Pretrained language models (PLMs) trained on large-scale unlabeled corpus are typically fine-tuned on task-specific downstream datasets, which have produced state-of-the-art results on various NLP tasks. However, the data discrepancy issue in domain and scale makes fine-tuning fail to efficiently capture task-specific patterns, especially in the low data regime. To address this issue, we propose Task-guided Disentangled Tuning (TDT) for PLMs, which enhances the generalization of representations by disentangling task-relevant signals from the entangled representations. For a given task, we introduce a learnable confidence model to detect indicative guidance from context, and further propose a disentangled regularization to mitigate the over-reliance problem. Experimental results on GLUE and CLUE benchmarks show that TDT gives consistently better results than fine-tuning with different PLMs, and extensive analysis demonstrates the effectiveness and robustness of our method. Code is available at https://github.com/lemon0830/TDT.

1 Introduction

In recent years, pretrained language models (PLMs) trained in a self-supervised manner like mask language modeling have achieved promising results on various natural language processing (NLP) tasks (Devlin et al., 2019; Yang et al., 2019; Liu et al., 2019b), which learn general linguistic and semantic knowledge from massive general corpus. To adapt PLMs to specific NLP tasks, a commonly-used approach is fine-tuning, where the whole or part of model parameters are tuned by task-specific objectives. Despite its success, the fine-tuned models have been proven ineffective to capture task-specific patterns due to the gap between task-agnostic pre-training and the weak fine-tuning with limited task-specific data (Gu et al., 2020; Gururangan et al., 2020; Kang et al., 2020).

To address this problem, most existing methods focus on adapting PLMs to downstream tasks by continual pre-training on in-domain unsupervised data (Gururangan et al., 2020; Gu et al., 2020; Wu et al., 2021; Kang et al., 2020; Ye et al., 2021). For example, Gu et al. (2020) propose intermediate continual pre-training with a selective masking strategy, and Gururangan et al. (2020) adapt PLMs to in-domain tasks by domain-adaptive pretraining. Although straightforward, these kinds of methods heavily rely on the selection of large-scale additional domain corpora and the design of appropriate intermediate training tasks (Wang et al., 2019; Aghajanyan et al., 2021a).

In this paper, we propose a Task-guided Disentangled Tuning (TDT) for PLMs by auto-
matically detecting task-specific informative inputs without the need of additional corpora and intermediate training. The core component of TDT is a confidence model which assigns each token a confidence score, and we construct distilled samples by retaining informative tokens with high confidence scores while perturbing the rest. The confidence model performs a “deletion game” strategy, which encourages the model to perturb inputs as much as possible and to maintain the performance of downstream tasks to the greatest extent with the distilled samples. Although the informative tokens are important for downstream predictions, existing work shows that over-relying on part of these words may result in pool generalization, i.e., over-reliance problem (Moon et al., 2020; Geirhos et al., 2020; Sun et al., 2019). Take the sentences in Figure 1 as an example, when the context word “Apple” frequently co-occurs with the label “tech”, fine-tuned models may learn a spurious association by binding “Apple” and “tech”, leading to incorrect predictions of sentences which contain “apple” but belong to other categories.

Based on the observation, we further enhance our method with a disentangled regularization, aiming to distinguish task-relevant and task-irrelevant features. First, we construct two variants of the original input in a complementary view: (1) positive variant, which maintains the high-confidence keywords, and (2) negative variant, derived by a “cut-out-keyword” operation on the original input. Next, we propose a “triplet-style loss”, which makes predictions between the original input and the positive variant similar while the predictions between the negative variant and the other two different. To illustrate the mechanism of our disentangled regularization, we go back to Figure 1 and take the sentence “Jobs founded apple in 1976” as an example. Under the influence of the disentangled regularization, the positive variant tends to retain clue words for predictions (i.e., “founded apple”), while the negative variant, as the complement (i.e., “Jobs in 1976”), tends to be task-irrelevant.

We evaluate our TDT on a wide range of neural language understanding benchmark datasets in English and Chinese, i.e., GLUE and CLUE, and our TDT affords strong predictive performance compared with standard fine-tuning. Moreover, we conduct extensive analysis with respect to robustness to perturbation, domain generalization, and low-resource settings, from which we conclude:

- TDT learns reasonable confidence scores for input tokens.
- TDT is robust to input perturbation and domain shift by encouraging the model to learn more generalized features.
- TDT effectively captures the high-confidence decisive cues for downstream tasks, thus alleviating over-fitting in low-resource scenarios.

2 Method

In this section, we begin with a brief introduction of the vanilla Fine-tuning, and then introduce Task-guided Disentangled Tuning (TDT) in detail. Figure 2 shows the overall framework. TDT is composed of two parts: (1) token-level confidence model, which discovers the essential parts of inputs for the model prediction; (2) task-guided regularization, which promotes the model to decouple task-relevant keywords from non-keyword context.

2.1 Vanilla Fine-tuning

Given an example of training data <X, y>, where X={x_1, ..., x_n} is the input sequence and y is its corresponding label. We first map each token x_i to a real-valued vector e_i by an embedding layer. Then, the packed embedding output E={e_i} is fed into the PLM to get the contextualized sentence representations H={h_dsa, h_1, ..., h_n}, and the hidden state h_dsa is used to conduct classification with an MLP head. We fine-tune the parameters of the PLM with the cross entropy loss:

$$L_{cla} = -\log P(y|H).$$  (1)

2.2 Token-level Confidence Model

For each token x_i, we generate a scalar c_i ∈ [0, 1], coined confidence score, by stacking a single-layer feed-forward network with sigmoid activation on the top of the embedding layer:

$$c_i = \sigma(We_i + b),$$  (2)

where W and b are trainable parameters. Based on the confidence score, we obtain a distilled sample \{e_i^+\} defined as

$$e_i^+ = c_i \odot e_i + (1 - c_i) \odot \mu_0,$$  (3)

where \mu_0 is a perturbation term and \odot denotes element-wise multiplication. Specifically, the perturbation term \mu_0 can be a zero vector, a random
Given the original input and the two derived variants, we feed them into the PLM with the classifier, and obtain three prediction distributions $P(y|H)$, $P(y|H^+)$, and $P(y|H^-)$. Finally, we regularize these distributions by a triplet ranking loss

$$L_R = \max (m + d(P(y|H^+), P(y|H)) - d(P(y|H^-), P(y|H)) - d(P(y|H^-), P(y|H^+)), 0)$$

where $m$ is a hyperparameter indicating a margin for the loss and $d(\cdot)$ denotes the Kullback-Leibler (KL) divergence. By minimizing $L_R$, the positive variant will be closer to the original input while the negative variant will be farther from the other two. Thus, the model is encouraged to disentangle task-relevant signals from task-irrelevant factors, and generate more general representations.

2.4 Overall Training Objective

The final training objective is

$$L = L_{cla} + \alpha L_C + \beta L_R,$$

where $\alpha$ and $\beta$ are non-negative hyper-parameters to balance the effect of each loss term.

3 Experiments

3.1 Datasets

We evaluate our proposed method by fine-tuning the pretrained models on the General Language Understanding Evaluation (GLUE) (Wang et al., 2018) and the Chinese Language Understanding Evaluation (CLUE) (Xu et al., 2020). Concretely, the GLUE benchmark has 8 different text classification or regression tasks including MNLI, MRPC, QNLI, QQP, RTE, SST-2, SST-B, and CoLA. The CLUE...
| Model     | MNLI | QQP  | QNLI | SST-2 | CoLA | STS-B | MRPC | RTE  | Avg  |
|-----------|------|------|------|-------|------|-------|------|------|------|
| BERT-base |      |      |      |       |      |       |      |      |      |
| FineTuning| 84.5 | 90.9 | 91.3 | 92.8  | 60.5 | 88.7  | 85.1 | 67.5 | 82.6 |
| TDT       | 85.3 | 91.2 | 91.9 | 93.7  | 62.4 | 89.3  | 87.5 | 71.8 | 84.1 |
| BERT-large|      |      |      |       |      |       |      |      |      |
| FineTuning†| 86.6 | 91.3 | 92.3 | 93.2  | 60.6 | 90.0  | 88.0 | 70.4 | 84.0 |
| FineTuning| 85.9 | 90.9 | 92.3 | 93.9  | 61.5 | 90.0  | 86.0 | 75.1 | 84.4 |
| TDT       | 86.4 | 91.4 | 92.6 | 94.3  | 66.2 | 89.9  | 88.5 | 75.8 | 85.6 |
| RoBERTa-large|    |      |      |       |      |       |      |      |      |
| FineTuning†| 90.2 | 92.2 | 94.7 | 96.4  | 68.0 | 92.4  | 90.9 | 86.6 | 88.9 |
| FineTuning| 90.5 | 92.3 | 94.4 | 96.6  | 67.4 | 92.2  | 91.9 | 87.7 | 89.1 |
| TDT       | 90.6 | 91.9 | 94.7 | 97.0  | 69.3 | 92.5  | 93.1 | 91.0 | 90.0 |
| XLNet †   | 90.8 | 92.3 | 94.9 | 97.0  | 69.0 | 92.5  | 90.8 | 85.9 | 89.1 |
| ELECRTA † | 90.9 | 92.4 | 95.0 | 96.9  | 69.1 | 92.6  | 90.8 | 88.0 | 89.4 |
| DeBERTa † | 91.1 | 92.4 | 95.3 | 96.8  | 70.5 | 92.6  | 91.9 | 88.3 | 89.8 |
| ALBERT †  | 90.8 | 92.2 | 95.3 | 96.9  | 71.4 | 93.0  | 90.9 | 89.2 | 89.9 |

Table 1: Experimental results on GLUE language understanding benchmark. When take RoBERTa-large as the PLM, for RTE and STS, we follow Liu et al. (2019b) to finetune starting from the MNLI model instead of the baseline pretrained model. Methods with † denote that we directly report the scores from corresponding paper, and others are from our implementation.

| Task     | BERT-www-base | MacBERT-large | RoBERTa-www-large |
|----------|---------------|---------------|-------------------|
|          | FineTuning    | TDT           | FineTuning        | TDT           | FineTuning    | TDT           |
| OCNLI    | 74.6          | 75.3          | 78.3              | 79.8          | 78.1          | 79.5          |
| IFLYTEK  | 60.8          | 62.2          | 61.5              | 61.8          | 61.8          | 62.9          |
| CSL      | 84.7          | 85.5          | 86.8              | 87.0          | 86.1          | 87.2          |
| TNEWS    | 56.9          | 57.3          | 58.5              | 58.7          | 59.0          | 59.2          |
| AFQMC    | 74.0          | 75.0          | 76.2              | 76.8          | 76.0          | 76.2          |
| Avg      | 70.20         | 71.06         | 72.26             | 72.82         | 72.20         | 73.00         |

Table 2: Experimental results on CLUE language understanding benchmark. For TNEWS, we only use the raw “sentence” for classification without the “keywords” information. For CSL, we only mask the “abst” sequence and keep the “keywords” sequence unchanged in our proposed method.

benchmark includes 9 tasks spanning several single-sentence/sentence-pair classification tasks, and we choose 5 tasks, OCNLI, IFLYTEK, CSL, TNEWS, and AFQMC. The detailed data statistics and metrics are provided in Appendix A.

3.2 Model & Training

We use the pretrained models and codes provided by HuggingFace1. We take BERT-base (Devlin et al., 2019), BERT-large (Devlin et al., 2019) and RoBERTa-large (Liu et al., 2019b) as our backbones on GLUE, while BERT-www-base (Cui et al., 2019), MacBERT-large (Cui et al., 2020), and RoBERTa-www-large (Cui et al., 2019) on CLUE. We tune the task specific hyper-parameters $m \in \{0, 2\}$, $\alpha \in \{0.5, 2, 4\}$ and $\beta \in \{0.5, 1\}$. Detailed experimental setups are shown in Appendix B. Following previous work (Lee et al., 2020; Aghajanyan et al., 2020), we report results of the development sets, since the performance on the test sets is only accessible on the leaderboard with a limitation of the number of submissions.

3.3 Main Results

Results on GLUE. We illustrate the experimental results on the GLUE benchmark in Table 1. We can observe that the PLMs enhanced by TDT outperforms FineTuning by a large margin across all the tasks. Specifically, TDTs achieve 1.48 points, 1.19 points and 0.88 points (on average) improvement over BERT-base, BERT-large, and RoBERTa-

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1https://github.com/huggingface/transformers
Figure 3: **Visualization of representations** of original input and two derived variants, where the triangle-shaped (pink), tri-up-shaped (purple), and tri-left-shaped (black) points denote the representations of original input, positive variants, and negative variants, respectively.

In particular, BERT-base+TDT achieves competitive performance compared with BERT-large+FineTuning, showing that our method is more efficient to find task-specific information for downstream tasks. This may be because our training strategy prompts the models to predict with as little information as possible, isolating the task-related signals from the whole representations.

RoBERT-large trained with TDT surpasses XLNet-large (Yang et al., 2019) ALBERT-xxlarge (Lan et al., 2019), DeBERTa-large (He et al., 2020), and ELECTRA-large (Clark et al., 2020), which are specially designed with different architectures and pre-training objectives.

**Results on CLUE.** Table 2 shows the overall results on the 5 tasks of CLUE benchmark. Concretely, TDT significantly outperforms FineTuning on CSL, IFLYTEK, AFQMC, and OCNLI, and shows competitive results on the short text classification task TNEWS, indicating the advantage of extracting important parts from long text or multiple input sequences. Note that TNEWS generally requires additional knowledge (e.g., keywords) as a supplement due to the short input, and thus cannot show the superiority of TDT.

4 Analysis & Discussion

4.1 Visualization of Representations

In Figure 3, we plot t-SNE visualizations (van der Maaten and Hinton, 2008) of three kinds of representations generated by BERT-large trained with TDT on CoLA dev set. We can see that the representations of the original input are close to those of the positive variant in the same class. Although the negative variant representations are really similar to the original ones which derive the former, they are clearly separated from the other representations. The learned disentangled representations reveal that the model trained with TDT is able to distinguish task-specific keywords and non-keyword context, which plays an important role in increasing models’ robustness.

4.2 Distribution of Confidence Scores

We investigate the learned confidence score distributions in Figure 4. It shows that although the initial distribution is consistent, the model learns different task-specific patterns (confidence distributions) on different tasks.


4.3 Does our Confidence Model make a meaningful estimation for input tokens?

In section 2.2, we mention that TDT uses a scalar for evaluating the contribution of each input token. To analyze whether the strategy can successfully learn a meaningful importance estimation, we construct two sets of datasets based on MRPC dev set and then evaluate the performance of BERT-large with TDT and standard fine-tuning. Specifically, we convert the confidence scores to probability distributions. We generate the first set of datasets by dropping input tokens in descending order of the distributions and generate the second set in ascending order. In order to ensure language fluency, we replace each dropped token with a “[MASK]” token. The results are shown in Figure 6 and we observe that:

- **TDT is more robust to incomplete input compared with Fine-tuning.** Specifically, although the performance of both FineTuning and TDT drops with the increase of dropout rate, our TDT achieves significantly better performance than FineTuning over all datasets.

- **Our learned confidence scores make reasonable assessments for each input token.** Particularly, regardless of the dropout rates and the training methods, dropping input tokens by the descending order of the masking scores always leads to worse performance.

4.4 Robustness to Input Perturbation

Based on the observation in Section 4.3, we further investigate the robustness of TDT on perturbed data. To construct perturbed data, we use the dev set of MRPC and possibly replace the input at each position with a “[MASK]” token or a token sampled from the input sequence. For each dropout rate, we construct 10 datasets with different random seeds and draw violin plots of the performance of BERT-large trained with TDT and fine-tuning (Figure 5). We can see that Ours is consistently better than FineTuning in all groups, indicating the superior robustness to noisy data.

4.5 Domain Generalization

We evaluate how well the trained models generalize to out-of-domain data on MNLI and OC-NLI, Natural Language Inference (NLI) tasks of GLUE and CLUE respectively. In detail, we fine-tune BERT-large on MNLI, and test the accuracy of the fine-tuned models on other NLI datasets.
Table 3: Performance of Domain Generalization. The models are trained on MNLI/OCNLI but tested on out-of-domain data.

| Task            | FineTuning | TDT | Δ    |
|-----------------|------------|-----|------|
| MNLI (BERT-large) | 85.8       | 86.4 | +0.6 |
| MNLI-m          | 73.1       | 74.2 | +1.1 |
| OCNLI (MacBERT-large) |           |     |      |
| CMNLI           | 70.6       | 71.8 | +1.2 |
| BUSTM           | 64.8       | 66.4 | +1.6 |

Table 4: Experimental results in low-resource scenarios. We run 4 times for each task with different random seeds and report the average accuracy and the standard deviation.

| Task        | FineTuning | TDT | Δ    |
|-------------|------------|-----|------|
| OCNLI       | 60.85 (+2.66) | 63.38 (+0.90) | +2.53 |
| IFLYTEK     | 54.12 (+0.75) | 54.78 (+0.94) | +0.66 |
| CSL         | 80.25 (+1.36) | 81.45 (+0.62) | +1.20 |
| TNEWS       | 53.50 (+0.58) | 53.33 (+0.25) | -0.17 |
| AFQMC       | 64.77 (+3.87) | 66.87 (+0.93) | +1.68 |
| Avg         | 62.70 | 63.88 | +1.18 |

4.6 Results in Low-resource Scenarios

Fine-tuning PLMs on very small amount of training data can be challenging and result in unstable performance due to the serious over-fitting issue. In this section, we explore the effectiveness of TDT in such scenarios. For each dataset in CLUE, we use MacBERT-large and sample 1k training examples as its training data. As Table 4 demonstrates, TDT improves the accuracy by 1.18 on average and reduces the standard deviation by up to 2.94. It suggests that our TDT is more stable and efficient than vanilla fine-tuning when training PLMs on limited data.

4.7 Compared with Variants

Ablation Studies. We first conduct ablation studies to explore the effectiveness of two additional loss functions introduced in this paper and show the results in Table 5. We find that removing any of them leads to a performance drop, which indicates their effectiveness on regularization for training.

Soft Perturbation vs. Hard Perturbation. The confidence score in this paper is continuous value ranging from 0 to 1, and we perturb the input in a soft way. It is straightforward to investigate the discrete counterpart. To this end, we model the discrete confidence score with the Gumbel-Softmax trick (Jang et al., 2017). More detailed is introduced in Appendix D. We denote the model trained with the hard strategy as TDT-hard and show the comparison in Table 5. From the table, both TDT-hard and TDT yield better performance than vanilla fine-tuning. This observation supports our claim that different tokens or phrases contribute differently to the final results, which can be detected by task-guided signal and then used to model more reliable encoders by our proposed regularization. Moreover, the inferior performance of TDT-hard shows that naively removing tokens has an adverse effect on context modeling and thus it is better to regularize the over-reliance in a soft manner.

4.8 Compared with Previous Methods

TDT vs. Token Cutoff. Our method can also be viewed as a soft variant of token cutoff (Shen et al., 2020), which is a data augmentation strategy. Table 5 shows the results where we find that TDT performs better than TokenCutoff, which demonstrates that the improvement of our method is not entirely due to the effect of data augmentation but stems from the design of the training objectives.

TDT vs. R-drop & R3F. Recently, Liang et al. (2021) proposed R-drop to regularize the consistency of sub-models obtained through dropout. Aghajanyan et al. (2021b) introduced R3F rooted in trust region theory, which adds noise into the input embedding and minimize the KL divergence between prediction distributions given original input and noisy input. Both of them are task-agnostic, while our proposed method constructs two derived variants with task signal, and concentrates on how to disentangle the task-relevant and task-irrelevant
### Table 5: Results of RoBERTa-large trained with TDT, variants or previous methods on 4 GLUE tasks and 4 CLUE tasks. For GLUE, results with † are taken from the corresponding paper.

| Model      | GLUE (RoBERTa-large) | CLUE (RoBERTa-www-large) |
|------------|----------------------|--------------------------|
|            | SST-2 | CoLA | MRPC | RTE | Avg | OCNL | IFLYTEK | CSL | TNEWS | Avg |
| FineTuning | 96.6  | 67.4 | 91.9 | 87.7| 85.90 | 78.1  | 61.8  | 86.1 | 59.0 | 71.25 |
| TokenCutOff† | 96.9  | 70.0 | 90.9 | 90.6| 87.10 | 78.2  | 61.8  | 86.1 | 59.2 | 71.33 |
| R-drop †   | 96.9  | 70.0 | 91.4 | 88.4| 86.67 | 78.9  | 61.6  | 86.6 | 58.9 | 71.50 |
| R3F †      | 97.0  | 71.2 | 91.6 | 88.5| 87.07 | -     | -     | -   | -   | -    |
| PostTraining | 95.0  | 64.7 | 91.2 | 84.1| 83.75 | 76.5  | 62.1  | 87.0 | 59.2 | 71.33 |
| TDT w/o $\mathcal{L}_C$ | 96.4  | 69.3 | 91.9 | 89.5| 86.77 | 78.6  | 61.9  | 86.9 | 59.0 | 71.60 |
| TDT w/o $\mathcal{L}_R$ | 96.4  | 66.7 | 91.4 | 90.6| 86.28 | 79.2  | 62.1  | 86.9 | 58.9 | 71.77 |
| TDT-hard   | 96.7  | 67.6 | 92.2 | 90.3| 86.70 | 79.1  | 62.5  | 87.0 | 59.1 | 71.93 |
| TDT        | 97.0  | 69.3 | 93.1 | 91.0| **87.60** | 79.5  | 62.9  | 87.2 | 59.2 | **72.20** |

Factors. The better performance of TDT compared with the strong R-drop and R3F baselines (Table 5) verify the advantage of task-driven regularization.

**TDT vs. Post-Training.** Post-training is an effective approach to reduce the objective gap between pretrained model and downstream tasks (Gu et al., 2020), which continues to train PLMs on task (or in-domain) training data with mask language model (MLM) loss. The difference lies in that we focus on the fine-tuning stage. Here, we compare TDT with the model first post-trained via MLM on training set of each task and then fine-tuned. It is surprising that post-training does not always have a positive effect on downstream fine-tuning, while TDT shows effective performance without additional post-training time consumption.

### 5 Related Work

Fine-tuning large-scale PLMs tends to be a popular paradigm of various NLP tasks (Devlin et al., 2019; Liu et al., 2019a; Yang et al., 2019). However, the fine-tuned models fail to capture task-specific patterns due to the imbalanced nature between the large number of parameters and limited training data (Aghajanyan et al., 2020). To address this issue, two main research lines are proposed: (1) continual pretraining after general pre-training, (2) regularization techniques in fine-tuning.

Continual pretraining of PLMs on unlabeled data of a given downstream domain or task has been proved effective for the end-task performance (Gururangan et al., 2020), and various continual pre-training objectives designed for different downstream tasks have been proposed (Tian et al., 2020; Wu et al., 2021). For example, Gu et al. (2020) propose a selective masking strategy to learn task-specific patterns based on mid-scale in-domain data. However, such methods usually rely on extra in-domain data and manually designed training objectives.

Due to the overfitting problems of fine-tuning, lots of regularization techniques have been proposed. Lee et al. (2019) and Chen et al. (2020) regularize fine-tuned weights with original pretrained weights while others design adversarial training objectives or introduce noise into the input (Zhu et al., 2020; Jiang et al., 2020; Aghajanyan et al., 2020; Shen et al., 2020; Yu et al., 2021; Hua et al., 2021; Qu et al., 2020). Liang et al. (2021) regularize the training by minimizing the KL-divergence between the output distributions of two sub-models sampled by dropout and Xu et al. (2021b) only updates a sub-set of the whole network during fine-tuning by selectively masking out the gradients in both task-free and task-driven ways. Moon et al. (2020) handle the over-reliance problem by reconstructing keywords based on other words and making low-confidence predictions without enough context.

### 6 Conclusion

In this paper, we propose task-guided disentangled tuning for enhancing the efficiency and robustness of PLMs in downstream NLP tasks. Our method is able to efficiently distinguish task-specific features and task-agnostic ones, and bridges the gap between pretraining and adaptation without the need of immediate continual training. Experiments on GLUE and CLUE benchmarks demonstrate the effectiveness of our method, and extensive analysis.
shows the advantage in domain generalization and low-resource setting over fine-tuning.

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A GLUE and CLUE Benchmark

In this paper, we conduct experiments on 8 datasets in GLUE benchmark (Wang et al., 2018), and 5 datasets in CLUE (Xu et al., 2020), including the short text classification task TNEWS, the long text classification tasks IFLYTEK and CSL, and sentence-pair classification tasks AFQMC and OC-NLI. The data statistics and evaluate metrics are illustrated in Table 6.

| Dataset | # Train | # Dev | Metrics |
|---------|--------|-------|---------|
| GLUE    |        |       |         |
| MNLI    | 393k   | 9.8k  | Accuracy |
| QQP     | 364k   | 40k   | Accuracy |
| QNLI    | 105k   | 5.5k  | Accuracy |
| SST-2   | 67k    | 872   | Accuracy |
| CoLA    | 8.5k   | 1.0k  | Matthews Corr |
| STS-B   | 5.7k   | 1.5k  | Spearman Corr |
| MRPC    | 3.7k   | 408   | Accuracy |
| RTE     | 2.5k   | 277   | Accuracy |
| CLUE    |        |       |         |
| OCNLI   | 50k    | 3k    | Accuracy |
| IFLYTEK | 12.1k  | 2.6k  | Accuracy |
| CSL     | 20k    | 3k    | Accuracy |
| TNEWS   | 53.3k  | 10k   | Accuracy |
| AFQMC   | 34.3k  | 4.3k  | Accuracy |
| CMNLI   | 391k   | 12k   | Accuracy |
| CLUEWSC | 1.2k   | 304   | Accuracy |

Table 6: Data Statistics and Evaluate Metrics.

B Settings for Different Pretrained Models

In this paper, we fine-tuned different pretrained models with TDT, including BERT-base, BERT-large, RoBERTa-large for GLUE and BERT-wwm-base, MacBERT-large, RoBERTa-wwm-large for CLUE. The batch size, training steps, warmup steps, and learning rate are listed in Table 7.

C Label Mapping in Domain Generalization

QQP has two labels, duplicate and not duplicate. We map entailment to duplicate and map both neutral and contradiction to not duplicate. BUSTM is a short text matching task of FewCLUE (Xu et al., 2021a). We use the public test set. BUSTM has two labels, 0 and 1. We map entailment to label 1, and map both neutral and contradiction to label 0.

D Detailed of TDT-hard

Gumbel-Softmax trick (Jang et al., 2017) is an approximation to sampling from the argmax. For-
Table 7: Hyperparameters settings for different pre-trained models on variant tasks.

![Table 7: Hyperparameters settings for different pre-trained models on variant tasks.](image_url)