	$\langle S_1 \rangle$ It was [MASK] .	culture: culture, science: science, health: health, education: education computer: computer, sports: sports, business: business music: music, family: family, politics: politics
<i>Sentence Pair Tasks</i>		
Task	Template	Label words
MNLI	$\langle S_1 \rangle$? [MASK] , $\langle S_2 \rangle$	entailment: Yes, neutral: Maybe, contradiction: No
SNLI	$\langle S_1 \rangle$? [MASK] , in this case $\langle S_2 \rangle$	entailment: Yes, neutral: Maybe, contradiction: No
QNLI	$\langle S_1 \rangle$? [MASK] , $\langle S_2 \rangle$	entailment: Yes, not_entailment: No
RTE	$\langle S_1 \rangle$? [MASK] , I think that $\langle S_2 \rangle$	entailment: Clearly, not_entailment: Yet
MRPC	$\langle S_1 \rangle$ [MASK] , $\langle S_2 \rangle$	equivalent: Yes, not_equivalent: No
QQP	$\langle S_1 \rangle$ [MASK] , $\langle S_2 \rangle$	equivalent: Yes, not_equivalent: No
STS-B	$\langle S_1 \rangle$ [MASK] , $\langle S_2 \rangle$	y_u : Yes, y_l : No

Table 5: Templates and label words used for “Prompt-based FT (hard)”. We use the STS-2 and STS-B template for all single sentence tasks and sentence pair tasks using “Prompt-based FT (soft)”, respectively.

FLEXMATCH. FLEXMATCH [99] also extends FIXMATCH by introducing the concept of curriculum learning [10] to flexibly adjust thresholds for different classes at each time step and select unlabelled data and their pseudo labels that are more likely to be informative.

ADAMATCH. ADAMATCH [13] aims to solve domain adaptation problems in SSL and build a high-accuracy model that trains on and tests on different data distributions. ADAMATCH builds on FIXMATCH and introduces a relative confidence threshold and a modified distribution alignment from [12].

D Supplementary Experiment

In this section, we evaluate the effect of continued pre-training (TAPT) with a larger pre-training corpus on the performance of the prompt-based FT on sentence pair tasks.

In Section 4.2, we randomly selected at most 10k unlabeled examples from the full training sets of MNLI, MNLI-mm, SNLI, QNLI, and QQP, as corpus for continued pre-training due to our limited academic computational resources. For all other tasks, we use the full training set for continued pre-training because there are fewer than 10k examples in their training sets. To verify our findings that “TAPT is not consistently beneficial for sentence pair tasks, nor when prompt-based FT is employed” holds true when utilising larger continued pre-training corpus, we perform conventional continued pre-training (TAPT) on the full training set on MNLI, MNLI-mm, SNLI, QNLI, and QQP.

Dataset Corpus Size	MNLI 393k	MNLI-mm 393k	SNLI 549k	QNLI 104k	QQP 364k
CLS-based FT	46.2 _{0.6}	48.5 _{1.0}	45.6 _{5.4}	61.4 _{8.2}	58.5 _{3.8}
+ TAPT	34.7 _{0.4} ↓	35.1 _{0.6} ↓	41.8 _{2.7} ↓	54.8 _{2.0} ↓	62.6 _{2.9} ↑
Prompt-based FT (hard)	67.3 _{1.3}	68.9 _{1.2}	76.7 _{1.6}	66.5 _{4.3}	66.8 _{1.9}
+ TAPT	47.8 _{5.6} ↓	47.9 _{5.2} ↓	47.5 _{9.4} ↓	53.5 _{0.8} ↓	53.5 _{0.8} ↓
Prompt-based FT (soft)	62.7 _{2.2}	65.9 _{1.2}	75.4 _{0.8}	64.2 _{4.7}	66.5 _{1.8}
+ TAPT	45.4 _{3.7} ↓	45.8 _{4.1} ↓	50.2 _{3.9} ↓	53.8 _{0.9} ↓	53.8 _{0.9} ↓

Table 6: Test Results using ROBERTA-LARGE, with corresponding continued pre-training corpus sizes for each task. The mean performance with standard deviations are reported across five seeds.

Table 6 presents the performance of the CLS-based FT, prompt-based FT (hard), and prompt-based FT (soft) using the TAPT. The experimental results reveal that the TAPT generally results in poorer performance, even when a larger continued pre-training corpus is used. Notably, the performance of these fine-tuning approaches could be even worse than those achieved using a smaller continued pre-training corpus (refer to results in Table 1), suggesting that training with a larger corpus is not an effective solution to the issues of conventional continued pre-training (TAPT).

E Implementation Details

Our code is implemented using Pytorch⁵ and Huggingface⁶. The semi-supervised approaches are implemented upon the repository⁷. Below, we provide a comprehensive list of the hyperparameters used in our code. For fine-tuning, as shown in Table 7, we conduct a grid search for learning rates within the set {1e5, 2e-5, 5e-5}, and choose a batch size of 8. In each trial, we train the model for 1,000 steps, evaluate performance every 100 steps, and select the best checkpoint based on optimal performance on the evaluation set. The best performance is determined by the relevant evaluation metric. For continued pre-training, we utilise the same set of hyperparameters for both TAPT and PCP, as shown in Table 8. The learning rate and unlabeled data size are closely linked and need to be adjusted simultaneously. As a general guideline, we suggest decreasing the learning rate as the unlabeled data size decreases. In contrast to its predecessor, BERT [26], which uses the next sentence prediction objective, ROBERTA [55] is trained solely with the masked language model (MLM) objective, specifically the cross-entropy loss on predicting randomly masked tokens. ROBERTA dynamically alters the masking pattern applied to training examples, typically employing a masking probability of 0.15. Additionally, Table 9 lists the hyperparameters for self-training approaches, where a grid search for learning rates within the set {1e5, 2e-5, 5e-5} is conducted.

⁵<https://pytorch.org/>

⁶<https://huggingface.co/>

⁷<https://github.com/amzn/pretraining-or-self-training>

Hyperparameter	Assignment
number of steps	1000 steps (evaluate every 100 steps)
batch size	8
maximum learning rate	1e-05, 2e-5, 5e-5
maximum sequence length	128, 256
learning rate optimizer	AdamW
Adam epsilon	1e-6
Adam beta weights	0.9, 0.98
learning rate scheduler	Warmup linear
Weight decay	0.01
Warmup proportion	0.06

Table 7: Hyperparameters for hard and soft prompt-based fine-tuning.

Hyperparameter	Assignment
number of steps	100 epochs
batch size	256
maximum learning rate	1e-05, 1e-4
learning rate optimizer	AdamW
Adam epsilon	1e-6
Adam beta weights	0.9, 0.98
learning rate scheduler	Warmup linear
Weight decay	0.01
Warmup proportion	0.06
Masking Probability	0.15

Table 8: Hyperparameters for both conventional continued pre-training (TAPT) and prompt-based conventional fine-tuning (PCP).

Hyperparameter	Assignment
number of steps	12 800 or 25 600 steps
batch size	16
learning rate	1e-05, 2e-05, 5e-05
learning rate optimizer	AdamW
maximum sequence length	256
learning rate scheduler	Warmup linear
Warmup proportion	0.05
learning rate decay	linear

Table 9: Hyperparameters for self training. Algorithm-specific hyperparameters will be released in configuration files with the code.