Interactive Deep Clustering via Value Mining

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Abstract

In the absence of class priors, recent deep clustering methods resort to data augmentation and pseudo-labeling strategies to generate supervision signals. Though achieved remarkable success, existing works struggle to discriminate hard samples at cluster boundaries, mining which is particularly challenging due to their unreliable cluster assignments. To break such a performance bottleneck, we propose incorporating user interaction to facilitate clustering instead of exhaustively mining semantics from the data itself. To be exact, we present Interactive Deep Clustering (IDC), a plug-and-play method designed to boost the performance of pre-trained clustering models with minimal interaction overhead. More specifically, IDC first quantitatively evaluates sample values based on hardness, representativeness, and diversity, where the representativeness avoids selecting outliers and the diversity prevents the selected samples from collapsing into a small number of clusters. IDC then queries the cluster affiliations of high-value samples in a user-friendly manner. Finally, it utilizes the user feedback to finetune the pre-trained clustering model. Extensive experiments demonstrate that IDC could remarkably improve the performance of various pre-trained clustering models, at the expense of low user interaction costs. The code is available at XLearning-SCU/2024-NeurIPS-IDC.

1 Introduction

Clustering aims at partitioning samples into semantically distinct groups. In recent years, deep clustering methods [5, 31, 15, 42, 13], powered by the feature extraction ability of neural networks, have excelled in handling large-scale and high-dimensional data across various domains, including image segmentation [7], anomaly detection [26], medical analysis [1], bioinformatics [20], and so on.

To discover the semantical data partitions, the core of deep clustering lies in designing supervision signals to extract discriminative information from data. To this end, early efforts reformulate the self-representation property [32], hierarchical structure [44], or assignment distribution prior [43] into differentiable objectives for model optimization. Recently, inspired by the success of contrastive learning [6, 11], the community has shifted towards constructing self-supervision signals via data augmentations, thus promoting the contrastive clustering paradigm [18, 47, 14]. The latest research indicates that pseudo-labels could further enhance the clustering performance [39, 21, 30, 22].

Despite these merits, almost all deep clustering methods suffer from the performance ceiling due to the limited information inherent in the data [19]. Particularly, this limitation is reflected in the poor discrimination of hard boundary samples as shown in Fig. 1a. Consequently, it has a great chance to

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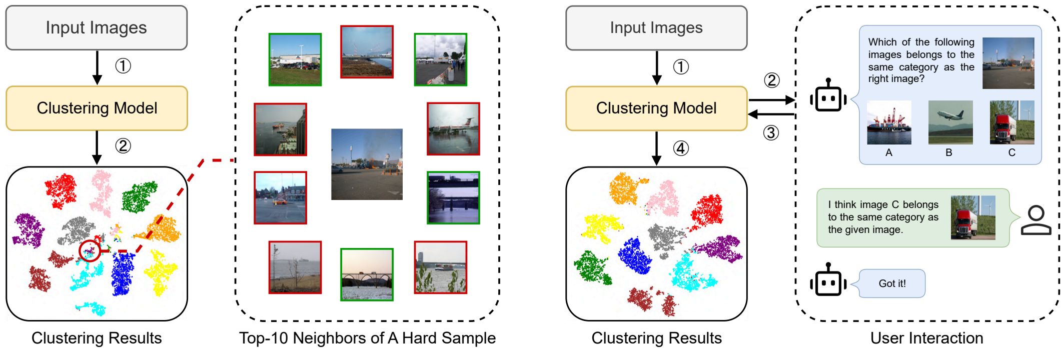


(a) Existing Deep Clustering Pipeline (b) Our Interactive Deep Clustering Pipeline

Figure 1: Our key idea. (a) Existing deep clustering methods suffer from poor discrimination of hard boundary samples. As a showcase, we highlight one hard sample (red circle) whose neighborhood includes visually similar but semantically different neighbors (red boxes), leading to a performance bottleneck. (b) Instead of exhaustively mining internal semantics from data, we propose incorporating external user interaction to address the hard sample problem. In brief, we select high-value samples and query their cluster affiliations, which improves the clustering performance remarkably as visualized in the T-SNE plots.

improve the overall performance remarkably through mining hard samples. Current pseudo-labeling strategies, however, focus on easy samples with high-confident cluster predictions, while failing to handle hard boundary samples with unreliable predictions. To tackle hard samples, a recent effort attempts to mitigate their impact by neglecting them when constructing neighborhoods [46]. Nevertheless, this approach, akin to an ostrich avoidance policy, essentially sidesteps the core problem rather than solving it, ultimately leaving hard samples inseparable.

Acknowledging limitations in tackling hard samples internally, we present a straightforward approach by incorporating external user interaction, as illustrated in Fig. 1b. In brief, given an arbitrary pre-trained clustering model, we aim to correct its cluster assignments of hard samples with minimal user interaction overhead. To achieve this, we confront two challenges: *i*) constructing an efficient and user-friendly interaction interface, and *ii*) effectively utilizing user feedback. To tackle the first challenge, we present a novel strategy to mine valuable samples based on hardness, representativeness, and diversity for user inquiries with mathematical formulations. Here, the representativeness is designed to avoid selecting outliers and the diversity is used to prevent the selected samples from collapsing into a small number of clusters. For user convenience, instead of directly requesting class labels, we inquire about the affiliation of each selected sample with its nearest cluster centers. For the second challenge, we design two new losses to finetune the pre-trained model using both positive and negative user feedback. Specifically, positive feedback indicates the semantic alignment w.r.t. the selected cluster, while negative feedback denies all candidate clusters as semantically inconsistent. Additionally, we propose a regularization loss to preserve the overall cluster boundary of the original model, preventing it from overfitting the inquired samples. Notably, our method is a model-irrelevant plug-in that can be effortlessly integrated into existing clustering methods, thereby enhancing their performance.

The major contributions of this work could be summarized as follows:

- We propose incorporating external user interaction to break through the performance ceiling of existing deep clustering methods, specifically correcting the hard samples that are indistinguishable internally.
- To reduce interaction costs, we present a value-mining strategy to select hard, representative, and diverse samples for user inquiry. To simplify the interaction, we design a user-friendly interface to ask for cluster affiliations of these selected valuable samples.
- The proposed IDC could be easily integrated into any pre-trained deep clustering model. Extensive experiments demonstrate that our IDC could significantly boost the performance of various state-of-the-art deep clustering methods with negligible user interaction costs.

2 Related Work

In this section, we briefly review two fields related to this work, namely, deep clustering and hard sample mining.

2.1 Deep Clustering

Thanks to the powerful feature extraction ability, deep clustering methods have shown promising results on complex real-world data and advanced rapidly in past years [43, 44, 5, 15, 23]. Recently, the success of self-supervised learning [6, 11, 10] gives rise to a series of contrastive clustering methods [18, 47, 21, 14]. However, even enhanced by data augmentation and pseudo-labeling strategies [39, 30, 21, 4], the performance of existing deep clustering methods is inherently upper-bounded by the limited internal supervision signals. Instead of exhaustively mining semantics from the data, a recent work attempts to leverage external data and models to facilitate clustering [19]. Another branch of study focuses on integrating prior class labels [3, 16] or pairwise constraints [40, 41, 25, 28] into the clustering process to boost the performance.

Different from existing studies that pursue overall performance improvements, this work aims to address the specific hard sample problem. Notably, the performance bottleneck of existing methods lies in the poor discrimination for hard samples at the cluster boundaries. Given the difficulty of internally correcting cluster assignments for hard boundary samples, we propose incorporating external user interaction as a straightforward solution. By inquiring about the cluster affiliations of representative and diverse hard samples, our method could significantly boost the performance of pre-trained clustering models with low interaction overhead.

2.2 Hard Sample Mining

Hard samples refer to data points that are difficult to recognize and understand due to their ambiguous or weak semantics, which widely exist in various tasks such as face recognition [34], person re-identification [45], image segmentation [29], object detection [2], and cross-modal retrieval [24]. On the one hand, the model is likely to make wrong predictions for these samples. On the other hand, mining these samples could significantly improve the model performance. Notably, hard sample mining is usually conducted in a supervised manner. For clustering, it is daunting to correct the assignments of hard samples at cluster boundaries by the model itself due to the absence of class label priors. As an attempt, SeCu [33] recently proposes assigning larger weights to hard samples when computing cluster centers for better cluster discriminability. However, the improvement is limited due to the unreliable cluster assignments of hard samples.

The differences between this work and previous hard sample mining methods are twofold. On the one hand, most existing works focus on enclosed supervised learning, while we explore hard sample mining for unsupervised clustering by incorporating user interaction. On the other hand, unlike previous works that solely pursue sample hardness, we further consider the representativeness and diversity of hard samples, resulting in a more comprehensive evaluation of data value. Such a value mining strategy helps to improve the cluster model with interaction costs as low as possible.

3 Method

In this section, we introduce our novel Interactive Deep Clustering method (IDC). As illustrated in Fig. 2, IDC consists of two primary stages: user interaction and model optimization. Initially, IDC solicits the user to determine the cluster affiliation of highly valuable samples, which are strategically selected based on their **hardness**, **representativeness**, and **diversity**. Subsequently, during the model optimization stage, IDC refines the cluster assignments of these samples according to the user feedback, while preserving the overall decision boundary of the pre-trained model. The two stages are further detailed in Sections 3.1 and 3.2.

3.1 User Interaction

To boost the pre-trained clustering model with minimal user interaction cost, we select the most valuable samples for user inquiries. The value of each sample is appraised based on three proposed

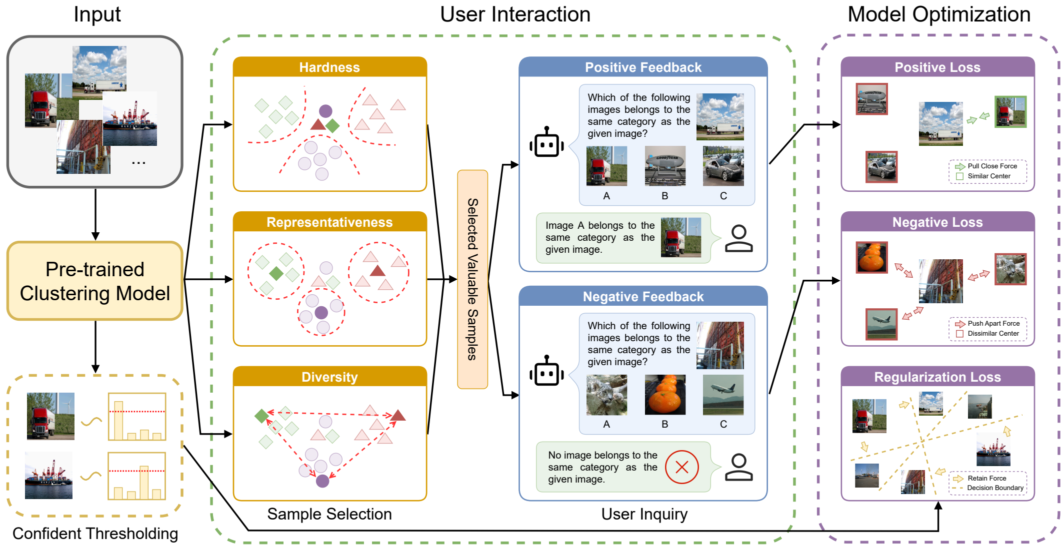


Figure 2: The overall framework of IDC consists of two stages: user interaction and model optimization. In the user interaction stage, given a pre-trained clustering model, IDC first selects high-value samples based on hardness, representativeness, and diversity. Then it inquires the user about the affiliations of the selected samples relative to their nearest cluster centers. In the model optimization stage, IDC utilizes both positive and negative user feedback to finetune the pre-trained model with positive and negative losses for cluster performance improvement. Meanwhile, IDC adopts a regularization loss on high-confident predictions to prevent overfitting inquired samples.

criteria: hardness h, representativeness r, and diversity d, encapsulated by the equation:

$$v_i = h_i + r_i + d_i, \tag{1}$$

where v_i denotes the importance of the i-th sample. We elaborate on the three metrics as follows:

Hardness. Typically, a pre-trained clustering model could accurately assign clusters to easy samples near cluster centers. However, it may fail on hard samples situated at cluster peripheries. In other words, identifying these boundary samples is pivotal for boosting the clustering performance. Therefore, we quantify the hardness of the i-th sample by its proximity to cluster centers:

$$h_i = \log(1 - z_i \cdot c_{g_1} + z_i \cdot c_{g_2}), \tag{2}$$

where z_i is the L2-normalized feature of the i-th sample, and c_{g_1}, c_{g_2} denote the closest and second-closet cluster centers to z_i, respectively. A higher h_i score indicates greater uncertainty in cluster assignment for the i-th sample.

Representativeness. While correcting hard samples is beneficial, focusing solely on hardness may lead to suboptimal results, as the most challenging samples could be outliers that negatively impact the model's generalization ability. To tackle this problem, we prefer samples reside in dense regions, where inquiring about a single sample could correct the cluster assignments of numerous adjacent ones. Formally, we define the representativeness of the i-th sample by the density of its K nearest neighbors as follows:

$$r_i = -\log \sum_{j=1}^{K} \|z_i - z_{i(j)}\|_2^2, \tag{3}$$

where $z_{i(j)}$ refers to the j-th nearest neighbor of z_i, and K is the number of nearest neighbors empirically set to 20. A higher r_i score suggests a more compact local structure, indicating that the i-th sample is more representative.

Diversity. In practice, we discover that pursuing hardness and representativeness may result in an unbalanced sample distribution, heavily collapsing into a small number of clusters as shown in Fig. 3. To avoid this, we present the "diversity" metric to ensure sufficient dispersion of the selected samples. Different from hardness and representativeness which are independent of the selection,

Algorithm 1 Valuable Sample Selection

Input: Sample features $\mathbf{Z} = \{\mathbf{z}_1, \dots, \mathbf{z}_N\}$, number of samples to be selected M

Output: Selected sample indices $\mathbf{S} = \{s_1, \dots, s_M\}$

```
Initialize the selected indices S = {} and the remaining indices R = {1, ..., N}
Compute cluster centers of Z by k-means
for i ∈ [1, N] do
    Compute the hardness score h_i by Eq. (2)
    Compute the representativeness score r_i by Eq. (3)
    Initialize the diversity score d_i = 0, since no sample has been selected
    Compute the value score v_i by Eq. (1)
end for
for j ∈ [1, M] do
    Select the s_j-th sample with the highest value from Z_R
    S = S ∪ {s_j}, R = R \ {s_j}
    Update the diversity score d for Z_R by Eq. (4)
    Update the value score v for Z_R by Eq. (1)
end for
```

the diversity of a given sample is measured by its deviation from previously selected samples. In our implementation, the sample with the highest v_i score is selected iteratively until M samples are selected. In each iteration, the diversity of the i-th sample is computed according to the already selected samples:

$$d_i = \min_{j \in \mathbf{S}} \quad \log(1 - z_i \cdot z_j), \tag{4}$$

where $\mathbf{S}$ represents the indices of the selected samples.

For user interaction, we select the top $M = 500$ valuable samples with the highest v_i scores in our experiments. The selection process is outlined in Algorithm 1. According to Theorem 1 proved below, IDC could select the most valuable samples to minimize the user interaction cost.

Theorem 1. *The value of the selected sample decreases as the selection progresses, i.e.,*

$$v^j_{s_j} \geq v^{j+1}_{s_{j+1}}, \forall j \in [1, M-1]. \tag{5}$$

where s_j denotes the index of the j-th selected sample, and v^j_i denotes the i-th sample's value in the j-th selection.

Proof. We denote $\mathbf{S}^j$ as the set of selected sample indices and $\mathbf{R}^j$ as the set of remaining sample indices after the j-th selection. Further, the i-th sample's hardness, representativeness, and diversity in the j-th selection (*i.e.*, $i \in \mathbf{R}^{j-1}$) are denoted as h^j_i, r^j_i, and d^j_i, respectively. By the definition of sample value in Eq. (1), we have

$$v^j_i = h^j_i + r^j_i + d^j_i, \tag{6}$$

Notably, since we choose s_j instead of s_{j+1} in the j-th selection, there must be

$$v^j_{s_j} \geq v^j_{s_{j+1}}. \tag{7}$$

By the definition of diversity in Eq. (4), we have

$$d^j_{s_{j+1}} = \min_{i \in \mathbf{S}^{j-1}} \log(1 - z_{s_{j+1}} \cdot z_i) \geq \min_{i \in \mathbf{S}^j} \log(1 - z_{s_{j+1}} \cdot z_i) = d^{j+1}_{s_{j+1}}, \tag{8}$$

where the inequality holds since $\mathbf{S}^j = \mathbf{S}^{j-1} \cup \{s_j\}$ and thus $\mathbf{S}^{j-1} \subset \mathbf{S}^j$. Furthermore, as hardness and representativeness scores are irrelevant to the selection process (*i.e.*, $h^j_{s_{j+1}} = h^{j+1}_{s_{j+1}}$, $r^j_{s_{j+1}} = r^{j+1}_{s_{j+1}}$), we have

$$v^j_{s_{j+1}} = h^j_{s_{j+1}} + r^j_{s_{j+1}} + d^j_{s_{j+1}} \geq h^{j+1}_{s_{j+1}} + r^{j+1}_{s_{j+1}} + d^{j+1}_{s_{j+1}} = v^{j+1}_{s_{j+1}}. \tag{9}$$

Finally, by combining Eq. (7) and Eq. (9), we arrive at

$$v^j_{s_j} \geq v^j_{s_{j+1}} \geq v^{j+1}_{s_{j+1}}, \tag{10}$$

which completes the proof of Theorem 1. □

Upon selecting the most valuable samples, we inquire about their cluster affiliations relative to the nearest cluster centers. For each selected sample, we provide $T = 5$ nearest cluster center candidates [2], and then request the user to determine which candidate shares the same semantics with the anchor as illustrated in Fig. 2. Notably, such an inquiry strategy is more user-friendly than directly asking about the pair-wise correlation between two samples, by aiding users in grasping cluster semantics and partitioning criteria. User feedback could be either positive (selecting a candidate) or negative (rejecting all candidates) to the given sample, which serves the subsequent model finetuning strategy introduced in the next section.

3.2 Model Optimization

Based on the user feedback, we present a positive loss $\mathcal{L}_{pos}$, a negative loss $\mathcal{L}_{neg}$, and a regularization loss $\mathcal{L}_{reg}$ to finetune the clustering model:

$$\mathcal{L} = \mathcal{L}_{pos} + \mathcal{L}_{neg} + \mathcal{L}_{reg}. \tag{11}$$

The three loss terms are designed to utilize positive feedback, to use negative feedback, and to prevent overfitting the queried samples, respectively, with details provided below.

Positive Loss. Positive user feedback refers to identifying the cluster centroid sharing the same semantics with the inquiry sample. To exploit this feedback, we draw the sample and the cluster centroid closer by the following positive loss:

$$\mathcal{L}_{pos} = -\frac{1}{M_{pos}} \sum_{i=1}^{M_{pos}} \sum_{j=1}^{C} y_{ij} \log p_{ij}, \tag{12}$$

where M_{pos} denotes the count of positive feedback, C is the number of clusters, p_{ij} refers to the probability of sample i belonging to cluster j, and $y_{ij} \in \{0, 1\}$ is an indicator that equals one iff the j-th cluster is selected by user.

Negative Loss. Negative user feedback indicates that no candidates match the semantics of the inquiry sample. To leverage the feedback, we enforce the sample apart from all candidate clusters using the following negative loss:

$$\mathcal{L}_{neg} = -\frac{1}{M_{neg}} \sum_{i=1}^{M_{neg}} \sum_{j=1}^{C} \tilde{y}_{ij} \log(1 - p_{ij}), \tag{13}$$

where M_{neg} is the count of negative feedback, and $\tilde{y}_{ij}$ is an indicator that equals one if the j-th cluster is the randomly chosen candidate, and zero otherwise.

Regularization Loss. To reduce the interaction cost, only a small amount of samples are selected for user interaction. However, exclusively finetuning the model with the above two losses risks overfitting to the inquiry samples, potentially compromising previously correct cluster predictions. To tackle this problem, we propose preserving the overall cluster boundary by retaining confident predictions. Formally, the regularization loss is defined as follows:

$$\mathcal{L}_{reg} = -\frac{1}{N} \sum_{i=1}^{N} \mathbb{1}[p_{i\hat{j}} > \tau] \log p_{i\hat{j}}, \quad \hat{j} = \operatorname{argmax} p_i \tag{14}$$

where N is the count of all samples, $\tau = 0.99$ is the confidence threshold, $\mathbb{1}[\mathrm{cond}] \in \{0, 1\}$ is an indicator that equals one iff the condition cond holds.

The above three losses are applied to optimize the pre-trained clustering model for performance improvement. After finetuning, we could directly obtain the improved cluster assignments from the model's cluster head[3].

[2] In practice, each cluster center is represented by its nearest sample.

[3] We append a cluster head for pre-trained clustering models that do not have one. More details are provided in Section 4.2.

4 Experiments

In this section, we first apply the proposed IDC to two state-of-the-art deep clustering methods, and evaluate the performance on five widely used image clustering benchmarks. Then we conduct ablation studies and parameter analyses to validate the robustness and effectiveness of IDC.

4.1 Datasets and Evaluation Metrics

We evaluate IDC on five widely used image clustering datasets, including CIFAR-10 [17], CIFAR-20 [17], STL-10 [8], ImageNet-10 [5] and ImageNet-Dogs [5], as detailed in Table 1.

Three widely used clustering metrics are adopted for performance evaluation, including Normalized Mutual Information (NMI), Accuracy (ACC), and Adjusted Rand Index (ARI). Higher scores signify superior clustering results.

Table 1: A summary of the used datasets.

Dataset	Split	Samples	Classes
CIFAR-10	Train+Test	60000	10
CIFAR-20	Train+Test	60000	20
STL-10	Train+Test	13000	10
ImageNet-10	Train	13000	10
ImageNet-Dogs	Train	19500	15

4.2 Implementation Details

Without loss of generality, we apply the proposed IDC on two recent methods TCL [21] and ProPos [14], on behalf of deep clustering models with and without a cluster head, respectively. Notably, for clustering models without a cluster head like ProPos, we append a randomly initialized two-layer fully connected network as an alternative. In the model optimization stage, we finetune the pre-trained clustering model for 100 epochs. For ProPos, we warm up the cluster head with the positive and negative loss in Eq. 12 and 13 in the first 50 epochs, since the prediction confidences are unreliable initially. To balance the effect of user feedback and model regularization, we use two independent data loaders for the inquiry and confident samples, with batch sizes of 100 and 500, respectively. All images are augmented consistently with the pre-trained clustering model for finetuning, while the original images are used for value evaluation and pseudo-labeling. All experiments are conducted on a single Nvidia RTX 3090 GPU on the Ubuntu 20.04 platform with CUDA 12.0.

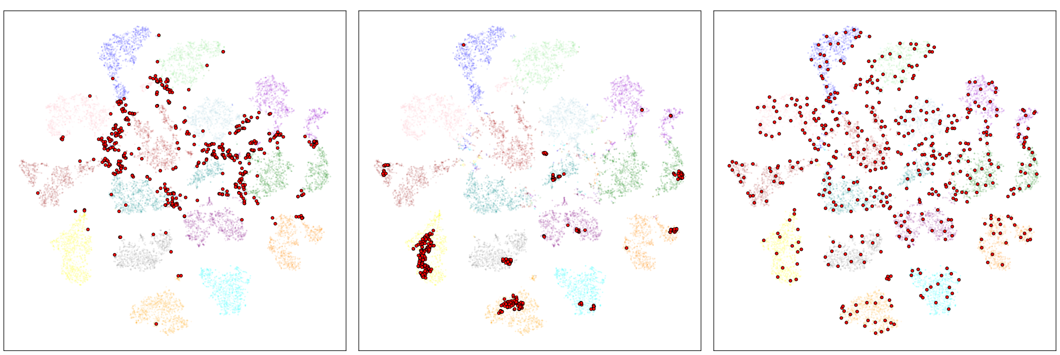
4.3 Comparisons with State of the Arts

We first compare the proposed IDC with 14 recent deep clustering methods, including CC [18], SCAN [39], NMM [9], MiCE [38], BYOL [10], GCC [47], SPICE [30], IDFD [37], TCC [35], DivClust [27], SeCu [33], CoNR [46], TCL [21], and ProPos [14]. In addition, we include two representative semi-supervised classification and clustering baselines FixMatch [36] and Cop-Kmeans [41] for benchmarking. For FixMatch, we use the ResNet-34 [12] as the backbone and annotate the inquiry images with positive user feedback for fair comparisons. For Cop-Kmeans, we use the TCL image features as the input and transform the user feedback as must- and cannot-link constraints.

As shown in Table 2, IDC gains consistent performance improvement, especially on more challenging datasets. Specifically, IDC boosts the clustering accuracy of TCL/ProPos by 16.3%/19.2% and 14.4%/9.2% on CIFAR-20 and ImageNet-Dogs, respectively. Besides, the results show that solely correcting the cluster assignments of 500 samples brings marginal performance improvement, since they are only a small portion of the data. Notably, IDC also outperforms the semi-supervised baseline FixMatch. Such a result could be attributed to its customized valuable sample selection strategy. Namely, the selected inquiry samples are catered to the pre-trained clustering model, which may not suit the general semi-supervised classification. Moreover, the superior performance of IDC compared with Cop-Kmeans demonstrates its stronger ability to utilize user feedback for model optimization.

Table 2: Clustering performance comparison with the state-of-the-art methods on five benchmarks. The performance of $\text{IDC}_{\text{ProPos}}$ is unavailable as the code of ProPos on STL-10 has not been released. To make a clear comparison, we add a baseline by manually correcting the cluster assignments of 500 query samples, denoted by TCL† and ProPos†.

Method	CIFAR-10			CIFAR-20			STL-10			ImageNet-10			ImageNet-Dogs		
	NMI	ACC	ARI	NMI	ACC	ARI	NMI	ACC	ARI	NMI	ACC	ARI	NMI	ACC	ARI
CC [18]	70.5	79.0	63.7	43.1	42.9	26.6	76.4	85.0	72.6	85.9	89.3	82.2	44.5	42.9	27.4
SCAN [39]	79.7	88.3	77.2	48.6	50.7	33.3	69.8	80.9	64.6	-	-	-	-	-	-
NMM [9]	74.8	84.3	70.9	48.4	47.7	31.6	69.4	80.8	65.0	-	-	-	-	-	-
MiCE [38]	73.7	83.5	69.8	43.6	44.0	28.0	63.5	75.2	57.5	-	-	-	42.3	43.9	28.6
BYOL [10]	81.7	89.4	79.0	55.9	56.9	39.3	71.3	82.5	65.7	86.6	93.9	87.2	63.5	69.4	54.8
GCC [47]	76.4	85.6	72.8	47.2	47.2	30.5	68.4	78.8	63.1	84.2	90.1	82.2	49.0	52.6	36.2
SPICE [30]	73.4	83.8	70.5	44.8	46.8	29.4	81.7	90.8	81.2	82.8	92.1	83.6	57.2	64.6	47.9
IDFD [37]	71.1	81.5	66.3	42.6	42.5	26.4	64.3	75.6	57.5	89.8	95.4	90.1	54.6	59.1	41.3
TCC [35]	79.0	90.6	73.3	47.9	49.1	31.2	73.2	81.4	68.9	84.8	89.7	82.5	55.4	59.5	41.7
DivClust [27]	72.4	81.9	68.1	44.0	43.7	28.3	-	-	-	89.1	93.6	87.8	51.6	52.9	37.6
SeCu [33]	86.1	93.0	85.7	55.1	55.2	39.7	73.3	83.6	69.3	-	-	-	-	-	-
CoNR [46]	87.1	93.3	86.5	60.3	59.0	44.8	84.6	92.2	83.8	89.8	95.8	90.9	74.2	80.2	67.6
FixMatch [36]	86.8	92.8	85.4	57.2	67.2	47.3	61.7	68.6	49.2	84.2	92.5	84.4	50.0	57.9	33.7
Cop-Kmeans [41]	82.3	89.0	78.6	52.2	52.4	34.7	78.1	85.4	73.1	85.5	88.6	81.0	61.5	63.5	49.7
TCL [21]	81.9	88.7	78.0	52.9	53.1	35.7	79.9	86.8	75.7	87.5	89.5	83.7	62.3	64.4	51.6
TCL†	82.2	88.9	78.4	53.2	53.5	36.1	82.0	88.6	78.5	88.6	90.4	85.0	62.8	65.6	52.3
IDC_{TCL}(Ours)	84.4	92.7	84.8	58.1	69.4	48.7	**85.3**	**92.7**	**84.6**	93.2	97.2	93.9	69.1	78.8	63.6
ProPos [14]	87.7	93.6	87.1	59.1	59.1	43.6	75.8	86.7	73.7	88.9	95.2	89.6	73.0	76.9	66.9
ProPos†	87.9	93.7	87.3	59.3	59.4	43.8	-	-	-	89.6	95.5	90.3	73.8	77.8	67.8
$\text{IDC}_{\text{ProPos}}$(Ours)	**90.5**	**95.7**	**90.9**	**69.2**	**78.3**	**61.4**	-	-	-	**93.2**	**97.3**	**94.1**	**77.6**	**86.1**	**74.8**



(a) Hard (b) Hard+Rep (c) Hard+Rep+Div

Figure 3: T-SNE visualizations of samples selected by different strategies among all data points, on the ImageNet-Dogs dataset where selected samples are highlighted by red dots.

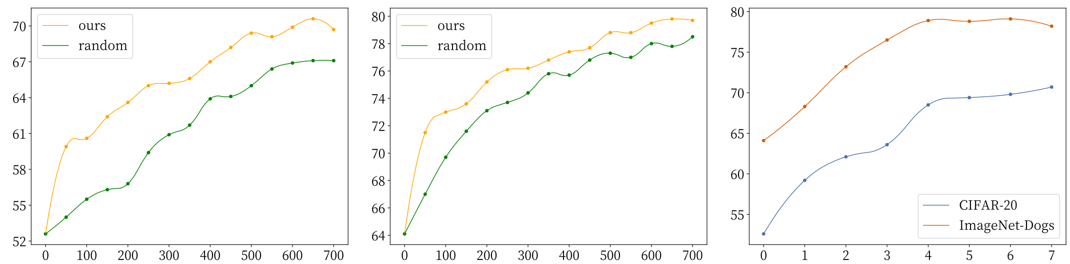
4.4 Ablation Study and Parameter Analysis

To prove the robustness and effectiveness of IDC, we conduct ablation studies and parameter analyses on the TCL-based model. Specifically, for the user interaction stage, we study the effectiveness of the valuable sample selection strategy, as well as the impact of the number of selected samples M and candidate cluster centers T. For the model optimization stage, we investigate the effectiveness of the three loss terms.

Effectiveness of the valuable sample selection strategy. As detailed in Section 3.1, starting with the clustering hardness, we additionally consider representativeness and diversity to quantify the value of each sample. Here, to provide an intuitive understanding of the three criteria, we visualize the selected samples among all data points in Fig. 3. As can be seen, solely considering hardness would select most boundary samples, which are not representative enough and thus sub-optimal for reducing

Table 3: Performance with different sample selection strategies on CIFAR-20 and ImageNet-Dogs.

Selection Strategy	CIFAR-20			ImageNet-Dogs		
	NMI	ACC	ARI	NMI	ACC	ARI
None (Pre-trained Model)	52.2	52.6	34.9	61.8	64.1	50.9
Hard	51.3	57.7	37.0	68.2	75.9	60.2
Hard+Rep	35.8	36.3	12.6	59.7	65.3	49.4
Hard+Rep+Div	**58.1**	**69.4**	**48.7**	**69.1**	**78.8**	**63.6**



(a) M on CIFAR-20 (b) M on ImageNet-Dogs (c) T on both datasets

Figure 4: Influence of different numbers of selected samples M and candidates T. (a)–(b) Clustering accuracy with different M on CIFAR-20 and ImageNet-Dogs respectively, compared with the random selection baseline. (c) Clustering accuracy with different T on both datasets.

the interaction cost. When additionally considering the representativeness, however, the selected samples would collapse into dense subsets, leading to a significant performance drop as shown in Table 3. Finally, further integrating the diversity results in samples simultaneously comprising the three expected characteristics, which gives the best clustering performance.

Impact of the number of selected samples and candidates. For interaction cost reduction, we select $M = 500$ most valuable samples for the user inquiry, and $T = 5$ nearest cluster centers as the candidates. Here, we investigate how different numbers of M and T influence the final clustering performance. As depicted in Fig. 4 (a) and (b), the performance of IDC improves as the number of selected samples increases. Notably, the improvement grows rapidly at the start but gradually levels off as more samples are selected. Moreover, valuable samples selected by IDC consistently outperform the random selection baseline. These results not only demonstrate the effectiveness of our valuable sample selection strategy, but also verify the monotonously decreased sample value as proved in Theorem 1. For the number of candidates, Fig. 4 (c) shows that comparing the inquiry sample with the five nearest centers strikes the best balance between performance and interaction cost.

Table 4: Performance with different combinations of loss terms on CIFAR-20 and ImageNet-Dogs.

$\mathcal{L}_{pos}$	$\mathcal{L}_{neg}$	$\mathcal{L}_{reg}$	CIFAR-20			ImageNet-Dogs		
			NMI	ACC	ARI	NMI	ACC	ARI
✓			56.8	65.8	46.2	68.3	76.9	62.5
	✓		7.0	9.6	2.4	26.8	24.1	3.1
		✓	50.9	52.9	35.2	61.7	64.9	51.8
✓	✓		55.0	66.2	44.1	67.9	77.5	61.6
✓		✓	**58.7**	67.6	47.8	68.8	77.5	62.7
	✓	✓	36.7	39.2	17.3	53.1	59.7	34.8
✓	✓	✓	58.1	**69.4**	**48.7**	**69.1**	**78.8**	**63.6**

Effectiveness of the loss terms. To prove the effectiveness of the positive loss $\mathcal{L}_{pos}$ in Eq. (12), the negative loss $\mathcal{L}_{neg}$ in Eq. (13), and the regularization loss in Eq. (14), we evaluate different combination of the three losses and the results are shown in Fig. 4. On the one hand, no single loss is adequate to yield promising clustering results. In particular, solely leveraging the negative loss would deny all the Top-5 predictions and thus severely damage the decision boundary of the pre-trained clustering model, leading to the model collapse. On the other hand, each loss is indispensable during the model optimization. Notably, the positive loss brings the most substantial performance improvement, as it offers the most direct clustering guidance to the model.

5 Conclusion

Instead of mining semantics from internal data, we propose an interactive deep clustering method IDC, which incorporates user interaction to address the hard sample problem. By mathematically measuring the sample value defined on hardness, representativeness, and diversity, IDC selects the highest-value samples and inquiries about their cluster affiliations through a user-friendly interaction interface. By fine-tuning the pre-trained clustering model leveraging user feedback, IDC remarkably improves the performance of various state-of-the-art deep clustering methods. For future studies, one potential direction is to consider the mistakes in user feedback, and correspondingly improve the robustness of IDC. Another possible direction is to design a more advanced interaction pipeline, for aligning clustering results with the user's personalized partition criterion. In general, we hope this work could provide novel insight to the community, attracting more attention to the interactive clustering paradigm which is a promising and less explored area.

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