Discriminative Language Model as Semantic Consistency Scorer for Prompt-based Few-Shot Text Classification

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Abstract
A successful prompt-based finetuning method should have three prerequisites: task compatibility, input compatibility, and evidence abundance. Bearing this belief in mind, this paper designs a novel prompt-based method (called DLM-SCS) for few-shot text classification, which utilizes the discriminative language model ELECTRA that is pretrained to distinguish whether a token is original or replaced. The method is built upon the intuitive idea that the prompt instantiated with the true label should have higher semantic consistency score than other prompts with false labels. Since a prompt usually consists of several components (or parts), its semantic consistency can be decomposed accordingly, which means each part can provide information for semantic consistency discrimination. The semantic consistency of each component is then computed by making use of the pretrained ELECTRA model, where no extra parameters get introduced. Extensive experiments have shown that our model outperforms several state-of-the-art prompt-based few-shot methods on 10 widely-used text classification tasks.

Keywords: discriminative language model, prompt

1. Introduction
Nowadays, with the upsurge of interest in a wide range of pretrained language models, the pretrained-finetuning paradigm (Radford et al., 2018; Dong et al., 2019) has become a de facto standard for various downstream NLU and NLG tasks. Different language models usually have different scopes of application. Auto-regressive language models (ARLM) such as GPT-3 (Brown et al., 2020) and Ernie-3 (Sun et al., 2021) predict the next token based on all the previous ones, usually in the left-to-right order. Since it is trained to encode a uni-directional context, it is not effective at downstream NLU tasks that often require bidirectional context information. In addition, these models are large and costly to finetune, or even not available publicly, which makes them impossible to use in the pretraining-finetuning paradigm. Masked language models (MLM) such as BERT (Devlin et al., 2019) and RoBERTa (Liu et al., 2019) mask some tokens in inputs and are trained to reconstruct the original tokens based on their bidirectional surrounding context, which is often preferable in NLU tasks such as text classification but not applicable in NLG.

Conventional finetuning method for downstream text classification task usually builds up a classification head together with additional parameters on top of the special [CLS] token from scratch and fine-tunes the whole model. Such models work well with abundant training examples in rich data regimes, but will be cornered in the few-shot scenario, not to mention the zero-shot, because of the gap between pretraining and downstream tasks.

Initiated by the in-context learning of the GPT series (Radford et al., 2018, 2019; Brown et al., 2020), prompt-based method was first developed for zero-shot learning, and then studied by PET and iPET (Schick and Schütze, 2021a) for fine-tuning. After that, prompt-based learning methods have become increasingly popular, and have been proven to work effectively under few-shot or even zero-shot setting. To bridge the gap between the downstream task and the pretrained task, these methods transform downstream tasks into the same (or similar) form as the pretraining tasks solved during the original LM training with the help of textual prompts. Most existing prompt-based methods are using generative prompts that contain answer slots for various pretrained language models to fill in (Liu et al., 2021). As to the downstream text classification tasks, most works have been directed against pretrained masked language models (MLMs) by formulating downstream tasks as a masked language modeling task (Schick and Schütze, 2021a,b; Gao et al., 2021). A template converts the original input example $x_{in}$ into a textual string (called prompt) $\tilde{x}$ that contains an unfilled [MASK] slot. A verbalizer is used to represent each class with a label word from the vocabulary. The model makes the prediction according to the probabilities of filling the [MASK] token with the label words. Such a prompt is called a generative prompt, which usually contains an unfilled [MASK] as the answer slot, and the pretrained masked language model is finetuned to generate a correct label name to fill this answer slot. A simple prompt-based framework that treats MLM as masked token predictor for text classification is illustrated in Figure 1(b).
Until the very recent, two prompt-based finetuning methods (Yao et al., 2022; Xia et al., 2022; Ni and Kao, 2022) have been proposed to exploit the pretrained ELECTRA (Clark et al., 2020) which is a discriminative language model (DLM). In contrast to the generative prompts, they use the prompts that contains no answer slot, which we call “discriminative prompts” and can be seen as the unmasked prompts which use label word(s) to fill in the [MASK] of generative prompts. The pretrained ELECTRA model is then applied on these discriminative prompts and tells us which label word is the original token (i.e., not a replaced token). However, these methods confine themselves only on the label word(s) in the discriminative prompts and expect the discriminative model to identify the semantic inconsistency incurred by the incorrect label words. This limited evidence is far from what can be obtained from the discriminative language model, and some available evidence is missing (Please refer to Section 3.2 for a simple motivating example).

The work done in this paper follows the thread of prompting the discriminative language model for few-shot text classification. The basic idea is that the DLM head can detect the discrepancy between inputs and label words. On the one hand, given an input example (a sentence or a sentence pair) and its true label, the DLM head is expected to assign low scores (or logits) to the salient tokens in the input example and the true label word. If a false label is given, it is desirable that the DLM head will assign high scores to both the false label word and the salient tokens in the input example.

To squeeze the most out of a pretrained language model such that it works best on a downstream few-shot learning task, three prerequisites are considered in designing a prompt-based method of finetuning a pretrained discriminative language model:

- **Prerequisite 1 (Task Compatibility):** As stated by most prompt tuning methods, the downstream task should be transformed into the same (or highly similar) form as the pretraining task, such that no (or few) additional parameters need introduced.

- **Prerequisite 2 (Input Compatibility):** The prompt template should be in the same form as the training data of the pretrained language model, such that the discriminative prompts are as much natural as possible. As a consequence, the pretrained language model can process them well and easily, without having to be tuned too far away.

- **Prerequisite 3 (Evidence/Information Abundance):** Last but not the least, the method should try its best to obtain and aggregate as much evidence and/or information as possible for decision making. Due to the nature of few-shot learning, it is unstable and has a big variance, and thus the aggregation of more evidence would be helpful in reducing the variance.

The contribution of this paper is threefold: (1) We propose a novel framework DLM-SCS1 for few-shot text classification, which uses the pretrained discriminative language model ELECTRA as the semantic consistency scorer. (2) We design a method to measure the semantic consistency of a subsequence in the input prompt on the basis of the discriminative head of ELECTRA which can only measure the semantic inconsistency of each single token, and then use it to instantiate the framework into a concrete prompt-based finetuning model (also called DLM-SCS). (3) The proposed method has achieved the state-of-the-art performance on a variety of downstream sentence classification and sentence-pair classification tasks.

2. Related Work

2.1. Prompting MLM for Text Classification

Existing prompt-based learning methods for text classification usually reformulate the downstream text classification task into a cloze question task, and then finetune a pretrained masked language model to generate the most likely label word in the unfilled [MASK] position of the generative prompt (Schick and Schütze, 2021a). A lot of research effort has been devoted to the automatic construction of prompt templates and label words. (Schick et al., 2020) and (Schick and Schütze, 2021a) studied the automatic identification of label words. (Gao et al., 2021) made use of the pretrained seq2seq model T5 (Raffel et al., 2020) to generate template tokens in the template search process. Motivated by idea of in-context learning from GPT series (Brown et al., 2020), (Gao et al., 2021) used a single unmasked example prompt (called a demonstration) as additional context, which can boost the performance of prompt-based few-shot text classification task. (Park et al., 2022) made two extensions by multiple demonstrations and soft demonstration memory. In addition, (Zhang et al., 2021) proposed the DART method that optimizes the differentiable prompt template and label words by error backpropagation.

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1Code available at https://github.com/liyahe/DLM-SCS.
2.2. Prompting DLM for Text Classification

Two prompt-based text classification methods for finetuning discriminative language model (DLM) have been recently proposed (Yao et al., 2022; Xia et al., 2022; Ni and Kao, 2022). These methods reformulate the text classification task into a discriminative language modeling problem, and predict the class label of an input example by using the DLM head to identify which label name is the original token instead of a replaced one. The DPT method proposed in (Yao et al., 2022) fills the input text \( x \) into the following template of discriminative prompt:

\[
[\text{CLS}] \quad x \quad \text{Class:} \quad v(l_1), v(l_2), \ldots, v(l_n) \quad [\text{SEP}]
\]

where the verbalizer \( v(\cdot) \) maps each class label \( l_i \) (1 \( \leq i \leq n \)) to a distinct label word. Then the DLM head is used to judge which label word is proper in the context. It should be noted that DPT is not designed and also not suited for few-shot learning, because it does not satisfy the Prerequisite 2 of input compatibility. As shown in Section 5, DPT cannot work well in few-shot scenario.

The other method, PromptELECTRA (Xia et al., 2022), was designed for few-shot text classification. Given an input example \( x \), it will generate one discriminative prompt for each possible class label. Thus, there are \( n \) discriminative prompts for \( x \). The DLM head is used to output the label word that has the highest probability of being original token in its corresponding prompt. This method satisfies Prerequisite 1 and 2, but it is not enough with respect to Prerequisite 3 because it makes decision based on the only evidence from the candidate label words. Analogously, (Ni and Kao, 2022) presents that ELECTRA can also perform well on downstream tasks without fine-tuning.

Recently, prompting discriminative language models have been also applied to various tasks including medical text classification (Wang et al., 2023) and biomedical domain adaptation (Lu et al., 2023).

3. Background and Motivation

3.1. The Pretrained ELECTRA Language Model

As a pretrained discriminative language model, ELECTRA (Clark et al., 2020) consists of an encoder and a discriminative head. The encoder first maps a sequence of input tokens \( x = [x_1, x_2, \ldots, x_n] \) into a sequence of contextualized vector representations \( \text{[h}_1, h_2, \ldots, h_n] \), and the discriminative head then predicts whether each token \( x_t \) (1 \( \leq t \leq n \)) is a “real” or “replaced” token. In particular, the discriminative head simply applies a linear layer with the sigmoid activation function on the contextualized representation \( h_t \) of \( x_t \):

\[
P_{\text{DLM}}(x_t, \hat{x}) = \text{sigmoid}(w^T h_t) \quad (1)
\]

where \( w \) denotes the parameter vector. In this paper, we interpret the value of \( w^T h_t \) as the un-normalized semantic inconsistency score of token \( x_t \) in the context \( x \). The larger the value of \( w^T h_t \) is, the more semantically inconsistent the token \( x_t \) is, and the more likely the token \( x_t \) is a replaced token in \( x \).

3.2. Motivation

Figure 2 shows a simple input sentence from the sentiment classification task SST-2:

\[x = \text{“The restaurant has excellent food.”}\]
The verbalizer $v$ maps the class label $pos$ (positive) to the label word “great”, and the class label $neg$ (negative) to “terrible”. Therefore, two discriminative prompts ($\tilde{x}^{neg}$ and $\tilde{x}^{pos}$) are generated by using the template “$x$ is $v(l)$”, one for each class label $l \in L = \{pos, neg\}$.

Applying the discriminative head of the pre-trained ELECTRA-large model to the label words: “terrible” in $\tilde{x}^{neg}$ and “great” in $\tilde{x}^{pos}$, we observe that $P_{DLM}(\text{terrible}, \tilde{x}^{neg}) = 0.13$ and $P_{DLM}(\text{great}, \tilde{x}^{pos}) = 0.04$. This evidence thus supports the conclusion that the input sentence is more likely to be positive, because the discriminative prompt $\tilde{x}^{pos}$ of $pos$ is semantically more consistent with respect to its label word (or in other words, $v(pos) = \text{“great”}$ is less likely to be a replaced token).

Besides the label tokens, the discriminative prompts contain tokens from the original input sentence, which may also provide us some evidence about the classification decision. As illustrated in Figure 2, by applying the DLM head on the token “excellent” in the discriminative prompts, we get $P_{DLM}(\text{excellent}, \tilde{x}^{neg}) = 0.60$ and $P_{DLM}(\text{excellent}, \tilde{x}^{pos}) = 0.02$, which also support the same conclusion that the input sentence is positive. This evidence from the token “excellent” is even stronger than the evidence provided by the label words.

**4. Method**

This section is devoted to a prompt-based framework for finetuning discriminative language models. The main thrust is to treat prompt-based text classification as a task of semantic consistency scoring, and calculate the semantic consistency of a prompt as a weighted average of the semantic consistency scores of multiple components (or parts) in the prompt.

Let $L$ be the set of class labels for the target text classification task at hand. A verbalizer $v$ is an injective function that maps each class label to a single token from $M$’s vocabulary, $v : L \rightarrow V$. We simply adopt the manual prompt templates used in the previous work (Gao et al., 2021). For sentence classification task, given an input example of single sentence $x_{in} = x^{(1)}$, we can generate a discriminative prompt $\tilde{x}^{l}$ for each label $l \in L$:

$$\tilde{x}^{l} = [\text{CLS}] \ x^{(1)} \text{ It is } v(l) \text{. [SEP]}$$ (2)

For sentence-pair classification task, given an input example of sentence pair $x_{in} = (x^{(1)}, x^{(2)})$ and a label $l \in L$, we can generate the discriminative prompt $\tilde{x}^{l}$ as:

$$\tilde{x}^{l} = [\text{CLS}] \ x^{(1)} \ ? \ v(l) \text{. [SEP]} \ x^{(2)}$$ (3)

Therefore, there are $|L|$ discriminative prompts $\{\tilde{x}^{l} | l \in L\}$ (one for each class label) generated for each input example.

The decision criterion of DLM-SCS model is based on the assumption that the discriminative prompt of true class label (true prompt in short) is semantically more consistent than the other discriminative prompts of false labels (false prompts). The class label $l$ whose prompt $\tilde{x}^{l}$ has the highest semantic consistency is chosen as the predicted label

$$\hat{l} = \arg\max_{l \in L} SC(\tilde{x}^{l})$$ (4)

where $SC(\tilde{x}^{l})$ denotes the semantic consistency of the discriminative prompt $\tilde{x}^{l}$. Figure 1(a) demonstrates this idea of using DLM as a semantic consistency scorer for text classification task.

Next, we move to the problem of how to calculate the semantic consistency $SC(\tilde{x}^{l})$ of a discriminative prompt $\tilde{x}^{l}$. Since each prompt consists of several components (or parts), its semantic consistency can be decomposed accordingly. In particular, the semantic consistency of $\tilde{x}^{l}$ is calculated as a weighted average of the semantic consistencies of some parts in $\tilde{x}^{l}$:

$$SC(\tilde{x}^{l}) = \lambda_0 \cdot sc (v(l), \tilde{x}^{l}) + \sum_{x^{(i)} \in x_{in}} \lambda_i \cdot sc (x^{(i)}, \tilde{x}^{l})$$ (5)

where:

- The term of form $sc(s, \tilde{x}^{l})$ denotes the semantic consistency of a token subsequence $s$ in the context of discriminative prompt $\tilde{x}^{l}$. Here, $v(l)$ is seen as a subsequence of single token.
- The $\lambda_i$’s are hyperparameters indicating the relative importance of the prompt parts ($i \in \{0, 1\}$ for sentence classification task, while $i \in \{0, 1, 2\}$ for sentence-pair classification).

Given a token subsequence $s$ in the discriminative prompt $\tilde{x}^{l}$, its semantic consistency can be simply measured by the softmax activation function over the mean negative logits of its tokens in the $|L|$ discriminative prompts:

$$sc(s, \tilde{x}^{l}) = \frac{\exp\left(-\frac{1}{|L|} \sum_{x \in s} W^T h^i_x\right)}{\sum_{v \in L} \exp\left(-\frac{1}{|L|} \sum_{x \in s} W^T h^i_x\right)}$$ (6)

where $h^i_x$ denotes the contextualized representation of $x$ in the discriminative prompt $\tilde{x}^{l}$. Here, because the value of $w^T h^i_x$ denotes the semantic inconsistency score of $x$ (i.e., the logit that $x$ is a replaced token), the minus sign is introduced into the exponent part in order to transform it into
where we use the cross-entropy function as the loss of \(m\) while

\[
\begin{align*}
\text{loss}_0 &= - \log \text{sc}(v(l^*), \tilde{x}^l) \\
\text{loss}_i &= - \log \text{sc}(\tilde{x}^{(i)}, \tilde{x}^{l_i})
\end{align*}
\]

where \(l^*\) is the true class label of the input example \(x_{in}\).

For the part of a sentence \(x^{(i)}\) in the input example (\(i = 1\) for single-sentence classification, while \(i \in \{1, 2\}\) for sentence-pair classification), the loss is measured as:

\[
\text{loss}_i = - \log \text{sc}(\tilde{x}^{(i)}, \tilde{x}^{l_i})
\]

where the hyperparameters \(\lambda_i\)'s are the same as the ones used in Equation 5.

### 4.2. Model Optimization

For model training, we adopt AdamW algorithm and set a linear learning rate variation with warmup ratio of 0.05. For all the datasets, we take learning rate as 1e-5, and batch size as 4 for few-shot samples. For each trial, we train the model for 15 epochs, validate the performance every 50 steps, and take the best checkpoint. Early stopping is used to avoid overfitting.

As to the hyperparameters \(\lambda_i\)'s, we set \(\lambda_1 = 1 - \lambda_0\) for single-sentence classification, while \(\lambda_1 = \lambda_2 = \frac{1 - \lambda_0}{2}\) for sentence-pair classification. The best value of \(\lambda_0\) is chosen based on its performance on the development set by a grid search from 0.0 to 1.0 with step size \(\frac{1}{10}\).

### 5. Experimental Results

To evaluate the performance of our approach, we follow the experimental setting from (Gao et al., 2021). For each task, we take only \(K\) training examples per class for the training set \(D_{train}\), and thus the total number of training examples is \(K \times |L|\). A development set \(D_{dev}\) of the same size as the few-shot training set is employed for model selection and hyper-parameter tuning. Unless specified otherwise, the value of \(K\) is set to 16 by default, and the reported performance metrics are averaged over the same set of 5 random seeds.

We conduct extensive experiments on 4 sentence classification tasks (SST-2, SST-5, MR, and CR) and 6 sentence-pair classification tasks (SNLI, MNLI, QNLI, RTE, MRPC and QQP). The templates and label words used are provided in Table 1, which are the same as the ones used in (Gao et al., 2021). On these text classification tasks, our DLM-SCS method is compared with the
Table 2: Performance evaluation on 6 sentence-pair classification tasks and 4 sentence classification tasks. The reported performance metrics are averaged over the same set of 5 random seeds, each random seed is used to sample 16 training example per class for training set, and the development set is of the same size as the training set. Both average results and standard deviations are reported above.

| Model             | SNLI (acc) | MNLI (acc) | QNLI (acc) | RTE (acc) | MRPC (F1) | QQP (F1) | SST-2 (acc) | SST-5 (acc) | MR (acc) | CR (acc) |
|-------------------|------------|------------|------------|-----------|------------|----------|-------------|-------------|----------|----------|
| Fine-tuning       | 48.4       | 45.8       | 60.2       | 54.4      | 76.6       | 60.7     | 81.4        | 43.9        | 76.9     | 75.8     |
| (4.8)             | (6.4)      | (6.5)      | (3.9)      | (2.5)     | (4.3)      | (3.8)    | (2.0)       | (2.0)       | (5.9)    | (3.2)    |
| LM-BFF (man)      | 77.2       | 68.3       | 64.5       | 69.1      | 74.5       | 65.5     | 92.7        | 47.4        | 87.0     | 90.3     |
| (3.7)             | (2.3)      | (4.2)      | (3.6)      | (5.3)     | (5.3)      | (0.9)    | (2.5)       | (1.2)       | (1.0)    |          |
| +demonstrations   | 79.7       | 70.7       | 69.2       | 68.7      | 77.8       | 69.8     | 92.6        | 50.6        | 86.6     | 90.2     |
| (1.5)             | (1.3)      | (1.9)      | (2.3)      | (2.0)     | (1.8)      | (0.5)    | (1.4)       | (2.2)       | (1.2)    |          |
| LM-BFF (auto)     | 77.1       | 68.3       | 68.3       | 73.9      | 76.2       | 67.0     | 92.3        | 49.2        | 85.5     | 89.0     |
| (2.1)             | (2.5)      | (7.4)      | (2.2)      | (2.3)     | (3.0)      | (1.0)    | (1.6)       | (2.8)       | (1.4)    |          |
| +demonstrations   | 77.5       | 70.0       | 68.5       | 71.1      | 78.1       | 67.7     | 93.0        | 49.5        | 87.7     | 91.0     |
| (3.5)             | (3.6)      | (5.4)      | (5.3)      | (3.4)     | (5.8)      | (0.6)    | (1.7)       | (1.4)       | (0.9)    |          |
| DART              | 75.8       | 67.5       | 66.7       | 68.7      | 78.3       | 67.8     | 93.5        | 49.6        | 88.2     | 91.8     |
| (1.6)             | (2.6)      | (3.7)      | (1.3)      | (4.5)     | (3.2)      | (0.5)    | (0.9)       | (1.0)       | (0.5)    |          |
| DPT               | 47.4       | 39.0       | 54.6       | 50.2      | 76.4       | 56.1     | 92.6        | 44.0        | 89.5     | 91.2     |
| (7.7)             | (1.8)      | (5.4)      | (2.8)      | (6.1)     | (1.1)      | (1.3)    | (3.8)       | (2.1)       | (1.6)    |          |
| PromptELECTRA     | 79.1       | 65.8       | 70.9       | 68.2      | 73.5       | 63.1     | 93.1        | 51.4        | 89.4     | 90.2     |
| (3.4)             | (2.5)      | (2.1)      | (2.8)      | (4.6)     | (3.3)      | (1.0)    | (2.2)       | (1.6)       | (1.4)    |          |
| DLM-SCS (ours)    | 82.2       | 71.0       | 77.0       | 75.0      | 78.3       | 72.2     | 93.6        | 51.5        | 90.2     | 91.0     |
| (1.5)             | (2.0)      | (2.4)      | (2.9)      | (3.1)     | (1.4)      | (0.6)    | (2.0)       | (0.7)       | (1.4)    |          |

5.1. Main Results

Table 2 reports the few-shot finetuning results of these methods on large-sized PLMs, where DLM-SCS, PromptELECTRA and DPT are based on the ELECTRA-large model, while all the other methods are based on the Roberta-large model. It can be easily observed that our DLM-SCS model is the best performer and has achieved the best performance on 9 of the 10 tasks among all the competitors. The Fine-tuning and DPT are not designed for the few-shot setting and have the worst performance. The conventional Fine-tuning method does not satisfy the Prerequisite 1 of Task Compatibility because the finetuning task does not match the pretraining task and additional parameters get introduced, while DPT does not satisfy the Prerequisite 2 of Input Compatibility because the prompts used are not natural. DLM-SCS outperforms PromptELECTRA on all the ten tasks, because DLM-SCS makes use of more evidence in the prompt than PromptELECTRA, which

conventional fine-tuning method and several state-of-the-art prompt-based finetuning methods:

- **Fine-tuning:** The conventional fine-tuning of Roberta-Large in the few-shot experimental setting.
- **LM-BFF(man):** The better few-shot finetuning of language models with manual prompts (Gao et al., 2021).
- **LM-BFF(auto):** The better few-shot finetuning of language models with automatically searched templates (Gao et al., 2021). For both LM-BFF (man) and LM-BFF (auto), “+demonstrations” means incorporating demonstrations as additional context, which leads to performance gains in majority of tasks as indicated in (Gao et al., 2021).
- **DART:** The differentiable prompt framework proposed in (Zhang et al., 2022), where the prompt template and the target labels are differentially optimized with backpropagation.
- **DPT:** The prompt tuning framework for discriminative PLMs proposed in (Yao et al., 2022). Although DPT does not aim at few-shot learning, we also include it in our experimental comparison. Its original implementation can only deal with sentence classification tasks, we make a straightforward extension by using the manual template: “[CLS] x(1) x(2) Class: v(l_i), v(l_2), ..., v(l_n) [SEP]” for a sentence-pair classification task with n classes.
- **PromptELECTRA:** The few-shot learning framework with discriminative pretrained models in (Xia et al., 2022).
5.2. Ablation Study

Two main techniques play important roles in the DLM-SCS model: the first is to integrate the evidences from multiple components (or parts) of the prompt, and the second is to weight tokens in each prompt part with IDF values. Table 3 shows the effects on the model performance by removing each technique. It can be seen that either of the techniques is indispensable: the removal of any technique will lead to substantial reduction of model performance. The evidence from the input example part of the prompt plays a crucial role in the success of our model, and its integration with the evidence of label word leads to substantial performance boosting in classification accuracy, which is consistent with the Prerequisite 3 we proposed.

5.3. Varying the number of training examples

Figure 3 compares the performance DLM-SCS with two competitors LM-BFF (man) and PromptELECTRA as the number of training examples (K) increases from 16 to 256. It can be observed that:

• On 9 datasets (except MRPC), DLM-SCS consistently outperforms LM-BFF (man) when K varies from 16 to 256.
• On 7 datasets (except MRPC, SST-2 and SST-5), DLM-SCS consistently outperforms PromptELECTRA for all K values. On SST-2 and SST-5, DLM-SCS wins PromptELECTRA for most K values (4 out of 5).

5.4. Reject Option: Unanimous vs. Disagreed Examples

The DLM-SCS model for text classification can be thought of as a weighted average of m semantic consistency scorers (refer to Equation 5). For sentence classification task, there are two component scorers (m = 2), one for the label words and the other for the input sentence. For sentence-pair classification task, there are three component scorers (m = 3), one for the label words, one for the...
Figure 3: Performance comparison of DLM-SCS, LM-BFF (man) and PromptELECTRA with different numbers of training examples. The shadow area denotes the standard deviation of the performance metric.

### Table 5: Performance analysis of unanimous versus disagreed test examples

| Dataset   | O.M | U.M | D.M | U.R  |
|-----------|-----|-----|-----|------|
| SNLI (Acc)| 82.9| 85.3| 41.7| 92.0%|
| MNLI (Acc)| 71.1| 75.4| 41.6| 82.0%|
| QNLI (Acc)| 78.5| 81.4| 37.2| 86.9%|
| RTE (Acc) | 73.3| 82.9| 56.7| 67.5%|
| MRPC (F1) | 79.4| 81.6| 33.9| 83.3%|
| QQP (F1)  | 71.4| 75.1| 28.0| 87.5%|
| SST-2 (Acc)| 93.3| 94.8| 30.0| 99.0%|
| SST-5 (Acc)| 53.9| 56.4| 44.1| 74.3%|
| MR (Acc)  | 90.8| 91.7| 34.9| 96.9%|
| CR (Acc)  | 91.3| 93.5| 59.3| 93.3%|

Table 5: Performance analysis of unanimous versus disagreed test examples. The column O.M denotes the overall performance metric on the whole test dataset, U.M denotes the performance on the unanimous test examples, D.M denotes the performance on the disagreed test examples, while the final U.R denotes the ratio of unanimous examples in the test dataset.

first sentence, and the other for the second sentence. Therefore, the test examples can be split into two parts: an example is called unanimous if all component scorers make the same decision for it; otherwise, it is a disagreed example.

**Reject option** means that a classifier can refuse to make a decision of a test example if the decision is thought of not sufficiently reliable, which is an important technique to improve the reliability of decision making. Traditional technique for reject option relies on whether the predictive probability (or predictive confidence) is higher than a pre-set threshold, which can be called quantitative reject option. However, in few-shot learning scenario, it is almost impossible to obtain reliable predictive probabilities. Instead, DLM-SCS can adopt the following qualitative reject option technique: it refuses to make prediction for a disagreed example.

From Table 5, it can be seen that the proportion of unanimous examples is high on the whole (larger than 80% on 8 datasets), which yields to the relatively low reject ratio. In addition, the performance metrics of disagreed examples are much lower than those of unanimous examples, which justifies the refusal of making decision for these disagreed examples.

6. Conclusion and Future Work

In this paper, we present DLM-SCS, a simple framework for finetuning discriminative language model using only a few examples, where the discriminative language model is used as a semantic consistency scorer of discriminative prompts. Given an input text example, it first constructs its discriminative prompts for all class labels, then calculates the consistency scores of these prompts, and finally outputs the class label whose prompt has the highest consistency. To calculate the consistency score of a prompt, it is decomposed into consistency scores of different prompt parts. The extensive empirical evaluation has shown that it achieves state-of-the-art performance on sentence (or sentence-pair) classification tasks.

At its current state, the DLM-SCS method simply works with manual and discrete prompt templates which may be suboptimal. It would be interesting to investigate how to adapt the techniques of automatically prompt generation (Gao et al., 2021) and/or differentiable prompting (Zhang et al., 2022) to our discriminative framework. In addition, it is also valuable to explore how to combine the discriminative PLMs and the generative PLMs, in order to achieve better performance.
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