CIMON: Towards High-quality Hash Codes

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Abstract

Recently, hashing is widely used in approximate nearest neighbor search for its storage and computational efficiency. Most of the unsupervised hashing methods learn to map images into semantic similarity-preserving hash codes by constructing local semantic similarity structure from the pre-trained model as the guiding information, i.e., treating each point pair similar if their distance is small in feature space. However, due to the inefficient representation ability of the pre-trained model, many false positives and negatives in local semantic similarity will be introduced and lead to error propagation during the hash code learning. Moreover, few of the methods consider the robustness of models, which will cause instability of hash codes to disturbance. In this paper, we propose a new method named Comprehensive \textit{Sim}ilarity \textit{Min}ing and \textit{cOn}sistency \textit{learN}ing (CIMON). First, we use global refinement and similarity statistical distribution to obtain reliable and smooth guidance. Second, both semantic and contrastive consistency learning are introduced to derive both disturb-invariant and discriminative hash codes. Extensive experiments on several benchmark datasets show that the proposed method outperforms a wide range of state-of-the-art methods in both retrieval performance and robustness.

1 Introduction

Hashing-based Approximate Nearest Neighbour search has attracted ever-increasing attention in the era of big data due to their high retrieval efficiency and low storage cost. The main idea of hashing methods is to project high dimensional datapoints into compact binary codes while preserving the semantic similarity of original datapoints.

Hashing methods include supervised hashing [Luo et al., 2020; Fan et al., 2020; Wang et al., 2020; Xie et al., 2020] and unsupervised hashing. However, it is difficult to apply supervised hashing methods in practice since large-scale data annotations are unaffordable. To address this problem, several deep unsupervised methods were proposed and provided a cost-effective solution to practical applications [Lin et al., 2016; Yang et al., 2018; Tu et al., 2020]. Recently, most unsupervised hashing methods employ a two-step framework: Firstly, the local semantic similarity structure is reconstructed from the pre-trained neural network. To be specific, the local semantic similarity relationships are often derived from the Euclidean distance or the cosine similarity of deep features extracted from the pre-trained model. Secondly, a hashing network is optimized to generate compact and similarity-preserving hash codes by incorporating the defined similarity structure as the guiding information.

However, the existing methods have two significant drawbacks that will harm the quality of hash codes. First, many false positives and negatives will be introduced in the similarity matrix for the insufficient representation ability of the pre-trained model, which will misguide the hashing model during hash code learning and further reduce the retrieval performance. As shown in Figure 1(a), false similar pairs can occur between the boundary points of two manifolds (blue points). Moreover, most methods treat the confident signals and uncertain signals equally (green and red points), which will also accumulate a lot of errors. Second, few of them consider the stability of models, which will cause hash codes
to be unstable under disturbances and greatly influence the
quality. For example, images of different classes with similar
background could be mapped to the same hash code (called
hash collisions) while the transformed image could be quite
far away from the original image in the hash code space (Fig-
ure 1(b)).

To address the above two issues, we propose a new method
named CIMON, which comprehensively explores semantic
similarity structure to achieve reliable semantic guidance and
considers the stability of hash codes by introducing consis-
tency learning. Specifically, CIMON firstly takes advantage
of the global information to remove false positives between
boundary points and smooths the unconfident signals by con-
fidence adjustment. Secondly, CIMON generates two groups
of deep features by data augmentation and constructs two
similarity matrices and both parallel semantic consistency
and cross semantic consistency are encouraged to generate
robust hash codes. Furthermore, contrastive consistency be-
tween hash codes is adopted to improve the quality of hash
codes. Through these improvements, CIMON could obtain
high-quality hash codes in both retrieval performance and
robustness, which is also demonstrated by extensive expe-
riments on several challenging benchmark datasets. Our main
contributions can be summarized as following:

• CIMON not only utilizes global refinement to refine the
initial local semantic similarity structure, but also ex-
plores the similarity statistical distribution to adjust the
weight for each image pair, which generates a reliable
and smooth guide for hash code learning.

• A novel consistency loss including semantic consistency
and contrastive consistency is proposed to optimize the
hashing network, which helps to generate robust and dis-
ctriminative hash codes.

• Experiments on several public datasets demonstrate that
CIMON outperforms existing state-of-the-art unsuper-
vised hashing techniques by a large margin.

2 Related Work

Deep Unsupervised Hashing. Most of the unsupervised
depth hashing methods extract deep features to construct a
semantic structure, by which unsupervised problems can be
turned into supervised problems. In a quite different way,
DeepBit [Lin et al., 2016] regards the original images and the
corresponding rotated images as similar pairs and attempts
to preserve the similarities when learning related hash codes.
Stochastic generative hashing [Dai et al., 2017] tries to learn
hash functions by using a generative model based on the min-
imum description length principle. SSDH [Yang et al., 2018]
makes use of a specific truncated function on the pairwise
distances and constructs the similarity structures. The hash-
ing model is then trained by supervised hashing techniques.
Afterwards, the performance of SSDH is improved by Distill-
Hash, which distills the image pairs with confident similarity
signals. Clustering-driven Unsupervised Deep Hashing [Gu
et al., 2019] recursively learns discriminative clusters by soft
clustering model and produces binary code with high simi-
arity responds. MLS’RDUH [Tu et al., 2020] reconstructs
the local semantic similarity structure by taking advantage of
the manifold structure in feature space, achieving the state-
of-the-art performance.

Contrastive Learning. [Hadsell et al., 2006] is the first
work to learn representations by contrasting positive pairs
against negative pairs. To solve the storage of large scale
dataset, [Wu et al., 2018] proposes to utilize a memory bank
for class representation vectors. Various pretext work is based
on several forms of contrastive loss function, which is re-
lated to the exemplar-based task and noise-contrastive esti-
mation [Dosovitskiy et al., 2014]. Recently, Momentum Con-
trast [He et al., 2020] proposes to build a dynamic dictionary
with a queue and a moving-averaged encoder, which enables
building a large and consistent dictionary on-the-fly that fa-
cilitates contrastive unsupervised learning. SimCLR [Chen
et al., 2020] further simplifies the learning algorithms with-
out requiring specialized architectures or a memory bank and
achieves better performance on ImageNet.

3 The Proposed Model

In this section, we first formally define the problem and fea-
ture our model with two parts as shown in Figure 2: (1)
Semantic information generating. A pre-trained VGG-
F [Simonyan and Zisserman, 2015] without the last fully-
connected layer $F(\cdot)$ is adopted to extract deep features,
which will be used to generate the similarity graph and the
confidence-based weight matrix. (2) Consistency learning.
The hashing network $G(\cdot)$ is modified from VGG-F by re-
placing the last fully-connected layer with a fully-connected
layer with $L$ hidden units to incorporate the hash code learn-
ing process. A novel consistency learning framework is
adopted to learn high-quality hash codes.

3.1 Problem Formulation

In the unsupervised hashing settings, $\mathcal{X} = \{x_i\}_{i=1}^N$ is the
training set with $N$ samples without label information. We
aim to learn a hash function $H : x \rightarrow b \in \{-1,1\}^L$, in
which $x$ is the input image and $b$ is a compact $L$-bit hash
code. This map should preserve similarity, i.e., images with
similar ground truth labels should correspond to hash codes
with small Hamming distances.

3.2 Semantic Information Generating

In our model, semantic information is composed of the simi-
arity pseudo-graph and the similarity confidence matrix.

From the local perspective, the pseudo-graph aims to
capture pairwise similarity information. Given the pre-
trained deep features $\{F(x_i)\}_{i=1}^N$, the cosine distance be-
tween the $i$-th and the $j$-th images is obtained by
$$d_{ij} = 1 - \frac{F(x_i) \cdot F(x_j)}{|F(x_i)||F(x_j)|}$$
Since most pairs should be negative in ground-truth, we set a relatively small threshold $t = 0.1$
following [Wu et al., 2019], and consider pairs with the cosi-
ne distance smaller than $t$ as potential positives ($S_{ij} = 1$) and
pairs with the cosine distance larger than $t$ as potential nega-
tives ($S_{ij} = -1$). Mathematically, the pseudo-graph $S$
can be constructed as:

$$S_{ij} = \begin{cases} 1 & d_{ij} \leq t, \\ -1 & d_{ij} > t \end{cases} \quad (1)$$
Global Refinement  As mentioned in Figure 1, the features of images with the same semantic information should lay on a high-dimensional manifold following [Yang et al., 2019; Tu et al., 2020] and many false positives and negatives will be introduced in local semantic similarity $S$ [Luo et al., 2021]. Hence, we propose to use the global clustering results to refine the semantic similarity by removing contradictory results. Since spectral clustering has been proven to be suitable for clustering high-dimensional manifold data, we take advantage of it to perform global refinement. Specifically, assume $c_i \in \{1, \ldots, K\}, i = 1, \ldots, N$ is the $i$-th cluster label of spectral clustering ($K$ is the number of clusters). Then each pair of two points with the same class is considered as global potential similar and vice versa. If an image pair has a different potential similarity signal with pseudo-graph $S$, its similarity is considered as unreliable. After removing the unreliable signals, the final refined pseudo-graph is $\hat{S}$ is formulated as:

$$\hat{S}_{ij} = \begin{cases} 
1 & c_i = c_j \& S_{ij} = 1 \\
-1 & c_i \neq c_j \& S_{ij} = -1 \\
0 & \text{otherwise}
\end{cases} \tag{2}$$

Confidence Adjustment  Note that the semantic confidence of similarity signal for each pair is different, we further construct the confidence matrix for pseudo-graph $S$ based on the semantic confidence. Inspired by recent works [Yang et al., 2018], we observe that the distribution of cosine distances for deep feature pairs can be estimated by two half Gaussian distributions, denoted as $N(m_1, \sigma^2_1)$ and $N(m_2, \sigma^2_2)$ respectively, in which $m_1, m_2$ and $\sigma^2_1$ and $\sigma^2_2$ are the corresponding means and variances. Intuitively, we hypothesize that image pairs with distances obviously smaller than others are semantically ‘similar’ and those with obviously larger distances are semantically ‘dissimilar’, which are denoted as highly confident pairs. Moreover, the confidence weights are approximated by Cumulative Distribution Function (CDF) of two half Gaussian distributions. Specifically, for potential similar signals, distances have a more confident similarity signal if $d_{ij}$ is closer to 0, and for potential dissimilar signals, distances have a more confident similarity signal if $d_{ij}$ is closer to 2. Therefore, confidence-based weight matrix is computed as following:

$$W_{ij} = \begin{cases} 
\Phi_1(t) - \Phi_1(d_{ij}) & d_{ij} \leq t \& \hat{S}_{ij} \neq 0, \\
\Phi_2(d_{ij}) - \Phi_2(0) & t < d_{ij} \& \hat{S}_{ij} \neq 0, \\
0 & \hat{S}_{ij} = 0
\end{cases} \tag{3}$$

in which $\Phi_k(x) = \Phi\left(\frac{x-m_k}{\sigma_k}\right)$ and $\Phi(\cdot)$ is the CDF of standard normal distribution. Under this setting, all $W_{ij} \in [0, 1]$ and the confidence weights on both ends are relatively larger.

3.3 Consistency Learning

In order to preserve the similarity structure of input images, similar (dissimilar) images are expected to be mapped into similar (dissimilar) hash codes. Different from previous models, here we adopt two groups of semantic information under two different kinds of data augmentation.

Semantic Consistency  For each image $x_i$, there are two transformed samples $x_i^{(1)}$ and $x_i^{(2)}$. At the semantic information generating stage, two refined similarity graphs with confidence matrices $\{W^{(1)}, \hat{S}^{(1)}\}$, $\{W^{(2)}, \hat{S}^{(2)}\}$ are generated with extracted features $\{F(x_i^{(1)})\}_{i=1}^N$ and $\{F(x_i^{(2)})\}_{i=1}^N$, as the guiding information. Simultaneously, images $x_i^{(1)}$ and $x_i^{(2)}$ are the inputs of the hashing network $G(\cdot)$, and hash codes $b_i^{(1)}$ and $b_i^{(2)}$ are obtained through activation function $sign(\cdot)$. Therefore, we derive two similarity outputs $H^{(1)}$ and $H^{(2)}$ from hash codes, which is formulated as

$$H^{(m)}_{ij} = \frac{1}{L} b_i^{(m) \top} b_j^{(m)}, \quad b_i^{(m)} = sign(G(x_i^{(m)}; \Theta)) \tag{4}$$

in which $m = 1$ or 2, and $\Theta$ represents the set of parameters of hashing network. For the purpose of preserving the semantic structures, we first minimize weighted $L_2$ loss between...
the hash code similarity and the corresponding pseudo-graph from the same group. The parallel semantic consistency loss can be formulated as:

\[
\mathcal{L}_{PSC} = \frac{1}{N^2} \sum_{i=1}^{N} \sum_{j=1}^{N} W_{ij} (H_{ij} - \hat{S}_{ij})^2 + W_{ij}^2 (H_{ij} - \hat{S}_{ij})^2
\]

(5)

Inspired by the cross-attention mechanism [Boussaha et al., 2019], we also match the hash code similarity with the pseudo-graph from the different groups. To be specific, the cross semantic consistency loss can be written as:

\[
\mathcal{L}_{CSC} = \frac{1}{N^2} \sum_{i=1}^{N} \sum_{j=1}^{N} W_{ij} (H_{ij} - \hat{S}_{ij})^2 + W_{ij}^2 (H_{ij} - \hat{S}_{ij})^2
\]

(6)

**Contrastive Consistency** Self-supervised learning has been proved to generate high-quality representations for downstream tasks [He et al., 2020]. From this point, we randomly sample a minibatch of \(M\) images, producing \(2M\) random transformed images \(\{x_i^{(1)}, x_i^{(2)}\}_{i=1}^{M}\). Given a positive pair \(x_i^{(1)}\) and \(x_i^{(2)}\), we treat the other \(2(M - 1)\) augmented images within a minibatch as negative examples. Denote \(b_i \ast b_j\) as cosine similarity of \(b_i\) and \(b_j\), the contrastive consistency loss is defined as

\[
\ell_{CC} = -\frac{1}{2M} \sum_{i=1}^{M} \left( \log \frac{e^{b_i^{(1)} \cdot b_i^{(2)}}}{1 + e^{b_i^{(1)} \cdot b_i^{(2)}}} + \log \frac{e^{b_i^{(1)} \cdot b_i^{(2)}}}{1 + e^{b_i^{(1)} \cdot b_i^{(2)}}} \right)
\]

(7)

where \(Z_i^{(1)} = \sum_{j \neq i} \left( e^{b_i^{(m)} \cdot b_j^{(1)}} + e^{b_i^{(m)} \cdot b_j^{(2)}} \right), m = 1 \) or 2, and \(\tau\) denotes a temperature parameter set to 0.5 following [Chen et al., 2020]. Note that the numerator of each term punishes the distance between hash codes of samples under different transformation while the denominator encourages to enlarge the distance between hash codes of different samples, which encourages the hash codes to be uniformly distributed in the hash code space from [Wang and Isola, 2020]. This point helps to maximize the capacity of each hash bit [Shen et al., 2018], preserving as much information of the data as possible.

Finally, the loss of consistency learning is formulated as

\[
\mathcal{L} = \mathcal{L}_{PSC} + \mathcal{L}_{CSC} + \eta \mathcal{L}_{CC}
\]

(8)

in which \(\eta\) is a balance coefficient to balance different consistency loss. However, the \(\text{sign}(\cdot)\) is in-differentiable at zero and the derivation of it will be zero for every non-zero input, with the result that the parameters of the hashing model will not be updated by the back-propagation algorithm when minimizing the Equation 8. Thus, we use \(\text{tanh}(\cdot)\) to approximate the sign function and generate the approximate hash code \(\hat{v}_i^{(m)} = \text{tanh}(G(x_i^{(m)}))\) to replace \(b_i^{(m)}\) in loss function. Our loss function is optimized by the mini-batch standard stochastic gradient descent (SGD) method. The whole learning procedure are shown in Algorithm 1.

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**Algorithm 1** CIMON’s Training Algorithm

**Require:** Training images \(\mathcal{X} = \{x_i\}_{i=1}^N\); Code length \(L\);

**Ensure:** Parameters \(\Theta\) for the neural network \(G(\cdot)\);

Hash codes \(B = \{b_i\}_{i=1}^N\) for training images.

1. Generate two transformed images via data augmentation for each image: \(\mathcal{X}^{(1)}\) and \(\mathcal{X}^{(2)}\);
2. for \(m = 1, 2\) do
3. Get pre-train features of \(\mathcal{X}^{(m)}\) through \(F(\cdot)\);
4. Construct the pseudo-graph \(S^{(m)}\) by Equation 1;
5. Perform global refinement to obtain refined pseudo-graph \(S^{(m)}\) by Equation 2;
6. Construct the confidence matrix \(W^{(m)}\) by Equation 3;
7. end for
8. repeat
9. Sample \(M\) images from \(\mathcal{X}\) and obtain their augmentation to construct a mini-batch;
10. Calculate loss function by Equation 8;
11. Update parameters of \(G(\cdot)\) through back propagation;
12. until convergence
13. Generate image hash codes \(B\)

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**4 Experiments**

We conduct extensive experiments on three popular benchmark datasets to evaluate our CIMON by comparisons with various unsupervised hashing methods.

**4.1 Datasets and Setup**

FLICKR25K [Huiskes and Lew, 2008] contains 25,000 images labeled by some of the 24 categories. We randomly sample 2,000 images as the query set and use the other images as the retrieval set. 10000 images are randomly selected from the retrieval set as the training set. CIFAR-10 [Krizhevsky et al., 2009] contains 60000 images of ten different categories. We randomly sample 1,000 images as the query set for each class, and take the rest as the retrieval set. We sample 500 images per class in the retrieval set as the training set. NUSWIDE [Chua et al., 2009] contains 269,648 images of 81 concepts. Here, we use the subset that contains the 10 most popular concepts. We randomly select 5,000 images as the query set and the remaining images make up the retrieval set. 5000 images randomly sampled from the retrieval set serve as the training set.

Our CIMON is compared with various state-of-the-art unsupervised hashing methods including both traditional methods and deep learning methods. Traditional methods include ITQ [Gong et al., 2012], DSH [Jin et al., 2013], SpH [Heo et al., 2012] and SGH [Dai et al., 2017]. Deep unsupervised hashing methods include DeepBits [Lin et al., 2016], SSDH [Yang et al., 2018], DistillHash [Yang et al., 2019], CUDH [Gu et al., 2019], and MLSRUDH [Tu et al., 2020]. For deep learning-based methods, we use raw pixels as inputs. For traditional methods, we extract 4096-dimensional feature vectors by the VGG-F model which is pre-trained on ImageNet for fair comparison.

As for evaluation, the ground-truth similarity information is obtained according to the ground-truth image labels. Specifically, two data points are considered similar if they
Methods | FLICKR25K | CIFAR-10 | NUS-WIDE
--- | --- | --- | ---
| | 16bits | 32bits | 64bits | 128bits | 16bits | 32bits | 64bits | 128bits | 16bits | 32bits | 64bits | 128bits |
| ITQ | 0.6492 | 0.6518 | 0.6546 | 0.6577 | 0.1942 | 0.2086 | 0.2151 | 0.2188 | 0.5270 | 0.5241 | 0.5334 | 0.5398 |
| DSH | 0.6452 | 0.6547 | 0.6551 | 0.6557 | 0.1616 | 0.1876 | 0.1918 | 0.2055 | 0.5123 | 0.5118 | 0.5110 | 0.5267 |
| SpH | 0.6119 | 0.6315 | 0.6381 | 0.6451 | 0.1439 | 0.1665 | 0.1783 | 0.1840 | 0.4458 | 0.4537 | 0.4926 | 0.5000 |
| SGH | 0.6362 | 0.6283 | 0.6253 | 0.6206 | 0.1795 | 0.1827 | 0.1889 | 0.1904 | 0.4994 | 0.4869 | 0.4851 | 0.4945 |
| DeepBit | 0.5934 | 0.5933 | 0.6199 | 0.6349 | 0.2204 | 0.2410 | 0.2521 | 0.2530 | 0.3844 | 0.4341 | 0.4461 | 0.4917 |
| SSDH | 0.7240 | 0.7276 | 0.7377 | 0.7343 | 0.2568 | 0.2560 | 0.2587 | 0.2601 | 0.6374 | 0.6768 | 0.6829 | 0.6831 |
| DistillHash | 0.7332 | 0.7426 | 0.7549 | 0.7561 | 0.2856 | 0.2903 | 0.3025 | 0.3000 | 0.6996 | 0.7222 | 0.7451 | 0.7418 |
| CUDH | 0.7587 | 0.7754 | 0.7870 | 0.7927 | 0.2876 | 0.2962 | 0.3139 | 0.3117 | 0.7056 | 0.7384 | 0.7629 | 0.7818 |
| MLS3 RDUH | 0.8049 | 0.8195 | 0.8281 | 0.8321 | 0.4506 | 0.4723 | 0.4944 | 0.4981 | 0.7883 | 0.8060 | 0.8214 | 0.8243 |

Table 1: MAP for different methods on FLICKR25K, CIFAR-10 and NUS-WIDE.

In our implementation, we optimize our model by minibatch SGD with momentum. The minibatch size is set to 24. The learning rate is fixed at 0.001. For all three datasets, training images are resized to 224 × 224 as inputs. Data augmentation we adopt includes random cropping and resizing, rotation, cutout, color distortion and Gaussian blur. As two introduced hyper-parameters, $\eta$ and the number of clusters $K$ in spectral clustering are set to 0.3 and 70 as default.

4.2 Experimental Results

The MAPs of different methods on datasets FLICKER25K, CIFAR-10 and NUSWIDE with hash code lengths varying from 16 to 128 are shown in Table 1. The following observations can be derived: 1) Deep learning-based algorithms overall perform better than the traditional methods, which shows that the strong representation-learning ability of deep learning helps to improve the performance of unsupervised hashing methods. 2) The methods that reconstruct semantic similarity structure with global information (CUDH, MLS3 RDUH) perform better than other deep unsupervised hashing methods, which indicates that semantic similarity reconstructed only by local information (i.e. pairwise distance of features) is inaccurate and unreliable. 3) We can find that CIMON has a significant improvement over the previous state-of-art MLS3 RDUH in all cases by a large margin. Specifically, the improvements of our model over the best baseline are 5.51%, 58.4% and 8.39% for average MAP on datasets FLICKER25K, CIFAR-10 and NUS-WIDE respectively, which shows the superiority of our model. We plot the precision-recall curves of SSDH, CUDH, MLS3 RDUH and CIMON on three datasets in the first column of Figure 3. We find that the curve of CIMON is always on top of the other three models’ curves, which demonstrates that the hash codes obtained by CIMON are also more appropriate for hash table lookup search strategy. The second column of Figure 3 shows that the Top-N precision curves of these four models on the same datasets. Our CIMON significantly outperforms the comparison methods by large margins. Since the precision curves are based on the ranks of Hamming distance, CIMON achieves superior performance under Hamming ranking-based evaluations.

To demonstrate the robustness of CIMON, we add perturbation or transformation noise to the query set, which doesn’t
break the semantic information. Figure 4(a) shows the distribution of changed bits number before and after adding noise in query images for MLS^3RUDH and our model. It is observed that the mean of changed bits number of CIMON is significantly smaller than that of MLS^3RUDH, which implies that CIMON can learn more disturb-invariant hash codes. The MAP of CIMON also decreases less after the noise attack compared with the baseline in Figure 4(b). Moreover, CIMON is able to generate informative hash bits because hash bits distribution of CIMON approximates a uniform distribution, making good use of full bit capacity in Figure 4(c).

Table 2: Ablation analysis on CIFAR-10. GR, CW, SC and CC correspond to Global Refinement, Confidence-based Weight, Semantic Consistency and Contrastive Consistency, respectively.

Ablation Study We investigate the effectiveness of various correlations in Table 2. M_1 uses the local similarity structure as guiding information, and trains the hashing network with the degraded loss following Yang et al., 2018. The difference between M_2 and M_1 lies in whether to use the global refinement or not. It can be seen that M_2 surpasses M_1 significantly, demonstrating the effectiveness of global refinement for reconstructing the accurate similarity graph. After considering the confidence of semantic similarity, M_3 achieves better results than M_2 because the refined similarity-graph is still noisy and M_3 further accounts for the variations in confident and unconfident pairs, which eases the effect of false similarity signals and enlarges the effect of highly confident signals in the similarity graph. M_4 makes use of the data augmentation and our novel semantic consistency loss function. We can see that M_4 performs much better than M_3, which demonstrates the strength of data augmentation and our well-designed semantic consistency loss. By comparing the results of M_3 and M_4, we can see that the contrastive consistency can further improve the performance of our model.

Parameter Sensitivity We study the influence of balance coefficient η and the number of clusters K in Figure 5. We first fix η to 0.1 and 0.3 and evaluate the MAP by varying K from 50 to 110. The performance of our model is not sensitive to the number of clusters in the range of [50, 110] and we can set K as any values in that interval. Furthermore, we show the MAP by varying η from 0.05 to 0.5 with K fixed to 70. The MAP of our model first increases and then keeps at a relatively high level. The result is not sensitive to η in the range of [0.2, 0.5]. Then for the proposed model, K and η are set to 70 and 0.3 respectively.

Visualization In Figure 6, we visualize the top 10 returned images of our model and the best baseline for the query image of CIFAR-10, which demonstrates that our model can retrieve much more relevant and user-desired images.

5 Conclusion

Here we propose a novel deep hashing method named CIMON, which generates reliable semantic information by comprehensive similarity mining from local and global views. Then a novel consistency loss function from the view of semantic matching and contrastive learning is proposed to optimize the hashing model by incorporating the semantic information into the training process. Extensive experiments reveal that CIMON boosts the state-of-the-art unsupervised hashing schemes in both image retrieval and robustness.

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