# Improving Few-Shot Performance of Language Models via Nearest Neighbor Calibration

# Feng Nie<sup>‡</sup>, Meixi Chen<sup>§</sup>\*, Zhirui Zhang<sup>‡</sup>†, Xu Cheng<sup>‡</sup>

‡Interactive Entertainment Group, Tencent Inc, Shenzhen, China §University of Cambridge ‡Tencent AI Lab

‡{jannie,alexcheng}@tencent.com §mc2125@cam.ac.uk ‡zrustc11@gmail.com

#### **Abstract**

Pre-trained language models (PLMs) have exhibited remarkable few-shot learning capabilities when provided a few examples in a natural language prompt as demonstrations of test instances, i.e., in-context learning. However, the performance of in-context learning is susceptible to the choice of prompt format, training examples and the ordering of the training examples. In this paper, we propose a novel nearest-neighbor calibration framework for in-context learning to ease this issue. It is inspired by a phenomenon that the incontext learning paradigm produces incorrect labels when inferring training instances, which provides a useful supervised signal to calibrate predictions. Thus, our method directly augments the predictions with a k-nearestneighbor (kNN) classifier over a datastore of cached few-shot instance representations obtained by PLMs and their corresponding labels. Then adaptive neighbor selection and feature regularization modules are introduced to make full use of a few support instances to reduce the kNN retrieval noise. Experiments on various few-shot text classification tasks demonstrate that our method significantly improves in-context learning, while even achieving comparable performance with state-of-theart tuning-based approaches in some sentiment analysis tasks.

#### 1 Introduction

Large-scale pre-trained language models (PLMs), such as BERT and GPT (Devlin et al., 2019; Radford et al., 2018, 2019), have been proven to be fundamental for solving a variety of NLP tasks. Recently, Brown et al. (2020) demonstrate that PLMs can perform few-shot learning when provided a few training examples in a natural language prompt as demonstrations with input sentences, i.e.,

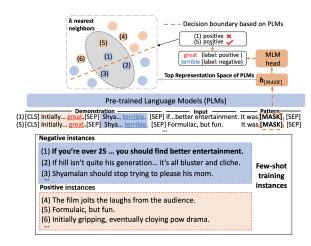


Figure 1: The issue illustration when inferring the label of few-shot training instances themselves via incontext learning. The predictions of in-context learning could conflict with their labels, which indicates the wrong decision boundary provided by PLMs.

in-context learning. Specifically, in the sentiment classification task, we use the template "<TEXT> It was [MASK]." for model prediction, where <TEXT> is the placeholder for the input text and the PLMs are asked to infer verbalizers (e.g., 'great' and 'terrible') for the [MASK] token to score the target labels (e.g., 'positive' or 'negative'). Then each input is further prepended with demonstrations of different sentiments as: "Formulaic, but fun. It was great. [SEP] Shyamalan should stop trying to please his mom. It was terrible. [SEP] <TEXT> It was [MASK].". This style of few-shot learning is appealing because it shows that the model can directly leverage information from few-shot support instances without parameter updates.

Despite promising results and potential benefits, the in-context learning is highly sensitive to the choice of prompting templates and verbalizers, training examples, and even a permutation (ordering) for training examples, causing accuracy to vary from near chance to near state-of-the-art. (Lester et al., 2021; Lu et al., 2022). Another interest-

<sup>\*</sup>This work was done during the second author's internship at Tencent.

<sup>†</sup>Corresponding author.

ing phenomenon is that this approach produces incorrect results when inferring few-shot support instances via in-context learning. As illustrated in Figure 1, given an input text with negative label in the training set (e.g., "If you're over 25 ... you should find better entertainment."), the remaining support instances are converted into demonstrations but PLMs make a contradicting prediction (e.g., "positive") on this input. The level of contradiction varies with different engineered templates and verbalizers. This inconsistency actually provides helpful supervised signals and another orthogonal perspective to improve in-context learning. That is to fully exploit the few-shot learning of PLMs by vertically retrieving small similar support samples to correct the decision boundary of PLMs, rather than horizontally concatenating them with input texts only.

In this paper, we propose a simple and effective nearest-neighbor calibration framework to improve the performance of in-context learning in few-shot text classification tasks. The whole approach is built on the top hidden representations of PLMs, and then directly enhances PLMs with a k-nearest-neighbor (kNN) classifier over a datastore of cached few-shot instance representations and their corresponding labels. In this way, similar training samples of input texts are dynamically retrieved to strengthen or rectify the original prediction distribution provided by PLMs, achieving better model performance and easing the large variance brought by different engineered prompts. Moreover, the performance of this method largely relies on the quality of kNN retrieval, but it may include noise when the inappropriate number of neighbors is adopted or representations produced by PLMs are problematic. We further design adaptive neighbor selection and feature regularization modules to reduce the kNN retrieval noises with the supervision of current few-shot instances: the former module is designed to dynamically decide the number of few-shot instances in the kNN classifier, while the latter module leverages a lightweight network to separate these instances with different labels but similar representations.

We present a systematic evaluation for analyzing few-shot performance on 6 single-sentence and 6 sentence-pair NLP tasks. We observe that given a small number of training examples, (1) our method proves the effectiveness of introducing instance-augmented classification, as it significantly outper-

forms in-context learning, especially superior in single-sentence tasks with 12.8% absolute accuracy improvement on average; (2) the proposed method is able to close the performance gap with tuning based methods in single-sentence tasks.

## 2 Background

Task Formulation. We consider the few-shot adaption of a pre-trained language model  $\mathcal{L}$  on the task  $\mathcal{D}$  with a label space  $\mathcal{Y}$ . task, we assume that the training data  $\mathcal{D}_{\mathrm{train}} =$  $\{(x^i,y^i)\}_{i=1}^{K\times |\mathcal{Y}|}$  only consists of K examples per class, where x represents the input, y is the target label and  $|\mathcal{Y}|$  denotes the number of unique classes. The goal of few-shot adaption is to develop taskagnostic learning strategies on  $\mathcal{D}_{train}$ , and generalize well to an unseen test set  $\mathcal{D}_{test}$ . We additionally assume access to development set  $\mathcal{D}_{\mathrm{dev}}$  with the same size as the training data for model selection and hyper-parameter tuning, as larger validation sets can grant a substantial advantage (Perez et al., 2021). For our experiments, we use 16 training examples (K = 16) and a development set with 16 examples per class for all tasks.

**Prompt-Based Fine-tuning.** The standard fine-tuning has a clear discrepancy between pre-training and fine-tuning phases, where the former is optimized by the prediction of masked tokens in the masked language modelling (MLM) task. An alternative way to eliminate this gap is prompt-based fine-tuning, in which the task is formulated in a cloze-format (Taylor, 1953). In this way, the language model  $\mathcal{L}$  predicts label words with the MLM objective. Specifically, inputs are converted using a pre-defined prompt template  $x_{\text{prompt}} = \mathcal{T}(x)$ , e.g., in the sentiment classification task,  $x_{\text{prompt}}$  is constructed as follow:

$$x_{\mathrm{prompt}} = \texttt{[CLS]} \ x \ \texttt{It was [MASK]}. \texttt{[SEP]}.$$

Then the language model  $\mathcal L$  decides which verbalizer (e.g., 'great' and 'terrible') is most likely for <code>[MASK]</code> in  $x_{\text{prompt}}$ . For the model training, let  $\mathcal M: \mathcal Y \to \mathcal V$  be a mapping from the task label space to words in the vocabulary  $\mathcal V$  of PLMs. The probability of class  $y \in \mathcal Y$  is calculated as:

$$\begin{aligned} p(y|x) &= p_{\mathcal{L}}(\texttt{[MASK]} = \mathcal{M}(y)|\mathcal{T}(x)) \\ &= \frac{\exp(\mathbf{W}_{\mathcal{M}(y)}h_{\texttt{[MASK]}})}{\sum_{\hat{y} \in \mathcal{Y}} \exp(\mathbf{W}_{\mathcal{M}(\hat{y})}h_{\texttt{[MASK]}})}, \end{aligned} \tag{2}$$

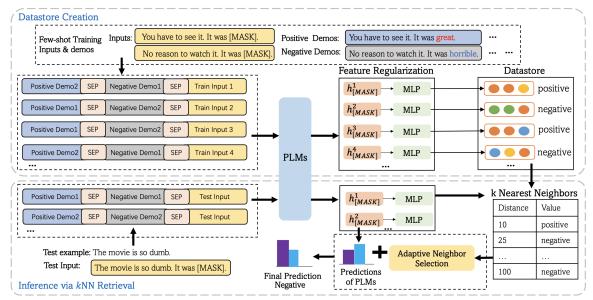


Figure 2: An overview of our nearest neighbor calibration framework (KNN-C) for the sentiment analysis task.

where  $h_{\texttt{EMASK}}$  denotes the hidden vector of EMASK token and  $\mathbf{W}_{\mathcal{M}(y)}$  refers to pre-softmax vector for word  $v \in \mathcal{V}$ . The entire model is trained by minimizing the cross-entropy loss with  $\mathcal{D}_{train}$  and select the best checkpoint on  $\mathcal{D}_{dev}$ .

**In-Context Learning.** Instead of directly fine-tuning model, Brown et al. (2020) show that PLMs themselves have the capability to perform few-shot learning without parameter updates. It explores an in-context learning paradigm, which simply concatenates randomly sampled training examples as demonstrations with inputs during inference:

$$x_{\text{demo}} = \mathcal{T}(x_{train}^{1}) \oplus \ldots \oplus \mathcal{T}(x_{train}^{|\mathcal{Y}|}) \oplus \mathcal{T}(x),$$
$$p(y|x) = p_{\mathcal{L}}([\text{MASK}] = \mathcal{M}(y)|x_{\text{demo}}),$$
(3)

where  $\oplus$  refers to concatenation of input texts, and we select one example per class as demonstrations  $(x_{\mathrm{train}}^1,...,x_{\mathrm{train}}^{|\mathcal{Y}|})$ . The final prediction of the incontext learning ensembles all results based on different sampled demonstrations. This method has practical advantages for the few-shot adaptation over the now-standard approach of finetuning, as we could hold only one model for serving many different tasks, avoiding expensive and time-consuming parameter updates.

## 3 Nearest Neighbor Calibration

In this paper, we attempt to further explore the potential of PLMs for few-shot adaptation along the research direction of in-context learning. As shown in Figure 1, inference over few-shot train-

ing instances via in-context learning may produce contradictory results, and the situation can be exaggerated by poor templates and verbalizers. This phenomenon motivates us to exploit few-shot support instances by retrieving similar training samples to strengthen or rectify the original prediction distribution generated by PLMs. In this work, we propose a novel nearest-neighbor calibration framework for in-context learning, as illustrated in Figure 2. Our method is built on the top representations of PLMs and it augments classification with a retrieval pipeline, which directly queries a datastore of cached few-shot instance representations and corresponding labels to produce prediction distribution. We further design lightweight adaptive neighbor selection and feature regularization modules to reduce retrieval noises. Next, we first introduce the instance-augmented classification, and then detail the adaptive neighbor selection and feature regularization modules.

### 3.1 Instance-Augmented Classification

We achieve this instance-augmented classification through a kNN classifier, which consists of two steps: creating a datastore and making predictions depending on it.

**Datastore Creation.** The datastore is the cache of a set of key-value pairs, which is constructed by the training set  $\mathcal{D}_{\text{train}} = \{(x^i, y^i)\}_{i=1}^{K \times |\mathcal{Y}|}$  using language model  $\mathcal{L}$ . Firstly, we convert input x through a prompt template, and then concatenate it with demonstrations sampled from the remaining few-

shot training examples following Eq. (3), yielding  $x_{\rm demo}$ . We further feed  $x_{\rm demo}$  into language model  $\mathcal L$  to obtain the hidden representation of <code>[MASK]</code> token (i.e., the representation of last transformer layer), denoted as  $f(x_{\rm demo}; \mathcal L) = h_{\rm [MASK]}$ . Thus, the whole datastore is constructed by taking  $h_{\rm [MASK]}$  as key and corresponding label y as value:

$$\bigcup_{(x,y)\in\mathcal{D}_{\text{train}}} \{ (f(x_{\text{demo}}; \mathcal{L}), y), \forall x_{\text{demo}} \in \mathcal{S}(x) \},$$

where S(x) is the set of x with different demonstrations. We randomly sample K times without replacement to involve all training samples, resulting in  $K \times K \times |\mathcal{Y}|$  records of datastore in total.

Inference via kNN Retrieval. After building the datastore, we augment the prediction of PLMs with kNN retrieval similar to Khandelwal et al. (2020). Specifically, the test instance  $x^t \in \mathcal{D}_{\text{test}}$  is converted into  $x^t_{\text{demo}}$  following the same data preprocessing process as the datastore construction, and we obtain corresponding vector representation  $f(x^t_{\text{demo}}; \mathcal{L})$  of [MASK] token for subsequent kNN retrieval. Then the kNN-based prediction distribution  $p_{k}$ NN over the label space  $\mathcal{Y}$  is obtained with nearest neighbors:

$$p_{k\text{NN}}(y|x_{\text{demo}}^t) \propto \sum_{(h_i, v_i) \in N_t} I_{y=v_i} \cdot \exp(\frac{-d(h_i, f(x_{\text{demo}}^t; \mathcal{L}))^2}{\tau}),$$
(4)

where d(.,.) stands for euclidean distance,  $N_t$  represents the set of k nearest neighbours, and  $\tau$  is the temperature to control the sharpness of softmax function. The final prediction distribution of y is calculated as the interpolation of two distributions with a tuned hyper-parameter  $\lambda \in [0,1]$ :

$$\begin{aligned} p(y|x^t) &= (1 - \lambda) \cdot p_{k \text{NN}}(y|x^t_{\text{demo}}) \\ &+ \lambda \cdot p_{\mathcal{L}}(\text{[MASK]} = \mathcal{M}(y)|x^t_{\text{demo}}). \end{aligned} \tag{5}$$

Note that we use the development set to select the appropriate hyper-parameters (interpolation factor  $\lambda$ , number of nearest neighbor k and temperature  $\tau$ ). Similar to in-context learning, we also ensemble all results with different demonstrations for each test instance during inference.

#### 3.2 Improving Robustness of kNN Retrieval

The performance of instance-augmented classification highly relies on the quality of kNN retrieval. However, the retrieved nearest neighbors typically

include noises due to the inappropriate pre-defined neighbor selection and messy vector space produced by PLMs. To address these issues, we design the adaptive neighbor selection and feature regularization modules, which utilize current all fewshot training instances to mitigate retrieval noise as much as possible.

Adaptive Neighbor Selection (ANS). Following Zheng et al. (2021a), instead of a pre-defined k, we consider a set of possible ks smaller than an upper bound  $k_{\max}$  and introduce a lightweight network for the importance estimation of utilizing different selections to reduce the risk of inappropriate neighbors. In practice, we consider multiples of 4 as the choices of k for simplicity, alone with k=0 utilizing only PLMs, i.e.,  $k\in\mathcal{A}$  where  $\mathcal{A}=\{0\}\cup\{k_i\in\mathbb{N}\mid k_i/4\in\mathbb{N}, k_i\leq k_{\max}\}$ . Then the lightweight network evaluates the confidence of different kNN retrieval results by taking retrieved neighbors as inputs.

Concretely, for test instance with a demonstration  $x_{\mathrm{demo}}^t$ , we first retrieve  $k_{\mathrm{max}}$  neighbors  $N_t$ from the datastore and compute their distance from the current representation, as well as the count of distinct values in top i neighbors  $c_i$ . We take the computed distances  $d = (d_1, ..., d_{k_{\text{max}}})$  and counts  $c=(c_1,...,c_{k_{\max}})$  of distinct values in corresponding labels  $v=(v_1,...,v_{k_{\max}})$  as model inputs to decide the best k. Intuitively, the distance of each neighbor is the most direct evidence when evaluating their importance. The intuition to take label counts c as model input is that inference should trust more on PLMs when retrieved labels are chaotic. The importance estimation network  $f_{\text{ANS}}(\cdot)$  is the two feed-forward layers with a non-linear function between them, in which the hidden size is set to 32 and we adopt q(.) = ReLU(.) (Agarap, 2018) as the non-linear function. The probability of selecting k is calculated as follows:

$$p_a(k|x_{\text{demo}}^t) = \text{softmax}(f_{\text{ANS}}([d,c])).$$
 (6)

Instead of introducing the hyper-parameter  $\lambda$  as Eq. (5), we aggregate the output of PLMs and different kNN predictions with the importance estimation network for final prediction:

$$p(y|x^{t}) = \sum_{k_{i} \in \mathcal{A}} p_{a}(k_{i}|x_{\text{demo}}^{t}) \cdot p_{k_{i}\text{NN}}(y|x_{\text{demo}}^{t}),$$
(7)

where  $p_{k_i \text{NN}}$  indicates the  $k_i$ -nearest-neighbor prediction results calculated as Eq. (4). For training

this lightweight network, we randomly split the  $\mathcal{D}_{\text{train}}$  into two equal parts. One part is used to build the datastore, while we train  $f_{\text{ANS}}(\cdot)$  on another part via minimizing the cross-entropy loss following Eq. (7).

**Feature Regularization (FR).** When facing the situation of instances having different labels but sharing similar representations, the  $k{\rm NN}$  classifier easily fails or makes mistakes, since retrieval results are noisy and the ANS module tends to ignore this case. To mitigate this, we further leverage a simple linear layer to separate such instance representations using the supervision of all few-shot instances. For key-value pair  $(h_i, v_i)$  in the datastore, we reconstruct the representation as follows:

$$h_i^f = g(\mathbf{W}_f h_i + b_f), \tag{8}$$

where  $\mathbf{W}_f \in \mathbb{R}^{H imes Z}$  and  $b_f \in \mathbb{R}^Z$  are trainable parameters, and Z is the new dimension of representation space. As the training data is very small, we select a small Z to avoid overfitting. We set Z=32 for our experiments to reduce the number of trainable parameters and the new datastore is constructed as  $\{(h_i^f, v_i)\}$ . This FR module targets to make representations belonging to the same class semantically close by maximizing kNN retrieval probability in Eq. (4). Similar to the training process of the ANS module, we optimize this linear layer by minimizing the cross-entropy loss of kNNclassifier. As for combining ANS and FR modules, we first train the FR module with two equal parts of  $\mathcal{D}_{\mathrm{train}}$ , and then exchange these two parts for the optimization of ANS module.

### 4 Experiments

We conduct extensive experiments on a wide variety of NLP tasks, and compare the performance of our proposed approach with existing the-state-of-art methods in the few-shot scenario.

#### 4.1 Experimental Setup

**Datasets.** We evaluate methods on 12 datasets for 7 tasks: (1) sentiment analysis datasets, SST-2 (Socher et al., 2013), SST-5 (Socher et al., 2013), CR (Hu and Liu, 2004) and MR (Pang and Lee, 2005); (2) the subjectivity classification dataset, SUBJ (Pang and Lee, 2004); (3) the question classification dataset, TREC (Voorhees and Tice, 2000); (4) natural language inference datasets, CB (De Marneffe et al., 2019) and RTE (Wang

et al., 2019); (5) the question answering dataset, QNLI (Rajpurkar et al., 2016); (6) paraphrase detection datasets, MRPC (Dolan and Brockett, 2005) and QQP<sup>1</sup>; (7) the word sense disambiguation dataset, WiC (Pilehvar and Camacho-Collados, 2019). Following Karimi Mahabadi et al. (2022), we evaluate on original test sets for MR, CR, SST-5, SUBJ, and TREC. For the remaining datasets, we test on original validation set. We sample K=16 examples per class from original training data to form few-shot training and validation sets.

**Baselines.** We adopt RoBERTa-large (Liu et al., 2019) as the underlying language model  $\mathcal{L}$  for all methods in our experiments, and compare our approach (**KNN-C**) with the following baselines: (i) **PV-Zero**: we take manual prompts and verbalizers to obtain prediction of PLMs without involving any training examples; (ii) In-Context Learning (ICL) (Brown et al., 2020): we adopt the same prompt formats as in PV-Zero, but augment the context with randomly sampled demonstrations (and still use RoBERTa-large, not GPT-3). Note that we sample K demonstrations from the training set without replacement to cover all training samples during inference; (iii) Contextual Calibration (ICL+CC): following Zhao et al. (2021), we introduce content-free input "N/A" to remove the prediction bias of in-context learning; (iv) Finetuning (FT): the standard fine-tuning method (Devlin et al., 2019), introducing a classifier on top of the [CLS] token and tuning all parameters of PLMs; (v) PET (Schick and Schütze, 2021): the promptbased fine-tuning method that employs manual prompts and requires fine-tuning over PLMs; (vi) PERFECT (Karimi Mahabadi et al., 2022): thestate-of-art fine-tuning method for few-shot adaptation, which avoids manual prompts and verbalizers by introducing adapters and multi-token label embeddings.

**Implementation Details.** For PLMs, we use the HuggingFace Pytorch implementation. In our experiments, we adopt the manually designed patterns and verbalizers used in Karimi Mahabadi et al. (2022) (usually 5 different options for each dataset). We evaluate all methods using 5 different random samples for creating the training/development sets and 4 different random seeds for model training. Thus, we report the results of  $5 \times 5 = 25$  runs for PV-Zero, ICL, and ICL+CC, while we perform

<sup>&</sup>lt;sup>1</sup>https://quoradata.quora.com

Methods	SST-2	SST-5	CR	MR	SUBJ	TREC	AVG
PV-Zero*	63.4/54.0/11.8	27.9/21.1/4.8	59.6/50.4/11.8	62.6/53.7/10.9	55.5/50.2/7.6	33.9/25.6/8.8	50.5/42.5/9.3
ICL	89.9/ <b>88.3/1.0</b>	43.6/37.3/4.8	88.0/83.1/2.5	86.1/ <b>83.9/1.2</b>	51.2/48.5/2.9	52.7/36.8/10.3	68.6/63.0/3.8
ICL+CC	84.6/82.3/1.9	38.3/33.2/3.8	85.4/80.9/2.5	80.7/77.1/2.3	53.4/50.5/2.8	49.8/33.4/9.1	65.4/59.6/3.7
FT	81.4/70.0/4.0	39.2/34.3/2.5	80.1/72.9/4.1	77.7/66.8/4.6	90.2/84.1/1.8	87.6/75.8/3.7	76.0/67.3/3.4
PET	89.7/81.0/2.4	45.9/40.3/2.4	88.4/68.8/3.0	85.9/79.0/2.1	88.1/79.6/2.4	85.0/70.6/4.5	80.5/69.9/2.8
PERFECT	<b>90.7</b> /88.2/1.2	42.7/35.1/2.9	90.0/85.5/1.4	<b>86.3</b> /81.4/1.6	89.1/82.8/2.1	90.6/81.6/3.2	81.6/75.8/2.1
KNN-C	92.6/90.1/0.8	48.5/41.5/2.5	90.5/86.0/1.3	89.0/85.8/1.2	90.5/86.9/1.5	77.3/64.2/7.9	81.4/75.7/2.5
- ANS	91.9/89.2/1.0	46.7/40.8/2.7	90.4/84.9/1.7	88.3/82.8/1.6	90.4/87.5/1.4	76.5/64.0/8.2	80.7/74.9/2.8
- FR	<b>92.7</b> /90.6/0.7	47.6/40.1/3.1	89.9/ <b>86.9</b> /1.6	89.5/87.3/0.8	<b>90.7</b> /86.3/1.3	69.8/46.2/10.2	80.0/72.9/3.0
- ANS,FR	91.2/88.3/1.5	47.1/40.1/3.0	89.3/84.9/1.7	88.8/85.9/1.3	89.9/83.7/2.3	69.8/50.0/10.4	79.3/72.1/3.4
- ANS,FR, $p_{\mathcal{L}}$	92.4/ <b>90.9/0.7</b>	44.8/38.7/3.2	89.6/86.7/1.8	88.9/87.1/1.0	90.6/ <b>88.2/1.2</b>	65.6/46.4/9.5	78.7/73.0/2.9
Methods	СВ	RTE	QNLI	MRPC	QQP	WiC	AVG
PV-Zero*	64.3/58.9/3.4	56.7/ <b>54.2</b> /1.8	50.1/49.4/ <b>0.6</b>	67.5/ <b>66.4/0.7</b>	36.8/36.8/ <b>0.1</b>	51.4/48.8/2.9	54.5/52.4/1.6
ICL	77.4/57.1/10.3	58.8/53.8/3.6	52.0/50.3/1.2	54.0/32.1/17.4	42.5/36.8/6.7	51.0/ <b>50.0</b> /1.6	55.9/46.7/6.8
ICL+CC	56.9/42.9/10.0	56.0/53.8/ <b>1.6</b>	54.4/52.8/0.8	62.2/37.8/10.4	45.0/36.7/6.6	49.3/47.5/ <b>1.0</b>	54.0/45.2/5.1
FT				E0 41/0 514 5	CE 0.150 0.10 C	50 ALAC 110 F	(2 2/5/ 4/4 2
1.1	72.9/67.9/ <b>2.5</b>	56.8/50.2/3.5	62.7/51.4/7.0	<b>70.1</b> /62.7/4.7	65.0/59.8/3.6	52.4/46.1/3.7	63.3/56.4/4.2
PET	72.9/67.9/ <b>2.5</b> 86.9/73.2/5.1	56.8/50.2/3.5 60.1/49.5/4.7	62.7/51.4/7.0 66.5/55.7/6.2	7 <b>0.1</b> /62.7/4.7 62.1/38.2/6.8	65.0/59.8/3.6 63.4/44.7/7.9	52.4/46.1/3.7 51.0/46.1/2.6	65.0/51.2/5.6
PET	86.9/73.2/5.1	60.1/49.5/4.7	66.5/55.7/6.2	62.1/38.2/6.8	63.4/44.7/7.9	51.0/46.1/2.6	65.0/51.2/5.6
PET PERFECT	86.9/73.2/5.1 <b>90.3/83.9</b> /3.5	60.1/49.5/4.7 <b>60.4</b> /53.1/4.7	66.5/55.7/6.2 <b>74.1/60.3</b> /4.6	62.1/38.2/6.8 67.8/54.7/5.7	63.4/44.7/7.9 <b>71.2/64.2</b> /3.5	51.0/46.1/2.6 <b>53.8</b> /47.0/3.0	65.0/51.2/5.6 <b>69.6/60.5</b> /4.2
PET PERFECT KNN-C	86.9/73.2/5.1 90.3/83.9/3.5 82.1/69.6/5.3	60.1/49.5/4.7 60.4/53.1/4.7 61.8/52.4/2.9	66.5/55.7/6.2 <b>74.1/60.3</b> /4.6 <b>54.2</b> /50.4/2.2	62.1/38.2/6.8 67.8/54.7/5.7 62.5/42.7/7.3	63.4/44.7/7.9 <b>71.2/64.2</b> /3.5 58.7/47.4/ <b>4.3</b>	51.0/46.1/2.6 <b>53.8</b> /47.0/3.0 53.1/46.2/3.1	65.0/51.2/5.6 69.6/60.5/4.2 62.1/51.4/4.2
PET PERFECT KNN-C - ANS	86.9/73.2/5.1 90.3/83.9/3.5 82.1/69.6/5.3 79.8/64.3/6.1	60.1/49.5/4.7 60.4/53.1/4.7 61.8/52.4/2.9 60.7/51.3/3.1	66.5/55.7/6.2 <b>74.1/60.3</b> /4.6 <b>54.2</b> /50.4/2.2 54.0/50.2/2.2	62.1/38.2/6.8 67.8/54.7/5.7 62.5/42.7/7.3 62.1/47.1/ <b>6.0</b>	63.4/44.7/7.9 <b>71.2/64.2</b> /3.5 58.7/47.4/ <b>4.3</b> <b>59.6/47.8</b> /4.6	51.0/46.1/2.6 <b>53.8</b> /47.0/3.0 53.1/46.2/3.1 52.8/45.6/2.9	65.0/51.2/5.6 69.6/60.5/4.2 62.1/51.4/4.2 61.5/51.0/4.2

Table 1: Performance of all methods on 6 single-sentence (top) and 6 sentence-pair (bottom) benchmarks. \*: no training examples are used. We report the average accuracy( $\uparrow$ )/worst-case accuracy( $\uparrow$ )/standard deviation( $\downarrow$ ) and bold fonts indicate the best results.

 $20 \times 5 = 100$  runs for methods that involve handcrafted prompts and training process, such as PET and KNN-C. We perform  $5 \times 4 = 20$  runs for methods without hand-crafted prompts, i.e., FT and PERFECT. As the variance of each method is usually high in few-shot learning (Perez et al., 2021; Zhao et al., 2021), we report average accuracy, worst-case performance, and the standard deviation across all runs. Note that we adopt the same random samples and seeds as Karimi Mahabadi et al. (2022) to achieve a fair comparison. We run all the experiments on one NVIDIA A100 with 40G of memory. For the training process of KNN-C, we deploy the Adam optimizer (Kingma and Ba, 2015) with a learning rate of 1e-3, batch size and total epoch are set to 64 and 30. We use the development set and Eq. (5) to select best hyperparameters: interpolation factor  $\lambda$ , temperature  $\tau$ and the number of retrieved neighbors k. We find that  $\tau$  and k are less sensitive to downstream tasks, thus  $\tau = 5$  and k = 8 are used for all tasks and we set  $k_{\text{max}}$  to 16 for our experiments;

#### 4.2 Main Results

Table 1 lists the performance of different methods on 6 single-sentence (top) and 6 sentence-pair (bottom) benchmarks. Baselines are divided into two categories: ICL-based and FT-based methods.

KNN-C vs. ICL-based Methods (PV-Zero, ICL, and ICL+CC). PV-Zero is almost the worst except for the MRPC dataset, indicating an obvious discrepancy between pre-training and downstream tasks. ICL introduces a few training samples with the format of demonstrations and generally performs better than PV-Zero. It should be noted that improvements of ICL are much smaller in pairwise tasks compared to those in single sentence tasks (1.4% vs. 18.1% on average accuracy), indicating that transferring knowledge to pairwise tasks (e.g., text entailment) is a lot more difficult than to single-sentence tasks (e.g., sentiment analysis). We argue this is because PLMs take inputs sentence by sentence, rather than sentence pairs during the pre-training, leading to poor few-shot performance of in-context learning. We also observe that the contextual calibration method hurts the few-shot performance of the Roberta-large model in most datasets. Compared with ICL, KNN-C further refines the decision boundary generated by PLMs with the help of similar retrieval instances from training data. It achieves 12.8% and 6.2% absolute improvements on average accuracy for singlesentence and sentence-pair datasets, respectively.

**KNN-C vs. FT-based Methods (FT, PET and PERFECT).** Our approach largely closes the performance gap between ICL-based methods and ex-

Dataset	PV-Zero	ICL	w/o Aug	w/ Aug(1)	KNN-C w/ Aug(4)	w/ Aug(8)	w/ Aug(Full)
SST-2	63.4/54.0/11.8	89.9/88.3/1.0	83.4/63.7/5.3	90.0/83.3/1.7	91.7/87.8/1.2	92.3/90.0/0.9	92.6/90.1/0.8
SST-5	27.9/21.1/4.8	43.6/37.3/4.8	37.9/29.1/3.4	44.9/38.6/2.7	47.8/41.5/ <b>2.4</b>	48.4/ <b>42.2/2.4</b>	<b>48.5</b> /41.5/2.5
CR	59.6/50.4/11.8	88.0/83.1/2.5	80.3/73.3/3.2	87.7/83.3/2.0	89.4/ <b>86.1</b> /1.4	90.2/85.6/ <b>1.2</b>	<b>90.5</b> /86.0/1.3
MR	62.6/53.7/10.9	86.1/83.9/1.2	80.4/55.9/4.8	86.3/77.8/2.0	88.6/ <b>86.2/1.1</b>	88.8/85.7/1.3	<b>89.0</b> /85.8/1.2
SUBJ	55.5/50.2/7.6	51.2/48.5/2.9	86.6/77.7/2.8	88.9/81.2/2.1	89.8/84.8/1.9	90.3/86.0/1.7	90.5/86.9/1.5
TREC	33.9/25.6/8.8	52.7/36.8/10.3	66.9/28.0/18.0	76.5/62.6/ <b>7.2</b>	76.8/63.2/8.1	77.1/63.8/8.0	<b>77.3/64.2</b> /7.9
СВ	64.3/58.9/3.4	77.4/57.1/10.3	68.6/57.1/4.3	72.5/39.3/12.7	80.4/60.7/7.0	81.7/71.4/5.5	82.1/69.6/5.3
RTE	56.7/54.2/1.8	58.8/ <b>53.8</b> /3.6	55.9/47.7/3.0	61.1/52.7/3.0	61.6/53.4/ <b>2.7</b>	61.6/53.1/2.8	<b>61.8</b> /52.4/2.9
QNLI	50.1/49.4/ <b>0.6</b>	52.0/50.3/1.2	52.2/48.6/2.0	53.8/50.3/2.2	54.1/50.7/2.2	54.1/ <b>50.8</b> /2.3	<b>54.2</b> /50.4/2.2
MRPC	68.4/68.1/0.2	54.0/32.1/17.4	58.7/41.9/6.8	62.4/44.9/5.9	63.1/41.2/6.7	62.8/38.7/6.8	62.5/42.7/7.3
QQP	36.8/36.8/ <b>0.1</b>	42.5/36.8/6.7	55.7/38.5/7.9	56.8/40.4/6.2	58.2/44.1/4.9	58.6/ <b>47.4</b> /4.3	<b>58.7/47.4</b> /4.3
WiC	51.4/48.8/2.9	51.0/ <b>50.0/1.6</b>	51.1/45.0/1.8	51.9/44.2/2.7	52.8/44.0/2.7	53.1/44.7/3.0	<b>53.1</b> /46.2/3.1
AVG	52.6/47.6/5.4	62.3/54.8/5.3	64.9/50.5/5.3	69.4/58.2/4.2	71.2/62.0/3.5	71.6/63.3/ <b>3.4</b>	71.7/63.6/3.4

Table 2: The performance comparisons of using kNN retrieval and demonstration, including only kNN retrieval (KNN-C w/o Aug), only demonstration (ICL), and their combination. We report the average accuracy( $\uparrow$ )/worst-case accuracy( $\uparrow$ )/standard deviation( $\downarrow$ ) and bold fonts indicate the best results.

isting state-of-the-art FT-based methods in both single and pairwise sentence tasks. For single-sentence tasks, KNN-C achieves the best average accuracy performance in 4 out of 6 tasks, and the overall performance is comparable with PERFECT. For sentence-pair tasks, transferring knowledge from PLMs to downstream tasks is difficult, and a large performance gap still exists, especially for text entailment and paraphrasing tasks. Our pilot study also presents the potential of ICL to gain comparable performance with FT-based methods. We also include the performance comparisons and discussions with more parameter-efficient fine-tuning methods in the Appendix A.1.

**Ablation Study.** We further verify the impact of AFS and FR modules in reducing the noises of kNN retrieval. The ANS module works well on reducing kNN retrieval noises in most cases, except for the QQP dataset. It proves the effectiveness of dynamically controlling the number of similar instances. The FR module brings better results and reduces the standard deviation on most datasets, especially for TREC and QQP datasets. These results show that the FR module helps regularize representations of the same class to be similar, when the gap between pre-training and downstream tasks is relatively large. But these two modules are not always complementary in our experiments. We believe that optimizing these two modules with small data sets results in instability and sometimes fails to search for the optimal solution. We also test the performance of our method when removing  $p_{\mathcal{L}}$ , i.e., we only use  $p_{kNN}$  for prediction. It outperforms ICL on average accuracy, indicating that errors made by

ICL could be remedied by our retrieval strategy.

#### 4.3 Analysis

Effect of Instance-Augmented Retrieval. Instead of concatenating training instances with test inputs, our method explores another orthogonal direction that attempts to retrieve similar support samples to augment or correct the original decision boundary. It can be also applied to PV-Zero, namely "w/o Aug". We compare the performance of these two different ways and verify their combination in different sampling settings. Table 2 illustrates the performance comparisons on all tasks, where "w/ Aug(1/4/8/Full)" denotes that we augment the context with 1/4/8/K sampled demonstrations. We can see that "w/o Aug" significantly outperforms PV-Zero, which verifies the effectiveness of our proposed method again. ICL and "w/o Aug" end in a tie, but shines in different tasks. Specifically, "w/o Aug" outperforms on SUBJ, TREC and QQP, while ICL works well on SST-5, CR and CB. By combining these two methods, KNN-C achieves significant improvements over "w/o Aug", even with only one sampled demonstration. The performance of KNN-C continues to improve with the increase of augmented demonstrations for each instance. These results prove that our approach is complementary to ICL and could further leverage the potential of PLMs on the few-shot adaptation.

Comparisons of BERT and RoBERTa. Table 3 compares the performance of using BERT-large (cased) as the PLMs backbone. According to previous results (in Table 2), KNN-C achieves significant improvements over the baselines when using

Dataset	PV-Zero	BERT-large ICL	KNN-C
SST-2	59.8/52.1/8.1	64.3/49.2/9.9	76.6/71.3/3.0
SST-5	26.2/23.6/2.7	28.3/24.2/2.6	35.9/30.7/1.9
CR	54.5/50.0/5.0	70.6/59.4/6.6	77.0/67.5/2.5
MR	58.1/50.8/7.0	64.7/51.9/7.7	75.4/69.2/2.4
SUBJ	53.7/50.2/4.9	51.1/48.8/ <b>1.6</b>	87.7/83.1/1.6
TREC	24.7/18.6/6.6	27.1/18.2/ <b>5.3</b>	<b>64.6/51.0</b> /6.1
СВ	54.3/46.4/6.5	51.1/44.6/ <b>4.1</b>	<b>66.9/55.4</b> /4.8
RTE	51.2/46.6/3.6	51.4/ <b>46.9</b> /3.5	53.0/44.4/3.3
QNLI	49.4/49.2/ <b>0.1</b>	49.5/ <b>49.0</b> /0.3	<b>52.8</b> /47.9/2.6
MRPC	67.8/65.9/0.9	54.6/32.8/15.4	57.1/42.4/5.5
QQP	37.0/36.8/ <b>0.2</b>	40.1/36.8/4.0	<b>56.3/44.9</b> /4.1
WiC	49.8/ <b>49.7/0.1</b>	49.8/48.6/0.5	<b>51.1</b> /45.5/2.5
AVG	48.9/45.0/3.8	50.2/42.5/5.1	62.9/54.4/3.4

Table 3: The performance of ICL-based methods when using BERT-large as the PLMs backbone. We report the average  $accuracy(\uparrow)/worst-case$   $accuracy(\uparrow)/standard\ deviation(\downarrow)$  and bold fonts indicate the best results.

either BERT or RoBERTa as the PLMs backbone. In addition, the improvement of ICL over PV-Zero on RoBERTa is significantly better than that on BERT, showing that RoBERTa performs better few-shot learning. Instead, our method benefits both models and shows better generalization ability.

Improvements vs. ICL Errors on Train Data. From Table 4, we see that ICL may make wrong predictions on train data, whose performance is similar to one on test data. KNN-C tends to achieve bigger improvements on the dataset that ICL performs poorly, as our method leverages *k*NN retrieval to calibrate predictions.

#### 5 Related Work

Few-Shot Learning with PLMs. The GPT series (Radford et al., 2018, 2019; Brown et al., 2020) raise the attention of prompt-based learning. Brown et al. (2020) propose the in-context learning and show the ability of PLMs to perform few-shot learning without any fine-tuning. In line with this work, Zhao et al. (2021) point out the bias issue in prompt-based PLMs and design contextual calibration method. Shin et al. (2020) optimize prompt engineering with automatic prompt search. Lu et al. (2022) present a generation-based probing method to decide ordering of prompts. Rubin et al. (2022) introduce retrieval modules to search prompts for improving the quality of demonstrations. Our approach further exploits the potential of in-context learning by retrieving similar training examples to augment or correct the original decision boundary

Datasat	IO	KNN-C - ICL		
Dataset	Train	Test	on Test	
SST-2	90.2/81.2/5.3	89.9/88.3/1.0	2.7/1.8/-0.2	
SST-5	43.3/31.2/7.0	43.6/37.3/4.8	4.9/4.2/-2.3	
CR	87.2/78.1/3.4	88.0/83.1/2.5	2.5/2.9/-1.2	
MR	89.8/81.2/6.2	86.1/83.9/1.2	2.9/1.9/0	
SUBJ	52.8/43.8/5.3	51.2/48.5/2.9	39.3/37.4/-1.4	
TREC	47.2/37.5/7.6	52.7/36.8/10.3	24.6/27.4/-2.4	
СВ	67.4/47.5/9.0	77.4/57.1/10.3	4.7/12.5/-5.0	
RTE	55.8/46.9/6.9	58.8/53.8/3.6	3.0/-1.4/-0.7	
QNLI	51.5/43.8/5.4	52.0/50.3/1.2	2.2/0.1/1.0	
MRPC	50.2/46.9/2.2	54.0/32.1/17.4	8.5/10.6/-10.1	
QQP	52.2/34.4/7.9	42.5/36.8/6.7	16.2/10.6/-2.4	
WiC	53.3/40.6/7.7	51.0/50.0/1.6	2.1/-3.8/1.5	

Table 4: The performance of ICL on training and test data. We report the average  $accuracy(\uparrow)/worst$ -case  $accuracy(\uparrow)/standard\ deviation(\downarrow)\ and\ highlight\ the\ 2-best\ improvements\ (i.e.,\ KNN-C\ -\ ICL)\ among\ all\ tasks.$ 

provided by PLMs.

More recently, substantial efforts have been made with optimizing the prompt format (Le Scao and Rush, 2021; Lester et al., 2021). Several studies replace the manual prompts and verbalizers with continuous prompt embeddings (Li and Liang, 2021; Qin and Eisner, 2021), adapter layers (Karimi Mahabadi et al., 2022), and automatic generated ones (Gao et al., 2021). Our proposed method takes a step forward, aiming to reduce the performance gap between in-context learning and existing fine-tuning methods.

**Retrieval-Augmented Methods.** Our proposed framework is closely related to the retrievalaugmented methods. Recently, these approaches enhance the pre-trained models with a retrieval component and have achieved promising results in a variety of natural language processing tasks, including language modeling (Guu et al., 2020; Borgeaud et al., 2022), machine translation (Khandelwal et al., 2020; Zheng et al., 2021a,b; Wang et al., 2022; Du et al., 2022) and open-domain question answering (Lewis et al., 2020; Izacard and Grave, 2021). Recent simultaneous work (Shi et al., 2022) propose a retrieval model to incorporates additional unsupervised data for zero-shot inference. Different from them, we design a novel retrieval-augmented method for in-context learning, and augment PLMs with kNN retrieval constructed by few-shot support samples.

# 6 Conclusion

In this paper, we present a simple and effective nearest-neighbor calibration framework to improve the performance of in-context learning on few-shot text classification tasks. This approach directly augments PLMs with additional kNN classifier based on current few-shot support instances, where the adaptive neighbor selection and feature regularization modules are introduced to reduce the kNNretrieval noises. Experimental results on various NLP tasks indicate that our method achieves significant improvements over in-context learning and is even comparable with the-state-of-art fine-tuning methods in single-sentence tasks. In the future, we would like to combine our method with bigger PLMs and further investigate the potential reason causing the performance gap between our method and current fine-tuning methods. Another interesting direction is to explore our method on larger training datasets, rather than the few-shot adaptation setting.

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# A Appendix

## A.1 Comparisons with Fine-tuning Methods

Table 5 illustrates the performance of ICL-based and FT-based methods on all datasets. In addition to FT, PET, and PERFECT, we include the results of other parameter-efficient tuning methods, including +Null-Prompt (Logan IV et al., 2022) and BitFit+mte (Ben Zaken et al., 2022). Among FTbased methods, PERFECT has obtained the best performance in 12 datasets on average. Surprisingly, KNN-C achieves better or comparable results than PERFECT in five single-sentence tasks. Another appealing capability of our method is to keep one model for all tasks in the Language-Model-asa-Service setting and maintain knowledge for different tasks by external datastore. This way could further promote the landing of Language-Modelas-a-Service.

Our approach requires the training of ANS and FR modules, but the training cost is far less than FT-based methods. We take the example of RoBERTa-large, which is used as the PLMs backbone in our paper: (1) the tunable parameters in our model are 32x32=1024 for the ANS module, and 1024x32+32=32800 for the FR module, thus KNN-C has 32800+1024=33824=0.03M tunable parameters in total; (2) fine-tuning the whole RoBERTalarge model (i.e., PET) or additional adapter layer (i.e., PERFECT) requires tuning 355M/3.3M parameters, respectively. In addition, KNN-C only needs one forward computation of the PLMs during the entire training process and the remaining computation is very small, thus the training time is far less than FT-based methods. For the inference time, KNN-C is almost the same as ICL, as the datastore is very tiny and performing kNN retrieval is negligible.

Methods	SST-2	SST-5	CR	MR	SUBJ	TREC	AVG
FT-based Methods							
FT	81.4/70.0/4.0	39.2/34.3/2.5	80.1/72.9/4.1	77.7/66.8/4.6	90.2/84.1/1.8	87.6/75.8/3.7	76.0/67.3/3.4
PET	89.7/81.0/2.4	<b>45.9</b> /40.3/2.4	88.4/68.8/3.0	85.9/79.0/2.1	88.1/79.6/2.4	85.0/70.6/4.5	80.5/69.9/2.8
+Null-Prompt	89.8/84.1/1.7	45.7/ <b>41.6/2.3</b>	89.9/87.2/1.1	84.9/76.2/3.2	81.8/73.5/4.0	84.7/81.8/1.6	79.5/74.1/2.3
BitFit+mte	89.5/81.7/3.0	42.3/36.8/3.3	90.1/87.8/1.0	85.6/80.5/1.9	89.1/82.4/2.4	90.4/85.0/1.4	81.2/75.7/2.2
PERFECT	90.7/88.2/1.2	42.7/35.1/2.9	90.0/85.5/1.4	86.3/81.4/1.6	89.1/82.8/2.1	90.6/81.6/3.2	81.6/75.8/2.1
ICL-based Methods							
PV-Zero*	63.4/54.0/11.8	27.9/21.1/4.8	59.6/50.4/11.8	62.6/53.7/10.9	55.5/50.2/7.6	33.9/25.6/8.8	50.5/42.5/9.3
ICL	89.9/88.3/1.0	43.6/37.3/4.8	88.0/83.1/2.5	86.1/83.9/1.2	51.2/48.5/2.9	52.7/36.8/10.3	68.6/63.0/3.8
+ CC	84.6/82.3/1.9	38.3/33.2/3.8	85.4/80.9/2.5	80.7/77.1/2.3	53.4/50.5/2.8	49.8/33.4/9.1	65.4/59.6/3.7
KNN-C	92.6/90.1/0.8	48.5/41.5/2.5	90.5/86.0/1.3	89.0/85.8/1.2	90.5/86.9/1.5	77.3/64.2/7.9	81.4/75.7/2.5
Methods	СВ	RTE	QNLI	MRPC	QQP	WiC	AVG
			FT-based	Methods			
FT	72.9/67.9/ <b>2.5</b>	56.8/50.2/3.5	62.7/51.4/7.0	70.1/62.7/4.7	65.0/59.8/3.6	52.4/46.1/3.7	63.3/56.4/4.2
PET	86.9/73.2/5.1	60.1/49.5/4.7	66.5/55.7/6.2	62.1/38.2/6.8	63.4/44.7/7.9	51.0/46.1/2.6	65.0/51.2/5.6
+Null-Prompt	<b>91.0/87.5</b> /2.7	64.4/58.5/3.9	71.2/ <b>66.5/2.6</b>	63.9/53.7/5.3	70.4/62.7/3.4	52.4/ <b>48.4/1.8</b>	68.9/ <b>62.9/3.3</b>
BitFit+mte	89.6/82.1/4.3	61.3/53.8/5.2	70.6/51.9/5.9	68.5/57.4/5.1	69.4/63.0/3.9	52.9/47.8/2.7	68.7/59.3/4.5
PERFECT	90.3/83.9/3.5	60.4/53.1/4.7	<b>74.1</b> /60.3/4.6	67.8/54.7/5.7	71.2/64.2/3.5	<b>53.8</b> /47.0/3.0	<b>69.6</b> /60.5/4.2
ICL-based Methods							
PV-Zero*	64.3/58.9/ <b>3.4</b>	56.7/ <b>54.2</b> /1.8	50.1/49.4/ <b>0.6</b>	67.5/66.4/0.7	36.8/36.8/ <b>0.1</b>	51.4/48.8/2.9	54.5/ <b>52.4/1.6</b>
ICL	77.4/57.1/10.3	58.8/53.8/3.6	52.0/50.3/1.2	54.0/32.1/17.4	42.5/36.8/6.7	51.0/ <b>50.0</b> /1.6	55.9/46.7/6.8
+ CC	56.9/42.9/10.0	56.0/53.8/ <b>1.6</b>	<b>54.4/52.8</b> /0.8	62.2/37.8/10.4	45.0/36.7/6.6	49.3/47.5/ <b>1.0</b>	54.0/45.2/5.1
KNN-C	<b>82.1/69.6</b> /5.3	<b>61.8</b> /52.4/2.9	54.2/50.4/2.2	62.5/42.7/7.3	<b>58.7/47.4</b> /4.3	<b>53.1</b> /46.2/3.1	<b>62.1</b> /51.4/4.2

Table 5: Performance of all methods on 6 single-sentence (top) and 6 sentence-pair (bottom) benchmarks. \*: no training examples are used. We report the average accuracy(↑)/worst-case accuracy(↑)/standard deviation(↓). Bold fonts indicate the best results.