Fine-Tuning Pre-Trained Language Model with Weak Supervision:
A Contrastive-Regularized Self-Training Approach

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Abstract
Fine-tuned pre-trained language models (LMs) achieve enormous success in many natural language processing (NLP) tasks, but they still require excessive labeled data in the fine-tuning stage. We study the problem of fine-tuning pre-trained LMs using only weak supervision, without any labeled data. This problem is challenging because the high capacity of LMs makes them prone to overfitting the noisy labels generated by weak supervision. To address this problem, we develop a contrastive self-training framework, COSINE, to enable fine-tuning LMs with weak supervision. Underpinned by contrastive regularization and confidence-based reweighting, this contrastive self-training framework can gradually improve model fitting while effectively suppressing error propagation. Experiments on sequence, token, and sentence pair classification tasks show that our model outperforms the strongest baseline by large margins on 7 benchmarks in 6 tasks, and achieves competitive performance with fully-supervised fine-tuning methods.

1 Introduction

Language model (LM) pre-training and fine-tuning achieve state-of-the-art performance in various natural language processing tasks (Peters et al., 2018; Devlin et al., 2019; Liu et al., 2019; Raffel et al., 2019). Such approaches stack task-specific layers on top of pre-trained language models, e.g., BERT (Devlin et al., 2019), then fine-tune the models with task-specific data. During fine-tuning, the semantic and syntactic knowledge in the pre-trained LMs is adapted for the target task. Despite their success, one bottleneck for fine-tuning LMs is the requirement of labeled data. When labeled data are scarce, the fine-tuned models often suffer from degraded performance, and the large number of parameters can cause severe overfitting (Xie et al., 2019).

To relieve the label scarcity bottleneck, we fine-tune the pre-trained language models with weak supervision. While collecting large amounts of clean labeled data is expensive for many NLP tasks, it is often cheap to obtain weakly labeled data from various weak supervision sources, such as semantic rules (Awasthi et al., 2020). For example, in sentiment analysis, we can use rules
‘terrible’ → Negative (a keyword rule) and ‘* not recommend *’ → Negative (a pattern rule) to generate large amounts of weak labels.

Fine-tuning language models with weak supervision is nontrivial. Excessive label noise, e.g., wrong labels, and limited label coverage are common and inevitable in weak supervisions. Although existing fine-tuning approaches (Xu et al., 2020; Zhu et al., 2020; Jiang et al., 2020) improve LMs’ generalization ability, they are not designed for noisy data and are still easy to overfit to the noise. Moreover, existing works on tackling label noise are flawed and are not designed for fine-tuning LMs. For example, Varma and Ré (2018); Ratner et al. (2020); Mallinar et al. (2019) use probabilistic models to aggregate multiple weak supervisions for denoising, but they generate weak-labels in a context-free manner, such that contextual information are not considered (Aina et al., 2019). Other works (Luo et al., 2017; Wang et al., 2019b) focus on noise transitions without explicitly conducting instance-level denoising, and they require clean training samples. Although some recent studies (Awasthi et al., 2020; Ren et al., 2020) design specific neural modules to denoise each sample, they require prior knowledge on the weak supervisions, which is often infeasible in practice.

Self-training (Rosenberg et al., 2005; Lee, 2013) is a proper tool for fine-tuning language models with weak supervision. It augments the training set with unlabeled data by generating pseudo-labels for them, which improves the models’ generalization power. This resolves the limited coverage issue in weak supervision. However, one major challenge of self-training is that the algorithm still suffers from error propagation—wrong pseudo-labels can cause model performance to gradually deteriorate.

We propose a new algorithm COSINE\(^1\) that fine-tunes pre-trained LMs with only weak supervision. COSINE leverages both weakly labeled and unlabeled data, as well as suppresses label noise via contrastive self-training. Weakly-supervised learning enriches data with potentially noisy labels, and our contrastive self-training scheme fulfills the denoising purpose. Specifically, contrastive self-training regularizes the feature space by pushing samples with the same pseudo-labels close while pulling samples with different pseudo-labels apart. Such regularization enforces representations of samples from different classes to be more distinguishable, such that the classifier can make better decisions. To suppress label noise propagation during contrastive self-training, we propose confidence-based sample reweighting and regularization methods. The reweighting strategy emphasizes samples with high prediction confidence, which are more likely to be correctly classified, in order to reduce the effect of wrong predictions. Confidence regularization encourages smoothness over model predictions, such that no prediction can be over-confident, and therefore reduces the influence of wrong pseudo-labels.

Our model is flexible and can be naturally extended to semi-supervised learning, where a small set of clean labels is available. Moreover, since we do not make assumptions about the nature of the weak labels, COSINE can handle various types of label noise, including biased labels and randomly corrupted labels. Biased labels are usually generated by semantic rules, whereas corrupted labels are often produced by crowd-sourcing (e.g., human annotators).

Our main contributions are: (1) A contrastive-regularized self-training framework that fine-

\(^1\) Short for **Contrastive Self-Training for Fine-Tuning Pre-trained Language Model**.
tune pre-trained LMs with weak supervision only. (2) Confidence-based reweighting and regularization techniques to reduce error propagation and prevent over-confident predictions. (3) Extensive experiments on 6 NLP classification tasks using 7 public benchmarks verifying the efficacy of COSINE. Moreover, our model achieves competitive performance in comparison with fully-supervised models on some datasets, e.g., on the Yelp dataset, we obtain a 97.2% (fully-supervised) v.s. 96.0% (ours) classification accuracy comparison.

Roadmap. The rest of this paper is organized as follows: Section 2 introduces relevant background. Section 3 presents our proposed method COSINE. Section 4 contains experiment results on 7 datasets, some case studies, and thorough ablation studies. In Section 5 we review related works, and we conclude this paper in Section 6. The appendices provide supplemental information on experiment setups and auxiliary results.

2 Background

In this section, we introduce weak supervision and our problem formulation.

Weak Supervision. Instead of using human-annotated data, we obtain labels from weak supervision sources, including keywords and semantic rules. From weak supervision sources, each of the input samples $x \in \mathcal{X}$ is given a label $y \in \mathcal{Y} \cup \{\emptyset\}$, where $\mathcal{Y}$ is the label set and $\emptyset$ denotes the sample is not matched by any rules. For samples that are given multiple labels, e.g., matched by multiple rules, we determine their labels by majority voting.

Problem Formulation. We focus on the weakly-supervised classification problems in natural language processing. We consider three types of tasks: sequence classification, token classification, and sentence pair classification. These tasks have a broad scope of applications in NLP. Formally, the weakly-supervised classification problem is defined as the following: Given weakly-labeled samples $\mathcal{X}_l = \{(x_i, y_i)\}_{i=1}^L$ and unlabeled samples $\mathcal{X}_u = \{x_j\}_{j=1}^U$, we seek to learn a classifier

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2Due to the space limit, examples of weak supervisions are deferred to Appendix A.3
\[ f(x; \theta) : \mathcal{X} \to \mathcal{Y} \]. Here \( \mathcal{X} = \mathcal{X}_l \cup \mathcal{X}_u \) denotes all the samples and \( \mathcal{Y} = \{1, 2, \cdots, C\} \) is the label set, where \( C \) is the number of classes.

## 3 Method

Our classifier \( f = g \circ \text{BERT} \) consists of two parts: BERT is a pre-trained language model that outputs hidden representations of input samples, and \( g \) is a task-specific classification head that outputs a \( C \)-dimensional vector, where each dimension corresponds to the prediction confidence of a specific class. In this paper, we use RoBERTa (Liu et al., 2019) as the realization of BERT.

The framework of COSINE is shown in Figure 1. First, the framework initializes the pre-trained LM with weakly labeled data. In this step, the semantic and syntactic knowledge of the pre-trained model is transferred to our model. Then, the framework uses contrastive self-training to suppress label noise propagation and continue training.

### 3.1 Overview

The training procedure of COSINE is as follows.

**Initialization with Weakly-labeled Data.** We fine-tune \( f(\cdot; \theta) \) with weakly-labeled data \( \mathcal{X}_l \) by solving the optimization problem

\[
\min_{\theta} \frac{1}{|\mathcal{X}_l|} \sum_{(x_i, y_i) \in \mathcal{X}_l} \text{CE}(f(x_i; \theta), y_i),
\]

where \( \text{CE}(\cdot, \cdot) \) is the cross entropy loss. We adopt early stopping to prevent the model from overfitting to the label noise. However, early stopping causes underfitting, and we resolve this issue by a contrastive self-training algorithm.

**Contrastive Self-training with All Data.** The goal of contrastive self-training is to leverage all data, both labeled and unlabeled, for fine-tuning, as well as to reduce the error propagation of wrongly labelled data. We generate pseudo-labels for the unlabeled data and incorporate them into the training set. To reduce error propagation, we introduce contrastive representation learning (Sec. 3.2) and confidence-based sample reweighting and regularization (Sec. 3.3). We update the pseudo-labels (denoted by \( \tilde{y} \)) and the model iteratively. The procedures are summarized in Algorithm 1.

- **Update \( \tilde{y} \) with the current \( \theta \).** To generate the pseudo-label for each sample \( x \in \mathcal{X} \), one straightforward way is to use hard labels (Lee, 2013)

\[
\tilde{y}_{\text{hard}} = \arg\max_{j \in \mathcal{Y}} [f(x; \theta)]_j.
\]

Note that \( f(x; \theta) \in \mathbb{R}^C \) is a probability vector and \([f(x; \theta)]_j\) indicates the \( j \)-th entry of it. However, these hard pseudo-labels only keep the most likely class for each sample and result in the propagation of labeling mistakes. For example, if a sample is mistakenly classified to a wrong class, assigning a 0/1 label complicates model updating (Eq. 4), in that the model is fitted on erroneous
Algorithm 1: Training Procedures of COSINE.

**Input:** Training samples \( \mathcal{X} \); Weakly labeled samples \( \mathcal{X}_l \subseteq \mathcal{X} \); Pre-trained LM \( f(\cdot; \theta) \).

// Fine-tune the LM with weakly-labeled data.

for \( t = 1, 2, \ldots, T_1 \) do

  Sample a minibatch \( B \) from \( \mathcal{X}_l \).
  Update \( \theta \) by Eq. 1 using AdamW.

// Conduct contrastive self-training with all data.

for \( t = 1, 2, \ldots, T_2 \) do

  Update pseudo-labels \( \tilde{y} \) by Eq. 3 for all \( x \in \mathcal{X} \).
  for \( k = 1, 2, \ldots, T_3 \) do
    Sample a minibatch \( B \) from \( \mathcal{X} \).
    Select high confidence samples \( \mathcal{C} \) by Eq. 9.
    Calculate \( L_c \) by Eq. 10, \( R_1 \) by Eq. 6, \( R_2 \) by Eq. 12, and \( \mathcal{L} \) by Eq. 4.
    Update \( \theta \) using AdamW.

**Output:** Fine-tuned model \( f(\cdot; \theta) \).

labels. To alleviate this issue, for each sample \( x \) in a batch \( B \), we generate soft pseudo-labels \(^3\) (Xie et al., 2016, 2019; Meng et al., 2020) \( \tilde{y} \in \mathbb{R}^C \) based on the current model as

\[
\tilde{y}_j = \frac{[f(x; \theta)]_j^2 / f_j}{\sum_{j' \in Y} [f(x'; \theta)]_{j'}^2 / f_{j'}} \quad (3)
\]

where \( f_j = \sum_{x' \in B} [f(x'; \theta)]_j^2 \) is the sum over soft frequencies of class \( j \). The non-binary soft pseudo-labels guarantee that, even if our prediction is inaccurate, the error propagated to the model update step will be smaller than using hard pseudo-labels.

- **Update \( \theta \) with the current \( \tilde{y} \).** We update the model parameters \( \theta \) by minimizing

\[
\mathcal{L}(\theta; \tilde{y}) = \mathcal{L}_c(\theta; \tilde{y}) + \mathcal{R}_1(\theta; \tilde{y}) + \lambda \mathcal{R}_2(\theta), \quad (4)
\]

where \( \mathcal{L}_c \) is the classification loss (Sec. 3.3), \( \mathcal{R}_1(\theta; \tilde{y}) \) is the contrastive regularizer (Sec. 3.2), \( \mathcal{R}_2(\theta) \) is the confidence regularizer (Sec. 3.3), and \( \lambda \) is the hyper-parameter for the regularization.

### 3.2 Contrastive Learning on Sample Pairs

The key ingredient of our contrastive self-training method is to learn representations that encourage data within the same class to have similar representations and keep data in different classes separated. Specifically, we first select high-confidence samples (Sec. 3.3) \( \mathcal{C} \) from \( \mathcal{X} \). Then for each pair \( x_i, x_j \in \mathcal{C} \), we define their similarity as

\[
W_{ij} = \begin{cases} 
  1, & \text{if } \arg\max_{k \in Y} [\tilde{y}_i]_k = \arg\max_{k \in Y} [\tilde{y}_j]_k \\
  0, & \text{otherwise,}
\end{cases} \quad (5)
\]

\(^3\)More discussions on hard vs. soft are in Sec. 4.5.
Figure 2: An illustration of contrastive learning. The black solid lines indicate similar sample pairs, and the red dashed lines indicate dissimilar pairs.

where $\bar{y}_i, \bar{y}_j$ are the soft pseudo-labels (Eq. 3) for $x_i, x_j$, respectively. For each $x \in C$, we calculate its representation $v = \text{BERT}(x) \in \mathbb{R}^d$, then we define the contrastive regularizer as

$$R_1(\theta; \bar{y}) = \sum_{(x_i, x_j) \in C \times C} \ell(v_i, v_j, W_{ij}),$$

(6)

where

$$\ell = W_{ij}d_{ij}^2 + (1 - W_{ij})(\max(0, \gamma - d_{ij}))^2.$$  

(7)

Here, $\ell(\cdot, \cdot, \cdot)$ is the contrastive loss (Chopra et al., 2005; Taigman et al., 2014), $d_{ij}$ is the distance between $v_i$ and $v_j$, and $\gamma$ is a pre-defined margin.

For samples from the same class, i.e. $W_{ij} = 1$, Eq. 6 penalizes the distance between them, and for samples from different classes, the contrastive loss is large if their distance is small. In this way, the regularizer enforces similar samples to be close, while keeping dissimilar samples apart by at least $\gamma$. Figure 2 illustrates the contrastive representations. We can see that our method produces clear inter-class boundaries and small intra-class distances, which eases the classification tasks.

### 3.3 Confidence-based Sample Reweighting and Regularization

While contrastive representations yield better decision boundaries, they require samples with high-quality pseudo-labels. In this section, we introduce reweighting and regularization methods to suppress error propagation and refine pseudo-label qualities.

**Sample Reweighting.** In the classification task, samples with high prediction confidence are more likely to be classified correctly than those with low confidence. Therefore, we further reduce label noise propagation by a confidence-based sample reweighting scheme. For each sample $x$ with the soft pseudo-label $\bar{y}$, we assign $x$ with a weight $\omega(x)$ defined by

$$\omega = 1 - \frac{H(\bar{y})}{\log(C)}, \quad H(\bar{y}) = -\sum_{i=1}^C \bar{y}_i \log \bar{y}_i,$$

(8)

where $0 \leq H(\bar{y}) \leq \log(C)$ is the entropy of $\bar{y}$. Notice that if the prediction confidence is low, then $H(\bar{y})$ will be large, and the sample weight $\omega(x)$ will be small, and vice versa. We use a pre-defined threshold $\xi$ to select high confidence samples $C$ from each batch $B$ as

$$C = \{x \in B \mid \omega(x) \geq \xi\}.$$

(9)

We use scaled Euclidean distance $d_{ij} = \frac{1}{d} \|v_i - v_j\|_2^2$ by default. More discussions on $W_{ij}$ and $d_{ij}$ are in Appendix F.
Then we define the loss function as
\[ L_c(θ, ˜y) = \frac{1}{|C|} \sum_{x \in C} \omega(x) D_{KL}( ˜y \| f(x; θ)), \] (10)
where
\[ D_{KL}(P\|Q) = \sum_k p_k \log \frac{p_k}{q_k} \] (11)
is the Kullback–Leibler (KL) divergence.

**Confidence regularization.** The sample reweighting approach promotes high confidence samples during contrastive self-training. However, this strategy relies on wrongly-labeled samples to have low confidence, which may not be true unless we prevent over-confident predictions. To this end, we propose a confidence-based regularizer that encourages smoothness over predictions, defined as
\[ R_2(θ) = \frac{1}{|C|} \sum_{x \in C} D_{KL}(u \| f(x; θ)), \] (12)
where \( D_{KL} \) is the KL-divergence and \( u_i = 1/C \) for \( i = 1, 2, \cdots, C \). Such term constitutes a regularization to prevent over-confident predictions and leads to better generalization (Pereyra et al., 2017).

## 4 Experiments

**Datasets and Tasks.** We perform experiments on 6 NLP classification tasks with 7 public benchmarks: *AGNews* (Zhang et al., 2015) is a Topic Classification task; *IMDB* (Maas et al., 2011) and *Yelp* (Meng et al., 2018) are Sentiment Analysis tasks; *TREC* (Voorhees and Tice, 1999) is a Question Classification task; *MIT-R* (Liu et al., 2013) is a Slot Filling task; *Chemprot* (Krallinger et al., 2017) is a Relation Classification task; and *WiC* (Pilehvar and Camacho-Collados, 2019) is a Word Sense Disambiguation (WSD) task. The dataset statistics are summarized in Table 1. More details on datasets and weak supervision sources are in Appendix A.

| Dataset | Task    | C | #Train | #Dev | #Test | Coverage | Accuracy |
|---------|---------|---|--------|------|-------|----------|----------|
| AGNews  | Topic   | 4 | 96k    | 12k  | 12k   | 56.4     | 83.1     |
| IMDB    | Sentiment | 2 | 20k    | 2.5k | 2.5k  | 87.5     | 74.5     |
| Yelp    | Sentiment | 2 | 30.4k  | 3.8k | 3.8k  | 82.8     | 71.5     |
| MIT-R   | Slot Filling | 9 | 6.6k   | 1.0k | 1.5k  | 13.5     | 80.7     |
| TREC    | Question | 6 | 4.8k   | 0.6k | 0.6k  | 95.0     | 63.8     |
| Chemprot| Relation | 10| 12.6k  | 1.6k | 1.6k  | 85.9     | 46.5     |
| WiC     | WSD     | 2 | 5.4k   | 0.6k | 1.4k  | 63.4     | 58.8     |

Table 1: Dataset statistics. Here C is the number of classes, Coverage (in %) is the fraction of instances covered by weak supervision sources in the training set, and Accuracy (in %) is the precision of weak supervision.

**Baselines.** We compare our model with different groups of baseline methods:
(i) **Exact Matching (ExMatch):** The test set is directly labeled by weak supervision sources.

(ii) **Fine-tuning Methods:** The second group of baselines are fine-tuning methods for LMs:

- RoBERTa (Liu et al., 2019) uses the RoBERTa-base model with task-specific classification heads.
- Self-ensemble (Xu et al., 2020) uses self-ensemble and distillation to improve the generalization ability of the model.
- FreeLB (Zhu et al., 2020) adopts adversarial training to enforce smooth outputs.
- Mixup (Zhang et al., 2018; Verma et al., 2019) is a data augmentation method that creates virtual training samples by linear interpolations.
- SMART (Jiang et al., 2020) adds adversarial and smoothness constraints to fine-tune LMs and achieves state-of-the-art result for many NLP tasks.

(iii) **Weakly-supervised Models:** The third group of baselines are weakly-supervised models:

- Snorkel (Ratner et al., 2020) aggregates different labeling functions based on their correlations.
- WeSTClass (Meng et al., 2018) trains a classifier with generated pseudo-documents and use self-training to bootstrap all samples.
- ImplyLoss (Awasthi et al., 2020) co-trains a rule-based classifier and a neural classifier to denoise.
- Denoise (Ren et al., 2020) uses attention network to estimate the reliability of weak supervision, then reduce the noise via aggregating weak labels.
- UST (Mukherjee and Awadallah, 2020) is the state-of-the-art method for self-training with limited labels. It estimates uncertainties via MC-dropout (Gal and Ghahramani, 2015), then select samples with low uncertainties for self-training.

**Evaluation Metrics.** We use classification accuracy on the test set as the evaluation metric for all datasets except MIT-R. MIT-R contains large number of tokens that are labeled as “Others”. Therefore, we use the micro $F_1$ score for this dataset.

**Miscellany.** We implement COSINE using PyTorch, and we use RoBERTa-base as our pre-trained language model. Datasets and weak supervision details are in Appendix A. Baseline settings and task-specific implementation details are in Appendices B and C, respectively. Training details and setups are in Appendix D. Discussions about early-stopping are in Appendix E. Comparison of different distance metrics and similarity measures are in Appendix F.
Table 2: Classification accuracy (in %) on various datasets. We report the mean over three runs.

4.1 Learning From Weak Labels

We summarize the weakly-supervised leaning results in Table 2. In all the datasets, COSINE outperforms all the baseline models. A special case is the WiC dataset, where we use WordNet\(^9\) to generate weak labels. However, this enables Snorkel to access some labeled data in the development set, making it unfair to compete against other methods. We will discuss more about this dataset in Sec. 4.3.

In comparison with directly fine-tuning the pre-trained LMs with weakly-labeled data, our model employs an “earlier stopping” technique\(^10\) so that it does not overfit to the label noise. As shown, indeed “Init” achieves better performance, and it serves as a good initialization for our framework. Other fine-tuning methods and weakly-supervised models either cannot harness the power of pre-trained language models, e.g., Snorkel, or rely on clean labels, e.g., other baselines. We highlight that although UST, the state-of-the-art method to date, achieves strong performance under few-shot settings, their approach cannot estimate confidence well with noisy labels, and this yields inferior performance. Our model can gradually correct wrong pseudo-labels and mitigate error propagation via contrastive self-training. It is worth noticing that on some datasets, e.g., AGNews, IMDB, Yelp, and WiC, our model achieves the same level of performance with models

| Method                     | AGNews | IMDB  | Yelp  | MIT-R | TREC  | Chemprot | WiC (dev) |
|----------------------------|--------|-------|-------|-------|-------|----------|-----------|
| ExMatch                    | 52.31  | 71.28 | 68.68 | 34.93 | 60.80 | 46.52    | 58.80     |
| **Fully-supervised Baseline** |        |       |       |       |       |          |           |
| RoBERTa-CL\(^\d\) (Liu et al., 2019) | 91.41  | 94.26 | 97.27 | 88.51 | 96.68 | 79.65    | 70.53     |
| **LM Fine-tuning Baselines** |        |       |       |       |       |          |           |
| RoBERTa-WL\(^\d\) (Liu et al., 2019) | 82.25  | 72.60 | 74.89 | 70.95 | 62.25 | 44.80    | 59.36     |
| Self-ensemble (Xu et al., 2020) | 85.72  | 86.72 | 80.08 | 72.88 | 66.18 | 44.62    | 62.71     |
| FreeLB (Zhu et al., 2020)   | 85.12  | 88.04 | 85.68 | 73.04 | 67.33 | 45.68    | 63.45     |
| Mixup (Zhang et al., 2018)  | 85.40  | 86.92 | 92.05 | 73.68 | 66.83 | 51.59    | 64.88     |
| SMART (Jiang et al., 2020)  | 86.12  | 86.98 | 88.58 | 73.66 | 68.17 | 48.26    | 63.55     |
| **Weakly-supervised Baselines** |        |       |       |       |       |          |           |
| Snorkel (Ratner et al., 2020) | 62.91  | 73.22 | 69.21 | 20.63 | 58.60 | 37.50    | —\(^*\)   |
| WeSTClass (Meng et al., 2018) | 82.78  | 77.40 | 76.86 | —\(^@\) | 37.31 | —\(^@\) | 48.59     |
| ImplyLoss (Awasthi et al., 2020) | 68.50  | 63.85 | 76.29 | 74.30 | 80.20 | 53.48    | 54.48     |
| Denoise (Ren et al., 2020)  | 85.71  | 82.90 | 87.53 | 70.58 | 69.20 | 50.56    | 62.38     |
| UST (Mukherjee and Awadallah, 2020) | 86.28  | 84.56 | 90.53 | 74.41 | 65.52 | 52.14    | 63.48     |
| **Our COSINE Framework**    |        |       |       |       |       |          |           |
| Init                       | 84.63  | 83.58 | 81.76 | 72.97 | 65.67 | 51.34    | 63.46     |
| COSINE                     | 87.52  | 90.54 | 95.97 | 76.61 | 82.59 | 54.36    | 67.71     |

\(^:\) Trained with clean labels. \(^\d\): Trained with weak labels. \(^*\): Unfair comparison. \(^@\): Not applicable.

\(^5\) All methods use RoBERTa-base as the backbone unless otherwise specified.
\(^6\) The Chemprot dataset also contains “Others” type, but such instances are few, so we still use accuracy as the metric.
\(^7\) [https://pytorch.org/](https://pytorch.org/)
\(^8\) Our code is available at [https://github.com/yueyu1030/COSINE](https://github.com/yueyu1030/COSINE).
\(^9\) [https://wordnet.princeton.edu/](https://wordnet.princeton.edu/)
\(^10\) We will discuss this technique in Appendix E.
(RoBERTa-CL) trained with clean labels. This makes COSINE appealing in the scenario where only weak supervision is available.

4.2 Robustness Against Label Noise

Our model is robust against excessive label noise. We corrupt certain percentage of labels by randomly changing each one of them to another class. This is a common scenario in crowd-sourcing, where we assume human annotators mis-label each sample with the same probability. Figure 3 summarizes experiment results on the TREC dataset. We use SMART and UST as baselines, which are designed to handle corrupted labels.\textsuperscript{11} Our model consistently outperforms the baselines.

![Figure 3: Results of label corruption on TREC. When the corruption ratio is less than 40%, the performance is close to the fully supervised method.](image)

4.3 Semi-supervised Learning and Transductive Learning

We can naturally extend our model to semi-supervised learning, where clean labels are available for a portion of the data. We conduct experiments on the WiC dataset. As a part of the SuperGLUE Wang et al. (2019a) benchmark, this dataset proposes a challenging task as to determine whether the same word in different sentences has the same sense (meaning).

Different from previous tasks where the labels in the training set are noisy, in this part, we utilize the clean labels provided by the WiC dataset. We further augment the original training data of WiC with unlabeled sentence pairs obtained from lexical databases (e.g., WordNet, Wictionary). Note that part of the unlabeled data can be weakly-labeled by rule matching. This essentially creates a semi-supervised task, where we have labeled, weakly-labeled and unlabeled data.

As the weak labels of WiC are generated by WordNet and partially reveal the true labels, Snorkel (Ratner et al., 2020) can take this unfair advantage by accessing the unlabeled sentences and weak labels of validation and the test data. To make the comparison fair, we consider the transductive learning setting, where we allow access to the same information by integrating unlabeled validation and test data and their weak labels into the training set.

\textsuperscript{11}Note that some methods in Table 2, e.g., ImplyLoss, are not applicable to this setting since they require weak supervision sources, but none exists in this setting.
As shown in Table 3, compared with semi-supervised baselines (e.g., VAT and MT) and fine-tuning methods with extra resources (e.g., SenseBERT), COSINE achieves better performance in both semi-supervised and transductive learning settings. Moreover, COSINE with transductive learning achieves better performance compared with Snorkel.
4.4 Case Study

**Error propagation mitigation and wrong-label correction.** Figure 4 visualizes this process. Before training, the semantic rules make noisy predictions. After the initialization step, model predictions are less noisy but more biased, e.g., many samples are mis-labeled as “Amenity”. These predictions are further refined by contrastive self-training. The rightmost figure demonstrates wrong-label correction. Samples are indicated by radii of the circle, and classification correctness is indicated by color, i.e., blue means correct and orange means incorrect. From inner to outer tori specify classification accuracy after the initialization stage, and the iteration 1,2,3. We can see that lots of incorrect predictions are rectified within three iterations. Moreover, we give two examples for illustration: the right black dashed line means the corresponding sample is classified correctly after the first iteration, while the left line indicates the case when the sample is mis-classified after the second iteration but corrected after the third iteration. These results demonstrate that our model can correct wrong predictions via contrastive self-training.

**Better data representations.** We visualize the embedding of sample representations in Fig. 5. By incorporating the contrastive regularizer $R_1$, our model learns more compact representations for data in the same class, e.g., the green class, and also extends the inter-class distances, e.g., the purple class is more separable from other classes in Fig. 5(b) than in Fig. 5(a).

![t-SNE visualization on TREC. Each color denotes a different class.](image-url)

**Label efficiency.** Figure 6 illustrates the number of clean labels needed for the supervised model to outperform COSINE. On both of the datasets, the supervised model requires a significant amount of clean labels (around 750 for Agnews and 120 for MIT-R) to reach the level of performance as ours, whereas our method assumes no clean sample.

**Higher Confidence Indicates Better Accuracy.** Figure 7 demonstrates the relation between prediction confidence and prediction accuracy on IMDB. We can see that in general, samples with higher prediction confidence yield higher prediction accuracy. With our sample reweighting method, we gradually filter out low-confidence samples and assign higher weights for others, which effectively mitigates error propagation.
4.5 Ablation Study

Components of COSINE. We inspect the importance of various components in our model, including the contrastive regularizer $R_1$, the confidence regularizer $R_2$, and the sample reweighting strategy (SR). Table 4 summarize the results and Fig. 8 visualizes the learning curves. We remark that the three components jointly contribute to the model performance, and removing any of them hurts the classification accuracy. For example, sample reweighting is an effective tool to reduce error propagation, and removing it causes the model to eventually overfit to the label noise, e.g., the red bottom line in Fig. 8 illustrates that the classification accuracy increases and then drops rapidly. On the other hand, replacing the soft pseudo-labels (Eq. 3) with the hard counterparts (Eq. 2) causes drops in performance. This is because using hard pseudo-labels loses prediction confidence information.

| Method         | AGNews | IMDB  | Yelp  | MIT-R | TREC  |
|----------------|--------|-------|-------|-------|-------|
| Init           | 84.63  | 83.58 | 81.76 | 72.97 | 66.50 |
| COSINE         | 87.52  | 90.54 | 95.97 | 76.61 | 82.59 |
| w/o $R_1$      | 86.04  | 88.32 | 94.64 | 74.11 | 78.28 |
| w/o $R_2$      | 85.91  | 89.32 | 93.96 | 75.21 | 77.11 |
| w/o SR         | 86.72  | 87.10 | 93.08 | 74.29 | 79.77 |
| w/o $R_1$/$R_2$| 86.33  | 84.44 | 92.34 | 73.67 | 76.95 |
| w/o $R_1$/$R_2$/SR | 86.61  | 83.98 | 82.57 | 73.59 | 74.96 |
| w/o Soft Label | 86.07  | 89.72 | 93.73 | 73.05 | 71.91 |

Table 4: Effects of different components. Due to space limit we only show results for 5 representative datasets.

Hyper-parameters of COSINE. In Fig. 9, we examine the effects of different hyper-parameters, including the confidence threshold $\xi$ (Eq. 9), the stopping time $T_1$ in the initialization step, the updating period for pseudo-labels $T_3$ during the contrastive self-training. From Fig. 9(a), we can see that setting the confidence threshold too big hurts model performance, which is because an over-conservative selection strategy can result in insufficient number of training data. The stop-
ping time $T_1$ has drastic effects on the model. This is because fine-tuning COSINE with weak labels for excessive steps causes the model to unavoidably overfit to the label noise, such that the contrastive self-training procedure cannot correct the error. Also, with the increment of $T_3$, the update period of pseudo-labels, model performance first increases and then decreases. This is because if we update pseudo-labels too frequently, the contrastive self-training procedure cannot fully suppress the label noise, and if the updates are too infrequent, the pseudo-labels cannot capture the updated information well.

5 Related Works

Fine-tuning Pre-trained Language Models. To improve the model’s generalization power during fine-tuning stage, several methods are proposed, e.g., adapting specific layers (Peters et al., 2019), incorporating adversarial training (Zhu et al., 2020), and enforcing smoothness constraints (Xu et al., 2020; Jiang et al., 2020). However, these methods rely heavily on large amounts of clean labels, which are not always available. To address this issue, we propose a contrastive self-training framework that fine-tune pre-trained models with only weak labels.

Self-training Methods. Self-training is successful in tasks such as text classification (Meng et al., 2018), reading comprehension (Niu et al., 2020) and machine translation (He et al., 2020). However, one drawback is the sensitivity to wrong labels – when trained with noisy labels, self-training suffers from error-propagation (Fig. 8). In our model, we reweight samples based on confidence to suppress label noise and reduce error propagation. Moreover, we add contrastive constraints on high-confidence sample pairs to regularize the feature spaces.

Learning From Weak Supervision. In weakly-supervised learning, the training data are usually noisy and incomplete. Existing methods aim to denoise the sample labels or the labeling functions by, for example, aggregating multiple weak supervisions (Ratner et al., 2020; Lison et al., 2020; Ren et al., 2020), using clean samples (Awasthi et al., 2020), and leveraging contextual information (Mekala and Shang, 2020). However, most of them can only use specific type of weak supervision on specific task, e.g., key words for text classification (Meng et al., 2018, 2020; Mekala and Shang, 2020), and they require prior knowledge on the weak supervision sources (Awasthi et al., 2020; Lison et al., 2020; Ren et al., 2020). Our work is orthogonal to them since we do not denoise the
labeling functions directly. Instead, we adopt contrastive self-training to leverage the power of pre-trained language models for denoising, and our method outperforms all weakly-supervised baselines on seven classification tasks.

6 Conclusion and Discussion

In this paper, we propose a contrastive self-training framework, COSINE, for fine-tuning pre-trained language models with weak supervision. Our framework can learn better data representations to ease the classification task, and also efficiently reduce label noise propagation by confidence-based reweighting and regularization. We conduct experiments on various classification tasks, including sequence classification, token classification, and sentence pair classification, and the results demonstrate the efficacy of our model.

COSINE is a general framework that can handle tasks and weak supervision sources beyond our conducted experiments. For example, other than semantic rules, crowd-sourcing can be another weak supervision source to generate pseudo-labels. For future research, it is interesting to adopt COSINE to existing self-training models on other applications such as reading comprehension (Niu et al., 2020). Moreover, we can combine COSINE with active learning (Fang et al., 2017; Zhang et al., 2020) to acquire labels for low confidence samples and improve model’s robustness.

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A Datasets and Weak Supervision Details

A.1 Data Source

The seven benchmarks in our experiments are all publicly available. Below are the links to downloadable versions of these datasets.

○ AGNews and Yelp: We use the datasets from (Meng et al., 2018): https://github.com/yumeng5/WeSTClass.
○ IMDB: Dataset is available at https://ai.stanford.edu/~amaas/data/sentiment/.
○ TREC: Dataset is available at https://cogcomp.seas.upenn.edu/Data/QA/QC/.
○ MIT-R: Dataset is available at http://groups.csail.mit.edu/sls/downloads/restaurant/.
○ ChemProt: The raw dataset is available at http://www.cbs.dtu.dk/services/ChemProt/ChemProt-2.0/. The preprocessed dataset is available at https://drive.google.com/drive/folders/1Uzi76WE5o0e7Rv_vhXs7W4LkQBt6udFX?usp=sharing.
○ WiC: Dataset is available at https://pilehvar.github.io/wic/.

A.2 Train/Test Split

For AGNews, Yelp, IMDB and ChemProt, we follow the split ratio in (Meng et al., 2018). We use 80% of the data as the training set, 10% as the validation set, and 10% as the test set.

For MIT-R and TREC, we split the data in the same way as (Awasthi et al., 2020).

For WiC, we use the same dataset and the train/test split ratio in (Pilehvar and Camacho-Collados, 2019).

A.3 Weak Supervision Details

COSINE does not require any human annotated examples in the training process, and it only needs weak supervision sources such as keywords and semantic rules. According to some studies in existing works (Awasthi et al., 2020; Zhou et al., 2020), such weak supervisions are cheap to obtain. And we can obtain significantly more labeled examples using these weak supervision sources than human labor.

There are two types of semantic rules that we apply as weak supervisions:

○ Keyword Rule: \( \text{HAS}(x, \ L) \rightarrow C \). If \( x \) matches one of the words in the list \( L \), we label it as \( C \).

○ Pattern Rule: \( \text{MATCH}(x, \ R) \rightarrow C \). If \( x \) matches the regular expression \( R \), we label it as \( C \).

In addition to the keyword rule and the pattern rule, we can also use third-party tools to obtain weak labels. These tools (e.g., TextBlob\(^{12}\)) are available online, but the generated annotations are not accurate (when using these tools, the accuracy on Yelp is around 60%).

We now introduce the semantic rules on each dataset:

○ AGNews: Examples are demonstrated in Table 5.

\(^{12}\)https://textblob.readthedocs.io/en/dev/index.html
- **IMDB**: Examples are demonstrated in Table 6.

- **Yelp**: Examples are demonstrated in Table 7. We provide labeling rules in eight views.

- **MIT-R**: There are 15 rules in (Awasthi et al., 2020). Please refer to the original paper for detailed information on rules.

- **TREC**: There are 68 rules in (Awasthi et al., 2020). Please refer to the original paper for detailed information on rules.

- **ChemProt**: There are 26 rules. We show part of the rules in Table 8.

- **WiC**: Each sense of each word in WordNet has example sentences. For each sentence in the WiC dataset and its corresponding keyword, we collect the example sentences of that word from WordNet. Then for a pair of sentences, the corresponding weak label is “True” if their definitions are the same, otherwise the weak label is “False”.

| Rule |
|------|
| [war, prime minister, president, commander, minister, military, militant, kill, operator] → POLITICS |
| [baseball, basketball, soccer, football, boxing, swimming, world cup, nba, olympics, final, fifa] → SPORTS |
| [delta, cola, toyota, costco, gucci, citibank, airlines] → BUSINESS |
| [technology, engineering, science, research, cpu, windows, unix, system, computing, compute] → TECHNOLOGY |

Table 5: Examples of semantic rules on AGNews.
| Rule |
|----------------------------------|
| [masterpiece, outstanding, perfect, great, good, nice, best, excellent, worthy, awesome, enjoy, positive, pleasant, wonderful, amazing, superb, fantastic, marvellous, fabulous] → POS |
| [bad, worst, horrible, awful, terrible, crap, shit, garbage, rubbish, waste] → NEG |
| [beautiful, handsome, talented] → POS |
| [fast forward, n’t finish] → NEG |
| [well written, absorbing, attractive, innovative, instructive, interesting, touching, moving] → POS |
| [to sleep, fell asleep, boring, dull, plain] → NEG |
| [than this, than the film, than the movie] → NEG |
| MATCH(x, +PRE*EXP*) → POS PRE = [will, ll, would, d, can’t wait to] EXP = [next time, again, rewatch, anymore, rewind] |
| PRE = [highly, do, would, definitely, certainly, strongly, i, we] |
| EXP = [recommend, nominate] |
| PRE = [high, timeless, priceless, has, great, of, real, instructive] EXP = [value, quality, meaning, significance] |

Table 6: Examples of semantic rules on IMDB.
| View         | Rule                                                                 |
|--------------|----------------------------------------------------------------------|
| General      | [outstanding, perfect, great, good, nice, best, excellent, worthy,   |
|              | awesome, enjoy, positive, pleasant, wonderful, amazing] → POS       |
| General      | [bad, worst, horrible, awful, terrible, nasty, shit,                 |
|              | distasteful, dreadful, negative] → NEG                              |
| Mood         | [happy, pleased, delighted, contented, glad, thankful, satisfied]   |
|              | → POS                                                                |
| Mood         | [sad, annoy, disappointed, frustrated, upset, irritated, harassed,   |
|              | angry, pissed] → NEG                                                |
| Service      | [friendly, patient, considerate, enthusiastic, attentive,            |
|              | thoughtful, kind, caring, helpful, polite, efficient, prompt] → POS |
| Service      | [slow, offended, rude, indifferent, arrogant] → NEG                  |
| Price        | [cheap, reasonable, inexpensive, economical] → POS                   |
| Price        | [overpriced, expensive, costly, high-priced] → NEG                   |
| Environment  | [clean, neat, quiet, comfortable, convenient, tidy, orderly, cosy,   |
|              | homely] → POS                                                        |
| Environment  | [noisy, mess, chaos, dirty, foul] → NEG                              |
| Food         | [tasty, yummy, delicious, appetizing, good-tasting, delectable,      |
|              | savoury, luscious, palatable] → POS                                 |
| Food         | [disgusting, gross, insipid] → NEG                                   |
|             | [recommend] → POS                                                     |
| Third-party  | POLARITY(α) > 0.5 → POS                                              |
| Tools        | POLARITY(α) > 0.5 → NEG                                              |

Table 7: Examples of semantic rules on Yelp.
| Rule | Example |
|------|---------|
| HAS (x, [amino acid,mutant, mutat, replace] ) → part_of | A major part of this processing requires endoproteolytic cleavage at specific pairs of basic [CHEMICAL]amino acid[CHEMICAL] residues, an event necessary for the maturation of a variety of important biologically active proteins, such as insulin and [GENE]nerve growth factor[GENE]. |
| HAS (x, [bind, interact, affinit] ) → regulator | The interaction of [CHEMICAL]naloxone estrone azine[CHEMICAL] (N-EH) with various [GENE]opioid receptor[GENE] types was studied in vitro. |
| HAS (x, [activat, increas, induc, stimulat, upregulat] ) → upregulator/activator | The results of this study suggest that [CHEMICAL]noradrenaline[CHEMICAL] predominantly, but not exclusively, mediates contraction of rat aorta through the activation of an [GENE]alphalD-adrenoceptor[GENE]. |
| HAS (x, [downregulat, inhibit, reduc, decreas] ) → downregulator/inhibitor | These results suggest that [CHEMICAL]prostacyclin[CHEMICAL] may play a role in downregulating [GENE]tissue factor[GENE] expression in monocytes, at least in part via elevation of intracellular levels of cyclic AMP. |
| HAS (x, [agoni, tagoni]* ) → agonist * (note the leading whitespace in both cases) | Alprenolol and BAAM also caused surmountable antagonism of [CHEMICAL]isoprenaline[CHEMICAL] responses, and this [GENE]beta 1-adrenoceptor[GENE] antagonism was slowly reversible. |
| HAS (x, [antagon] ) → antagonist | It is concluded that [CHEMICAL]labetalol[CHEMICAL] and dilevalol are [GENE]beta 1-adrenoceptor[GENE] selective antagonists. |
| HAS (x, [modulat, allosteric] ) → modulator | [CHEMICAL]Hydrogen sulfide[CHEMICAL] as an allosteric modulator of [GENE]ATP-sensitive potassium channels[GENE] in colonic inflammation. |
| HAS (x, [cofactor] ) → cofactor | The activation appears to be due to an increase of [GENE]GAD[GENE] affinity for its cofactor, [CHEMICAL]pyridoxal phosphate[CHEMICAL] (PLP). |
| HAS (x, [substrate, catalyz, transport, produc, conver] ) → substrate/product | Kinetic constants of the mutant [GENE]CrAT[GENE] showed modification in favor of longer [CHEMICAL]acyl-CoAs[CHEMICAL] as substrates. |
| HAS (x, [not] ) → not | [CHEMICAL]Nicotine[CHEMICAL] does not account for the CSE stimulation of [GENE]VEGF[GENE] in HFL-1. |

Table 8: Examples of semantic rules on Chemprot.
B Baseline Settings

We implement Self-ensemble, FreeLB, Mixup and UST based on their original paper. For other baselines, we use their official release:

- WeSTClass (Meng et al., 2018): https://github.com/yumeng5/WeSTClass.
- RoBERTa (Liu et al., 2019): https://github.com/huggingface/transformers.
- SMART (Jiang et al., 2020): https://github.com/namisan/mt-dnn.
- Snorkel (Ratner et al., 2020): https://www.snorkel.org/.
- ImplyLoss (Awasthi et al., 2020): https://github.com/awasthiabhijeet/Learning-From-Rules13.
- Denoise (Ren et al., 2020): https://github.com/weakrules/Denoise-multi-weak-sources.

C Adapting RoBERTa to Different Tasks

C.1 Data Tokenization

For different tasks we adopt different tokenization strategies as follows:

- For sentimental analysis, topic classification, question classification, and slot filling, we add a [CLS] token at the beginning of every sequences.

- For relation classification, we need to identify the relation between two given terms. We add the [CLS] tokens, as well as special tokens [ENT1] and [ENT2] around each of the terms.

- For word sense disambiguation, the data consist of two sentences, and each of them contains a target word. We add the [CLS] tokens, as well as a special token [ENT] before each of the term. We also add a [SEP] token between the two sentences.

C.2 Classification Heads

To adapt RoBERTa to downstream tasks, we use different classification heads as follows:

- For sentimental analysis, topic classification, and question classification, we use a sequence classification head and we use the embedding of the [CLS] token as the representation of the sequence.

- For slot filling, we use a token classification head. During loss computation and evaluation, we ignore the outputs corresponding to the special tokens.

- For relation classification and word sense disambiguation, we use the same classification head as Wu and He (2019). See https://github.com/monologg/R-BERT for details.

13 We use the RoBERTa embedding instead of the ELMo embedding for fair comparison.
D Detailed Information on Experiment Setups

D.1 Computing Infrastructure

*System:* Ubuntu 18.04.3 LTS; Python 3.7; PyTorch 1.2.
*CPU:* Intel(R) Core(TM) i7-5930K CPU @ 3.50GHz.
*GPU:* GeForce GTX TITAN X.

D.2 Hyper-parameters

We use AdamW (Loshchilov and Hutter, 2019) as the optimizer, and the learning rate is chosen from $1 \times 10^{-5}, 2 \times 10^{-5}, 3 \times 10^{-5}$). A linear learning rate decay schedule with warm-up 0.1 is used, and the number of training epochs is 5.

Hyper-parameters are shown in Table 9. We use a grid search to find the optimal setting for each task. Specifically, we search $T_1$ from 10 to 2000, $T_2$ from 1000 to 5000, $T_3$ from 10 to 500, $\xi$ from 0 to 1, and $\lambda$ from 0 to 0.5. All results are reported as the average over three runs.

| Hyper-parameter      | AGNews | IMDB | Yelp | MIT-R | TREC | Chemprot | WiC |
|----------------------|--------|------|------|-------|------|----------|-----|
| Dropout Ratio        |        |      |      |       |      |          | 0.1 |
| Maximum Tokens       | 128    | 256  | 512  | 64    | 64   | 400      | 256 |
| Batch Size           | 32     | 16   | 16   | 64    | 16   | 24       | 32  |
| Weight Decay         |        |      |      |       |      |          | $10^{-4}$ |
| Learning Rate        | $10^{-5}$ | $10^{-5}$ | $10^{-5}$ | $10^{-5}$ | $10^{-5}$ | $10^{-5}$ | $10^{-5}$ |
| $T_1$                | 160    | 160  | 200  | 150   | 500  | 400      | 1700 |
| $T_2$                | 3000   | 2000 | 2000 | 1500  | 2500 | 1000     | 3000 |
| $T_3$                | 250    | 50   | 100  | 15    | 30   | 15       | 80  |
| $\xi$                | 0.6    | 0.7  | 0.7  | 0.2   | 0.3  | 0.7      | 0.7 |
| $\lambda$            | 0.1    | 0.05 | 0.05 | 0.1   | 0.05 | 0.05     | 0.05 |

Table 9: Hyper-parameter configurations. Note that we only keep a certain number of tokens.

D.3 Number of Parameters

COSINE and most of the baselines (RoBERTa-WL / RoBERTa-CL / SMART / WeSTClass / Self-Ensemble / FreeLB / Mixup) are built on the RoBERTa-base model with about 125M parameters. Snorkel is a generative model with about 1M parameters. ImplyLoss freezes the embedding and has less than 1M parameters. However, the latter two models cannot achieve satisfactory performance in our experiments.
D.4 Running time

To accelerate contrastive learning, we adopt the doubly stochastic sampling approximation to reduce the computational cost. Specifically, the high confidence samples $C$ in each batch $B$ yield $O(|C|^2)$ sample pairs, and we sample $|C|$ pairs from them. Table 10 summarizes the running time of our model and the baselines. We can see that our framework does not impose much additional time costs.

| Time | AGNews | IMDB | Yelp | MIT-R | TREC | Chemprot | WiC |
|------|--------|------|------|-------|------|----------|-----|
| Running Time per Iteration (s) | 0.68 | 0.90 | 0.52 | 0.51 | 0.81 | 0.80 | 0.65 |
| Total Running Time (h)† | 1.54 | 1.02 | 0.91 | 0.35 | 0.45 | 0.71 | 0.67 |

Table 10: Running time of COSINE. †: Evaluation time is included, the actual training time is much shorter.

E Early Stopping and Earlier Stopping

Our model adopts the earlier stopping strategy during the initialization stage. Here we use “earlier stopping” to differentiate from “early stopping”, which is standard in fine-tuning algorithms. Early stopping refers to the technique where we stop training when the evaluation score drops. Earlier stopping is self-explanatory, namely we fine-tune the pre-trained LMs with only a few steps, even before the evaluation score starts dropping. This technique can efficiently prevent the model from overfitting. For example, as Figure 9(b) illustrates, on the IMDB dataset, our model overfits after 240 iterations of initialization when using weak labels. In contrast, the model achieves good performance even after 400 iterations of fine-tuning when using clean labels. This verifies the necessity of earlier stopping.

F Comparison of Distance Measures in Contrastive Learning

The contrastive regularizer $R_1(\theta; \tilde{y})$ is related to two designs: the sample distance metric $d_{ij}$ and the sample similarity measure $W_{ij}$. In our implementation, we use the scaled Euclidean distance as the default for $d_{ij}$ and Eq. 5 as the default for $W_{ij}$. Here we discuss other designs.

F.1 Sample distance metric $d$

Given the encoded vectorized representations $v_i$ and $v_j$ for samples $i$ and $j$, we consider two distance metrics as follows.

**Scaled Euclidean distance (Euclidean):** We calculate the distance between $v_i$ and $v_j$ as

$$d_{ij} = \frac{1}{d} \|v_i - v_j\|_2^2.$$  \hspace{1cm} (13)
Cosine distance (Cos)\textsuperscript{14}: Besides the scaled Euclidean distance, cosine distance is another widely-used distance metric:

\[
d_{ij} = 1 - \cos(v_i, v_j) = 1 - \frac{\|v_i \cdot v_j\|}{\|v_i\|\|v_j\|}.
\]  

(14)

F.2 Sample similarity measures \( W \)

Given the soft pseudo-labels \( \widetilde{y}_i \) and \( \widetilde{y}_j \) for samples \( i \) and \( j \), the following are some designs for \( W_{ij} \). In all of the cases, \( W_{ij} \) is scaled into range \([0, 1]\) (we set \( \gamma = 1 \) in Eq. 7 for the hard similarity).

**Hard Similarity**: The hard similarity between two samples is calculated as

\[
W_{ij} = \begin{cases} 
1, & \text{if } \arg\max_{k \in \mathcal{Y}} [\widetilde{y}_i]_k = \arg\max_{k \in \mathcal{Y}} [\widetilde{y}_j]_k, \\
0, & \text{otherwise}.
\end{cases}
\]  

(15)

This is called a “hard” similarity because we obtain a binary label, i.e., we say two samples are similar if their corresponding hard pseudo-labels are the same, otherwise we say they are dissimilar.

**Soft KL-based Similarity**: We calculate the similarity based on KL distance as follows.

\[
W_{ij} = \exp\left(-\frac{\beta}{2}\left(D_{KL}(\widetilde{y}_i|\widetilde{y}_j) + D_{KL}(\widetilde{y}_j|\widetilde{y}_i)\right)\right),
\]  

(16)

where \( \beta \) is a scaling factor, and we set \( \beta = 10 \) by default.

**Soft L2-based Similarity**: We calculate the similarity based on L2 distance as follows.

\[
W_{ij} = 1 - \frac{1}{2}(\widetilde{y}_i - \widetilde{y}_j)^2,
\]  

(17)

F.3 COSINE under different \( d \) and \( W \).

We show the performance of COSINE with different choices of \( d \) and \( W \) on Agnews and MIT-R in Table 11. We can see that COSINE is robust to these choices. In our experiments, we use the scaled euclidean distance and the hard similarity by default.

| Distance (\( d \)) | Similarity (\( W \)) | Euclidean | Cos |
|-------------------|----------------------|-----------|-----|
|                   | Hard | KL-based | L2-based | Hard | KL-based | L2-based |
| AGNews            | 87.52 | 86.44    | 86.72    | 87.34 | 86.98    | 86.55    |
| MIT-R             | 76.61 | 76.68    | 76.49    | 76.55 | 76.76    | 76.58    |

Table 11: Performance of COSINE under different settings.

\textsuperscript{14}We use Cos to distinguish from our model name COSINE.