# ENHANCING NOISY LABEL LEARNING VIA UNSUPERVISED CONTRASTIVE LOSS WITH LABEL CORRECTION BASED ON PRIOR KNOWLEDGE

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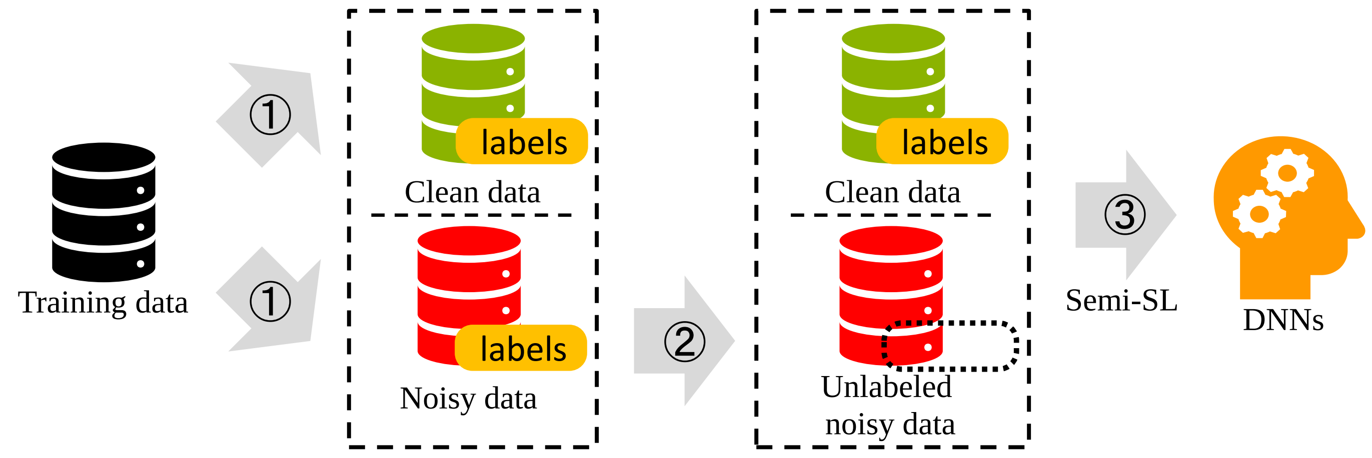
## INTRODUCTION

**Noisy Labels : Mistaken labels introduced into the training data**

- It has been shown that deep neural networks (DNNs) trained on noisy labeled data suffer from degradation of generalization performance [4].
- Several noise-robust methods of noisy label learning (NLL) have been proposed [5].

**Sample Selection** [10-12] **: A mainstream NLL approach to filter out noisy labels**

① Splitting the training data into clean data and noisy data
② Alleviating the negative impacts of noisy labels by discarding the labels of noisy data
③ Semi-supervised learning (Semi-SL) with both clean and unlabeled noisy data




✔ **Sample selection can robustly train on noisy labeled data by selective use of clean samples.**

✘ **When the noise ratio is high, inappropriate training data splitting can negatively impact classification performance.**

**Most of previous NLL methods are highly dependent only on the improvement of a classification loss.**

**Multi-objective interpolation training (MOIT) [14] : Introducing another approach independent of classification loss to NLL**

- In addition to conventional sample selection, MOIT focuses on similarities between feature representations of the samples.
- MOIT introduces a regularization of the contrastive loss based on supervised contrastive learning.

✔ **MOIT can obtain noise-robust feature representations by introducing contrastive loss based on supervised approach.**

✘ **Supevised contrastive approachs may not eliminate the negative impacts of noisy labels.**

## PROPOSED METHOD

**Proposed method (PM) : A novel sample selection-based NLL method via the unsupervised contrastive loss with label correction based on prior knowledge**

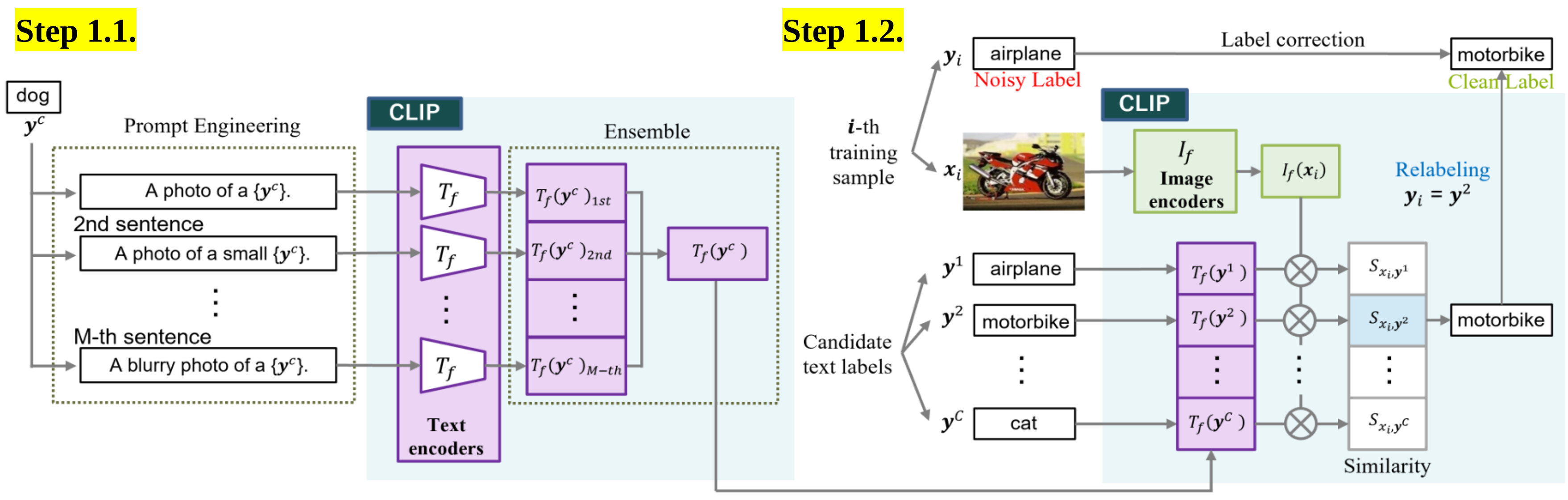
**① Label Correction Based on Prior Knowledge :** Reducing noise ratio of the training data before the start of NLL training

**PM utilizes a latent space constructed by Contrastive Language-Image Pre-training [16] (CLIP) for label correction.**

**Approach 1**
Utilizing prior knowledge of models pre-trained on large datasets

**Step 1.1. Prompt engineering to obtain label-embedded representations**
PM embeds candidate labels for each class into the latent space to obtain the respective label-embedded representations.

**Step 1.2. Label correction based on the distance**
For each obtained label-embedded representation of the classes and the image-embedded representation of the training images, the labels are corrected based on the distance between these embedded representations.



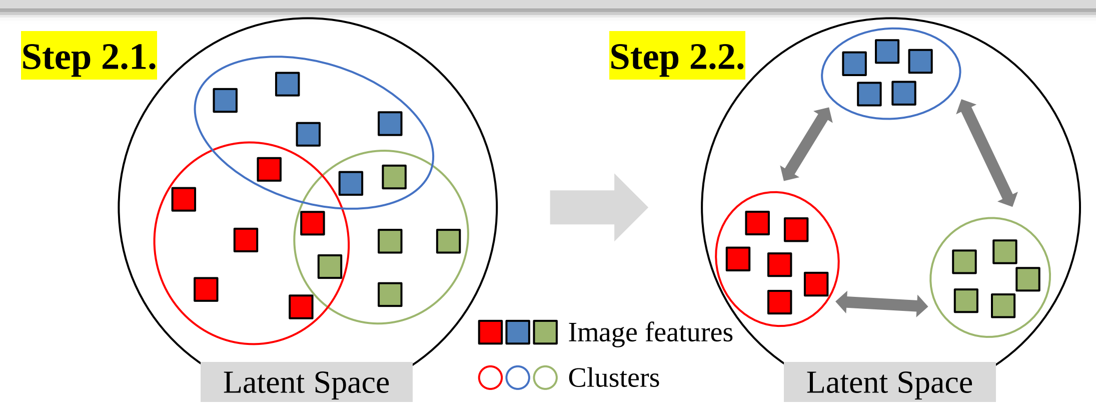

**② Unsupervised Contrastive Loss Based on Clustering :** Obtaining noise-robust feature representations even in the existence of noisy labels via an unsupervised approach

**PM introduces an unsupervised contrastive loss based on similarity between image features.**

**Approach 2**
Introducing an unsupervised contrastive learning approach to NLL

**Step 2.1 Clustering on image features**
PM performs clustering on image features extracted in the NLL training process.

**Step 2.2 Introducing an unsupervised contrastive loss**
PM learns feature representations based on clustering results so that similar samples are close to each other.




✔ **Approach 1 : Expected to improve sample selection under the high noise ratio due to the reduction of noisy labels before the start of NLL training**
**Approach 2 : Expected to realize robust NLL against noisy labels without requiring label information for being based on an unsupervised approach**

## EXPERIMENTAL RESULTS

### Conditions

◆**Dataset : CIFAR-10 and CIFAR-100 [15]**
- 10 and 100 classes, respectively
- 50,000 training data and 10,000 test data
- Training data was used by injecting symmetric label noise (Sym.).
  - Sym. randomly replaces the ground-truth labels with all candidate labels.
  - Noise Ratio was set to 80-90%.

◆**Label correction**
- Utilizing the ensemble of 80 different prompt engineering results.

◆**Unsupervised contrastive loss $\mathcal{L}_{\mathrm{con}}$**
- Clustering method : k-means
- Number of clusters : 10 for CIFAR-10 and 20 for CIFAR-100
- Temperature parameter $\tau$ : Experimentally set to 0.3

◆**Implementation details**
- PM employed ProMix [12] as the sample selection-base NLL method.
- Other settings such as hyperparameters are according to [12].
- Evaluation metric : Classification accuracy

◆**Comparative Methods**
- MOIT [14] : Supevised contrastive approach-based NLL method
- ProMix [12] : State-of-the-art sample selection-based NLL method
- PM w/o CLIP : Evaluation against label correction based on CLIP
- PM w/o $\mathcal{L}_{\mathrm{con}}$ : Evaluation against unsupervised contrastive loss

### Quantitative Results

**PM vs MOIT and ProMix**
➢ The robustness of PM under the high noise ratio is demonstrated.

**PM vs PM w/o CLIP**
➢ From PM > PM w/o CLIP, PM achieves high accuracy independent of the noise ratio.
➢ The effectiveness of Approach 1

**PM vs PM w/o $\mathcal{L}_{\mathrm{con}}$**
➢ From PM ≥ PM w/o $\mathcal{L}_{\mathrm{con}}$, PM achieves performance equivalent to or better than PM w/o $\mathcal{L}_{\mathrm{con}}$ under both the high noise ratio.
➢ The effectiveness of Approach 2

**Accuracy (%) comparisons on CIFAR-10 and CIFAR-100**

| Dataset | CIFAR-10 | | CIFAR-100 | |
|---|---|---|---|---|
| | Sym. | | Sym. | |
| Methods\Noise Ratio | 80% | 90% | 80% | 90% |
| MOIT | 75.8 | 70.1 | 51.4 | 24.5 |
| ProMix | 95.5 | 93.4 | 69.4 | 42.9 |
| PM w/o CLIP | 95.9 | 93.5 | 68.2 | 34.6 |
| PM w/o $\mathcal{L}_{\mathrm{con}}$ | 96.7 | **96.8** | 71.9 | 71.6 |
| PM | **96.8** | **96.8** | **72.3** | **72.1** |

✔ **We validated that PM achieves higher classification performance for NLL under high noise ratio.**

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