CrossTune: Black-Box Few-Shot Classification with Label Enhancement

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Abstract

Training or finetuning large-scale language models (LLMs) requires substantial computation resources, motivating recent efforts to explore parameter-efficient adaptation to downstream tasks. One approach is to treat these models as black boxes and use forward passes (Inference APIs) to interact with them. Current research focuses on adapting these black-box models to downstream tasks using gradient-free prompt optimization, but this often involves an expensive process of searching task-specific prompts. Therefore, we are motivated to study black-box language model adaptation without prompt search. Specifically, we introduce a label-enhanced cross-attention network called CrossTune, which models the semantic relatedness between the input text sequence and task-specific label descriptions. Its effectiveness is examined in the context of few-shot text classification. To improve the generalization of CrossTune, we utilize ChatGPT to generate additional training data through in-context learning. A switch mechanism is implemented to exclude low-quality ChatGPT-generated data. Through extensive experiments on seven benchmark text classification datasets, we demonstrate that our proposed approach outperforms the previous state-of-the-art gradient-free black-box tuning method by 5.7% on average. Even without using ChatGPT-augmented data, CrossTune performs better or comparably than previous black-box tuning methods, suggesting the effectiveness of our approach.

Keywords: Black-Box Tuning, Few-shot Text Classification, Large Language Model

1. Introduction

In the past few years, significant progress has been made in research on large-scale language models (LLMs) (Devlin et al., 2019; Liu et al., 2019; Ouyang and et al., 2022; Chowdhery et al., 2022). Scaling up language models has been demonstrated to boost performance and sample efficiency on a great variety of downstream tasks (Raffel et al., 2020; Brown et al., 2020b, *inter alia*). However, training such LLMs is not practical with typical research hardware. Even finetuning them on task-specific data is extremely challenging. Many research efforts have been devoted to more parameter-efficient adaptation approaches, including (1) parameter-efficient finetuning (PEFT) (Lester et al., 2021; Li and Liang, 2021; Houlsby et al., 2019; Hu et al., 2022), which optimizes a small portion of task-specific parameters, while keeping the language model intact; (2) prompt-based learning, where a carefully-designed task-specific sequence, known as a prompt, is added to the input text sequence of a pre-trained language model (LM). The LM is repurposed to adapt to the downstream tasks without additional training.

Due to commercial reasons, powerful LLMs are provided as a service in the cloud, and end users can only interact with them through inference APIs. This setup is referred to as Language-Model-as-a-Service (LMaaS) Sun et al. (2022b). Popular PEFT approaches are impractical in this context since they require access to model gradients. To address this challenge, an emerging line of prompt-based learning research focuses on gradient-free prompt optimization techniques (Brown et al., 2020b; Sun et al., 2022b,a; Deng et al., 2022; Prasad et al., 2023; Hou et al., 2023). However, these methods are also problematic because (1) prompt optimization is highly sensitive to the template design and demonstration selection (Gao et al., 2021a; Zhao et al., 2021) leading to unstable performance and poor generalization. (2) The prompt search process, either manual or automatic, is also time-consuming. For example, the covariance matrix adaptation evolution strategy (CMA-ES) adopted by Sun et al. (2022b) requires tens of thousands of forward passes through the LLMs to achieve satisfactory performance even in few-shot text classification scenarios.

To this end, we propose CrossTune, a label-enhanced black-box few-shot learner for the adaptation of the black-box LMs without prompt search. Following existing works, we assume the inference APIs provide forward-pass LM outputs and study our approach in the context of few-shot text classification. In CrossTune, the black-box model is treated as a feature extractor where hidden states of the input text sequence are derived. Besides, the original label words are expanded to long text

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descriptions. A cross-attention network is trained to align the input text sequence with its associated label. In this way, we can steer the model to focus on specific aspects of the input text data that are semantically related to the label descriptions, which act as a form of contextual input and provide additional semantic guidance to the model about what each label means.

In the few-shot scenarios, the model can easily overfit the training data resulting in poor generalization to unseen test data. Existing works mainly rely on semi-supervised and weakly-supervised methods to boost the generalization of the text classifiers. Both assume the presence of abundant in-distribution unlabeled data (Schick and Schütze, 2021; Chen et al., 2021; Fei et al., 2022; Du et al., 2021; Cho et al., 2023)[1]. Contrary to prior works, we do not make such an assumption. Instead, we harness the strong instruction-following capability of ChatGPT[2] to generate data conditioned on the labels through in-context learning (Brown et al., 2020b). To filter out low-quality generation, we implement an additional switch mechanism as described in §3.4.

In summary, our contributions are as follows:

- We introduce CrossTune, a new approach for the few-shot adaptation of black-box language models. Different from existing methods, CrossTune does not rely on the expensive prompt search process. Additionally, CrossTune leverages the rich semantic information in label descriptions to perform the classification task.

- Instead of relying on in-distribution unlabeled training data, which are rarely available in real-life scenarios, we harness the power of a strong instruction-following text generator, ChatGPT, to generate data conditioned on the labels through in-context learning. A pipeline is designed to generate and clean the data. Our experiments demonstrate that the quality of data generated by ChatGPT is on par with the original training data.

- Extensive experiments are performed on 7 few-shot text classification datasets and CrossTune significantly outperforms previous the state-of-the-art gradient-free prompt optimization approach with an absolute improvement of 5.7% on average.

[1]The unlabeled data are either the original training set with their ground-truth labels removed or retrieved sentences from a sentence bank based on their similarity to the few-shot training examples.

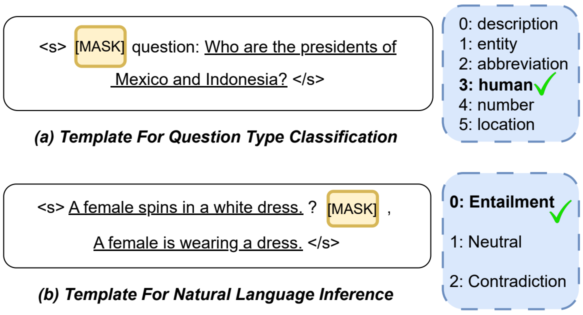
[2]https://openai.com/chatgpt

2. Related Work

Gradient-Free Black-Box Tuning The success of prompt-based learning with GPT-3 (Brown et al., 2020b) has inspired fruitful research in NLP community. A typical line is to optimize the prompts for downstream tasks based on the gradients of pretrained language models such that the output can align closely with the desired results (Gao et al., 2021a; Chen et al., 2021; Li and Liang, 2021; Liu et al., 2021). However, many practical applications involve models where internal parameters or gradients are obscured or inaccessible, leading to a so-called "black-box" tuning setting (Sun et al., 2022b; Diao et al., 2023).

Several studies have ventured into black-box tuning challenges. BBT (Sun et al., 2022b) and BBTv2 (Sun et al., 2022a) utilize the CMA evolution strategy to optimize prompts but face challenges in efficiency and flexibility. RLPrompt (Deng et al., 2022) and Black-box Discrete Prompt Learning (BDPL) (Diao et al., 2023) both use reinforcement learning to fine-tune discrete prompts, with BDPL featuring a streamlined search approach. TEMPERA (Zhang et al., 2023) expands optimization components, while GrIPS (Prasad et al., 2023) focuses on phrase-level editing. However, many of these black-box tuning methods suffer from efficiency issues and may not always deliver optimal results. Recently, PromptBoosting (Hou et al., 2023) adapts the ensembling idea of AdaBoost to black-box tuning and achieves state-of-art performance in multiple black-box few-shot classification tasks. Different from the existing approaches, CrossTune does not require the expensive prompt search and offers a much simpler and more effective adaption of the black-box language models.

Few-shot Text Classification with Augmented Data Popular research directions for enhancing the generalization of few-shot text classifier include semi-supervised learning (Xie et al., 2020; Sohn et al., 2020; Zoph et al., 2020) and weakly-supervised learning (Meng et al., 2020; Zhang et al., 2021; Fei et al., 2022; Cho et al., 2023). Both line of works assume the presence of a substantial amount of unlabeled data. Common techniques to obtain unlabeled text data include (1) removing the gold labels of the original full training data for a specific task (Chen et al., 2021; Schick and Schütze, 2021), (2) applying a retriever to retrieve sentences from a large-scale sentence bank that are semantically similar to the few-shot training data (Du et al., 2021), and (3) text data augmentation, such as paraphrasing and back-translation (Bayer et al., 2022). However, these techniques have several limitations: Using the full training data as an unlabeled source is often impractical because sub-



(a) Template For Question Type Classification

(b) Template For Natural Language Inference

Figure 1: Input template examples. The blue boxes contain the labels for the corresponding classification tasks.

stantial in-distribution unlabeled data is not always available in real-life scenarios. Moreover, retrieval and text augmentation tend to produce similar unlabeled data to the few-shot training set, limiting the diversity of the augmented data. Furthermore, both semi- and weakly-supervised learning rely on potentially inaccurate pseudo-labeling of the unlabeled data.

Motivated by the recent imitation learning research on distilling high-quality training data from strong LLMs, like ChatGPT and GPT-4 (Wang et al., 2023; Xu et al., 2023; Mukherjee et al., 2023), we tackle the above limitations by prompting ChatGPT to generate high-quality training data through in-context learning. With its strong instruction-following and text-generation capabilities, ChatGPT serves as a powerful tool for text data augmentation.

3. Methodology

3.1. Problem Formulation

In a few-shot text classification task T with a label space $\mathcal{Y}$, we assume there are K labeled training examples per class in the training set, $\mathcal{D}^T_{train}$. The training data size, $|\mathcal{D}^T_{train}| = K \times |\mathcal{Y}|$. We also assume an development set, $\mathcal{D}^T_{dev}$, which is of equal data size as $\mathcal{D}^T_{train}$. Both $\mathcal{D}^T_{train}$ and $\mathcal{D}^T_{dev}$ consist of data instances (X_i, y_i) where $y_i \in \mathcal{Y}$ and X_i denotes the input text sequence, which contains n tokens, i.e., $X_i = \{x_i^1, x_i^2, \dots, x_i^n\}$. Assume that we have task-specific template mapping function $\mathcal{F}_T$, which maps X_i to a specific input format $\mathcal{F}_T(X_i)$. Figure 1 shows two examples of $\mathcal{F}_T(X_i)$. The underlined texts in the boxes are the original input texts, X_i. Note that no additional prompt token is prepended to the transformed input. Moreover, assume a black-box language model denoted as $\mathcal{M}$, which is for inference only. Through its API, we can obtain the logits of "[MASK]" tokens and the hidden states of the input text sequences. Our goal is to develop a model that generalizes well to an unseen test set $\mathcal{D}^T_{test}$.

3.2. CrossTune Architecture

Figure 2 presents the model architecture of CrossTune. Using the frozen black-box language model $\mathcal{M}$, we derive a sequence of hidden states after each layer l with respect to the reformatted input text $\mathcal{F}_T(X_i)$. As we are interested in the hidden vectors of the "[MASK]" token that is $\{\mathbf{h}^{mask}_{i,l} \in \mathbb{R}^d\}^L_{l=1}$, we perform max pooling on $\{\mathbf{h}^{mask}_{i,l}\}^L_{l=L-3}$ to derive a single vector representation, $\mathbf{h}^{mask}_i \in \mathbb{R}^d$. This operation is motivated by previous works on sentence representation learning (Ethayarajh, 2019; Li et al., 2020; Hosseini et al., 2023) which state that combining embeddings from multiple layers leads to better semantic representation than using only the last-layer embedding.

Furthermore, each label in the space $\mathcal{Y}$ is converted into its corresponding label text description, which is either the definitions specified in the original datasets or from Wikipedia. Using the same model $\mathcal{M}$, we obtain the single-vector label embeddings $\mathbf{h}_{y_i}$ for each y_i in $\mathcal{Y}$. The $\mathbf{h}_{y_i}$ embeddings are obtained by applying the same max pooling procedure described above on the hidden states of the label description and then followed by a token-level mean pooling operation.

A multi-head cross-attention module is implemented such that $\mathbf{h}^{mask}_{X_i}$ can attend to each $\mathbf{h}_{y_i}$ in $\mathcal{Y}$. More specifically, $\mathbf{h}^{mask}_{X_i}$ and all label embeddings, $\mathbf{H}_{\mathcal{Y}}$, are first linearly transformed into query vector and key matrix for each head:

$$\mathbf{q}^k = W^k_Q \mathbf{h}^{mask}_{X_i}$$

$$\mathbf{K}^k = W^k_K \mathbf{H}_{\mathcal{Y}}$$

where k denotes the k-th head. $W^k_Q \in \mathbb{R}^{d \times d}, W^k_K \in \mathbb{R}^{d \times d}$ are the k-th head weight matrices for the query and key respectively. The cross attention is then computed as:

$$\text{CrossAttn}^k(\mathbf{q}^k, \mathbf{K}^k) = \text{softmax}\left(\frac{\mathbf{q}^k(\mathbf{K}^k)^T}{\sqrt{d}}\right)$$

where d is the dimensionality of the weight matrices. To obtain the final attention scores, we average the scores from each head. These resulting attention scores indicate the significance of each label description in relation to the input text sequence. Finally, cross entropy loss is chosen as the training objective:

$$\mathcal{L} = \sum_{(X_i, y_i) \in \mathcal{D}^T_{train}} -y_i \; log \; \hat{y}_i$$

where y_i is converted to one-hot vector while $\hat{y}_i$ is the final attention score vector, i.e., probability distribution across the labels in the label space $\mathcal{Y}$.

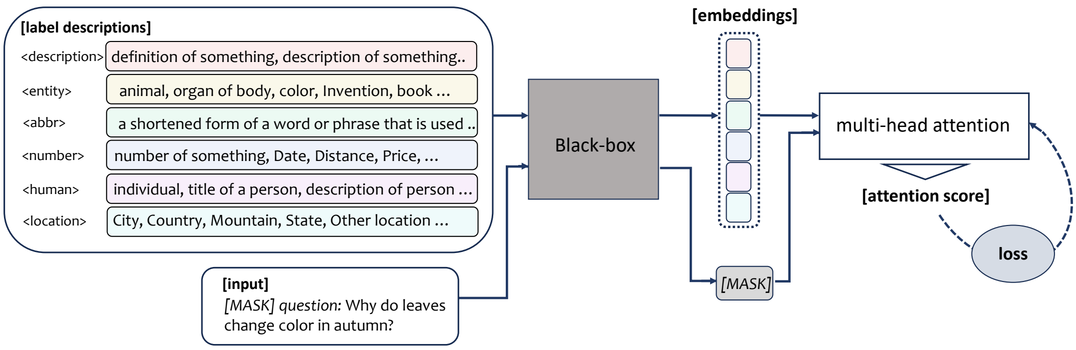


Figure 2: System Overview of CrossTune.

Instruction:
{Label} is defined as {Label Definition}.

Follow the below examples and generate 10 diverse questions of {Label} type and output one question at a line.

Examples:
{Here are the in-context exemplars}

Your Output:
{Here are the ChatGPT-generated texts}

(a) Question Type Classification

Instruction:
{Label} is defined as {Label Definition}.

Generate 10 diverse {Label} sentence pairs in the following format: [Premise | Hypothesis] and output one pair at a line.

Examples:
{Here are the in-context exemplars}

Your Output:
{ChatGPT Generated Text}

(b) Natural Language Inference

Table 1: Example instruction templates for prompting ChatGPT to generate task-specific data conditioned on a specific label. In "Label Definition", we provide the meaning of the label. For instance, "Entailment is defined as when the hypothesis can be logically inferred or implied from the premise" in the case of natural language inference.

3.3. ChatGPT for Data Generation

We propose to generate task-specific data with ChatGPT (gpt-3.5-turbo). Task-specific instruction templates are designed to prompt ChatGPT to generate relevant text data belonging to a specific class. ChatGPT offers richer data variations, and through in-context learning, it can be prompted for task- and context-specific text generation, ensuring more precise and natural outputs. Table 1 presents two examples of how we prompt ChatGPT to generate training data. The in-context exemplars are the task- and seed-specific few-shot training data associated with a particular class for which we aim to perform data augmentation with ChatGPT. For selecting the in-context exemplars, we follow the most common setup, which is random sampling, i.e., to generate samples of a particular class, we random sample 8 training samples of that class. When calling the inference API of ChatGPT, we set the temperature, top_p, frequency_penalty, and presence_penalty to 0.8, 0.95, 0.8, and 1.4 respectively. For each class, we iteratively call the inference API until a sufficient amount of training data is obtained.

3.4. The Switch Mechanism

Even though ChatGPT is a strong instruction-following text generator, it does not always guarantee the production of high-quality labeled data. Therefore, we utilize the text-understanding capability of another teacher model. We select DeBERTa-base as the teacher model due to its manageable size (suitable for a standard research GPU) and its superior performance on popular text classification benchmarks (Wang et al., 2019) compared to similar sized models, such as BERT (Devlin et al., 2019), RoBERTa (Liu et al., 2019), and ELECTRA (Clark et al., 2020). A switch mechanism is introduced such that both ChatGPT and DeBERTa teachers can complement each other and collaboratively determine the labels of the augmented data. Let $\mathcal{A}_{chagpt}$ and $\mathcal{A}_{deberta}$ denote the ChatGPT and DeBERTa teachers respectively. Motivated by the findings in previous works (Gao et al., 2021a; Chen et al., 2021) that prompt-based finetuning of the language model with demonstrations can drastically outperform standard fine-tuning procedures in the low resource setting, we apply prompt-based finetuning for adapting $\mathcal{A}_{deberta}$ to task T. The parameter size of $\mathcal{A}_{deberta}$ is significantly smaller than black-box LM, thus it can be viewed as a readily accessible auxiliary model designed to enhance the quality of the augmented data. Our experimental results reveal that incorporating a switch mechanism with $\mathcal{A}_{deberta}$ enhances the performance of CrossTune.

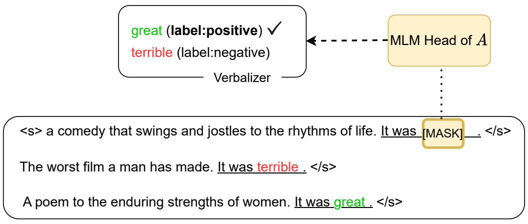


Figure 3: Prompt-based finetuning of $\mathcal{A}_{deberta}$. The underlined text is the prompt template. In the bottom box, the first, second, and third lines are the input text sequence, the demonstration for label:negative, and the demonstration for label:positive respectively. The verbalizer maps the labels to the corresponding words.

Prompt-based Finetuning of $\mathcal{A}_{deberta}$ Figure 3 illustrates how we finetune $\mathcal{A}_{deberta}$. Given $(X_i, y_i) \in \mathcal{D}^T_{train}$, the X_i is first transformed into $\mathcal{F}_T(X_i)$ according to the task-specific templates[3]. The verbalizer converts y_i to the corresponding word in the vocabulary of $\mathcal{A}_{deberta}$. To fill in the "[MASK]" position in $\mathcal{F}_T(X_i)$, $\mathcal{A}_{deberta}$ learns to assign a higher probability to the word mapped to y_i than other label words. For example, $\mathcal{A}_{deberta}$ should predict a higher probability of "great" than "terrible" for the example input in Figure 3. To further enhance the prompt-based finetuning process, we append demonstrations after $\mathcal{F}_T(X_i)$. A demonstration is an input text example. For each category, one demonstration is added. $\mathcal{A}_{deberta}$ is finetuned with the standard MLM loss on $\mathcal{D}^T_{train}$. In addition, for model selection, we perform the grid search procedure on different training hyperparameters. The checkpoint with the best performance on $\mathcal{D}^T_{dev}$ is used as the teacher model.

Switch Rule The data generated by $\mathcal{A}_{chagpt}$ is equipped with pseudo labels that it deems correct. To validate these labels, we implement a rule to decide if $\mathcal{A}_{deberta}$ should annotate the data. The decision is based on the classification performance of both $\mathcal{A}_{chagpt}$ and $\mathcal{A}_{deberta}$ on $\mathcal{D}^T_{dev}$. If $\mathcal{A}_{chagpt}$ outperforms $\mathcal{A}_{deberta}$, we retain the pseudo labels. Otherwise, we employ $\mathcal{A}_{deberta}$ for further annotations, discarding any data on which $\mathcal{A}_{deberta}$ and $\mathcal{A}_{chagpt}$ disagree and keeping those $\mathcal{A}_{deberta}$ is confident about.

[3]In our experiments, we use the same set of task-specific manual templates for both prompt-based finetuning of $\mathcal{A}_{deberta}$ and the training of CrossTune.

4. Experiment Setup

Datasets CrossTune is evaluated on 7 text classification datasets, including 3 single-sentence and 4 sentence-pair classification datasets. Among them, AGNews (Zhang et al., 2015) is for topic classification. SST-2 (Wang et al., 2019) is for sentiment analysis. TREC (Hovy et al., 2001) is for question classification. MRPC (Wang et al., 2019) and QQP (Wang et al., 2019) are paraphrasing tasks. QNLI (Wang et al., 2019) and MNLI (Bowman et al., 2015) are for natural language inference. Following Sun et al. (2022a), K samples are randomly drawn from the original training set for each class to construct the training set and another K samples from the original training set for the development set. For the test sets, we use the original development set if it exists, otherwise, the original test set is used. K is set to be 16 across all datasets.

Baselines We compare our approach with full-model fine-tuning methods and state-of-the-art black-box tuning methods described as follows: (1) **Finetuning**, the standard way of finetuning a language model for few-shot text classification. (2) prompt-based fine-tuning as implemented by Gao et al.(2021). The approach is referred to as **LM-BFF**. Both (1) and (2) require updating the weights of the LLM. Hence, they can be seen as white-box methods. (3) **ICL-RoBERTa**, which applies the in-context learning approach proposed in Brown et al. (2020) (Brown et al., 2020b) with RoBERTa-large. (4) **Black-Box Tuning (BBT)** (Sun et al., 2022b). (5) **BBTv2** (Sun et al., 2022a). (4) and (5) are derivative-free optimization methods that are based on the covariance matrix adaptation evolution strategy to optimize the continuous prompt (Hansen and Ostermeier, 2001). (6) **RLPrompt** (Deng et al., 2022), which optimizes the discrete prompts with reinforcement learning and adopts Q-learning to find the best prompt. (7) **Promptboosting** (Hou et al., 2023), which searches the verbalizer and ensemble hundreds of verbalizers via AdaBoost to weight different training samples. (8) To validate the effectiveness of CrossTune, we consider another feature-based variant, which is implemented as an MLP classifier. Specifically, the MASK token embedding is extracted from the frozen black-box model and fed to a 2-layer MLP for classification. We name the baseline MLP-Classifier.

Implementation Details To align with previous studies on black-box tuning, we employ RoBERTa-Large (Liu et al., 2019) (with 354 million parameters) as our large-scale black-box language model. It is important to note that our methodology is model-agnostic. This means that the black-box LLMs can be any encoder-only or encoder-decoder models, even those with billions of parameters.

Task Name	Template
TREC	[MASK] question: <X>
AGNews	[MASK] News: <X>
SST-2	<X> . It was [MASK] .
MRPC	$<X_1>$? [MASK] , $<X_2>$
QQP	$<X_1>$? [MASK] , $<X_2>$
QNLI	$<X_1>$? [MASK] , $<X_2>$
MNLI	$<X_1>$? [MASK] , $<X_2>$

Table 2: Task-specific prompt templates and label words.

For training the teacher model $\mathcal{A}_{deberta}$, we set the training batch size, the maximum sequence length, and the maximum number of training steps as 2, 128, and 2000 respectively. We perform grid search on the learning rate of (1e-5, 2e-5) and gradient accumulation steps (1, 2) respectively. The DeBERTa finetuning is conducted on a Nvidia 1080 card, utilizing 5GB of GPU memory. The time cost is quite light. The average hyperparameter search time for a seed is about 30 minutes. When filtering the ChatGPT-augmented data with the DeBERTa teacher, we set the confidence threshold of the output probability to 0.9 according to its distribution, preserving up to M samples for each class. Empirically, $1000 <= M <= 1500$. Table 3 presents the statistics of the data used in our experiment. To ensure a fair comparison, the baseline MLP-Classifier model is trained on the same data as CrossTune.

For training CrossTune, we set the train batch size, the learning rate, the total number of training epochs, and the maximum sequence length as 32, 4e-5, 100, and 512 respectively. Grid search is performed on the number of attention heads (1, 2, 4, 8). The model is evaluated with the development set at the end of each epoch and if the validation performance does not improve for consecutive 5 epochs, we early stop the training process. Table 2 describes the templates we use for training CrossTune. It is worth noting that we do not need a verbalizer in our approach and no additional prompt is prepended to the template. In Figure 2, we present the label descriptions of TREC and those of the remaining datasets will be included in the Appendix of the final version.

5. Results & Analysis

5.1. Main Results

Table 4 summarizes the main results. We can observe that on average, CrossTune outperforms BBTv2 by 9.4% on average. It also matches the performance of LM-BFF, which is a strong white-box adaptation method employing prompt-based tuning. Compared to the current SoTA black-box tuning approach, PromptBoosting, CrossTune achieves significantly better results on MRPC, QNLI, and MNLI. It outperforms PromptBoosting by an absolute margin of 5.7% on average.

Task Name	#classes	#augmented data	#filtered data
TREC	6	8400	5500
AGNews	4	7000	4540
SST-2	2	3700	2800
MRPC	2	4000	2000
QQP	2	2800	1900
QNLI	2	3000	2000
MNLI	3	10000	2500

Table 3: The amount of augmented data and filtered data. The data quantity in the table represents the total count across all categories.

Compared to MLP-Classifier, which also does not rely on the expensive prompt search process and is trained on the same augmented data, CrossTune achieves an improvement of 1.8% on average across the seven datasets, underscoring that our proposed label cross-attention network is more effective than using an MLP classifier. Furthermore, CrossTune is more lightweight and efficient than MLP-Classifier as their numbers of trainable parameters are 2.10M and 3.15M respectively.

Additionally, we can see that the performance of CrossTune is more consistent with a smaller standard deviation across different data splits compared to prompt-based black-box methods, such as BBTv2 and RLPrompt, suggesting that CrossTune is less likely to overfit to specific data splits and exhibits better generalization.

Impact of Augmented Data Amount We study how the performance of CrossTune varies w.r.t. the amount of augmented data. The results of MLP-Classifier are also included in Table 5 for comparison. Specifically, we compare the cases when the amount of augmented data for each class is 0, 300, and full respectively. Full amount refers to the same setting shown in Table 3.

When the quantity of augmented data is 0, i.e., only the original K-shot data is used, the performance of both CrossTune and MLP-Classifier drastically declines by around 10% on average. The most pronounced performance drop is evident on TREC and QNLI, which contain test cases with diverse semantic and syntactic variations. This observation highlights the importance of boosting the generalization of feature-based black-box tuning approaches with data augmentation. Notably, even without data augmentation, CrossTune performs comparably or better than the prompt-based black-

	TREC acc	AGNews acc	SST-2 acc	MRPC f1	QQP f1	QNLI acc	MNLI acc	Average
Finetuning†	88.8 (2.1)	86.2 (1.4)	81.4 (3.8)	76.6 (2.5)	60.7 (4.3)	56.3 (1.5)	45.8 (6.4)	70.8
LM-BFF†	83.4 (2.7)	87.1 (1.2)	92.3 (1.5)	77.8 (2.0)	69.8 (1.8)	64.4 (4.6)	68.7 (2.0)	77.6
ICL-RoBERTa‡	26.2 (2.4)	62.2 (13.5)	85.9 (0.7)	45.8 (6.7)	36.1 (5.2)	53.8 (0.4)	52.0 (0.7)	51.7
BBT‡	39.3 (5.2)	81.2 (2.7)	88.2 (1.7)	61.6 (4.3)	48.6 (8.3)	56.8 (2.0)	42.3 (2.8)	59.7
BBTv2‡	42.0 (4.5)	85.3 (0.5)	83.8 (0.8)	77.0 (4.7)	56.3 (3.9)	66.3 (2.3)	51.4 (3.3)	66.0
RLPrompt‡	37.3 (3.5)	76.2 (2.7)	**90.5** (1.2)	68.9 (2.1)	53.7 (2.2)	52.1 (2.9)	40.7 (4.7)	59.9
PromptBoosting‡	81.6 (4.0)	85.2 (0.9)	87.6 (3.0)	70.5 (2.9)	64.8 (3.7)	58.0 (3.3)	52.5 (1.5)	71.5
MLP-Classifier‡	80.8 (0.2)	85.9 (0.5)	89.1 (2.3)	80.4 (0.5)	64.8 (2.1)	70.4 (1.3)	56.7 (1.5)	75.4
CrossTune‡	**85.0** (1.8)	**86.6** (1.1)	90.2 (2.5)	**82.3** (0.6)	**66.1** (1.8)	**71.4** (0.8)	**58.5** (1.8)	**77.2**

Table 4: Main experiment results. † refers to white-box methods while ‡ refers to black-box methods. In the black-box category, the best score for each task is highlighted in bold and the second best is underlined.

#data	model	TREC acc	AGNews acc	SST-2 acc	MRPC f1	QQP f1	QNLI acc	MNLI acc	Average
0	MLP-Classifier	46.1	82.3	88.9	76.2	64.8	54.0	53.6	66.6
	CrossTune	46.4	82.5	88.2	79.5	63.8	58.8	52.5	67.4
300	MLP-Classifier	73.9	85.8	88.9	78.9	67.0	67.3	54.2	73.7
	CrossTune	78.6	85.1	88.6	81.8	65.7	69.1	54.7	74.8
full	MLP-Classifier	80.8	85.9	89.1	80.4	64.8	70.4	56.7	75.4
	CrossTune	85.0	86.6	90.2	82.3	66.1	71.4	58.5	77.2

Table 5: Impact analysis of the augmented data amount on the performance of MLP-Classifier and CorssTune. "Full" refers to the same amount of data as that presented in Table 3.

box tuning methods on most datasets (Table 4) while requiring no expensive prompt or verbalizer search process.

After increasing the number of augmented data to 300 per class, the performance on TREC and QNLI improves drastically. The average performance of both MLP-Classifier and CrossTune becomes almost on par with their respective variants trained on the full data, surpassing all the prompt-based black-box methods like BBTv2 and RLPrompt. This suggests that feature-based black-box tuning methods exhibit high data efficiency.

Finally, regardless of the amount of augmented data used, CrossTune consistently outperforms MLP-Classifier. This further emphasizes the efficacy of utilizing the rich semantics of label descriptions with a cross-attention network.

5.2. Ablation Analysis

In-Distribution vs ChatGPT-Augmented Data To examine whether ChatGPT is effective in providing augmented data for enhancing the few-shot learners, we compare the performance of learning with the in-distribution augmented data against learning with our augmented data using ChatGPT. The in-distribution augmented data are the original task-specific training data with their ground-truth labels removed and then pseudo-labeled with the DeBERTa teacher model. In the case of using ChatGPT-augmented data, we also apply the same DeBERTa teacher to pseudo-label and filter the augmented data. Note that we keep the maximum amount of filtered data the same for both data sources to ensure a fair comparison. Table 6 showcases the results of the MLP-Classifier trained on the two data sources across six different datasets. Except for QQP, training on ChatGPT-Augmented data yields better or comparable results than when trained on in-distribution augmented data. The observation implies that ChatGPT is capable of producing high-quality task-specific data. In practical scenarios, we often have access to limited labeled data and lack in-distribution training data. In these situations, using ChatGPT for data augmentation is a viable option to improve the performance of few-shot learners.

We further analyze the data distributions of ChatGPT-augmented data, the original training data, and the test data. We first encode the text to high-dimensional embeddings with the SimCSE sentence embedder[4] (Gao et al., 2021b) and then apply the T-SNE transformation. Figure 4 shows the plots of TREC, QQP, and AGNews. We can observe that for TREC and AGnews, ChatGPT-augmented data is distributed relatively evenly across the space of the in-distribution training data and resemble a large portion of the test data.

[4] `https://huggingface.co/princeton-nlp/`

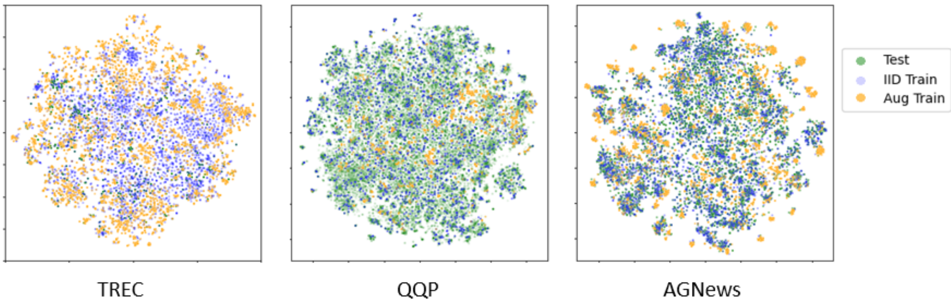


Figure 4: T-SNE Plots of embeddings w.r.t. original training, test, and ChatGPT-augmented training data. Note that we randomly sample the same amount of in-distribution training data as the ChatGPT-augmented data from the original training set.

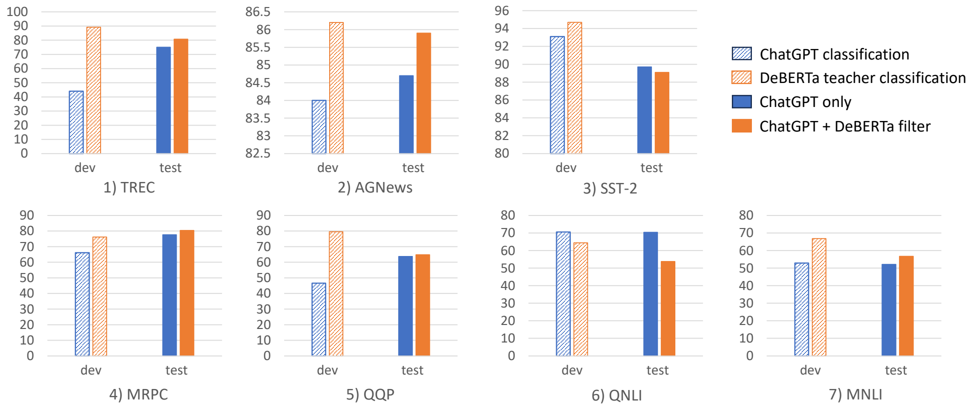


Figure 5: The performance of ChatGPT vs DeBERTa on the development set, which helps determine when to filter the ChatGPT-augmented data. A positive correlation can be observed between the performance of the teacher model on the development set and that of CrossTune on the test set across most datasets.

Data Source	TREC acc	AGNews acc	SST-2 acc	MRPC f1	QQP f1	QNLI acc	Avg
I.I.D	78.4	86.1	88.5	75.3	77.8	66.6	78.8
ChatGPT	80.8	85.9	89.1	80.4	64.8	70.4	78.6

Table 6: Performance of MLP-Classifier trained on in-distribution vs ChatGPT-Augmented Data.

However, for QQP, the distribution of ChatGPT-augmented data does not overlap well with the original training data. Besides, because the amount of test data in QQP is much greater than that of the augmented data ($40400 \gg 1900$), most of the test data are not covered. The observations are in line with results in Table 6 that MLP-Classifier trained on ChatGPT-augmented data performs on par with that trained on the original training data in TREC and AGNews, but worse in the case of QQP. A possible solution is to optimize the prompts input to ChatGPT such that more diverse data can be generated. We leave such prompt engineering efforts to future work.

Effectiveness of the Switch As introduced in §3.4, a switch mechanism is implemented to determine whether to filter the ChatGPT-augmented data with an additional DeBERTa teacher. As depicted in Figure 5, there is a consistent positive correlation between the teachers' performance on the few-shot development set and the final test performance of CrossTune across all the tasks except for SST-2. That is, when the switch is activated (indicating the DeBERTa teacher outperforms ChatGPT), CrossTune, which is trained on data filtered by the DeBERTa teacher, surpasses its variant trained on the unfiltered augmented data, and vice versa. For example, on TREC, AGNews, MRPC, QQP, and MNLI, the test performance of CrossTune improves with DeBERTa filter (as the DeBERTa teacher exhibits superior performance to ChatGPT on the few-shot development set) while on QNLI, the performance of CrossTune is better without the DeBERTa filter, given that the DeBERTa teacher underperforms compared to ChatGPT. These observations confirm that our proposed switch mechanism is reasonable.

Impact of label descriptions we further study the effect of using different label descriptions. In Table 7, we compare the performance of using long and informative vs short and non-informative

description type	TREC acc	AGNews acc	QNLI acc
Short	83.6	85.3	70.9
informative	85.0	86.6	71.4

Table 7: Effect of using informative vs non-informative descriptions.

label descriptions. When the non-informative descriptions are employed, CrossTune still works but performs slightly worse than when using the long and informative label descriptions. Hence, we can conclude that informative label descriptions help to improve CrossTune's text classification capability. The details of different label descriptions will be presented in appendix in the final version.

Additionally, we examine whether label descriptions also help improve other approaches. Experiments are conducted on MRPC and SST-2 with the MLP-Classifier baseline. Specifically, the input to the model is the concatenation of $\{desc_1, desc_2, \ldots, desc_c, x_i\}$ where $desc_j$ is the label description of the j-th class and x_i is the text sequence to classify. We notice that the performance of the MLP-classifier drops from 89.1% to 74.65% on SST-2 and 80.4% to 75.92% on MRPC, suggesting a negative impact of label descriptions on the MLP-classifier.

Impact of Augmented Data on Other Baselines We further perform experiments with the baselines, BBTv2 and RLprompt on SST2, with the same ChatGPT-augmented data as that used on CrossTune. No significant improvement is observed compared to training with the original 16-shot data. BBTv2 achieves 83.8% vs 82.8% accuracy while RLPrompt achieves 90.5% vs 91.0% accuracy before and after data augmentation respectively. It shows these prompt-optimization-based methods do not utilize the augmented data as effectively as CrossTune.

Impact of Other Augmentation Techniques Besides ChatGPT augmentation, we explore whether traditional data augmentation techniques, also enhance CrossTune. Experiments are conducted with CrossTune on MRPC and SST2, using data augmented from the EDA techniques (Wei and Zou, 2019), including random swap, deletion, and insertion of the input text. Our findings indicate that with 300 EDA-augmented data points, CrossTune's performance matches models trained with ChatGPT-augmented data. However, as we increase the data augmentation to 2000, the performance using EDA augmentation deteriorates compared to using no augmentation at all. This decline could be because a significant volume of EDA-augmented data introduces excessive noise into the language model. The deletion, insertion, and swapping operations risk altering the original sentence's semantic meaning. Compared to EDA, ChatGPT-based augmentation emerges as a more reliable method.

6. Conclusion

In summary, we propose CrossTune for few-shot text classification under the black-box setting. CrossTune treats the black-box LM as a feature extractor and leverages label descriptions as additional input semantic context. To boost the generalization of CrossTune, we avoid relying on in-distribution unlabeled data, instead utilizing ChatGPT to generate pseudo-labeled training samples. A switch mechanism is implemented to ensure the quality of the generated data. Our extensive empirical assessments across seven benchmark datasets reveal CrossTune's effectiveness in black-box tuning, outperforming existing state-of-the-art by an impressive 5.7% score on average. Even without data augmentation, CrossTune performs better or comparably than previous methods on most datasets.

Acknowledgement

We thank the anonymous reviewers for their insightful comments. This work is supported by Human Robot Collaborative AI under its AME Programmatic Funding Scheme (Project No. A18A2b0046), the National Natural Science Foundation of China (Grant No. 62271432), Shenzhen Science and Technology Research Fund (Fundamental Research Key Project Grant No. JCYJ20220818103001002), and the Internal Project Fund from Shenzhen Research Institute of Big Data under Grant No. T00120220002.

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A. Addtional Dataset Details

Dataset	Label	Description
TREC	description	Answer to the question is a description.
	entity	Answer to the question is an entity.
	abbreviation	Answer to the question is an abbreviation.
	number	Answer to the question is a number.
	human	Answer to the question is a human.
	location	Answer to the question is a location.
AGNews	tech	It is a technology news.
	world	It is a world news.
	sports	It is a sports news.
	business	It is a business news.
QNLI	entailment	The statement contains the answer to the question.
	non_entailment	The statement contains no answer to the question.

Table 8: Short and Non-informative Label Descriptions

Table 8 depicts the short and non-informative label descriptions used in our ablation study (§5.2) where we compare the effects of using informative label descriptions against using non-informative ones. Table 9 shows the label descriptions we use in our main experiments.

Dataset	Label	Description
TREC	description	Definition of something, description of something, manner of an action, reason.
	entity	Animal, Organ of body, Color, Invention, book and other creative piece, Currency name, Disease and medicine, Event, Food, Musical instrument, Language, Letter like a-z, Other entity, Plant, Product, Religion, Sport, Element and substance, Symbols and sign, Techniques and method, Equivalent term, Vehicle, Word with a special property.
	abbreviation	A shortened form of a word or phrase that is used to represent the full meaning.
	number	Number of something, Date, Distance, Price, Order, rank, Lasting time, Percent, fraction, Speed, Temperature, Size, area and volume, Weight, Postcode or other code.
	human	Individual, Title of a person, Description of a person, Group or organization of persons.
	location	City, Country, Mountain, State, Other location.
AGNews	tech	The Sci/Tech category is designed to encompass articles related to science and technology. It might include news about scientific discoveries or research breakthroughs, technology product launches, technology company updates, coverage of scientific and technology conferences, interviews with scientists or tech leaders, articles on new theories or models in various scientific disciplines, advancements in medical technology, and many more.
	world	It's a news article about international affairs, geopolitics, global events, or any topic that has a worldwide or international scope. Examples may include news on international diplomacy, major global events like the United Nations General Assembly, international conflicts or wars, significant elections or political events in different countries, global environmental issues, and more.
	sports	Articles related to various sporting events, news, and updates. the Sports category could encompass a wide range of topics such as game results, player transfers, injuries, interviews with athletes, coverage of international sporting events like the Olympics, football (soccer) world cup, tennis grand slams, and more.
	business	The Business category typically cover topics related to commerce, economics, and finance on a local, national, or international scale. It may include news about company mergers, financial reports, stock market updates, changes in economic policies, interviews with business leaders, innovation in business models, trends in various industry sectors, and so on.
QNLI	entailment	The given statement logically contains the answer to the associated question. If the truth of the statement provides the answer to the question, it's considered an entailment.
	non_entaiment	The given statement does not logically contain the answer to the associated question. Even if the statement is true, it does not provide a valid answer to the question.
MNLI	entailment	The hypothesis can be logically inferred or implied from the premise.
	neutral	The premise and the hypothesis do not have a clear logical relationship.
	contradiction	The hypothesis contradicts or conflicts with the information presented in the premise.
MRPC	equivalent	Two sentences in the pair are semantically equivalent - they express the same, or very similar, meaning.
	non_equivalent	Two sentences in the pair are not semantically equivalent - they do not convey the same meaning.
QQP	equivalent	That's to say,
	non_equivalent	Another different questions is,
SST-2	positive	sentences from movie reviews that express favorable, complimentary, or praiseworthy viewpoints about a movie. The concept of positive sentiment in this context typically includes feelings of enjoyment, admiration, appreciation, or satisfaction with elements of a movie such as its plot, acting, direction, cinematography, or other aspects of its production.
	negative	Sentences that express unfavorable, critical, or disparaging viewpoints about a movie. The concept of negative sentiment here typically includes feelings of disappointment, dissatisfaction, frustration, or displeasure with elements of a movie such as its plot, acting, direction, cinematography, or other aspects of its production.

Table 9: Label Descriptions used in main experiments