Many-Class Text Classification with Matching

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Abstract

In this work, we formulate Text Classification as a Matching problem between the text and the labels, and propose a simple yet effective framework named TCM. Compared with previous text classification approaches, TCM takes advantage of the fine-grained semantic information of the classification labels, which helps distinguish each class better when the class number is large, especially in low-resource scenarios. TCM is also easy to implement and is compatible with various large pre-trained language models. We evaluate TCM on 4 text classification datasets (each with 20+ labels) in both few-shot and full-data settings, and this model demonstrates significant improvements over other text classification paradigms. We also conduct extensive experiments with different variants of TCM and discuss the underlying factors of its success. Our method and analyses offer a new perspective on text classification.

1 Introduction

Text classification is an important task in NLP and has been widely studied a long time ago. Among text classification tasks, many-class text classification deals with the setting when the number of labels is large (Gupta et al., 2014)(for instance, >20), which is more challenging in practical NLP applications because the distinguish between classes is subtler with the increase of class number.

Recently, thanks to the success of pre-trained language models (PLMs), fine-tuning PLMs has become a mainstream approach for various text classification tasks (Han et al., 2021a). The fine-tuned model inherits versatile knowledge from the pre-training corpus and shows remarkable classification performance. We illustrate two common fine-tuning approaches for text classification in Figure 1. The first one (Figure 1 (a)), denoted as “Text Classification with Task-Head”, adds a task-specific classification layer on top of PLMs and trains the classifier together with the pre-trained models (Howard and Ruder, 2018). The second one (Figure 1 (b)) is “Text Classification with Prompts”, which formulates text classification as a language modeling problem by inserting natural language prompts into the input. This method bridges the gap between pre-training and fine-tuning, and achieves better performance in few-shot settings (Liu et al., 2021a).

However, classification with Task-Head usually represents classification labels using the serial numbers of the classes, which ignores their rich semantic and task-related information. Although classification with prompts maps each label to several concrete words that reflect the meaning of the corresponding class (Schick and Schütze, 2021a,b; Han et al., 2021b), the limited number of the mask positions restricts the use of more elaborate class information. In addition, most previous works with prompts are tested on tasks with a small number of classes (typically less than 10 classes) (Gao et al., 2021a; Schick and Schütze, 2021a,b; Liu et al., 2021b). In many-class text classification, the differences between the classes become more difficult and vague to distinguish.

Therefore, in this work, we propose Text Classification as Matching (TCM), a new framework for many-class text classification (Figure 1 (c)). We first represent the labels with natural language sentences that explain the corresponding classes precisely. To better utilize the information of each label, we adopt a Siamese Network (Koch et al., 2015) to formulate text classification as a matching problem between the input texts and the class descriptions. As shown in Figure 1, compared to classification with Task-Head that mainly learns the class meanings from the data, TCM directly informs the model the semantic meaning of each class. And compared to classification with
prompts which represents each label with several soft/discrete tokens, TCM is more flexible for introducing complex and fine-grained label information through complete sentences, which is critical for many-class text classification. TCM is also easy to implement, scalable to different language representation models of various sizes, and does not increase much inference time.

To verify the effectiveness of TCM, we conduct extensive experiments on 4 many-class classification datasets. Our findings are summarized as follows:

1. Through formulating text classification as matching between the input text and class descriptions, TCM can easily incorporate complicated label information to boost model performance.

2. Different types of class descriptions significantly affect the model performance especially under few-shot settings and for different classification tasks the proper class description content type is different.

3. Though TCM is designed for text classification with massive labels, it still shows competitive performance on that with several labels.

2 Related Work

Many-Class Text Classification Many-class text classification is a fundamental task in natural language processing (Gupta et al., 2014). Unlike conventional classification tasks, the number of labels is large in many-class text classification, and the differences between the classes are vaguer. This requires the classifiers to capture more fine-grained class semantics. Typical many-class text classification tasks include relation extraction (Han et al., 2018), intent detection (Casanueva et al., 2020) and large-scale emotion classification (Rashkin et al., 2019a). To solve these tasks, some previous works adopt hierarchical methods which find the correct classes in a coarse-to-fine manner (Chang et al., 2020). Other works use additional data such as the task meta-data (Zhang et al., 2021). In contrast, our approach is simpler and does not require additional meta information.

Text Classification with PLMs Recently, a variety of powerful PLMs such as the GPT family (Radford et al., 2018, 2019; Brown et al., 2020), BERT (Devlin et al., 2019), RoBERTa (Liu et al., 2019) and T5 (Raffel et al., 2020) have emerged and been adapted to downstream text classification tasks. Early methods add a task-specific classification head on the PLMs and train the entire model together with the additional head (Howard and Ruder, 2018; Peters et al., 2018). To bridge the gap between the pre-training and the downstream tasks, recent methods use task-related prompts to convert classification tasks to language modeling problems (Schick and Schütze, 2021a,b; Han et al., 2021b). To overcome the shortcomings of manually designing prompts, some works propose to automatically search the prompts (Shin et al., 2020; Gao et al., 2021a), or optimize them in a continuous space (Liu et al., 2020; Lester et al., 2021; Gu et al., 2022). However, most of these works are only evaluated on classification tasks with a small number of labels.

Matching as Supervision There are many works using matching as the supervision to train neural networks. In CV, models such as CLIP (Radford et al., 2021) and ConVIRT (Zhang et al., 2020) are trained by matching the representations of the images and their captions. These meth-
ods often yield impressive low-resource classification performance. In NLP, sentence matching is widely used in training sentence representation models (Conneau et al., 2017; Cer et al., 2018; Reimers and Gurevych, 2019; Gao et al., 2021b). A commonly used architecture for encoding sentence pairs is Siamese Network (Koch et al., 2015), which adopts two parameter-shared encoders (e.g., BERT) to compute the representation of each sentence. There are also works that employ the input-label matching signal for text classification (Soares et al., 2019; Wang et al., 2021; Liu et al., 2022; Müller et al., 2022). Unlike these works, we focus on applying the matching paradigm to various classification tasks with large class numbers and comprehensively analyze the usage of class semantics, which significantly influence model performance.

3 Text Classification as Matching

3.1 Overall Framework

Formally, we consider many-class text classification task $\mathcal{T} = \{\mathcal{X}, \mathcal{Y}\}$ where $\mathcal{X}$ is the set of the input samples, $\mathcal{Y}$ is the set of the classes, and the $i$-th sample $x_i \in \mathcal{X}$ is annotated with a label $y_i \in \mathcal{Y}$. In TCM, we formulate any task $\mathcal{T}$ to a matching problem between the representation of $x_i$ and $y_i$. We first define a label mapping that maps each label $y_i$ to a piece of text $t_{y_i}$ consisting of concrete words. Then, we adopt a Siamese Network (Koch et al., 2015) as the backbone to encourage the matching between input texts and its label. In the following sections, we describe the key components of our framework in detail.

3.2 Label Mapping

Though there are many ways to mapping class description, we consider three label mapping approaches:

Class Names Inspired by most of the prompt-based methods (Schick and Schütze, 2021a,b), we can directly map each label to its corresponding class name. However, for many-class classification tasks, simple names may not provide enough information to distinguish different classes, and it’s often hard to name each class with only a few words.

Class Definitions To enrich the semantic information of the labels, we try mapping each label to its class definitions. For some tasks like relation extraction, where the class definitions are naturally provided in the datasets, we directly use these definitions. For other tasks, we manually write definitions for each class.

Same-Class Samples We can also assume that the meaning of each label is reflected by the samples in the corresponding class. Therefore, we also try using a randomly selected sample in each class for the label mapping.

3.3 Matching Loss

Then, we encourage the input text $x_i$ to match the mapped label $t_{y_i}$. We optimize the similarities between $x_i$ and $t_{y_i}$ with a cross-entropy loss:

$$L_m = -\frac{1}{N} \sum_{i=1}^{N} \log \frac{\exp \left(\text{sim}(x_i, t_{y_i})/\tau\right)}{\sum_{y' \in \mathcal{Y}} \exp \left(\text{sim}(x_i, t_{y'})/\tau\right)},$$

where $\tau$ is a hyper-parameter, $N$ is the total number of the training samples, and $\text{sim}(x_i, t_{y})$ represents the similarity between $x_i$ and $t_{y}$. We adopt a pre-trained encoder to get the $d$-dimension representation vectors of $x_i$ and $t_{y}$: $f_\theta(x_i), f_\theta(t_{y}) \in \mathbb{R}^d$, where $\theta$ denotes the parameters of the encoder. Note that we share the parameters of the models that encode $x_i$ and $t_{y}$. Then $\text{sim}(x_i, t_{y}) = f_\theta(x_i)^\top f_\theta(t_{y})$.

3.4 Regularization

To help the model learn to distinguish classes with similar meanings, we also add a regularization term:

$$L_t = \frac{1}{|\mathcal{Y}|} \max_{y \in \mathcal{Y}} \left\{ \delta, \max_{y' \in \mathcal{Y}\setminus\{y\}} \text{sim}(t_{y}, t_{y'}) \right\},$$

where $\delta$ is a constant threshold. By minimizing this term, the similarities between different classes are lowered, which makes them more distinguishable.

The final loss function is shown as following:

$$L = L_m + \alpha L_t,$$

where $\alpha$ is a hyper-parameter to balance the matching loss and the regularization.

3.5 Inference

During inference time, for every test sample $x$, we calculate the similarities between the input text and all the mapped labels:

$$y^* = \arg \max_{y \in \mathcal{Y}} \text{sim}(x, t_{y}).$$

Note that after the model is trained, $f_\theta(t_{y})$ can be pre-computed for a given task, which means...
the computational overhead is similar to classification with Task-Head. Compared to some work that formulates text classification as text entailment problems and concatenates the input texts and the labels (Wang et al., 2021), our method is much more efficient during inference.

4 Experiment

4.1 Setup

Data We conduct experiments on two datasets for relation extraction: FewRel (Han et al., 2018), TACRED (Zhang et al., 2017), and two datasets for large-scale emotion classification: EmpatheticDialogue (Rashkin et al., 2019b), GoEmotions (Demszky et al., 2020). Each of these datasets contains more than 20 classes. Detailed data statistics can be found in the Appendix A. For the few-shot settings (Perez et al., 2021), we randomly select $K$ training samples for each class for both the training and validation sets. To reflect the uncertainty of few-shot learning, we run the experiments on 5 train/valid sets sampled with different random seeds. For the full-data setting, we randomly shuffle and split the train/valid/test sets except for TACRED on which we use the original splits.

Model Details We use BERT (Devlin et al., 2019) and RoBERTa (Liu et al., 2019) as the pre-trained encoder. We use the class descriptions as the mapped label $t_y$ in our main experiments. A comparison of different label mappings can be found in Section 5. We pass the output hidden states of the [CLS] token through an MLP layer to get the sentence representation for both the input text and the label.

Baselines We compare TCM with the two paradigms in Figure 1 (a), (b): text classification with Task-Head, denoted as “Task-Head” and text classification with prompts, denoted as “Prompt”. For Task-Head, we use the representation of the [CLS] token for classification. For Prompt, we mainly follow PET (Schick and Schütze, 2021b) to convert classification tasks to language modeling by hand-craft templates and train the model to predict the names of each class, which is widely used in current prompt-based methods. We do not use the unlabeled corpus or the ensembling tricks in PET for a fair comparison. The detail of prompt templates can be found in the Appendix B.

Training Configurations We set batch size to 8 for few-shot setting and 32 for full-data setting.¹ We use the learning rate 5e-5 for BERT\textsubscript{BASE} and 2e-5 for RoBERTa\textsubscript{BASE}. We adopt the AdamW optimizer and constant learning rate scheduler.

4.2 Main Results

We present our main results in Table 1.

Few-shot Results From the rows where $K = 5, 10, 15, 20$ in Table 1, we have three observations. First, the Task-Head method fails to achieve satisfactory performance when the data is insufficient. Although Prompt method improves the performance on the emotion classification tasks (EmpatheticDialogue and GoEmotions), it fails on relation extraction tasks (FewRel and TACRED). The results indicate that without fine-grained information and representations of labels, the models cannot well handle the few-shot classification scenarios.

Second, TCM constantly outperforms the baselines by a large margin in all few-shot settings. The improvement is most significant when the number of the training samples is extremely low ($K = 5, 10$) and the performances of all methods gradually converge when $K$ increases. We also find that the performance boost of emotion classification is greater than relation extraction. We conjecture that the difference of the labels in emotion classification is vaguer than that of relation extraction and requires longer and more complex sentences to precisely represent their semantic information, where the matching paradigm of TCM shows its advantage.

Third, TCM shows a much smaller standard deviation than the baselines in most cases, which indicates that TCM is more stable across different few-shot training sets in the same task. This is probably because TCM directly informs the model the accurate semantic meanings of each label while the baselines learn the meanings of each label mainly from the datasets, resulting in a high variance of the label representations. Since few-shot learning is notorious for its instability, we conclude that TCM helps the practical use of few-shot learning by providing more reliable and robust results.

Full-data Results We also show the results under the full-data setting ($K = \text{Full}$) in Table 1.

¹For FewRel and TACRED datasets, we set batch size to 8 because of memory limitation for full-data setting.
We can see that although the performance of each method converges when the training samples increase, TCM still slightly outperforms the other two classification paradigms.

### 4.3 Other Results

To measure TCM performance on datasets with few class number, we evaluate it on some commonly used classification tasks. We use BERT$_{LARGE}$ as encoder. We use the settings and the data split from (Gao et al., 2021a), except for setting learning rate to $2e^{-5}$ and batch size to 2. Results are shown in Table 2. We can see that TCM can handle the situation where the class number is few.

### 4.4 Analysis

In this section, we further analyze the inner workings of TCM.

First, we explore the role of class description during the entire training period. On the one hand, the class description gives a reasonable initialization to the label embedding; on the other hand, it also puts some constraints when updating the label embedding because we re-encode the class description every training step. We conduct a simple experiment: just initialize the label embedding using the class description and do not use the class description again. The results are shown in Table 3.

We can see that initializing label embeddings using class description will apparently boost model performance when the training sample is scarce, say, several per class. This shows another advantage of our matching method: the matching model can easily incorporate prior knowledge about label information. Meanwhile, we can conclude that the...
major contribution of class description is during the updating rather than initializing.

5 Ablation Study

Siamese Network In order to verify the effectiveness of the siamese network, we use two independent encoders to encode samples and class descriptions individually. The results are shown in Figure 2. We can see that the two encoder model always shows worse performance than the model using the siamese network even though the former has two times of parameters as the latter. We can also observe that the standard deviation of the two encoders is much bigger than that of the siamese network for GeEmotions dataset. This demonstrates that the siamese network is more stable under few-shot settings.

Class Number We test the effect of the number of categories on performance, and the results are shown in Figure 3. We use 20 samples per category and test on FewRel and EmpatheticDialogue datasets. We can see that TCM always makes better than the Task-Head method and the gap is larger with the increase of class number. For example, when the number of classes equals 5, TCM gains a nearly equal accuracy score with the Task-Head method. However, when the number of classes increases to 20, 40, or 60, TCM can perform better than that. So we can conclude that TCM can handle both few and many categories scenarios but is more suitable for many categories.

Description Content In order to explore the possible relationship between model performance and description content, we try to compare the performance of TCM with different description content, including label definition, label name, and a single training sample. Results are shown as Figure 4. We can see that different class descriptions can significantly affect the model performance under few-shot setting. This experiment demonstrates that a reasonable class description like label definition or label name indeed provides some information needed to deal with the classification task. However, when the training samples are sufficient, the performance gap caused by different descriptions is faint.

Regularization We expect this term can effectively help the model learn to distinguish similar categories. To verify its effectiveness, we observe description embedding and confusion matrix on GoEmotions dataset. First, we disable this term during training, and the results are shown in Table 4. We can see that the test accuracy is significantly dropped without this term. Then, we extract the label embedding from the model trained on GoEmotions dataset and $K = 20$ and check their similarity. We can see that the label embeddings are not well distinguished. For example, seen in Figure 5a, the embedding of anger is almost same with that of training sample.
Table 4: Results of with and without label regularization. TCM-reg denotes model trained without regularization.

| $K$  | TCM-reg | TCM | $\Delta$ |
|------|---------|-----|---------|
| 5    | 21.1_{12} | 36.1_{10,9} | -15.0 |
| 10   | 28.1_{13,6} | 39.5_{10,6} | -11.4 |
| 15   | 29.0_{13,5} | 41.6_{10,4} | -12.6 |
| 20   | 29.1_{12,3} | 42.8_{10,3} | -13.7 |
| Full | 49.9     | 87.3 | -37.4  |

Figure 5: Label embedding similarity without regularization.

- annoysance, disapproval, disgust and even neutral.
  Even if we use check this under full-data setting, it only distinguishes neutral from the others seen in Figure 5b.

6 Conclusion

This paper presents a simple yet effective framework TCM for many-class text classification. It learns the matching relation between samples and corresponding class descriptions using the siamese network and can easily incorporate prior knowledge of label information. Experimental results show the superior performance of TCM on different text classification tasks, especially under few-shot settings. We also explore how class descriptions contribute to the model and find that it gives a reasonable initialization for label embeddings and puts a constraint during parameter updating.

Ablation study shows that siamese network is essential, and using different description content will impact model performance under few-shot settings. Moreover, TCM is more suitable for large class number classification.

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### A Datasets

**FewRel** a few-shot relation classification dataset containing 100 relations. We rearrange its data distribution in train and valid set for experimentation, and there are only 80 available classes because test set is not accessible.

**TACRED** a large-scale relation extraction dataset containing 41 relation types and a “no_relation” type. We first drop the “NA” class for all experiments and then drop 10 classes in experiments under few-shot settings because the number of samples in these classes is too small. Also, we rearrange its data in few-shot experiments.

**EmpatheticDialogue** a large-scale multi-turn empathetic dialogue dataset containing 32 evenly distributed emotion labels. We select the first sentence in every dialog as our sample according to its collecting principle and rearrange it.

**GoEmotions** a 27 categories fine-grained emotion classification dataset containing 12 positive, 11 negative, 4 ambiguous emotions categories and 1 “neutral”. We discard all samples with multi-label and rearrange it.

### B Prompt Templates

**EmpatheticDialogue and GoEmotions** for emotional classification datasets, we construct template for each sample like this: [CLS] {sample} [SEP] this person feels [MASK] [SEP].

**FewRel and TACRED** for relational classification datasets, we construct template for each sample like this: [CLS] {sample} [SEP] the relation of these two entities is [MASK]*(8 for FewRel/5 for TACRED) [SEP].