Multi-Scale Prompt Memory-Augmented Model for Black-Box Scenarios

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Abstract

Black-box few-shot text classification handles text classification in limited data without accessing the parameters and gradients of language models (LMs). Existing black-box optimization methods have demonstrated strong few-shot learning capabilities. However, they still require numerous LMs' calls to search optimal prompts, thus resulting in overfitting performance and increasing computational cost. To address this issue, we present MuSKPrompt (**Mu**lti-**s**cale **K**nowledge **Prompt** for Memory Model), an efficient multi-scale knowledge prompt-based memory model in black-box few-shot text classification task. MuSKPrompt extracts instance-level and class-level knowledge at different scales and stores them in memory banks during training. Then, it references multi-scale memory banks to perform quick inference on new samples via a novel scoring module. MuSKPrompt achieves competitive performance in limited data through multi-scale instance-level and class-level knowledge. Moreover, it realizes gradient-free optimization with zero training parameters in the black-box scenario. Experiments on different benchmarks and parameter analysis demonstrate the effectiveness and efficiency of MuSKPrompt in black-box few-shot text classification tasks.

1 Introduction

Over the past few years, large language models (LLMs) have achieved significant success (Radford et al., 2019; Brown et al., 2020; Touvron et al., 2023). Brown et al. (2020) propose in-context learning (ICL), which aids LMs in adapting to downstream tasks by providing a few context examples before the input. Due to its demonstrated good performance, prompt-based learning has become a popular method for low-resource adaptation of LLMs to downstream tasks. However, ICL exhibits significant instability, and its performance depends on the selection of context examples (Liu et al., 2022b). To that end, numerous studies have focused on optimizing continuous prompts (Liu et al., 2022c; Gu et al., 2022), ensuring that most parameters of LLMs remain unchanged. However, they are ineffective in certain situations where access to internal parameters and gradients of LLMs is restricted, a.k.a. the black-box scenario. Many existing LLMs provide only APIs, thus making gradient-based prompt learning challenging (Sun et al., 2022b). Furthermore, deploying LLMs in the black-box manner across various industries has become a trending topic (Lu et al., 2023; Na et al., 2023; Li et al., 2023).

Method	Number of API calls	Interpretable	Non-Parametric
BBT	8000	✗	✗
BBTv2	8000	✗	✗
RLPrompt	1200	✗	✗
k**NN Prompting**	1	✓	✓
Ours	<10	✓	✓

Table 1: Comparison of BBT, BBTv2, RLPrompt, kNN Prompting and MuSKPrompt Number of API calls, Interpretable and non-parametric. The calculation of API call counts references BBT(Sun et al., 2022b).

Existing approaches (Sun et al., 2022b,a) employ gradient-free optimization methods to search for optimal continuous prompts. RLPrompt (Deng et al., 2022) and TEMPERA (Zhang et al., 2022a) use reinforcement learning to find optimal discrete prompts. However, these methods require many queries to LMs, resulting in low computational efficiency. PromptBoosting (Hou et al., 2023) constructs numerous weak learners by pairing the prompt pool generated by T5 with the output distribution of the LMs and then integrates these weak learners using the AdaBoost algorithm. It requires a larger LMs to generate the prompt pool. To this end, kNN Prompting (Xu et al., 2022a) introduces a non-parametric memory module and

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Code: github.com/cuteyuqing/MuSKPrompt

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achieves excellent performance in text classification tasks. The memory module, storing knowledge from downstream tasks, has demonstrated excellent performance in text classification tasks. In Natural Language Processing (NLP), memory models have been applied to various tasks such as named entity recognition and machine translation (Zhong et al., 2022; Fang et al., 2023). However, the application of memory models to few-shot classification in the black-box scenario remains unexplored.

The term "multi-scale" in this paper is referenced from previous works (Huang et al., 2023a; Lei et al., 2023). Moreover, previous works (Liu et al., 2022b; Min et al., 2022c) have demonstrated that prompts composed of more examples can assist LMs in learning deeper knowledge. Wang et al. (2023) demonstrate that in shallow layers, label words accumulate information from demonstrations to form semantic representations, while deep layers integrate information from these label words. Based on these insights, we propose MuSKPrompt, a novel non-parametric memory-augmentation method. Multi-scale prompts allow LMs to extract deep and shallow instance-level and class-level knowledge. We store this knowledge in a memory bank and accomplish text classification tasks through a scoring module. Experimental results demonstrate that MuSKPrompt achieves competitive performance in few-shot text classification tasks in the black-box scenario. Importantly, because it doesn't require training to find optimal prompts, it simply stores instance-level knowledge obtained through fewer than 10 API calls for each instance, as shown in Table 1. Compared to RLPrompt, BBT, and BBTv2, our prompts are interpretable, meaning prompts can be understood by humans(Zhang et al., 2022a).

The contributions of this paper can be summarized as follows:

- We propose a non-parametric memory model structure with multiple scales, achieving competitive performance with fewer than ten calls to LMs.
- We introduce multi-scale prompts that capture deep and shallow knowledge from LMs.
- We design a memory bank that stores instance-level and class-level knowledge at different scales.
- We propose an effective scoring module synthesizing knowledge from different scales and levels.

2 Related Work

Prompt-Based learning With the scaling of language models(Radford et al., 2019; Brown et al., 2020), there are emergent capabilities for language modeling in various tasks. GPT-3 demonstrates remarkable few-shot learning capabilities, efficiently performing downstream tasks through a few in-context demonstrations (Brown et al., 2020; Liu et al., 2022b; Dong et al., 2022). Subsequently, other forms of prompt-based learning have emerged as new approaches to adapting pre-trained language models for downstream tasks, becoming a new paradigm in NLP (Liu et al., 2023). Optimization methods for continuous prompts treat prompts as embeddings that can be optimized efficiently (Liu et al., 2022a). Prefix-tuning (Li and Liang, 2021) inserts continuous prompt embeddings into each layer of LMs. P-tuning (Liu et al., 2022c) utilizes a BiLSTM network to output continuous prompts embedding. PPT (Gu et al., 2022) found that prompt-based fine-tuning is less effective in a few-shot learning setting, and initializing the prompt with pre-trained prompts can achieve superior performance.

Despite the effectiveness of the above methods in achieving competitive performance with minimal parameter updates, they need access to the gradient information inside LMs. Calculating gradients requires significant computational overhead and is not allowed in the black-box scenario. Therefore, BBT (Sun et al., 2022b) and BBTv2 (Sun et al., 2022a) employ the gradient-free CMA evolution algorithm to optimize continuous prompts. Clip-Tuning (Chai et al., 2022) adopts diverse subnetworks to obtain a mixed reward and thus optimize continuous prompts. Moreover, recent developments include optimization algorithms for discrete prompts in the black-box scenario. BDPL (Diao et al., 2022) adopts a variance-reduced policy gradient algorithm to estimate LMs gradients in the categorical distribution of each discrete prompt, achieving prompt tuning through reinforcement learning. RLPrompt (Deng et al., 2022) optimizes prompt tokens through reinforcement learning, using downstream task performance as a reward. TEMPERA (Zhang et al., 2022a) employs reinforcement learning at the testing phase to optimize various prompt components such as contextual examples and instructions. GrIPS (Prasad et al., 2023) performs discrete prompt editing at the phrase level for prompt tuning. TreePrompt(Singh et al., 2023) constructs a decision tree of prompts to adapt to downstream tasks.

In-Context Learning With the success of ICL (Dong et al., 2022; Chen et al., 2023; Zhang et al., 2022b), investigating why ICL is suitable for LLMs across various tasks has become a prominent research topic. Recent work (Xu et al., 2022b; Liu et al., 2022b; Yoo et al., 2022; Min et al., 2022c) found that in-context demonstrations with different numbers and permutations can influence the model's performance on downstream tasks exhibiting significant instability and vulnerability. To address this issue, Vote-k (Hongjin et al., 2022) proposes to select diverse and representative contextual examples to achieve more robust and superior performance. Self-adaptive ICL (Wu et al., 2023) employs a TopK (Gao et al., 2021; Liu et al., 2022b) selection module and a Minimal Description Length ranking module, aiming to select high-quality contextual examples. Furthermore, to exploit the capabilities of LLMs in ICL, Min et al. (2022b) and Chen et al. (2023) introduce meta-learning, which enables LLMs to better adapt to ICL settings. Zhao et al. (2021), Han et al. (2022) and Min et al. (2022a) found significant label bias in ICL, propose to calibrate the bias via either probing the bias or reversing the conditional prediction formulation. Our work adopts contextual examples as prompts to enhance the few-shot learning capability of LMs.

Memory Models Similar methods for constructing memory modules have been proposed in the fields of computer vision (Wu et al., 2018) and NLP (Khandelwal et al., 2019; He et al., 2021; Shi et al., 2022; Huang et al., 2023b; Fang et al., 2023). RETROPROMPT (Chen et al., 2022) constructs an open knowledge base, enabling the model to retrieve relevant examples from the training corpus as enhanced prompts. kNN prompting (Xu et al., 2022a) introduces a retrieval mechanism in ICL, addressing issues related to label bias and context length limitations. Our approach falls into the category of memory models. The main difference is the use of a memory bank that stores class-level and instance-level knowledge at multi-scale to guide LMs during reasoning.

3 Problem Formulation

For notation, we define the training set in few-shot learning as $\mathcal{D}_{\text{train}} = \{x_i, y_i\}_{i=1}^{K\times|\mathcal{Y}|}$, where K represents the number of samples in the k-shot setting, and $|\mathcal{Y}|$ denotes the number of classes in the task. Context examples are sampled from $\mathcal{D}_{\text{train}}$.

Given a test sample $\{x_{\text{test}}, y_{\text{test}}\}$ and context example prompts, the probability produced by LMs $\mathcal{L}$ over the vocabulary set can be represented as:

$$p(v \mid x_{\text{test}}) = \mathcal{L}(v|\mathcal{P}, \pi(x_{\text{test}}, *)) \tag{1}$$

where $\pi(\cdot)$ denotes template-based transformations (see Table 10 in Appendix §B for details), and v represents the probability distribution over the vocabulary set. The output distribution in this paper represents logits generated by the model on placeholders, so $p \in \mathbb{R}^{|\mathcal{V}|\times 1}$ is a $|\mathcal{V}|$-dimensional vector, where $|\mathcal{V}|$ denotes the vocabulary size. We set $\mathcal{P}_i$ to construct prompts containing $i \times |\mathcal{Y}|$ context examples:

$$\begin{aligned}\mathcal{P}_i =&\pi(x_1^1, y_1^1) \oplus \ldots \oplus \pi(x_i^1, y_i^1) \oplus \ldots \oplus \\ &\pi(x_1^{|\mathcal{Y}|}, y_1^{|\mathcal{Y}|}) \ldots \oplus \pi(x_i^{|\mathcal{Y}|}, y_i^{|\mathcal{Y}|})\end{aligned} \tag{2}$$

where $\oplus$ denotes the concatenation operation, and these context examples are selected from $\mathcal{D}_{\text{train}}$.

4 Method

In this section, we introduce MuSKPrompt, a framework that employs multi-scale prompts to encapsulate knowledge, thereby guiding LMs to excel in various few-shot text classification tasks within the black-box scenario. The primary objective of MuSKPrompt is to extract knowledge at both the class and instance levels from context examples across multiple scales. The non-parametric memory bank stores this knowledge at multiple scales and varying levels to enhance the diversity of the knowledge base. Finally, the scoring module utilizes this enriched few-shot knowledge to complete classification tasks. As shown in Figure 1, MuSKPrompt consists of the following modules.

4.1 Memory Bank for a Single Scale

We primarily discuss the construction process of the memory bank at a single scale. This memory bank is designed to store the output distributions of LMs for all samples in the training set $\mathcal{D}_{\text{train}}$ (i.e., instance-level knowledge). For each sample x_i ($\{x_i, y_i\} \subset \mathcal{D}_{\text{train}}$), we concatenate it to the prompt

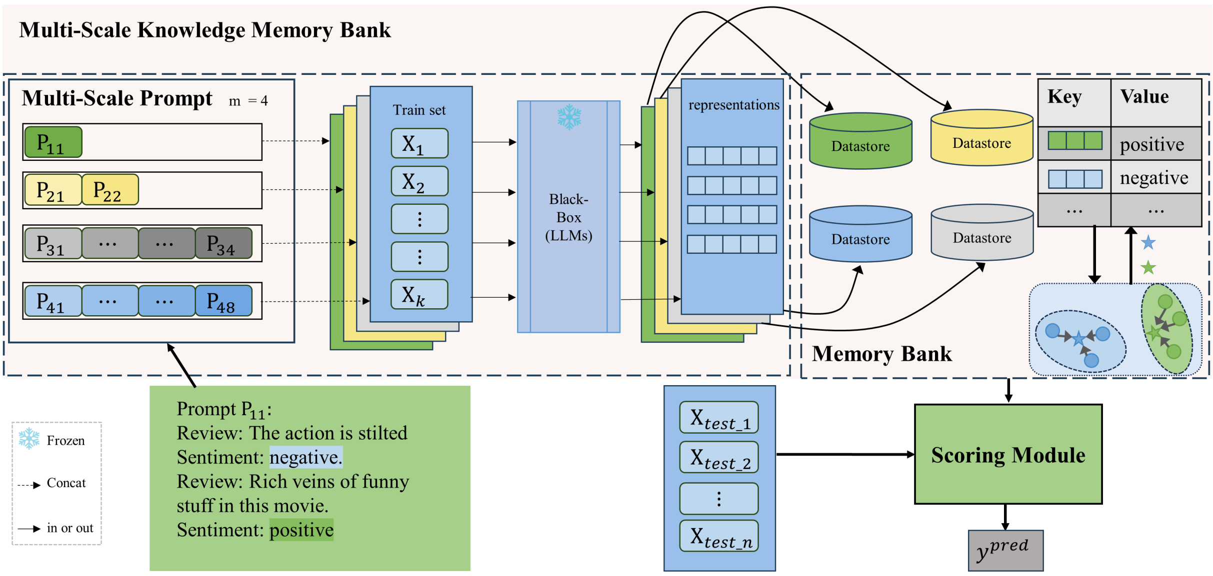


Figure 1: Overview of MuSKPromt. LLMs are frozen and inaccessible to internal parameters and gradient information. Knowledge is extracted using prompts of four different scales ($m = 4$), and stored in various datastores constituting the memory bank. P_{ic} represents the prompt at the i-th scale, where c denotes the number of examples selected from each class. The bottom-left illustrates an example of a prompt with a scale size of 1.

$\mathcal{P}_c$, where c indicates the number of context examples connected for each category. The prompt $\mathcal{P}_c$ aids LMs in extracting instance-level knowledge $p(v \mid x_i)$ for downstream tasks. Specifically, we denote the memory bank as $\mathcal{M}$, which contains key-value pairs corresponding to the output representation $\boldsymbol{k}_i$ and labels y_i of each sample i.e., $\{\boldsymbol{k}_i, y_i\}$. The memory bank $\mathcal{M}$ stores instance-level knowledge, with the value corresponding to the sample's label y_i and the key representing instance-level knowledge (Xu et al., 2022a):

$$\boldsymbol{k}_i = p(v \mid \mathcal{P}_c, x_i) \tag{3}$$

The memory bank should not only store instance-level knowledge but also class-level knowledge. Instance-level knowledge contributes to understanding unique aspects of each example, such as specific content and tone. Class-level knowledge aids in comprehending common features within the same category, such as overall themes and concepts. Combining both facilitates more accurate classification. Therefore, we introduce class-level knowledge to the memory bank:

$$\boldsymbol{k}_j^{\text{cls}} = \frac{\sum_i^{|\mathcal{M}|} \boldsymbol{k}_i \mathbb{1}(y_i = j)}{\sum_i^{|\mathcal{M}|} \mathbb{1}(y_i = j)} \tag{4}$$

where j denotes the category, and $|\mathcal{M}|$ represents the number of instance-level representations in the memory bank at a single scale.

4.2 Multi-Scale Knowledge Memory Bank

The memory bank includes instance-level knowledge and class-level knowledge through equations (3) and (4). However, in few-shot settings, the memory bank can store only limited knowledge due to the scarcity of training samples. Additionally, Cífka and Liutkus (2023) perceive that Prompts with longer contexts are more likely to reveal information about the target text that is not captured by prompts with shorter contexts. Liu et al. (2022b) and Min et al. (2022c) found that the prompt composed of more examples can learn deeper knowledge.

Inspired by this, we design multi-scale prompts to aid LMs in extracting knowledge at deep and shallow levels for constructing the memory bank. We stratify and select as diverse examples as possible from each category to form the prompt at different scales. We define $\mathcal{M}_{m,i}$ to represent the i-th key-value pairs storing knowledge in the case of prompt scale c for $c \in \{2^0, 2^1, \ldots, 2^{m-1}\}$ (where m denotes the scale dimension). The corresponding key is defined as follows:

$$\boldsymbol{k}_{m,i} = p(v \mid \mathcal{P}_c, x_i), \quad \text{s.t.} \quad c = 2^{m-1} \tag{5}$$

Our approach increases the amount of knowledge stored in the memory bank by a factor of m. Further details are shown in Algorithm 1, as shown in Appendix §6. Intuitively, it can be seen as a bank that enhances multi-scale diversity knowledge under few-shot learning conditions. Context examples are arranged, making the computation efficient. It is worth noting that the above method can also be applicable to other memory models (Xu et al., 2022a). We conduct a preliminary exploration in Section §5.

4.3 Non-Parametric Scoring Module

We introduce a completely non-parametric scoring module. It guides LMs to calculate the score matrix S for each category based on the different levels of knowledge stored in the memory bank. For simplicity, we first calculate S under a single-scale prompt $\mathcal{P}_1$, corresponding to the memory bank denoted as $\mathcal{M}_1$. Firstly, during the inference phase, for each test sample x_{test}, we compute the output distribution p_{test} using equation (3). p_{test} and $\boldsymbol{k}_i$ represent output probabilities over the entire vocabulary, potentially containing numerous other uninterpretable pieces of information. For this reason, we propose using the Kullback-Leibler (KL) divergence to measure the information difference between the two to generate the corresponding scores. We utilize the instance-level knowledge stored in $\mathcal{M}_1$ to compute instance-level scores for x_{test}:

$$\begin{aligned} D_i^{ins} =& D_{KL}(p_{\text{test}}||\boldsymbol{k}_i) \\ =& \sum_{v=0}^{|\mathcal{V}|} p_{\text{test}}(v|\mathcal{P}_1, x_{\text{test}}) \log \frac{p_{\text{test}}(v|\mathcal{P}_1, x_{\text{test}})}{p(v|\mathcal{P}_1, x_i)} \\ & \text{s.t.} \quad D^{ins} \in \mathbb{R}^{|\mathcal{M}_1|\times 1}, \forall i \in [|\mathcal{M}_1|] \end{aligned} \tag{6}$$

$$S_j^{ins} = \frac{\sum_{i \in \text{Top}^k(D^{ins})} 1}{\sum_{i \in \text{Top}^k(D^{ins})} D_i^{ins}} \quad \text{s.t.} \quad y_i = j \tag{7}$$

where $\text{Top}^k(D^{ins})$ denotes the set of the top k values in D^{ins}, and $S^{ins} \in \mathbb{R}^{|\mathcal{Y}|\times 1}$ represents scores in different categories. Here, the score corresponds to the reciprocal of the KL divergence.

Similarly, the formula for class-level scores for the test sample is as equation:

$$S_j^{cls} = \frac{1}{D_{KL}(p_{\text{test}}||\boldsymbol{k}_j^{\text{cls}})} \tag{8}$$

Next, we combine the scores at both instance and class levels with the following formula:

$$S = (1-\lambda)\frac{S^{ins}}{\|S^{ins}\|_1} + \lambda\frac{S^{cls}}{\|S^{cls}\|_1} \tag{9}$$

where λ denotes the weight of class-level knowledge, and $\|S\|_1$ denotes the corresponding $L1$ norm. Adjusting the value of λ determines the degree of attention given to class-level knowledge. Finally, we perform a weighted average of the scores at different scales:

$$S = \sum_{i=0}^{m} d_i \cdot S_i \tag{10}$$

where m indicates the number of different scales. After obtaining the final score matrix S, we determine the predicted category of the test sample as the category with the highest score:

$$y_{\text{pred}} = \underset{y_i \in [|\mathcal{Y}|]}{\arg\max} S \tag{11}$$

5 Experiments

5.1 Datasets and Tasks

For comparability, we follow the same settings as kNN Prompting (Xu et al., 2022a), including five different random seeds and dataset splits. GPT-2 (Radford et al., 2019) model is our primary language model in this study. Our main experiments focus on few-shot learning across seven established text classification datasets. These datasets include SST-2 (Socher et al., 2013), MPQA (Wiebe et al., 2005), CR (Hu and Liu, 2004), MR (Pang and Lee, 2005), TREC (Voorhees and Tice, 2000), RTE (Dagan et al., 2006), and SUBJ (Pang and Lee, 2004). Additionally, other experiments involve four text classification datasets: AGNews (Zhang et al., 2015), CB (Marneffe et al., 2019), MRPC (Dolan and Brockett, 2005), and DBPedia (Zhang et al., 2015). The statistical details of datasets can be found in Table 8 in Appendix §6. For each dataset, we design intuitive prompt templates (see Table 10 in Appendix §6).

Our goal is to evaluate the performance of MuSKPrompt in a few-shot setting within the black-box scenario. We randomly extract k examples from each class of the original training set to construct the k-shot training set $\mathcal{D}_{\text{train}}$. For BBT (Sun et al., 2022b), BBTv2 (Sun et al., 2022a) and RLPrompt (Deng et al., 2022), prompts are selected based on the best performance on the validation set. Unlike them, our method does not require a validation set as it does not involve parameter optimization.

Backbone Models In our main experiments, we choose the GPT2-XL as our backbone model for two reasons: (1) Previous memory models (Xu et al., 2022a) have used GPT2-XL as the backbone model, and knowledge-guided methods are more effective on larger models. (2) Currently, LLMs available in the black-box manner are mainly autoregressive.

5.2 Baselines

To comprehensively evaluate our method, we select various types of baselines. We select the best black-box optimization algorithms, such as BBT, BBTv2, and RLPrompt as baselines. Furthermore, we include parameter-free ICL, calibration-enhanced ICL, and the memory model kNN Prompting as baselines. Baselines also include gradient-based fine-tuning methods and recent tree-based prompting methods like TreePrompt. Implementation details of these baselines can be found in Appendix §C. The overview of these methods is as follows: (1) Fine-tuning represents standard fine-tuning of GPT2-XL under few-shot settings. (2) BBT utilizes the CMA evolution algorithm to optimize continuous prompts. (3) BBTv2 improves the performance of BBT by inserting continuous prompts in front of each layer of LMs. (4) RLPrompt (Deng et al., 2022) utilizes a smaller generative model, distilGPT2, as the policy network. Subsequently, it optimizes the policy network to discover the best prompts through soft Q-learning (Guo et al., 2021). (5) ICL uses a simple combination of examples as prompts to guide model classification. (6) Noisy Channel (Min et al., 2022a) represents ICL formulated as the probability of computing inputs given the condition of labels. (7) TreePrompt(Singh et al., 2023) employs decision trees as a method to adapt LMs to specific tasks without fine-tuning the model. (8) kNN Prompting (Xu et al., 2022a) infers by storing representations of few-shot samples and using a nearest neighbor algorithm. We reproduce all baseline methods using official experimental settings and hyper-parameters or adopt published results. Some baselines (Zhang et al., 2022a; Hou et al., 2023) are not included as their official implementations are unavailable, and the selected baselines above are competitive.

5.3 Implementation Details

Experiments are conducted on a single NVIDIA RTX A6000 GPU using PyTorch (Paszke et al., 2019). This section provides a brief overview of the main hyper-parameters for our method. For our approach, we set the weight for class-level scores as $\lambda = 0.5$ and for instance-level scores as $(1 - \lambda)$. We choose the number of scales as four by default, considering that GPT-2 XL can handle a maximum text sequence length of 1024 tokens (on RTE and TREC datasets, we set the number of scales as 3). To emphasize the effectiveness of multi-scale knowledge, we do not learn weights for different scale knowledge but simply average them.

5.4 Results

Overall Comparison We present the results of few-shot text classification in Table 2. Our method outperforms all baselines on average performance across seven datasets. Moreover, we achieve the best performance on five datasets, except for the RTE dataset and the TREC dataset. Notably, our method achieves these results without training any parameters, demonstrating its high computational efficiency. Additionally, our method makes fewer than ten calls to LMs in Table 1. This further highlights our approach's robust few-shot learning capability in the black-box scenario. Compared to BBT, BBTv2, and RLPrompt, our prompts are interpretable. kNN Prompting also requires no parameter training and achieves competitive performance. Our method outperforms kNN Prompting by 5 points on average performance across seven datasets. Our method also exhibits better robustness. This suggests that, in the black-box scenario, our method achieves better performance and demonstrates more stability. Moreover, our method does not rely on validation set tuning to select the best results.

To further evaluate the effectiveness of our approach, we also include GPT2-XL fine-tuning as a comparison. Our method performs less than fine-tuning on the SUBJ, RTE, and TREC datasets. Our method primarily guides LMs in text classification tasks through the memory of downstream task knowledge, and the intrinsic capabilities of LMs determine its upper limit. Because the memory model without parameter optimization lacks in-depth exploration of the deep capabilities of LMs, or the intrinsic capabilities of GPT2-XL are still insufficient. Our method may be relatively disadvantaged in challenging NLI tasks, such as RTE. However, the average performance of our method outperforms fine-tuning by 8.9 points in few-shot classification tasks. Moreover, our method shows greater robustness on all seven datasets than fine-tuning. Interestingly, on some seeds of the SST-2 and CR datasets, our method's performance on a 16-shot training set is close to or even higher than

Method	Trainable Params	SST2 acc	MPQA acc	CR acc	SUBJ acc	MR acc	RTE acc	TREC acc	AVG acc
Fine-tuning	**1.5B**	59.9(10.8)	65.4(2.9)	73.0(10.7)	88.9(2.5)	74.5(5.2)	52.6(3.0)	79.8(5.9)	70.6
BBT	**25K**	76.6(4.5)	78.5(1.6)	82.7(1.4)	72.9(3.6)	76.6(4.3)	51.6(2.2)	38.8(8.8)	68.2
BBTv2	**1.2M**	<u>89.5(1.3)</u>	<u>84.1(1.4)</u>	<u>85.8(1.9)</u>	80.1(1.9)	82.1(3.1)	51.0(4.6)	48.3(4.9)	74.4
RLPrompt	**3M**	75.2(3.3)	62.3(5.6)	72.5(7.4)	75.6(4.1)	66.5(14.0)	50.9(2.6)	50.6(3.0)	64.8
ICL	**0**	67.7(10.8)	77.6(7.6)	73.3(11.9)	75.5(11.4)	61.8(5.6)	<u>53.0(1.7)</u>	52.0(5.1)	65.8
Noisy Channel	**0**	84.4(10.8)	70.4(6.2)	83.7(3.3)	62.4(7.2)	79.6(2.7)	52.5(4.8)	54.2(7.8)	69.6
TreePrompt	**-**	83.6	83.9	80.6	76.2	78.8	**54.9**	**72.8**	<u>75.8</u>
kNN Prompting	**0**	88.8(2.1)	68.2(7.6)	80.1(4.7)	<u>80.9(4.0)</u>	<u>84.8(2.7)</u>	51.2(5.4)	67.7(4.9)	74.5
Ours	**0**	**90.2(0.8)**	**84.4(1.9)**	**89.4(1.1)**	**83.6(1.2)**	**87.0(1.5)**	52.3(1.9)	<u>69.6(4.1)</u>	**79.5**

Table 2: Overall comparison on various 16-shot text classification tasks. All methods use GPT2-XL as the backbone model for a fair comparison. We report the average performance and standard deviation across five random seeds(Xu et al., 2022a). In each track, the best results are highlighted in bold, and the second-best results are marked with underlines.

the final performance of fine-tuning on the entire training dataset.

Data Efficiency for MuSKPrompt To illustrate the data efficiency of our method, we compare the performance of MuSKPrompt with fine-tuning across different-sized training sets. Additionally, we include the performance of other baselines under a 16-shot setting. As shown in Figure 2, it is evident that our method achieves competitive performance on the SST-2 dataset while utilizing merely one thirty-two percent of the data required for fine-tuning. Similarly, on the MR dataset, our method demonstrates an eightfold increase in data utilization efficiency compared to fine-tuning. On the CR dataset, we approach the best performance of fine-tuning using only $(64 \times |\mathcal{Y}|)$ training samples. Furthermore, we notice an abnormal performance drop in the fine-tuning method when the training set size reaches 512-shot for the CR dataset. The CR dataset has a maximum of 368 samples for one category, and we attribute this anomaly to the class imbalance in the CR dataset. Class imbalance leads to fine-tuning overfitting on the majority class, resulting in decreased performance. It is worth noting that our method not only eliminates the need for parameter optimization but also alleviates the issue of class imbalance. For more detailed results, refer to Figure 3 in Appendix §D.

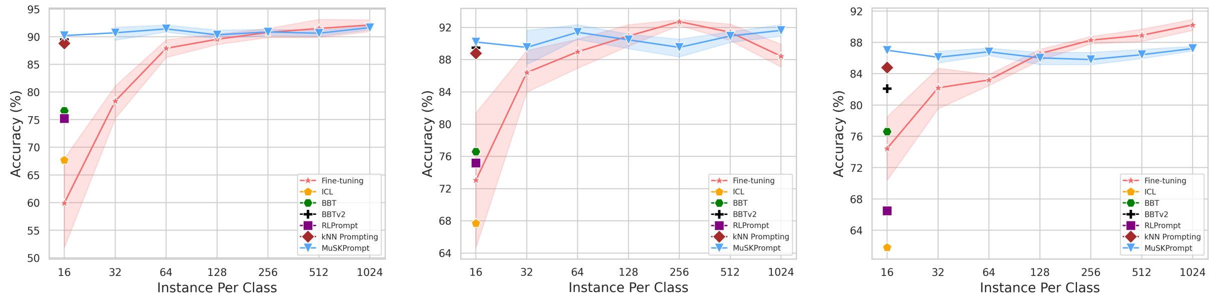
Effect of Model Scale It has been demonstrated that LMs with larger parameter sizes possess stronger capabilities (Kaplan et al., 2020; Wei et al., 2022). The performance of our method is positively correlated with the intrinsic capabilities of the backbone model. To validate this, we conduct experiments using GPT-2 models of different sizes, i.e., GPT2-SMALL, GPT-MEDIUM, GPT2-LARGE, and GPT2-XL, corresponding to 124M, 335M, 744M, and 1.5B parameters. As shown in Table 3, in few-shot text classification tasks, MuSKPrompt performs better with larger LMs than smaller ones. Additionally, MuSKPrompt gains more benefits on larger LMs when the parameter size is relatively small.

GPT2 Params	SST-2	CR	MRPC	TREC
124M	59.1	70.6	48.0	56.6
355M	72.3	83.4	51.7	62.5
744M	85.8	88.1	59.5	69.2
1.5B	**90.2**	**89.4**	**66.0**	**69.6**

Table 3: Results of MuSKPrompt in the 16-shot setting across different scales of GPT-2.

Effect of Multi-Scale Prompt It has demonstrated that prompts with more examples can help LMs learn deeper knowledge, and vice versa (Liu et al., 2022b; Min et al., 2022c). To validate that prompts of different scales enable the model to learn knowledge at different depth levels, we compare our method with multiple prompts of the same scale. Table 4 shows a clear advantage of multi-scale prompts. It confirms that LMs learn complementary deep and shallow knowledge based on prompts of different scales. As our method's performance depends on stored knowledge, multi-level class-level and instance-level knowledge contributes to guiding LMs for better classification.

To further investigate the role of the multi-scale knowledge bank, we incorporate it into the previous kNN Prompting method. The results are shown in



(a) Performance on SST-2 (b) Performance on CR (c) Performance on MR

Figure 2: Data efficiency for MuSKPrompt. We compare the data efficiency of MuSKPrompt with fine-tuning in few-shot learning, and report the performance of MuSKPrompt and fine-tuning in different training set sizes.

Method	SST-2	CR	TREC	MRPC
Multi-prompt-2	88.2(1.3)	88.4(1.4)	69.0(3.6)	56.9(13.8)
Multi-prompt-3	89.1(1.7)	89.1(2.0)	65.5(4.3)	49.4(10.7)
Multi-prompt-4	89.1(3.2)	89.0(2.2)	66.0(4.0)	59.6(4.7)
MuSKPrompt	**90.2(0.8)**	**89.4(1.1)**	**69.6(4.1)**	**66.0(7.3)**

Table 4: Performance of multi-scale prompts and multiple prompts of the same scale in the 16-shot setting. Multi-prompt-m indicates that the number of examples under each prompt is ($|\mathcal{Y}| \times m$).

Table 5, demonstrating that the multi-scale knowledge bank not only enhances the effectiveness of our method but also improves the performance of other memory models such as kNN Prompting.

Method	SST-2	MPQA	CR	RTE
kNN Prompting	88.8	68.2	80.1	51.2
w/ MSP	**89.8**	**82.4**	**88.8**	**52.3**
MuSKPrompt(w/o MSP)	89.5	80.6	87.5	50.8
MuSKPrompt	**90.2**	**84.4**	**89.4**	**52.3**

Table 5: Performance in the 16-shot setting. "w/ MSP" denotes the inclusion of multi-scale prompts, while "w/o MSP" denotes the removal of multi-scale prompts.

Effect of the Scale Dimension In our main experiments, we default the scale dimension to 4, without learning different weights for each scale. Intuitively, a greater number of different scales bring more complementary deep and shallow knowledge. However, considering the limitations of the maximum sequence length for GPT-2XL input and the few-shot learning setting, the maximum value for the scale dimension m is set to 4. As shown in Table 6, a larger scale dimension achieves more significant performance improvements. Moreover, the benefits of increasing the scale dimension are more significant when the task is more challenging such as on the MRPC task.

Method	SST-2	MR	CR	MRPC
MuSKPrompt-2	87.1	84.0	84.7	46.7
MuSKPrompt-3	89.4	86.4	88.3	52.0
MuSKPrompt-4	**90.2**	**87.0**	**89.4**	**66.0**

Table 6: Performance of MuSKPrompt with different scale dimensions in the 16-shot setting. MuSKPrompt-m indicates the scale dimension is m.

Effect of Class-Level Knowledge We consistently employ a fixed value of 0.5 for the class-level weight, denoted as λ, without any tuning. Our experiments aim to explore the impact of class-level knowledge on performance. Class-level knowledge demonstrates its significant impact in the few-shot text classification tasks illustrated in Table 7.

Method	SST-2	MR	CR	MPQA
MuSKPrompt(w/o cls)	89.8	86.4	89.1	82.0
MuSKPrompt	**90.2**	**87.0**	**89.4**	**84.4**

Table 7: Performance of the model on SST-2, MR, CR, and MPQA datasets. "w/o cls" indicates without incorporating class-level knowledge.

6 Conclusion

In this paper, we present MuSKPrompt, a novel memory-augmented framework. It does not require access to the internal information of LMs and achieves remarkable performance with few-shot training samples. MuSKPrompt acquires instance-level and class-level knowledge of various depths through multi-scale prompts. This knowledge is then stored in a memory bank. The scoring module efficiently performs classification tasks using the stored knowledge, without training any parameters. The significant improvements brought solely by memory knowledge will encourage future memory model solutions for few-shot classification in the black-box scenario.

Limitations

The limitations of this work are summarized as follows: (1) We conducted experiments on 11 language understanding tasks (including sentiment analysis, natural language inference, and topic classification) using the GPT-2 backbone model. Although MuSKPrompt achieved commendable results in the majority of these tasks, it did not show a distinct advantage over full-model fine-tuning, especially in challenging tasks like natural language inference. This could be due to the lack of parameter optimization in MuSKPrompt or the inherent limitations in GPT-2 XL's reasoning capabilities. Enhancing performance by efficiently learning weight parameters might address this issue. We leave the optimization of parameters in the scoring module as future work. Furthermore, exploring MuSKPrompt's effectiveness in chain-of-thought, generation tasks and Named Entity Recognition remains an area to be investigated. (2) Experiments demonstrate that relying solely on memory knowledge can yield competitive performance. We hypothesize that improvements in knowledge extraction prompts, such as hierarchical prompts, could lead to further enhancements. This aspect is reserved for future work.

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A Datasets

Dataset information is detailed in Table 8. For fair comparison, the main experiments in this paper adopt a 16-shot setting, where 16 samples are drawn from each class.

B Templates

Regarding the use of templates, please refer to Table 10 (adapted from Xu et al. (2022a) and (Lu et al., 2022)). They are intuitively designed, and the proposed methods should exhibit robustness with respect to the template chosen.

C Implementation Details

For full model fine-tuning, the GPT-2 XL backbone model is loaded using the Huggingface transformers library (Wolf et al., 2019). The hyperparameters set follow previous work (Xu et al., 2022a), with a learning rate of 1e-5, batch size of 16, and a training step of 125. For the RTE dataset, we set the batch size to 8 to prevent out-of-memory (OOM) issues. For RLPrompt (Deng et al.,

Dataset	$\|\mathcal{Y}\|$	Data split	Task
SST-2	2	67k/256	sentiment
MPQA	2	8.6k/256	sentiment
CR	2	1.7k/256	sentiment
MR	2	8.6k/256	sentiment
TREC	6	5.5k/256	topic
RTE	2	2.5k/256	NLI
SUBJ	2	8k/256	subjectivity
AGNews	4	120k/256	topic
CB	3	250/56	NLI
MRPC	2	3.7k/256	paraphrase
DBPedia	14	500k/256	topic

Table 8: Details of datasets. The dataset split is adapted from Lu et al. (2022) and Xu et al. (2022a).

2022), BBT (Sun et al., 2022b), and BBTv2 (Sun et al., 2022a), we use their official implementations with their default hyper-parameters. Notably, for RLPrompt, due to its lower efficiency, we set its training epochs to 1200 instead of 12000, as suggested in (Hou et al., 2023). For other baselines, we refer to the results reported in the papers on kNN prompting(Xu et al., 2022a) and TreePrompt(Singh et al., 2023).

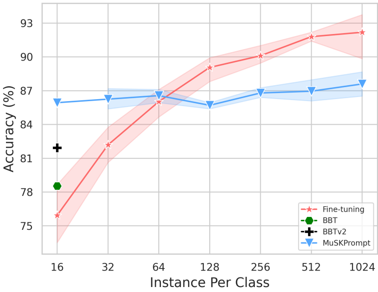
D Additional Results

Data Efficiency for MuSKPrompt We compare the performance of MuSKPrompt with GPT-2 XL fine-tuning on larger data scales. The hyper-parameters for model fine-tuning are set in accordance with previous work (Xu et al., 2022a). We set a learning rate of $1e-5$, with a batch size of 16, and training steps of 125, 250, or 500, respectively for $k \in \{32, 64\}, \{128, 256\}, \{512, 1024\}$ (k denotes the number of samples selected from each class.). To prevent OOM issues, the batch size is adjusted to 8 for the AGNews, RTE, and MRPC datasets. For the CB and SNLI datasets, the batch size is adjusted to 4, and for the DBPedia dataset, it is adjusted to 2. In the AGNews and CB datasets, we also include baselines from BBT and BBTv2. For the TREC dataset, all baselines except Noisy Channel are included. As shown in Figure 3, our method exhibits higher data efficiency in few-shot settings on the AGNews, MRPC, and DBPedia datasets compared to full model fine-tuning. Furthermore, the performance of our method improves with increasing data scale across all datasets. On the TREC and CB datasets, our results are relatively weaker, as full model fine-tuning represents the theoretical upper limit of our approach.

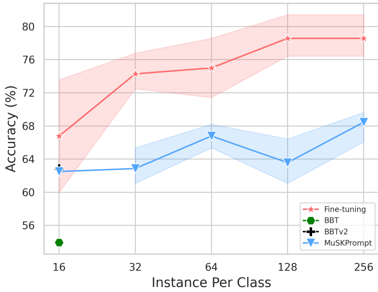
Effect of Model Scale To further demonstrate the effectiveness of our method, we applied it to a larger language model, OPT. As shown in Table 9, results indicate that larger language models yield better performance for our method. Furthermore, our method outperforms the baseline method kNN Prompting(Xu et al., 2022a) even in larger language models.

Algorithm 1 Multi-Scale Knowledge Memory Bank

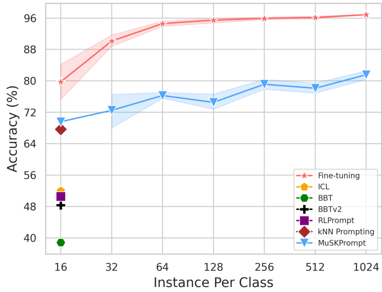
Input: Language Model $\mathcal{L}$,
Training set $\mathcal{D}_{\text{train}}$,
The scale dimension m
Output: Memory bank $\{\mathcal{M}\}_{i=1}^{m}$
Set up template-based transformation $\pi(\cdot)$.
for $t = 1$ to m **do**
  Get number of context examples $c = 2^{t-1}$
  Stratified select diverse samples $\mathcal{B} = \{x_i, y_i\}^{|\mathcal{Y}|\times c} \sim \mathcal{D}_{\text{train}}$
  Get prompt $\mathcal{P}_c \xleftarrow{\text{Eq. (2)}} \mathcal{B}$
  for each $\{x_i, y_i\}$ in $\mathcal{D}_{\text{train}}$ **do**
    Get instance-level representation $\boldsymbol{k}_i = \mathcal{L}(\mathcal{P}_c, x_i)$
    Update: $\mathcal{M}_t \leftarrow \{\boldsymbol{k}_i, y_i\}$
  end for
  Update: $\mathcal{M}_t \xleftarrow{\text{Eq. (4)}} \{\boldsymbol{k}^{\text{cls}}, \text{cls}\}$
end for
return Memory bank $\{\mathcal{M}\}_{i=1}^{m}$



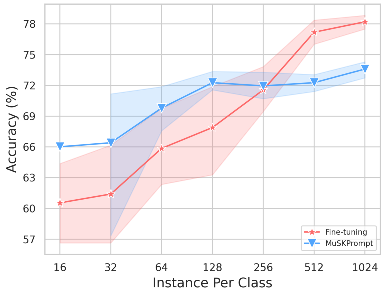
(a) Performance on AGNews



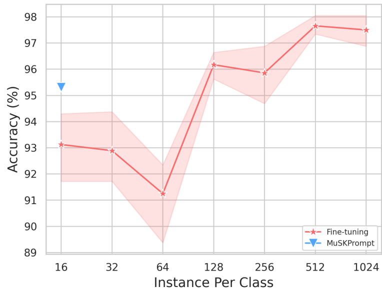
(b) Performance on CB



(c) Performance on TREC



(d) Performance on MRPC



(e) Performance on DBPedia

Figure 3: Data efficiency for MuSKPrompt on AGNews, CB, TREC, MRPC and DBPedia datasets.

Model	Method	SST2	CR	MR	AGNews	RTE	TREC
OPT-2.7B	kNN Prompting	87.7	89.9	91.2	84.4	52.8	75.1
OPT-2.7B	MuSKPrompt	**93.4**	**91.8**	**91.7**	**86.3**	**53.5**	**75.4**
OPT-6.7B	kNN Prompting	92.7	91.0	91.8	83.0	55.2	71.2
OPT-6.7B	MuSKPrompt	**94.1**	**91.4**	**91.8**	**86.3**	**55.9**	**76.2**

Table 9: Results of MuSKPrompt and kNN Prompting in the 16-shot setting across different scales of OPT.

Dataset	Template	Label words
SST-2	Review: finds amusing juxtapositions that justify his exercise . Sentiment: positive Review: the story and structure are well-honed . Sentiment:	negative, positive
MPQA	Review: with the help of the almighty god Sentiment: positive Review: elevates its image in international society Sentiment:	negative, positive
CR	Review: 5 stars all the way ! . Sentiment: positive Review: new cds almost always began skipping after a few plays . Sentiment:	negative, positive
MR	Review: dismally dull sci-fi comedy . Sentiment: negative Review: enjoy it for what it is ; you can hate yourself later . Sentiment:	negative, positive
TREC	Question: What type of currency is used in China ? Type: entity Question: What French province is cognac produced in ? Type:	description, entity, expression, human, location, number
RTE	premise: The death penalty is not a deterrent. hypothesis: Capital punishment is a deterrent to crime. prediction: false premise: Capital punishment acts as a deterrent. hypothesis: Capital punishment is a deterrent to crime. prediction:	fasle, true
SUBJ	Input: a counterfeit 1000 tomin bank note is passed in a bazaar . Type: objective Input: the film is to be produced by jules , melina's husband . Type:	subjective, objective
AGNews	Input: SI.com. ST. LOUIS (Ticker) – The Cincinnati Reds continue to find new ways to lose to the St. Louis Cardinals. Type: sports Input: IBM Chips May Someday Heal Themselves. New technology applies electrical fuses to help identify and repair faults. Type:	world, sports, business, technology
CB	premise: Clever. Klug means clever. Would you say that Abie was clever? hypothesis: Abie was clever prediction: neither premise: A: Your turn. B: Okay. Uh, I don't think they should abolish it. hypothesis: they should abolish it prediction:	false, true, neither
MRPC	premise: The notification was first reported Friday by MSNBC . hypothesis: MSNBC.com first reported the CIA request on Friday . prediction: yes premise: Columbia broke up over Texas upon re-entry on Feb. 1 . hypothesis: Columbia broke apart in the skies above Texas on Feb. 1 . prediction:	no, yes
DBPedia	Input: Geoffrey D.Falksen (born July 31 1982) is an American steampunk writer. Type: artist Input: Arbach (Wildebach) is a river of North Rhine-Westphalia Germany. Type:	company, school, artist, athlete, politics, transportation, building, nature, village, animal, plant, album, film, book

Table 10: The template for ICL. These represent the minimum conditions, with only one demonstration example for illustration.