Self-distillation with Online Diffusion on Batch Manifolds Improves Deep Metric Learning

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Abstract

Recent deep metric learning (DML) methods typically leverage solely class labels to keep positive samples far away from negative ones. However, this type of method normally ignores the crucial knowledge hidden in the data (e.g., intra-class information variation), which is harmful to the generalization of the trained model. To alleviate this problem, in this paper we propose Online Batch Diffusion-based Self-Distillation (OBD-SD) for DML. Specifically, we first propose a simple but effective Progressive Self-Distillation (PSD), which distills the knowledge progressively from the model itself during training. The soft distance targets achieved by PSD can present richer relational information among samples, which is beneficial for the diversity of embedding representations. Then, we extend PSD with an Online Batch Diffusion Process (OBDP), which is to capture the local geometric structure of manifolds in each batch, so that it can reveal the intrinsic relationships among samples in the batch and produce better soft distance targets. Note that our OBDP is able to restore the insufficient manifold relationships obtained by the original PSD and achieve significant performance improvement. Our OBD-SD is a flexible framework that can be integrated into state-of-the-art (SOTA) DML methods. Extensive experiments on various benchmarks, namely CUB200, CARS196, and Stanford Online Products, demonstrate that our OBD-SD consistently improves the performance of the existing DML methods on multiple datasets with negligible additional training time, achieving very competitive results. Code: https://github.com/ZelongZeng/OBD-SD_Pytorch

1 Introduction

Deep Metric Learning (DML) aims to learn an embedding space that uses predefined distance metrics (e.g., Euclidean distance) to reasonably measure the similarity between training samples and then transfer to unseen test data. The generalization capability of embedding space is very essential for many downstream applications of DML, such as image retrieval [8, 9], face recognition [38, 4], person re-identification [48, 12] and representation learning [47].

Most existing DML methods utilize a pre-defined
distance metric, depending on the class label, to in-
crease the inter-class distance in the embedding space
while decreasing the intra-class distance [41]. Typi-
cally, these methods promote intra-class samples to
form a compact cluster with a large margin from
other clusters, thus learning a strongly discrimina-
tive representation for the seen class, but ignoring
the intrinsic relationships of the samples, such as
intra-class variation. In particular, since the rela-
tionships of samples in the embedding space are de-
veloped solely from the distance metric based on the
class labels, the diversity of the relationships of sam-
ples in the embedding space is suppressed. However,
ignoring the intrinsic relationships of the samples ac-
tually harms the generalization of learned embed-
ding space since they are useful to identify unseen
classes [37, 26, 50, 57, 56].

To enhance this diversity, we propose a simple
yet effective method called Online Batch Diffusion-
based Self-distillation (OBD-SD), which is composed
of two complementary components. Specifically, in-
spired by recent typical knowledge distillation tech-
niques [6, 53, 19, 52], we first propose Progressive
Self-distillation (PSD) that can be integrated into
many typical DML methods [49, 46, 35]. For PSD,
we define the student model trained in the previous
epoch as the teacher model, which means that the
student model serves as its own teacher model. This
procedure does not require any modifications to the
network architecture and incurs no further computa-
tional cost. In other words, in a dynamic manner,
PSD distills the distance metric from the model
at the previous epoch and then adaptively assigns a
soft distance target for each training pair of data. We
theoretically and experimentally analyze that the soft
distance targets learned from PSD have more infor-
mation about how the training samples are related to
each other (rather than only considering the class la-
bel information). This helps to learn more diverse
embedding representations and solves the problem
described above.

It’s worth noting that a better distance met-
cr should consider the local geometric structure of
manifolds, rather than just using the rigid dis-
tance metrics, which is disregarded by our proposed
PSD. Therefore, inspired by existing diffusion pro-
cess methods [59, 1, 51], we use the diffusion process
to refine the distance target provided by the teacher
model of PSD. We further proposed an Online Batch Diffusion Process (OBDP) technique, which aims to
capture the local geometry structure of manifolds
in a mini-batch. Our OBDP is able to learn the
high-order information from batch manifolds, which
presents the intrinsic relationships between samples
and makes the soft distance targets more accurate.
Note that, our OBDP makes use of a mini-batch
to construct the manifold structure, which belongs
to the online learning scheme, thereby significantly
enhancing the computational efficiency. Our exper-
iments and observations show that, compared with
the existing methods doing diffusion on the global
manifolds, this online learning scheme can achieve
competitive or even better results.

We reformulate our OBD-SD model combing PSD
and OBDP. The OBD-SD is a plug-and-play tech-
nique that can be integrated into most conventional
DML methods with negligible extra computation
cost. Our theoretical studies (as presented in Sec-
tion 4) reveal that our OBD-SD can take into account
the high-order relationship of samples, especially for
hard samples. That is, our OBD-SD can learn a more
accurate distance metric, which benefits the overall
performance.

Finally, we conduct extensive experiments on
three widely-used DML benchmarks, i.e, CUB200-
2011 [44], CARS196 [23] and Stanford Online Prod-
cts [28], on which the results validate the merits
of the proposed OBD-SD over the state-of-the-art
(SOTA) DML methods. Moreover, experiments in
Section 5.6 indicate that our OBD-SD indeed makes
the learned embedding features achieve higher diver-
sity and mitigate over-clustering [34], both encour-
ging better generalization to unseen test classes.

2 Related Works

2.1 Deep Metric Learning

Metric learning aims to learn a good metric space,
in which we can measure the similarity between
samples by using distance metrics. Recent works
leverage deep learning techniques to facilitate a better distance metric, which is called deep metric learning (DML). The pioneering works consider the relationship between a tuple of samples, such as pairs [10], triplets [45, 38, 49], and other variants (like N-pairs [40] and lifted structured loss [28]). Recently, AP-based losses [3, 31] and proxy-based methods [27, 29, 20] have demonstrated the capacity to learn distance-preserving embedding spaces. In addition, many different sampling schemes have been introduced to reduce the computational complexity caused by a large number of training pairs [38, 49, 7, 32, 33].

Recently, a promising direction is to explore how to learn a discriminative embedding space with good generalization to unseen classes. Most existing methods of this type consider learning an ensemble of embeddings by manually designing different learning objectives or constraints and demonstrate that the diversity of embedding representations is crucial to the generalization of embedding space [37, 32, 26, 50, 57, 56]. However, they usually face the problem of less scalability and high computational complexity. In contrast, our OBD-SD is efficient and straightforward, showing good scalability and generalization capabilities.

### 2.2 Knowledge Distillation

Early knowledge distillation (KD) attempts to compress models by transferring the “dark knowledge” from the larger teacher model to a compact student model [13, 54, 42]. Many recent works find that the student model can outperform the teacher model when the student is configured with the same capacity as its teacher [6, 52]. Based on this observation, they introduce a novel self-distillation (Self-KD) scheme. In addition, some other works, such as PS-KD [19], BYOT [55], and CS-KD [53], present a more effective and efficient simultaneous Self-KD scheme.

More recently, researchers begin to apply the Self-KD for improving the generalization of DML, taking RCL [21], BAR [30], and S2SD [34] as representative works. BAR applies the conventional strategy, i.e., using a pre-trained model as the teacher. And S2SD extends DML with knowledge distillation from multiple auxiliary heads with high-dimension, all auxiliary heads share the same backbone with the base networks so they can be trained simultaneously. It’s worth noting that our work is somewhat similar to S2SD. We elaborate on some major differences between S2SD and ours as follows: First, S2SD targets the task of “feature compression”, i.e., using high-dimensional embedding space with better generalization capacity to assist the training of low-dimensional embedding space. In contrast, Our OBD-SD proposes that the same dimensional embedding (as opposed to the high-dimensional embedding of S2SD) space itself can provide helpful information to improve performance, while S2SD does not. Second, our OBD-SD proposes Online Batch Diffusion Process (OBDP) for refining soft distance targets from the teacher. We also apply our OBDP to the existing Self-KD-based methods, and the experiments in Section 5.4 show that our OBDP can significantly improve the performance of the compared Self-KD-based DML methods.

### 2.3 Diffusion Process

The diffusion process is commonly used as a re-ranking method in retrieval tasks [59, 5, 1, 16, 51]. Due to the diversity of data, there is usually a distribution difference between training data and unknown test data [39]. The difference often results in manifolds in the embedding space that are not conducive to measuring the relationships between test samples using the rigid distance metric [51]. To handle this problem, diffusion process can capture the local geometry structure of the data manifolds based on a neighborhood graph, which can make distance metric more accurately [1]. Such a neighborhood graph consists of various nodes and edges, where each node represents a feature from the database and the edge presents the connection between each node and its neighborhood with corresponding weights proportional to the pairwise affinities between nodes. Additionally, diffusion process is often applied in label propagation for deep semi-supervised learning [58, 15, 14]. Different from these diffusion process methods proposed as the post-processing method, our OBD-SD uses diffusion process as an auxiliary
module that can refine the soft distance targets well during the training. Moreover, our OBD-SD uses only the mini-batch data for each diffusion process, which is more efficient than the conventional methods of using global data.

3 Proposed Method

3.1 Problem Formulation

For metric learning, we denote \( \mathcal{X} = \{\mathbf{x}_1, \mathbf{x}_2, \ldots, \mathbf{x}_n\} \) as the training data, and \( y_i \) is the corresponding label of \( \mathbf{x}_i \). Our goal is to learn an embedding function \( f : \mathcal{X} \rightarrow \Phi \subset \mathbb{R}^d \) that maps each input \( \mathbf{x} \in \mathcal{X} \) to the \( d \)-dimensional embedding space \( \Phi \) that allows measuring the similarity between inputs. To this end, Let \( f \) be formulated as a differentiable deep network \( f(\cdot, \theta) \) with a trainable parameter \( \theta \). The output \( \mathbf{v}_i = f(\mathbf{x}_i, \theta) \) is typically normalized to \( \mathbf{z}_i = \frac{\mathbf{v}_i}{\|\mathbf{v}_i\|} \). The distance (or similarity) between two inputs \( \mathbf{x}_i, \mathbf{x}_j \) in the learned metric space is defined as \( D_{i,j} := d(\mathbf{z}_i, \mathbf{z}_j) \), where \( d(\cdot, \cdot) \) is the pre-defined distance (or similarity) function. In this paper, we use cosine similarity as the default, i.e., \( D_{i,j} = \mathbf{z}_i \cdot \mathbf{z}_j \).

3.2 Progressive Self-distillation

In this paper, we aim to solve the problem of ignoring the intrinsic relationships, so that a feasible way is to assign a more precise distance target for each pair. However, we usually only have the class labels of the data with the lack of characteristic annotations (e.g., attribute labels), which makes current DML difficult to get actual distance targets only by the annotation of the samples. Inspired by previous works [6, 30], we exploit knowledge distillation strategy to obtain soft distance targets from a teacher model.

To achieve this goal, the first problem we need to solve is how to obtain the teacher model. Previous works usually use a pre-trained model [30, 21] or add auxiliary architecture [34] as the teacher model. However, these methods are inflexible and require a longer training time.

An interesting observation [52] is that a relatively poorly-trained teacher model can still help improve the student model. Inspired by this, we proposed a Progressive Self-distillation (PSD), which dynamically exploits the model trained in the previous epoch as the teacher model. In special, when finishing the training of the model in epoch \((t - 1)\), we copy and freeze this model as the teacher model used in the next epoch, which is defined as \( f^{(T)} \). When we continue to train the student model \( f^{(S)} \) in the epoch \((t)\), we use the \( f^{(T)} \) to provide soft distance targets for knowledge distillation.

Then, the second problem is how to design the knowledge distillation loss function. Similar to previous works [30, 34], PSD matches sample relationships within a mini-batch \( \mathcal{B} \) in base space and target space, which can ensure the generality of the KD functions while fully utilizing the information of samples in the batch. Specifically, we calculate the similarity matrix \( D \in \mathbb{R}^{|\mathcal{B}| \times |\mathcal{B}|} \), where \( D_{i,j} \) indicates the cosine similarity between \( i \)-th and \( j \)-th sample in the mini-batch \( \mathcal{B} \). Then, we use KL divergence as the basic of our PSD loss, which is shown as:

\[
L_{PSD}(\mathcal{B}) = \frac{1}{|\mathcal{B}|} \sum_{i=1}^{|\mathcal{B}|} \sum_{j=1}^{|\mathcal{B}|} \sigma(D_{i,:}/\tau) \ln \frac{\sigma(D_{i,:) / \tau)_i}{\sigma(D_{i,:}/\tau)_j},
\]

where \( \sigma() \) is the softmax operation, \( \tau \) is a temperature parameter, \( D_{i,:} \) indicates the \( i \)-th row of the matrix \( D \), and \( D^{(T)} \) and \( D^{(S)} \) are the similarity matrix of \( f^{(T)} \) and \( f^{(S)} \), respectively.

However, the teacher model cannot learn sufficient knowledge from the training data in early epochs of training but becomes increasingly reliable as the epoch grows. Considering this, we use a dynamic weight updating scheme [19] to change the weight of PSD loss online. The dynamic weight formulation is \( \frac{1}{T} \lambda \), where \( \lambda \) is the final weight for distillation, \( t \) is the current epoch, and \( T \) is the total epoch of training. We find that this dynamic updating scheme can reach a better performance than static weight. Finally, we extend the typical DML with our PSD, whose final objective function is written as:

\[
\mathcal{L} = L_{DML} + \tau^2 \frac{t}{T} \lambda L_{PSD},
\]

where \( L_{DML} \) is an arbitrary metric learning loss function and \( \tau^2 \) is a balanced parameter often applied in
KD loss [13].

### 3.3 Online Batch Diffusion Process

However, there is another key problem in the PSD scheme, i.e., the soft distance targets from the teacher model cannot fully reflect the intrinsic relationships among samples, because of the limitation of the rigid distance metrics [1, 51]. To solve this problem, we proposed Online Batch Diffusion Process (OBDP) for refining the soft distance targets from the teacher model. OBDP can help the embedding space learn more about intrinsic relationships among samples and improve performance.

#### 3.3.1 Preliminaries of Diffusion Process

We first revisit the standard diffusion process in image retrieval (mainly following the steps from [50, 51]). Given a data set \( \mathcal{U} = \{u_1, \ldots, u_q, u_{q+1}, \ldots, u_n\} \), the first \( q \) samples are the queries and the rest are the gallery. We define \( f^0 = [f^0_1, \ldots, f^0_n]^T \), in which \( f^0_i = 1 \) if \( u_i \) is a query and \( f^0_i = 0 \) otherwise. The typical diffusion process has three steps, which can be described as follows:

1. Use a pre-trained model to extract the features \( \mathcal{Z} = \{z_1, \ldots, z_n\} \) from dataset \( \mathcal{U} \) and calculate the affinity matrix \( W \in \mathbb{R}^{n \times n} \), where each component \( W_{ij} = d(z_i, z_j) \). Note that \( W_{ii} = 0 \) because there are no loops in the graph.

2. Symmetrically normalize \( W \) by \( S = V^{-1/2} W V^{-1/2} \in \mathbb{R}^{n \times n} \), in which \( V \in \mathbb{R}^{n \times n} \) is the diagonal matrix with \( V_{ii} = \sum_{j=1}^{n} W_{ij} \). We refer to \( S \) as transition matrix.

3. Use random walk to iterate \( f^{t+1} = \omega S f^t + (1 - \omega) f^0 \) until convergence, where \( \omega \in (0, 1) \) is the transition probability of random walk.

It can be proved that the above iteration converges to a closed-form solution:

\[
f^\infty = (1 - \omega) (I - \omega S)^{-1} f^0 \in \mathbb{R}^n. \tag{3}
\]

where \( f^\infty \) can be used as ranking scores for re-ranking.

#### 3.3.2 Online Diffusion on Batch Manifolds

The standard diffusion process is commonly used as a re-ranking method. Though the Eq 3 requires \( O(N^3) \) time complexity (\( N \) is the number of samples), we only need to compute it once offline. However, if we want to use diffusion process during training, we...
need to update and maintain the Eq 3 online, which is impractical since the size of the training set is large.

To solve this problem, we proposed Online Batch Diffusion Process (OBDP), in which we only use the samples in the mini-batch to construct the neighborhood graph for diffusion process each time. This means that we only diffuse information on batch manifolds. Specifically, for each mini-batch \( \mathcal{B} \), we first use a teacher model to extract the features \( \mathcal{Z}^{(T)} \in \mathbb{R}^{|\mathcal{B}| \times d} \) and then calculate the similarity matrix \( D \in \mathbb{R}^{|\mathcal{B}| \times |\mathcal{B}|} \). Note that since our aim is to refine relationships between samples rather than simply calculate ranking scores, we use \( D \) as the initial state for diffusion in OBDP, which is different from the standard diffusion process. Then we calculate the affinity matrix \( W \in \mathbb{R}^{ | \mathcal{B} | \times | \mathcal{B} | } \) and transition matrix \( S \in \mathbb{R}^{ | \mathcal{B} | \times | \mathcal{B} | } \) based on the extracted \( \mathcal{Z}^{(T)} \). Finally, we use random walk to refine the initial states \( D \):

\[
A = (1 - \omega) (I - \omega S)^{-1} D \in \mathbb{R}^{ | \mathcal{B} | \times | \mathcal{B} | }, \quad \omega \in (0, 1)
\]

where \( A \) is the refined similarity matrix of the mini-batch \( \mathcal{B} \). Since \(|\mathcal{B}|\) is usually much smaller than the size of training set \( N \), OBDP can be efficiently computed online. Moreover, if \(|\mathcal{B}|\) is fixed, Eq 4 only requires \( O(N) \) for each epoch, which is more efficient than the standard diffusion process.

### 3.4 Online Batch Diffusion-based Self-distillation

Now, we can use OBDP to refine the soft distance targets from PSD. Specifically, for each mini-batch \( \mathcal{B} \), we use the teacher model \( f^{(T)} \) to extract the features \( \mathcal{Z}^{(T)} \) and apply OBDP to calculate the refined similarity matrix \( A^{(T)} \):

\[
A^{(T)} = (1 - \omega) (I - \omega S^{(T)})^{-1} D^{(T)},
\]

where the similarity matrix \( D^{(T)} \) and transition matrix \( S^{(T)} \) are both calculated by using \( \mathcal{Z}^{(T)} \). Then, we replace \( D^{(T)} \) in Eq 1 with \( A^{(T)} \). Thus our OBD-SD loss is:

\[
L_{\text{OBD-SD}}(\mathcal{B}) = \frac{1}{|\mathcal{B}|} \sum_{i=1}^{|\mathcal{B}|} \sum_{j=1}^{|\mathcal{B}|} \frac{\sigma(A^{(T)}_{i,j}/\tau) \ln \frac{\sigma(A^{(T)}_{i,j}/\tau)}{\sigma(D^{(S)}_{i,j}/\tau)}}{\sigma(D^{(S)}_{i,j}/\tau)},
\]

Overall, the final objective function can be described as:

\[
\mathcal{L} = L_{\text{DML}} + \tau^2 \frac{4}{T} \lambda L_{\text{OBD-SD}},
\]

### 4 Theoretical Support

In this section, we show why OBD-SD can improve metric learning. We analyze PSD and OBDP, respectively.

#### 4.1 Analysis for PSD

We analyze the gradients of PSD. First, the gradient for \( L_{\text{PSD}} \) (for convenience, \( L_{\text{PSD}} \) here is for an anchor \( x_i \)) w.r.t. the embedded feature \( v_i \) is:

\[
\frac{\partial L_{\text{PSD}}}{\partial v_i} = \sum_j (z_j - (z_i \cdot z_j) z_i) (P_{ij} - S_{ij}),
\]

where \( P_{ij} \) and \( S_{ij} \) are the relationships between \( x_i \) and \( x_j \) predicted by the student and teacher, respectively. We can observe that Eq 8 contains two parts: “attention part” \( (z_j - (z_i \cdot z_j) z_i) \) and “difference part” \( (P_{ij} - S_{ij}) \).

First, we analyze the “attention part”. Take positive samples as an example, for an easy positive sample \( z_i \cdot z_j \approx 1 \), we can achieve:

\[
\|z_p - (z_i \cdot z_p) z_i\| = \sqrt{1 - (z_i \cdot z_p)^2} \approx 0,
\]

And for an hard positive sample \( 0 < z_i \cdot z_p \ll 1 \), we have:

\[
\|z_p - (z_i \cdot z_p) z_i\| = \sqrt{1 - (z_i \cdot z_p)^2} \approx 1,
\]

Obviously, for easy samples, the gradient of \( L_{\text{PSD}} \) along \( v_i \) is close to 0, while for hard samples is equal to \( \|z_p - (z_i \cdot z_p) z_i\| \approx |P_{ip} - S_{ip}| \). This shows that the gradient contribution of easy samples is relatively small while the gradient contribution of hard samples is large. This result implies that PSD encourages the model to pay more attention to hard samples.
samples during training. We argue that there is usually more intrinsic information (such as intra-class variations) in hard samples that conventional methods would suppress.

Second, we analyze the “difference part”. The “difference part” shows that PSD forces the student’s output $P_{ip}$ to become similar to the teacher’s $S_{ip}$, rather than leverage solely class labels to increase inter-class distances and decrease intra-class distances. Hence, the student can learn more information in the process of imitation, especially for hard samples, thus alleviating the problem of ignoring the intrinsic relationships of samples.

4.2 Analysis for OBDP

Inspired by [2, 1], our OBDP can be seen as the following optimization problem:

$$\min_A \frac{1}{2} \sum_{i,j,k=1}^{[8]} W_{j,k} \left( \frac{A_{i,j}}{\sqrt{V_{i,i}V_{j,j}}} - \frac{A_{i,k}}{\sqrt{V_{i,i}V_{k,k}}} \right)^2 + \frac{1 - \omega}{\omega} \sum_{i,j=1}^{[8]} (A_{i,j} - D_{i,j})^2$$

(11)

where $A$ represents the refined similarity and $D$ is the initial similarity matrix. Eq. 11 consists of two terms. From the first term, we can find that OBDP takes into account high-order relationship information between samples. For example, the relationships between $x_i$ and $x_j$ (denoted by $A_{i,j}$) is interrelated to relationship between $x_i$ and all other samples in the batch (denoted by $A_{i,k}$, $k = 1, \ldots, [B]$) with weights $W_{j,k}$. In contrast, $D_{i,j}$ only considers pairwise relationships on rigid distance metrics and ignores the intrinsic relationships between samples. We infer that such high-order information on batch manifolds can help the embedding space better reveal the intrinsic relationships between objects as the high-order information on the global manifolds does [5]. The second term suggests that the initial states should be preserved to a certain extent. It emphasizes that a good distance measurement should not differ too much from the initial states.

5 Experiments

5.1 Experimental Details

Datasets. To evaluate the generalization on unseen classes, we followed the existing experiment setting from [35, 34], which is a zero-shot setting where the training set has no intersection with the test set. We conduct experiments on three benchmark dataset, such as CUB200-2011 [44], CARS196 [23] and Stanford Online Products (SOP) [28]. The CUB200-2011 contains 11,788 images of 200 classes of birds. We use the first/last 100 classes (5,864/5,924 images respectively) as the training/test subsets. The CARS196 contains 16,185 images of 196 car categories. We use the first/last 98 classes (8,054/8,131 images) as the training/test subsets. The SOP contains 120,053 online product images in 22,634 categories. We use the first 11,318 classes of 59,551 images as the training subset and the remaining 11,316 classes of 60,502 images as the test subset.

Evaluation Metrics. Recall@K (R@K) [17] and Normalized Mutual Information (NMI) [25] are used, where R@k measures the image retrieval performance while NMI measures the image clustering performance. Please see the supplementary (Section S.1) for more information.

Implementation Details. We utilize a ImageNet pretrained ResNet50 (R50/d) or Inception BN (IBN/d) with frozen Batch-Normalization layers as the backbone network, where the $d$ is the embedding dimension. If not specifically emphasized, we use R50/128 by default in experiments. We use Adam optimizer with a fixed learning rate of $10^{-5}$ and a weight decay of $4 \times 10^{-4}$. Note that there is no learning rate scheduling for unbiased comparison, if not mentioned. We set the distillation weight $\lambda$/transition probability $\omega$ to 1000/0.3 for CUB200-2011, 75/0.99 for CARS196 and 100/0.5 for Stanford Online Products, and the temperature to 1 by default. Each training was run over 150 epochs for CUB200-2011/CARS196 and 100 epochs for Stanford Online Products. All experiments were performed on a single Nvidia V100 GPU and all results are computed over multiple seeds averages. Additional details are available in the supplementary (Section S.3).
### Table 1: Comparison with strong metric learning baselines. **Bold** denotes the better result between using OBD-SD and not using OBD-SD with the same metric learning loss function.

| Benchmarks  | CUB200-2011 | CARS196 | SOP |
|-------------|-------------|---------|-----|
| Approaches  | R@1 NMI     | R@1 NMI | R@1 NMI |
| Margin ($\beta = 1.2$) [49] | 63.15 68.05 | 61.49(1.47) 68.18(0.68) | 78.20 90.32 |
| Margin ($\beta = 0.6$) + OBD-SD (Ours) | 65.78(2.63) 69.67(1.62) | 81.49(1.47) 68.18(0.68) | 78.81(0.61) 90.51(0.19) |
| R-Margin ($\beta = 0.6$) [35] | 64.54 68.31 | 82.39 68.57 | 77.45 90.36 |
| R-Margin ($\beta = 0.6$) + OBD-SD (Ours) | 66.54(2.00) 69.24(0.93) | 84.49(2.10) 70.24(1.67) | 77.75(0.30) 90.50(0.14) |
| MS [46] | 63.10 68.33 | 81.56 69.38 | 77.75 90.01 |
| MS + OBD-SD (Ours) | 67.76(4.66) 70.81(2.48) | 84.10(2.54) 70.93(1.55) | 78.83(0.18) 90.22(0.21) |

### Table 2: Comparison with state-of-the-art metric learning methods across different Architecture (Arch) and Dimensionality (Dim). **Bold** indicates that use combinational pooling in backbone as done in [20]. **Boldblue** indicates the best results overall.

| Benchmarks  | Venue | Arch/Dim | CUB200-2011 | CARS196 | SOP |
|-------------|-------|----------|-------------|---------|-----|
| Approaches  |       |          | R@1 NMI     | R@1 NMI |
| Div&Cconq [37] | CVPR'19 | R50/128 | 65.9 76.6 69.6 | 84.6 90.7 70.3 |
| MIC [32] | ICCV'19 | R50/128 | 66.1 76.8 69.7 | 82.6 89.1 68.4 |
| PADS [33] | CVPR'20 | R50/128 | 67.3 78.0 69.9 | 83.5 89.7 68.8 |
| RankMI [18] | CVPR'20 | R50/128 | 66.7 77.2 71.3 | 83.3 89.8 69.4 |
| MS+PLG 30 | CVPR'20 | R50/128 | 67.7(1.46) 70.8(2.48) | 84.1(2.54) 70.9(1.55) |
| MS + OBD-SD (Ours) | - | R50/128 | 67.8 78.1 70.8 | 84.9 91.0 72.1 |
| ProxyAnchor (PA) [20] | CVPR'20 | IBN/512+D | 68.4 79.2 - | 86.1 91.6 - |
| ProxyGML [60] | ICCV'20 | IBN/512 | 66.1 77.6 69.8 | 85.5 91.8 72.4 |
| PA+DML, [37] | ICCV'21 | IBN/512 | 68.7 78.6 69.3 | 86.9 92.1 72.3 |
| PA+MemVir [22] | ICCV'21 | IBN/512 | 69.0 79.2 - | 86.7 92.0 - |
| EPSHN [50] | ECCV'20 | R50/512 | 64.9 75.3 - | 82.7 89.3 - |
| DiVA [20] | ECCV'20 | R50/512 | 69.2 79.3 71.4 | 87.6 92.9 72.2 |
| DCML-MDW [56] | CVPR'21 | R50/512 | 68.4 77.9 71.8 | 85.2 91.5 73.9 |
| MS+DAS [24] | CVPR'22 | R50/512+D | 69.2 79.3 - | 87.8 93.1 - |
| MS + OBD-SD (Ours) | - | IBN/512 | 65.8 76.8 68.8 | 85.4 91.4 70.4 |
| - | IBN/512+D | 65.8 76.9 68.7 | 85.8 92.1 71.6 |
| - | R50/128 | 69.1 79.5 71.1 | 86.5 92.3 72.0 |
| - | R50/128+D | 69.4 79.7 71.4 | 88.7 93.6 74.5 |

### 5.2 Effectiveness of OBD-SD

To validate the effectiveness, we use R50/128 as the backbone. We select three methods that can achieve top-3 performance evaluated in [35], i.e., Similarity (MS) loss [46], Margin loss with Distance-based Sampling [49] and Regularized Margin loss [35], and follow their experimental training pipeline. Note that the setup utilizes no learning rate scheduling and fixes common implementational factors of variation (such as batch-size) in DML pipelines to ensure comparability. The results are presented in Table 1, which shows that our OBD-SD improves the original DML approaches on all benchmarks.

To further highlight the benefits, we compare our OBD-SD with other state-of-the-art methods and report results in Table 2. The compared methods can be divided into different groups (i.e., R50/128, R50/512 and IBN/512), according to their backbone and embedding dimensions. Note that we apply learning rate scheduling and extend the number of the training epoch appropriately. The results in Table 1 show that OBD-SD can achieve competitive performance across different architectures and benchmarks.

### 5.3 Ablation Studies

**Ablation study of each element.** We perform ablation studies to evaluate the effectiveness of each
Table 3: Ablation study using different elements of OBD-SD.

| Datasets | CUB200-2011 | CARS196 |
|----------|-------------|---------|
| Methods  | R@1 NMI    | R@1 NMI |
| MS [46]  | 63.1 68.3  | 81.6 69.4 |
| + PSD w/o dynamic weight | 62.9 68.6  | 81.9 69.4 |
| + PSD    | 63.5 69.1  | 82.3 70.0 |
| + OBD-SD (PSD+OBDP) | 67.8 70.8  | 84.1 70.9 |

Table 4: Ablation studies on different sampling strategies. The suffixes '(R)', '(H)', '(S)' and '(D)' denote the random, semi-hard, soft-hard and distance-based sampling strategy, respectively.

| Datasets | CUB200-2011 | CARS196 |
|----------|-------------|---------|
| Methods  | R@1 NMI    | R@1 NMI |
| Margin (R) | 55.5 61.7  | 66.1 59.5 |
| + OBD-SD | 62.3 67.1  | 73.3 63.1 |
| Margin (H) [38] | 61.2 66.5  | 76.1 64.4 |
| + OBD-SD | 63.6 67.8  | 78.3 65.6 |
| Margin (S) [32] | 61.3 66.5  | 77.7 66.1 |
| + OBD-SD | 63.3 68.1  | 78.6 66.4 |
| Margin (D) [49] | 63.2 68.1  | 80.0 67.5 |
| + OBD-SD | 65.8 69.7  | 81.5 68.2 |

Table 5: Comparison with other self-distillation methods of DML.

| Datasets | CUB200-2011 | CARS196 |
|----------|-------------|---------|
| Methods  | R@1 NMI GPU-Time | R@1 NMI GPU-Time |
| MS [46]  | 63.1 68.3 - | 81.6 69.4 - |
| MS+BAR [30] | 64.1 68.4 +105.3% | 82.6 69.6 +101.9% |
| MS+PSD (Ours) | 63.5 69.1 +5.3% | 82.3 70.0 +1.9% |
| MS+S2SD-MSD [34] | 65.2 70.6 +50.4% | 84.0 71.3 +35.4% |
| MS+OBD-SD (Ours) | 67.8 70.8 +17.4% | 84.1 70.9 +7.4% |

5.4 Comparison with Self-KD of DML.

Then, we compare OBD-SD with recently proposed Self-KD-based DML methods, such as BAR [30] and S2SD [34]. We use MS loss as the basic DML loss for all experiments in this part. For BAR, we select the best distillation weights by ablation experiments (100/50 for CUB200/CARS196) since the paper doesn’t show the experiments on the datasets we used, and for S2SD, we follow the setting of its paper. The results are shown in Table 5. Compared with BAR, our proposed Self-KD method, PSD, can achieve competitive results with only 5.3% and 1.9% extra training time on CUB200 and CARS196 datasets, while BAR requires almost double training time. We also compare OBD-SD with S2SD, a SOTA Self-KD method for DML. The results in Table 5 show that our OBD-SD requires much less extra training time, 17.4% and 7.4% on the two datasets, and achieves competitive performance.

Since our OBDP is a plug-and-play technique, we combine OBDP with recent Self-KD-based DML, i.e., BAR and S2SD, to study the benefits of OBDP. Specifically, similar to our OBD-SD, we use OBDP to refine the soft labels generated by teachers (in BAR and S2SD), then use the refined soft labels for knowledge distillation. The results are reported in Table 6, which shows that OBDP can also improve the performance of other Self-KD methods.

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2Require pretrained natural language models.

3We carefully reproduce the experiments by using the official code.
Table 6: Experimental results of applying OBDP to other self-distillation of methods of DML.

| Methods          | CUB200-2011 | CARS196 |
|------------------|-------------|---------|
| R@1 NMI          | R@1 NMI     |         |
| MS+BAR [30]      | 64.1        | 68.4    |
| MS+BAR+OBDP      | 66.7        | 70.2    |
| MS+S2SD-MSD [34] | 65.2        | 70.6    |
| MS+S2SD-MSD+OBDP | 65.8        | 70.9    |

5.5 Batch Manifolds versus Global Manifolds

In this section, we conduct experiments comparing the diffusion in batch manifolds and in global manifolds. We use batch diffusion and global diffusion (Section 3.3.1) for refining the soft distance targets, respectively. As mentioned in Section 3.3, Eq. 3 requires $O(N^3)$ time complexity, so it’s impossible for us to update it for each mini-batch (online diffusion). Instead, in our experiments, we update the matrix once after each training epoch (offline diffusion). Specifically, after the training of each epoch, we use the new teacher to extract features of the training set and calculate the refined similarity matrix for all data. When we train the student in the next epoch, for each batch, we select the related elements from the refined similarity matrix for knowledge distillation. Note that this strategy leads to ignoring some variation factors, such as those caused by data augmentations. In addition, to reduce the space complexity and the noise from negative pairs, we construct the affinity matrix $W$ as follows:

$$ W_{i,j} = \begin{cases} 
  d(z_i, z_j) & i \neq j, z_i \in \text{NN}_k(x_j), z_j \in \text{NN}_k(x_i) \\
  0 & \text{otherwise} 
\end{cases} $$

where $\text{NN}_k(z)$ denotes the top-k nearest samples of $z$. This way can also improve the speed of diffusion. In our experiments, we set $k = 50$ and use MS loss, the size of the training set for CUB200 and CARS196 datasets are 5,864 and 8,054 respectively, and the size of the mini-batch is 112. The results are reported in Table 7. From the results, we can find that diffusion in batch manifold can achieve almost the same result as diffusion in global manifold and with much less extra time.

Table 7: The results of “Batch Manifolds vs Global Manifolds”.

| Methods         | CUB200-2011 | CARS196 |
|-----------------|-------------|---------|
| R@1 NMI GPU-Time| R@1 NMI GPU-Time |
| In global manifold | 67.3 70.6 +248.8% | 84.4 71.9 +345.0% |
| In batch manifold (Ours) | 67.8 70.8 +17.4% | 84.1 70.9 +7.4% |

5.6 Embedding Space Metrics

We investigate the effect of OBD-SD on embedding space. We observe the differences between the embedding space learned with and without OBD-SD by using different structural measurements.

1. **Embedding Space Density** [35]: $\pi_{\text{ratio}}(\Phi) = \pi_{\text{intra}}(\Phi)/\pi_{\text{inter}}(\Phi)$, which measures the ratio of mean inter-class distances $\pi_{\text{inter}}(\Phi)$ and mean intra-class distances $\pi_{\text{intra}}(\Phi)$. Note that the higher value of embedding space density indicates lower class concentration and is linked to stronger generalization.

2. **Spectral Decay** [35]: $\rho(\Phi) = \text{KL}(U\|S(\Phi))$, where $\rho(\Phi)$ calculates the KL-divergence between uniform distribution $U$ and singular value decomposition $S(\Phi)$ of embedding space $\Phi$. The spectral decay measures the number of directions of significant variance in the learned embedding space. Note that the lower value of spectral decay indicates high feature variety and is linked to stronger generalization. In our experiments, we exclude the two largest spectral values for a more robust estimate. Please see the supplementary (Section S.2) for more information.

The experimental results are reported in Table 8. The results show that both PSD and OBDP improve the embedding space density and reduce the spectral decay, linked to more robust generalization as described above. In other words, OBD-SD can reduce the over-clustering in the embedding space and increase embedding representation diversity, which means OBD-SD can encourage the model to find more intrinsic relation information. The result is consistent with our initial motivation for OBD-SD.
Table 8: Results of embedding space density $\pi_{\text{ratio}}(\Phi)$ and spectral decay $\rho(\Phi)$.

| Datasets     | CUB200-2011 | CAR5196 |
|--------------|-------------|---------|
| Methods      | $\pi_{\text{ratio}}(\Phi)$ | $\rho(\Phi)$ | $\pi_{\text{ratio}}(\Phi)$ | $\rho(\Phi)$ |
| MS           | 0.4427      | 0.1544  | 0.3962      | 0.1622      |
| MS+PSD       | 0.4504↑     | 0.1444↓ | 0.4256↑     | 0.1496↓     |
| MS+OBD-SD    | 0.6291↑     | 0.0292↓ | 0.7083↑     | 0.0264↓     |

5.7 Robustness to Mislabeled Data

Since our approach alleviates the constraints imposed by sample annotation, a natural question is raised: *Does it also improve the robustness to mislabeled data?*

To answer this question, we generate mislabeled data on the three datasets (CUB200, CARS196 and Stanford Online Products) with $\{0.1, 0.2, 0.3, 0.4\}$ symmetric mislabeled ratios, following [11] and [43]. We then use MS loss as the baseline and train models on the mislabeled data with and without OBD-SD. The results in Table 9 indicate that OBD-SD consistently achieves performance promotions on mislabeled training data. Moreover, we calculate the percentage of improvement relative to the baseline for each metric as follows:

$$P_{\text{metric}} = (V_{SD} - V_{base}) / V_{base},$$

where $V_{SD}$ and $V_{base}$ are the value of the metric for OBD-SD and the baseline, respectively. We can find that the performance promotions become more pronounced as the mislabeled ratio increases. This result shows that OBD-SD can improve the robustness to mislabeled data.

Table 9: Results on the three datasets validation with different noisy ratios on the training sets.

| Noisy ratio | Benchmarks | Approaches | CUB200 | CAR5196 |
|------------|------------|------------|--------|---------|
|            | R@1 NMI    | R@1 NMI    |        |         |
| 0.1        | MS         | 59.69      | 66.70  | 76.81   |
|            | MS+OBD-SD  | 66.11 (+10.75%) | 69.93 (+4.44%) | 80.47 (+4.77%) | 67.85 (+4.97%) |
| 0.2        | MS         | 55.83      | 63.92  | 71.33   |
|            | MS+OBD-SD  | 64.23 (+15.05%) | 68.84 (+7.70%) | 76.57 (+7.35%) | 65.09 (+6.85%) |
| 0.3        | MS         | 52.93      | 61.96  | 66.53   |
|            | MS+OBD-SD  | 61.83 (+18.84%) | 67.00 (+9.73%) | 71.16 (+6.96%) | 59.98 (+6.65%) |
| 0.4        | MS         | 48.25      | 57.75  | 60.97   |
|            | MS+OBD-SD  | 58.11 (+20.44%) | 65.05 (+13.97%) | 65.58 (+7.56%) | 54.43 (+6.39%) |

6 Conclusion

In this paper, we propose Online Batch Diffusion-based Self-distillation (OBD-SD) to alleviate the "ignore intrinsic relation" issue of DML methods. To this end, we propose Progressive Self-distillation (PSD) to encourage the model to learn more relational information among samples. Then, we further propose Online Batch Diffusion Process (OBDP) to help PSD reveal the intrinsic relationships among samples on batch manifolds. Extensive experiments with various loss functions on three benchmarks show that OBD-SD is effective and efficient. However, our proposed method can't consistently improve the performance of proxy-based DML, which is a strong method of DML. In the feature, we plan to explore the diffusion process on the proxies-manifold for optimizing the embedding space for proxy-based DML. In addition, we also plan to apply OBD-SD to other areas such as self-supervised learning.

7 Supplemental Material

You can download the Supplemental Material from https://github.com/ZelongZeng/OBD-SD_Pytorch.

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