CHMATCH: Contrastive Hierarchical Matching and Robust Adaptive Threshold Boosted Semi-Supervised Learning

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Abstract

The recently proposed FixMatch and FlexMatch have achieved remarkable results in the field of semi-supervised learning. But these two methods go to two extremes as FixMatch and FlexMatch use a pre-defined constant threshold for all classes and an adaptive threshold for each category, respectively. By only investigating consistency regularization, they also suffer from unstable results and indiscriminative feature representation, especially under the situation of few labeled samples. In this paper, we propose a novel CHMatch method, which can learn robust adaptive thresholds for instance-level prediction matching as well as discriminative features by contrastive hierarchical matching. We first present a memory-bank based robust threshold learning strategy to select highly-confident samples. In the meantime, we make full use of the structured information in the hierarchical labels to learn an accurate affinity graph for contrastive learning. CHMatch achieves very stable and superior results on several commonly-used benchmarks. For example, CHMatch achieves $\mathbf{8.44}\%$ *and* $\mathbf{9.02}\%$ *error rate reduction over FlexMatch on CIFAR-100 under WRN-28-2 with only 4 and 25 labeled samples per class, respectively*[1].

1. Introduction

Deep learning achieves great success in the past decade based on the large-scale labeled datasets. However, it is generally hard to collect and expensive to manually annotate such kind of large dataset in practice, which limits its application. Semi-supervised learning (SSL) attracts much attention recently, since it can make full use of a few labeled and massive unlabeled data to facilitate the classification.

For the task of SSL [9, 16, 31, 32], various methods have been proposed and promising results have been achieved. Consistency regularization [43] is one of the most influential techniques in this area. For example, pseudo-ensemble [3] and temporal ensembling [23] investigate the instance-level robustness before and after perturbation. Mean teacher [36] introduces the teacher-student framework and studies the model-level consistency. SNTG [27] further constructs the similarity graph over the teacher model to guide the student learning. However, the supervised signal generated by only this strategy is insufficient for more challenging tasks.

Recently, by combining pseudo-labeling and consistency between weak and strong data augmentations, FixMatch [33] achieves significant improvement. But it relies on a high fixed threshold for all classes, and only a few unlabeled samples whose prediction probability is above the threshold are selected for training, resulting in undesirable efficiency and convergence. Towards this issue, FlexMatch [41] proposes a curriculum learning [4] strategy to learn adjustable class-specific threshold, which can well improve the results and efficiency. But it still suffers from the following limitations: (1) The results of both FixMatch and FlexMatch are unstable and of large variances, which is shown in Figure 1(a), especially when there are only a small amount of labeled samples; (2) Only instance-level consistency is investigated, which neglects inter-class relationship and may make the learned feature indiscriminative.

To address the above issues, we propose a novel CHMatch method based on hierarchical label and contrastive learning, which takes both the instance-level prediction matching and graph-level similarity matching into account. Specifically, we first present a memory-bank based robust adaptive threshold learning strategy, where we only need one parameter to compute the near-global threshold for all categories. We compare this strategy with FixMatch in Figure 1(b). Then this adaptive threshold is used for instance-level prediction matching under the similar Fix-

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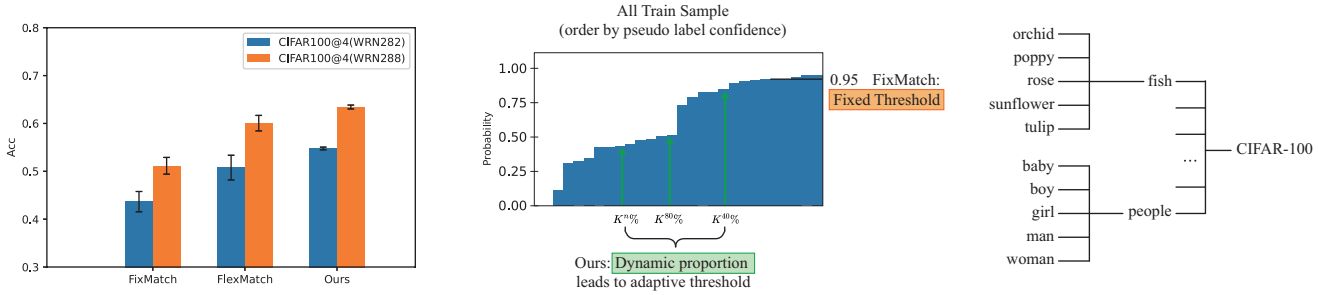


(a) Results on CIFAR-100 (b) Different threshold learning strategy (c) Hierarchical label structure

Figure 1. Motivation of our method. (a) The results of FixMatch and FlexMatch are unstable and of large variances, while our method can handle this issue. (b) FixMatch sets fixed threshold, while our method sets dynamic proportions in different epoch, leading to adaptive threshold. (c) Many datasets have hierarchical label structure, and we aim to take advantage of this to promote the SSL.

Match paradigm. More importantly, we further propose a hierarchical label guided graph matching module for contrastive feature learning, where the key lies in the construction of an accurate affinity graph. As shown in Figure 1(c), we notice that categories in many datasets as well as real-world applications have a hierarchical structure, which is neglected by existing methods for semi-supervised learning. We aim to make use of the coarse-grained labels to guide the general classification, which can also provide extra supervision signals especially under the situation of limited labeled samples. For implementation, we first add another head for the coarse-grained classification. Then each affinity graph is constructed by the fine-grained and coarse-grained classification branches. Together with the near-global threshold, we can get the precise affinity relationship after graph matching, which is then used for contrastive learning. We also conduct extensive experiments on several commonly-used datasets to verify the effectiveness of the proposed method as well as each module.

Our main contributions can be summarized as follows:

- We propose a novel CHMatch method, which contains instance-level and graph-level matching for assignment and feature learning, respectively. To the best of our knowledge, this is the *first* study that makes full use of the structured information matching in hierarchical labels to promote semi-supervised learning.
- We come up with a memory-bank based highly-confident sample selection strategy, which can generate robust adaptive threshold for prediction-level matching, leading to more robust results, and accelerate the training process.
- Benefit from the contrastive hierarchical matching, our method can construct a more accurate affinity graph for the proposed contrastive learning module, leading to more discriminative feature representation.
- We conduct extensive experiments on four benchmark datasets under different backbones, and the proposed CHMatch outperforms these state-of-the-art methods.

2. Related Work

Semi-supervised learning (SSL) [1, 2, 7] is a classic and important research area in the machine learning community since it only needs a few labeled samples. Along with the success of deep learning, SSL achieves significant improvement recently. We briefly review some highly-related deep learning based SSL methods in this section.

Pseudo-label [19, 24, 30, 35, 37] and consistency regularization are two effective strategies in SSL. Pseudo-label [24] picks up the class which has the maximum predicted probability as true labels for supervised learning, which has the equivalent effect to entropy regularization. Consistency regularization assumes that under small perturbations, the results should be consistent and robust, which can be further divided into instance-level, model-level, and graph-level [20,25] consistency. Temporal ensembling [23], VAT [29], UDA [38], and MixMatch [5, 6] well investigate the influence of data augmentation and image fusion. Pseudo-ensemble [3] and mean teacher [36] study the effect of dropout and teacher-student framework, respectively. SNTG [27] further constructs the similarity graph over teacher model to guide the student learning.

By combining the pseudo-label and consistency regularization, FixMatch [33] simplifies the SSL by introducing a new paradigm, where it adopts the highly-confident pseudo label of weak augmentation sample to guide the training of the corresponding sample after strong augmentation. Most lateral methods also follow this setting since it achieves state-of-the-art performance. CoMatch [25] further incorporates the graph based contrastive learning. FlexMatch [41] proposes a curriculum learning strategy to learn adaptive threshold for each category, which can well accelerate the convergence. HierMatch [14] also incorporates the hierarchical label information, but it simply adds the coarse-label based cross-entropy loss for classification without investigating their connection and contrastive learning.

Our method also follows FixMatch, one of the main dif-

ferences lies in the threshold learning. Besides, while existing methods mainly focus on consistency regularization, we incorporate the hierarchical label guided contrastive learning into the SSL to learn discriminative feature representation. Though CoMatch also combines with graph contrastive learning, it is very sensitive to the hyper-parameters, and how to use the graph information is also very different in our method. CoMatch assigns a consistency regularization on two graphs generated by weak and strong augmentations, while our method learns a more accurate graph for contrastive learning based on the matching between coarse-grained and fine-grained classification results. Compared with CoMatch, our method is more stable and achieves much better results.

3. CHMatch

3.1. Preliminary

Given a batch of B labeled samples $\mathcal{X} = \{(x_b, y_b)\}_{b=1}^{B}$ and μB unlabeled samples $\mathcal{U} = \{u_b\}_{b=1}^{\mu B}$, where y denotes the one-hot label and μ is a parameter that controls the relative sizes of $\mathcal{U}$ and $\mathcal{X}$, the general deep learning based SSL method aims to learn a encoder $f(\cdot)$ and a classification head $h(\cdot)$ for discriminative feature representation and good performance. For this task, FixMatch first introduces the random strong augmentation $\mathcal{A}(\cdot)$ and weak augmentation $\alpha(\cdot)$, and then investigates their prediction-level consistency based on the pseudo-label learned by a high fixed threshold τ. Denote $p(y|x)$ as the predicted class probability and $H(p, q)$ as the cross-entropy loss between two probability distributions p and q. Then the objective function of FixMatch can be formulated as:

$$\begin{aligned}\min_{\theta_f,\theta_h} \mathcal{L}_s + \lambda\mathcal{L}_u = \frac{1}{B}\sum_{b=1}^{B} H(y, p(y|\alpha(x_b))) \\ + \lambda\frac{1}{\mu B}\sum_{b=1}^{\mu B} \mathbb{1}(\max(q_b) \geq \tau) H(\hat{q}_b, p(y|\mathcal{A}(u_b))),\end{aligned} \tag{1}$$

where θ denotes the learnable parameters, $q_b = p(y|\alpha(u_b))$ represents the predicted class probability for the weakly augmented unlabeled sample, $\hat{q}_b = \arg\max(q_b)$ is its pseudo-label, λ is a hyperparameter to balance the contribution of two items, $\mathcal{L}_s$ and $\mathcal{L}_u$ denote the losses for labeled and unlabeled samples, respectively.

Due to the fixed high threshold, only a few unlabeled data join the training with higher prediction confidence than the threshold, therefore FixMatch suffers from long training time. FlexMatch further proposes a curriculum pseudo labeling strategy to assign a specific threshold for each category.

Most existing SSL methods mainly focus on the above consistency regularization to make positive samples closer, and neglect the discriminative feature learning to push negative samples apart. Contrastive learning is a good choice to handle the above issue, which attracts much attention in the field of self-supervised learning. The basic contrastive loss for the sample u_b can be formulated as:

$$l_b^{simclr} = -\log \frac{\exp(f(\alpha(u_b)) \cdot f(\alpha(u_b))/t)}{\sum_{j=1,j\neq b}^{\mu B} \exp(f(\alpha(u_b)) \cdot f(\alpha(u_j))/t)}, \tag{2}$$

where t denotes a temperature parameter. We can see that general contrastive learning treats all others in the batch as negative samples, which contains much noisy correspondence. Different from self-supervised learning, we have a few labeled samples in SSL. How to appropriately combine contrastive learning with SSL remains an open problem. And the key lies in how to learn an accurate graph. We follow the general pipeline of FixMatch, and propose strategies in the following to handle the above issues of threshold and accurate graph learning.

3.2. Overview of CHMatch

The framework of our proposed CHMatch is shown in Figure 2. Based on the feature encoder $f(\cdot)$, different from general SSL methods that only have one classification head, CHMatch jointly learns the fine-grained classification head $h_f(\cdot)$, the coarse-grained classification head $h_c(\cdot)$, and the projection head $g(\cdot)$ for contrastive feature representation.

In practice, categories have a hierarchical structure, which is often neglected by existing methods. But it contains extra supervision signals for network training. So we add an extra coarse-grained classification head $h_c(\cdot)$ first. For each classification head, we learn an robust adaptive threshold, denoted as τ_c and τ_f, to select highly-confident samples for consistent pseudo-label learning, which will be introduced in Section 3.3. Then we define the unsupervised classification losses, $\mathcal{L}_u^f$ and $\mathcal{L}_u^c$, for these two fine-grained and coarse-grained heads as follows:

$$\begin{aligned}\mathcal{L}_u^f + \mathcal{L}_u^c = \frac{1}{\mu B}\sum_{b=1}^{\mu B}\Big(\mathbb{1}(\max(q_b^f) \geq \tau_f) H(\hat{q}_b^f, p(y|\mathcal{A}(u_b))) \\ + \mathbb{1}(\max(q_b^c) \geq \tau_c) H(\hat{q}_b^c, p(y|\mathcal{A}(u_b)))\Big),\end{aligned} \tag{3}$$

where $q_b^f = h_f(f(\alpha(u_b)))$ and $\hat{q}_b^f$ denote the predicted class probability and its pseudo-label for the fine-grained classification head, respectively, which is also the similar to q_b^c and $\hat{q}_b^c$.

Based on the predicted probability of these two classification heads, we can generate an affinity graph for each branch. Then we perform graph matching to acquire an accurate graph for contrastive learning. We define the contrastive loss as $\mathcal{L}_u^{ctl}$ and impose it on the projection head $g(\cdot)$ to learn discriminative features. Details will be introduced in Section 3.4.

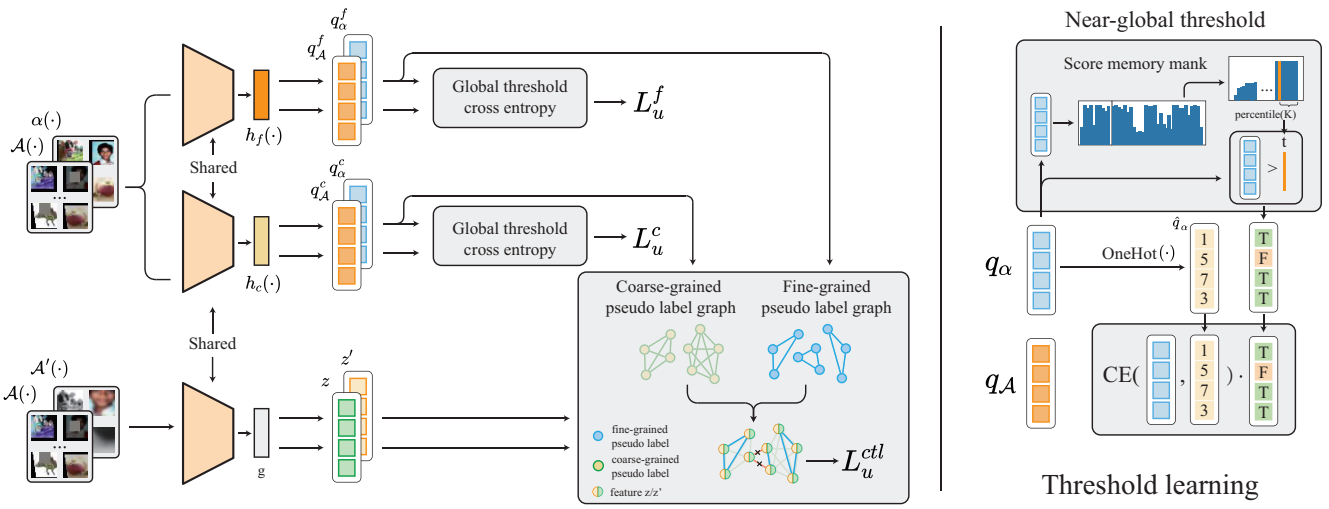


Figure 2. Framework of our CHMatch. (Left) Besides the general classification head $\mathcal{L}_u^f$ in FixMatch, we add a coarse-grained classification head $\mathcal{L}_u^c$ and a projection head $g(\cdot)$. We utilize the hierarchical label information, performing graph matching between fine-grained and coarse-grained pseudo label graphs to guide contrastive feature learning. (Right) A memory-back based strategy is proposed to learn robust adaptive threshold to guide instance-level prediction matching.

The overall training objective of CHMatch can be formulated as:

$$\min_{\theta_f,\theta_g,\theta_{h_c},\theta_{h_f}} \mathcal{L} = \mathcal{L}_s + \alpha\mathcal{L}_u^f + \beta\mathcal{L}_u^c + \gamma\mathcal{L}_u^{ctl}. \quad (4)$$

We simply fix all weights before each loss term as 1 since our method is robust and insensitive to these parameters.

3.3. Memory-bank based Robust Adaptive Threshold Learning

In FixMatch and related SSL methods, threshold plays an important role in selecting highly-confident samples to construct pseudo-label for consistency learning. FixMatch manually set a fixed high threshold for all classes without learning, leading to undesirable training efficiency. FlexMatch learns class-specific thresholds based on curriculum learning. But results of these two methods are relatively unstable, especially when the labeled samples are limited.

Inspired by MoCo [17], we propose a memory-bank based strategy to learn a near-global threshold for all classes, which can well handle the above issue of FixMatch and FlexMatch. Specifically, for each sample u_b, take the fine-grained classification head for example, we compute its maximum predicted probability by $\tilde{q}_b^f = \max q_b^f = \max h_f(f(\alpha(u_b)))$. Then we construct a memory-bank to save the maximum probability of the previous N weakly augmented samples as $Q_{MB}^f = [\tilde{q}_1^f, \tilde{q}_2^f, \cdots, \tilde{q}_N^f]$, where N is much larger than the mini-batch size. At each epoch, we hope that a certain percentage $K\%$ of the samples are chosen for pseudo-label learning. For example, at the early stage of the training, $K\%$ should be small to ensure that the selected samples are of high confidence to guide the network training. In contrast, at the end of the training, $K\%$ should be large enough to guarantee that most samples can join the training. In this case, we gradually increase $K\%$ as the training progresses. There is a negative correlation between $K\%$ and τ_f, which can be formulated based on the memory-bank by:

$$|Q_{MB}^f > \tau_f|/N = K\%, \quad (5)$$

where $|Q_{MB}^f > \tau_f|$ denotes the number of samples in the memory-bank that have a larger prediction probability than τ_f. τ_f can be easily computed by the function $\tau_f = \text{percentile}(Q_{MB}^f, K)$ for each batch, which is equivalent to select the $N \times K\%$-th value after the descend sorting. Then we can get τ_c for the coarse-grained classification head in the same way, after which the classification loss can be computed according to Eq. (3).

Based on only one dynamically changed parameter K, the thresholds τ_f and τ_c for all classes can be learned adaptively. The memory-bank mechanism can help the model acquire a good approximation of the global threshold for all samples with neglectable computational cost.

Note that the number of highly-confident samples that join the training matters, especially in the SSL settings. For two independent experiments, the dynamic proportion strategy in our CHMatch can select the same number of samples for training in different epochs. However, the fixed threshold in FixMatch or adaptive threshold in FlexMatch cannot guarantee this since their prediction is highly related to the random initialized network parameters. Besides, FixMatch and FlexMatch are more sensitive to manually set thresh-

old than our CHMatch. For example, the simple threshold warm-up strategy in FlexMatch can lead to more than 1% difference in the results on CIFAR100. The fixed threshold in FixMatch can cause more than 2% difference on CIFAR10. As a comparison, our method is insensitive to parameters, which will be verified in experiments. In this case, the results of CHMatch is much more stable.

3.4. Graph-based Contrastive Hierarchical Matching

Consistency learning can only lead to instance-level correspondence in the feature space, which makes the representation not discriminative enough. In this situation, samples that belong to the same category might be of large variance and the margin between categories is not clear. Therefore, we propose a contrastive learning loss for SSL by leveraging pseudo-label information. According to the supervised contrastive learning [21], the way to incorporate label information matters, and it is very important to construct a precise graph to guide the contrastive learning based on pseudo-labels.

For each sample u_b, given its fine-grained classification pseudo-label $\hat{q}_b^f$, we construct the fine-grained affinity graph $W^f \in \mathbb{R}^{\mu B \times \mu B}$ by:

$$W_{bj}^f = \begin{cases} 1 & \text{if } \hat{q}_b^f = \hat{q}_j^f, \\ 0 & \text{otherwise}, \end{cases} \tag{6}$$

where the edge between two samples equals to 1 only when they share the same fine-grained pseudo-label, which also denotes that they are positive pairs. Note that we do not assign any constraint on the pseudo-label during the above graph construction, so its accuracy could be improved. We further turn to the hierarchical label for help and propose a graph matching strategy.

For the hierarchical labels, it can not only provide extra supervision information, but can also correct the affinity graph. Similar to Eq. (6), we can construct the coarse-grained affinity graph W^c. For each coarse-grained category, it contains several fine-grained classes. In this case, if two samples belong to the same fine-grained class, then they should have the same coarse-grained pseudo-label. However, this relationship is not always satisfied by the model, especially at the early training stage. So we can take advantage of W^c to correct W^f, and we name this process as graph matching, which can be formulated as:

$$W_{bj} = \begin{cases} 1 & \text{if } W_{bj}^f = 1 \text{ and } W_{bj}^c = 1, \\ 0 & \text{otherwise.} \end{cases} \tag{7}$$

Give the precise graph W, two samples are positive pairs if $W_{bj}^f = 1$, otherwise they are negative pairs. Contrastive learning [8, 17, 26] aims to minimize the distance between positive pairs and maximize the distance between negative pairs. Denote $z_b = g(f(\mathcal{A}(u_b)))$ and $z_b' = g(f(\mathcal{A}'(u_b)))$ as the output features after projection head $g(\cdot)$ for sample u_b under two different strong augmentations. The graph matching based contrastive learning loss can be written as:

$$\mathcal{L}_u^{ctl} = -\frac{1}{\mu B}\sum_{b=1}^{\mu B}\left(\frac{1}{\sum_j W_{bj}}\log\frac{\sum_{j=1}^{\mu B} W_{bj}\exp((z_b \cdot z_j')/t)}{\sum_{j=1}^{\mu B}(1-W_{bj})\exp(z_b \cdot z_j')/t)}\right), \tag{8}$$

where we also investigate the self-consistency between different augmentations when $b = j$.

We summarize the overall training process in Algorithm 1. By making full use of the hierarchical label, our method benefits from the following three aspects: (1) The coarse-grained classification head can provide extra supervision for the network learning, which is important for the situation of limited labeled samples; (2) By the graph matching of fine-grained and coarse-grained results, we can learn a more accurate graph, which can well filter the wrong relations and reduce the influence of noisy correspondence; (3) Contrastive learning with precise graph connections can lead to more discriminative feature representation.

Algorithm 1 Training algorithm for CHMatch.

Input: $\mathcal{X} = \{(x_m, y_m) : m \in (1, \ldots, M)\}$, $\mathcal{U} = \{u_l : l \in (1, \ldots, L)\}$. M labeled and L unlabeled data.
while not reach the maximum iteration **do**
  for $b \in \{1, \ldots, B\}$ **do**
    Compute prediction $q_{x_b}^f = h_f(f(\alpha(x_b))), q_{x_b}^c = h_c(f(\alpha(x_b)))$ for each labeled sample.
  end for
  for $b \in \{1, \ldots, \mu B\}$ **do**
    Compute the maximum probability $\tilde{q}_b^f = \max h_f(f(\alpha(u_b)))$, and $\tilde{q}_b^c = \max h_c(f(\alpha(u_b)))$.
    Update the memory-bank Q_{MB}^f,Q_{MB}^c by $\tilde{q}_b^f, \tilde{q}_b^c$.
    Update K according to the current number of epochs.
    Compute $\tau_f = \text{percentile}(Q_{MB}^f, K)$ and $\tau_c = \text{percentile}(Q_{MB}^c, K)$.
    for $j \in \{1, \ldots, \mu B\}$ **do**
      Calculate W_{bj}^f, W_{bj}^c, and W_{bj} according to Eqs. (6) and (7).
    end for
  end for
  Compute L_s, L_u^f, L_u^c, and L_u^{ctl} via Eqs. (1), (3), and (8).
  Update parameters $\theta_f, \theta_g, \theta_{h_c}, \theta_{h_f}$ by optimizing Eq. (4) based on SGD.
end while
Return: A deep SSL model with desirable parameters.

Table 1. Error rates comparison on CIFAR-10, CIFAR-100, and STL-10.

Methods	CIFAR-10			CIFAR-100@WRN-28-2			CIFAR-100@WRN-28-8			STL-10
Label Amount	40	250	1000	400	2500	10000	400	2500	10000	1000
MixMatch (NeurIPS'19)	36.19± 6.48	13.63± 0.59	6.66± 0.26	-	-	-	67.61± 1.32	39.94± 0.37	28.31± 0.33	61.98± 8.29
FixMatch (NeurIPS'20)	13.91± 3.37	5.07± 0.65	4.26± 0.05	56.34± 2.12	34.53± 0.31	27.89± 0.10	48.85± 1.75	28.29± 0.11	22.60± 0.12	34.62± 0.42
CoMatch (ICCV'21)	6.91± 1.39	4.91± 0.33	4.56± 0.20	58.46± 2.31	36.84± 0.43	31.6± 0.14	41.89± 2.34	28.37± 0.35	**20.86± 0.36**	**20.20± 0.38**
FlexMatch (NeurIPS'21)	**4.97± 0.06**	4.98± 0.09	**4.19± 0.01**	**49.23± 2.58**	**32.51± 0.20**	**26.58± 0.11**	**39.94± 1.62**	**26.49± 0.20**	21.90± 0.15	-
DP-SSL (NeurIPS'21)	6.54± 0.98	**4.78± 0.26**	**4.23± 0.20**	-	-	-	43.17± 1.29	28.00± 0.79	22.24± 0.31	-
CHMatch (ours)	**5.98± 0.19**	**4.91± 0.13**	4.48± 0.10	**45.23± 0.28**	**31.32± 0.47**	**24.84± 0.27**	**36.57± 0.41**	**24.10± 0.10**	**19.92± 0.29**	**10.36± 0.31**

4. Experiments

We conducted extensive experiments on four commonly-used SSL image classification datasets, including CIFAR-10 [22], CIFAR-100, STL-10 [11], and ImageNet [13], under different amounts of labeled data and backbones.

Datasets. The CIFAR-10 dataset has $60,000$ images that belong to 10 fine-grained classes. Each image has the size of 32×32. Similarly, CIFAR-100 consists of $60,000$ images corresponding to 100 fine-grained classes. STL-10 contains $5,000$ labeled images of 10 classes and $100,000$ unlabeled images with size 96×96. For the hierarchical labels, CIFAR-100 naturally has 20 coarse-grained categories. As for CIFAR-10 and STL-10, we manually summarized two super classes, including animal and vehicle. For the ImageNet dataset, its hierarchical structure is unbalanced, so we first found these coarse-grained classes that contain at least 10 fine-grained classes. After sorting based on names, we selected the first 20 super classes as well as the first 10 fine-grained categories in each super class. Therefore, this ImageNet subset contains 20 coarse-grained categories and 200 fine-grained categories of about $256,483$ images.

Compared Methods. We mainly compared the results with current state-of-the-art SSL methods published in recent three years, including MixMatch [6], FixMatch [33], CoMatch [25], DP-SSL [39], FlexMatch [41].

Implementation Details. For fair comparison, we adopted the similar settings following FlexMatch and CoMatch. For CIFAR-10, we used WideResNet (WRN)-28-2 [40]. For CIFAR-100, both WRN-28-2 and WRN-28-8 are adopted. ResNet-18 [18] is used for STL-10, which is the same as CoMatch [25] since it has much lower computation cost compared to the WRN-37-2 used in [41]. For ImageNet, ResNet-50 is adopted. The total training step is 2^{20}. The size of memory-bank N is set to $50,000$. The commonly used distribution alignment strategy [5] is also adopted in our method. For all these datasets except ImageNet, we used the standard stochastic gradient descent (SGD) [15, 34] with a momentum of 0.9 for all experiments. The initial learning rate is set to 0.03 and a cosine learning rate decay schedule is adopted. The batch size is set to 64. μ is set to 7. We randomly run the experiments for three times and reported the average result. For ImageNet, we used the same settings as CoMatch, where the initial learning rate is set to 0.1 with weight decay [42] $1e-5$, the batch size is 160, and $\mu = 4$. For CIFAR-100 and ImageNet, $K\%$ is initialized as 5%, and linearly increases to 80% until the 100-th epoch. At the t-th epoch, $K^t = 5 + t * 0.75$ when $0 < t \leq 100$, and $K^t = 80$ when $t > 100$. For other two datasets, the upper value for $K\%$ is set to 95% since they are much simpler.

Augmentation. Our augmentation strategy is the same as CoMatch. For the weak augmentation, we used the standard crop-and-flip is adopted. For two kinds of strong augmentations $\mathcal{A}$ and $\mathcal{A}'$, RandAugment [12] and augmentation strategy in SimCLR [10] (random color jittering and grayscale conversion) are adopted, respectively.

4.1. Main Results

In Table 1, we presented the semi-supervised classification results on CIFAR-10 under WRN-28-2, CIFAR-100 under both WRN-28-2 and WRN-28-8, and STL-10 under ResNet-18. We can see that on the CIFAR-100 dataset, our proposed CHMatch method achieves much better results than all these related methods under all various number of labeled samples and two different backbones. Specifically, compared with the strong baseline FlexMatch, our method can achieve an average 7.47% error rate reduction on these six settings of CIFAR-100. The error rate reduction is even larger over FixMatch, which is 15.29% on average. The above results can well demonstrate the effectiveness of CHMatch, especially when the number of classes is large and the hierarchical structure is relatively balanced.

For STL-10, we simply copy the results of several related methods from CoMatch. We can see that our proposed method achieves the best results among these compared methods. Specifically, We can achieve the error rate of 10.36%, while the second best result is 20.20% realized by CoMatch. Moreover, we can observe that the error rate results on STL-10 are higher than that of CIFAR-10. The reason is that there exist out-of-distribution images in the unlabeled set of STL-10, which makes it more challenging and realistic. While the dataset is more challenging, our superiority is more significant, which can also verify the ef-

Table 2. Error rates results on the ImageNet subset.

Method	Top1		Top5	
Label fraction	1%	10%	1%	10%
MixMatch	-	-	-	-
FixMatch	60.81	34.33	35.84	14.83
CoMatch	42.88	26.48	17.99	9.23
FlexMatch	54.37	29.82	31.61	12.27
DP-SSL	-	-	-	-
CHMatch(ours)	**34.18**	**24.17**	**12.33**	**7.64**

fectiveness of our method from another aspect.

On CIFAR-10, our results are also comparable with FixMatch. The main reason is that CIFAR-10 is relatively simple, where it only has 2 coarse-grained and 10 fine-grained classes. The difference between two super categories (animal and vehicle) is very clear. In this case, the accuracy of both fine-grained and coarse-grained classification is very high, and the coarse label graph cannot provide useful information in graph matching. Even though, our results are better than FixMatch under 40 and 250 labeled samples, which validates the superiority of our memory-bank based near-global threshold learning strategy, especially under limited labeled samples.

We also noticed that our results are very stable on all these datasets, where the maximum variance is less than 0.5%. In comparison, the variance of FlexMatch is larger than 2.5% and 1.6% on CIFAR-100 with 4 labeled samples per class under two different backbones, respectively. Other methods also have the similar disadvantage, especially under the situation of very limited labeled samples. The reason for this phenomenon can be found in the end of Subsection 3.3.

4.2. Results on the ImageNet Subset

We validated our method on the more challenging ImageNet dataset, where we used a subset containing 20 super and 200 general classes to construct a balanced hierarchical structure. For a fair comparison, we used the similar parameters as CIFAR-100 for all these compared methods, which can also verify its robustness. The results are shown in Table 2. CHMatch achieves the best results among all these compared methods under both 1% and 10% settings. For example, the top-1 error rate of our method with 1% labeled samples is 34.18%, which significantly surpasses the result 42.88% of the second best method CoMatch. The above results can well demonstrate the superiority of our method.

4.3. Ablation Study

We conducted experiments to verify the effectiveness of each proposed module on CIFAR-100 with 400 labeled samples under WRN-28-2. Experiments in the following subsection are also under this setting. The results are presented in Table 3. Based on the error rate on lines 1, 2, and 5, we can see that our dynamic proportion based adaptive threshold learning strategy is much better than the fixed proportion and fixed threshold strategies. By comparing the results on lines 3, 4, and 5, both coarse-grained classification head and graph matching strategy can obviously improve the performance.

Table 3. Effect of each module.

Modules					Error rate
Graph matching	Coarse label	Fixed threshold	Fixed proportion	Dynamic proportion	
✓	✓	✓			50.14
✓	✓		✓		49.56
				✓	48.83
	✓			✓	47.14
✓	✓			✓	**45.23**

Table 4. Error rate on CIFAR100 under WRN-28-2 with different weights. We vary each parameter and fix other weights as 1.

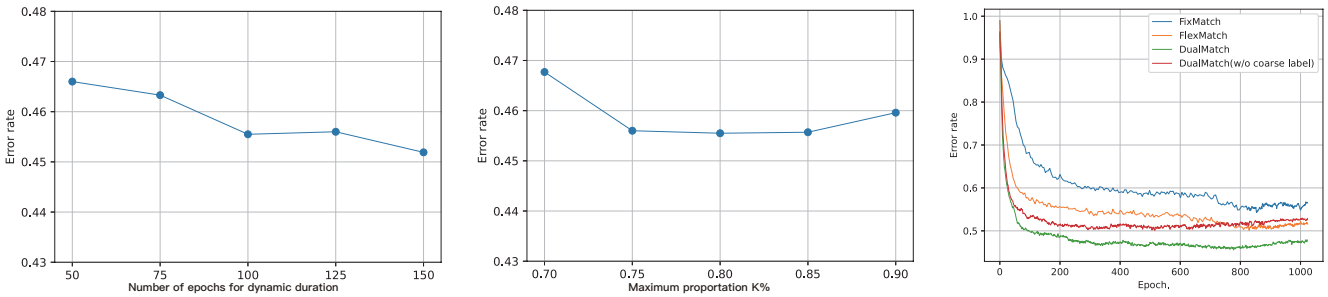
	0.75	1	1.5	2
α	46.37	45.23	46.51	44.53
β	46.60	45.23	46.15	44.96
γ	45.61	45.23	44.99	45.05

4.4. Qualitative Analysis

Parameter Sensitivity Analysis. For the weight parameters before each loss term, we directly set all of them to 1 for all datasets, which demonstrates that our method is very robust and not sensitive to these parameters. We further conduct experiments to analyze the sensitivity. We vary each parameter in the range of [0.75, 1, 1.5, 2] while fixed other weights as 1. The error rate results on CIFAR100 under WRN-28-2 is presented in Table 4. The reported error rate results in the paper is 45.23%. We can see that our results can be further improved to 44.53% based on other settings of these parameters. Besides, our results are relatively stable when these weights vary in a certain range.

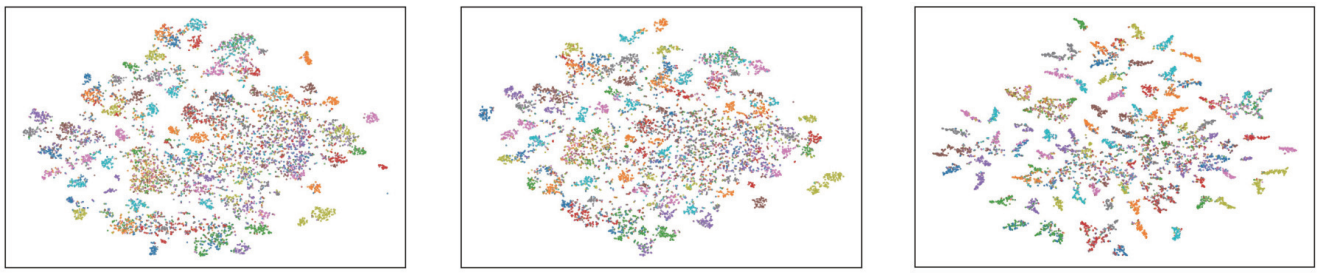
For the number of epochs for dynamic duration and the maximum proportion $K\%$, we tested their influence and showed the results in Figure 3 (a) and (b). We can observe that the influence is neglectable for these two hyper-parameters. For the dynamic duration, the performance could even be improved if we set it to 150, which further demonstrates the robustness of CHMatch.

Convergence Analysis. We presented the change of top-1 error rate during the training process in Figure 3 (c), and compared it with FixMatch and FlexMatch. We can see that our CHMatch converges very fast, which only needs less than 400 epochs to achieve almost the best performance. In contrast, both FixMatch and FlexMatch need more than



(a) Influence of dynamic duration (b) Influence of max proportion (c) Top-1 error rate

Figure 3. Parameter sensitivity and convergence analysis on CIFAR-100.



(a) FixMatch (b) FlexMatch (c) CHMatch

Figure 4. t-SNE visualization for feature representation on CIFAR-100.

800 epochs to get the best results. In this case, our method is much faster than them, which can be accumulated to the fact that we adopted the dynamic proportion mechanism and a large proportion of samples join training after 100 epochs.

Influence of Increasing Manner on K. We also conducted additional experiments on CIFAR-100 with 40 labeled samples under WRN-28-2 based on exponentially increasing (slow first and then fast) and log-type increasing (fast first and then slow) manners on K. The error rates of these two settings are 46.63% and 47.51%, both of which are worse than linear increasing manner 45.23% but still better than FlexMatch 49.23%.

Affinity Graph Correction Analysis. To further verify that the graph matching can correct the affinity graph, we compute the inconsistent rate of samples that have mispredicted coarse labels between these two branches under different settings, which is shown in Table 5. We can see that the inconsistent rate is very high if we simply trained these two branches based on limited labeled samples. By incorporating the dynamic threshold learning and graph matching strategy, the error rate can be significantly decreased, demonstrating the effectiveness of graph matching. Moreover, large model WRN-28-8 can further improve results.

Visualization. The proposed graph-based contrastive hierarchical matching module can help model learn discriminative feature representations. To verify this, we visualized the learned features by t-SNE [28] and compared it with FixMatch and FlexMatch in Figure 4. It is obvious that the inter-class distance of our method is much larger than these of other two methods, which can lead to better results.

Table 5. Inconsistent rate of coarse labels on CIFAR100.

Method	Backbones	Label Amount		
		400	2500	10000
Supervised	WRN-28-2	78.63%	48.79%	29.99%
CHMatch w/o Graph Matching	WRN-28-2	30.94%	19.58%	16.15%
CHMatch	WRN-28-2	27.91%	17.52%	14.56%
CHMatch	WRN-28-8	23.75%	12.68%	8.56%

5. Conclusion and Future Work

In this paper, we came up with a new semi-supervised learning method CHMatch, which performs both instance-level prediction matching and contrastive graph-level matching. We first introduced a memory-bank based strategy to learn near-global adaptive threshold, which can efficiently select highly-confident samples for pseudo-label consistency. Besides, we utilized the hierarchical label structure to improve the SSL from two aspects, including an extra head for fine-grained classification and graph matching for contrastive feature learning. Extensive experiments on various benchmarks demonstrate our superiority in classification results and robustness. In the future, we would like to improve our method under the unbalanced hierarchical label structure, where different super classes may have different number of fine-grained categories.

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