

Deep Hash Distillation for Image Retrieval

Supplementary Material

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Introduction In this supplementary material, we present a proof in **A.a**, detailed explanations in **B.a** and **B.c**, statistics in **B.b**, additional ablations in **C.a**, and additional visualized results in **C.b** to better understand the main paper. To reproduce our work, we provide a pseudo-code and training scheme in **A.b**, and an anonymous Github link which contains an executable code and a list of data.

A. Details on Deep Hash Distillation

A.a. Hamming Distance Analysis

For a given input image x_i and x_j , a deep hashing model \mathcal{H} produces corresponding hash codes h_i and h_j , which are quantized to binary codes b_i and b_j in $\{-1, 1\}^K$ with sign operation ($b_i = \text{sign}(h_i)$, $b_j = \text{sign}(h_j)$), respectively. For retrieval, Hamming distance \mathcal{D}_H is computed with the binary codes as:

$$\mathcal{D}_H(b_i, b_j) = \text{XOR}(b_i, b_j), \quad (\text{i})$$

where XOR is a bit-wise count operation that outputs in the range $[0, K]$. From a mathematical point of view, XOR can be interpreted as:

$$\begin{aligned} \text{XOR}(b_i, b_j) &= \frac{1}{2} (K - b_i^T \cdot b_j) \\ &= \frac{1}{2} (K - \|b_i\|_2 \|b_j\|_2 \mathcal{S}(b_i, b_j)) \quad (\text{ii}) \\ &= \frac{K}{2} (1 - \mathcal{S}(b_i, b_j)), \end{aligned}$$

where $\|b_i\|_2 = \|b_j\|_2 = \sqrt{K}$, and $\mathcal{S}(\cdot, \cdot)$ denotes cosine similarity which also can be notated as:

$$\begin{aligned} \mathcal{S}(b_i, b_j) &= \cos \alpha_{ij} \\ &= \frac{b_i^T \cdot b_j}{\|b_i\|_2 \|b_j\|_2}, \quad (\text{iii}) \end{aligned}$$

where α_{ij} is the angle between b_i and b_j . It should be noted that $1 - \mathcal{S}(b_i, b_j)$ presents a cosine distance between b_i and b_j and can be approximated with h_i and h_j as:

$$1 - \mathcal{S}(b_i, b_j) \simeq 1 - \mathcal{S}(h_i, h_j) \quad (\text{iv})$$

where $1 - \mathcal{S}(h_i, h_j)$ is a cosine distance between h_i and h_j . Therefore, minimizing the cosine distance between hash codes during the deep hashing training allows to reduce the Hamming distance between their binary codes.

A.b. Pseudo-code and Learning Algorithm

We provide a PyTorch-like pseudo-code in Algorithm 1 and detailed training process in Algorithm 2 and 3 for reproducibility of our Deep Hash Distillation (DHD) framework.

Algorithm 1 Data augmentation and loss functions.

```

1 # Import pytorch
2 import torch as T
3 # Import kornia library for augmentation
4 # https://github.com/kornia/kornia
5 import kornia.augmentation as Kg
6
7 # Augmentation class to separate teacher/student.
8 class Augmentation():
9
10 # Transformation defined in kornia
11 # Apply augmentation sequentially
12 def init(self, sT):
13     self.Aug = Sequential(
14         Kg.RandomResizedCrop(p=1.0 * sT),
15         Kg.RandomHorizontalFlip(p=0.5 * sT),
16         Kg.ColorJitter(p=0.8 * sT),
17         Kg.RandomGrayscale(p=0.2 * sT),
18         Kg.RandomGaussianBlur(p=0.5 * sT))
19
20 def forward(self, x):
21     return self.Aug(x)
22
23 # Hash Proxy-based learning in Eqn 4 of paper.
24 class HP_Loss():
25
26 # Employ trainable hash proxies
27 def init(self, N_cls, N_bit):
28     self.HP = Parameter(shape=(N_cls, N_bit))
29
30 def forward(self, h, tau, L):
31     # Compute cosine similarity
32     # and Temperature scaling
33     D = cos_sim(h, self.HP) / tau
34     # Label normalization
35     L = normalize(L)
36     return (-L * log_softmax(D)).sum()
37
38 # Reducing quantization error in Eqn 6 of paper.
39 class BCE-Q_Loss():
40
41 # Utilize two Gaussian estimators
42 def init(self, std):
43     self.gp = T.exp(-0.5 * ((x-1)/std) ** 2)
44     self.gn = T.exp(-0.5 * ((x+1)/std) ** 2)
45     self.BCE = T.nn.BCELoss()
46
47 def forward(self, x):
48     # Likelihood estimate
49     hp = self.gp(x)
50     hn = self.gn(x)
51     # Define binary goals
52     y = (x.sign().detach() + 1.0) / 2.0
53     # Compute Binary Cross Entropy
54     lp = self.BCE(hp, y)
55     ln = self.BCE(hn, 1-y)
56     return lp + ln

```

Algorithm 2 Self-distilled Hashing training scheme.

```

1 # H: deep hashing model
2 # sT: transformation occurrence scale
3 augT = augmentation(sT) # teacher group
4 augS = augmentation(1.0) # student group
5
6 for x in loader: # load a minibatch of n-samples
7     xT, xS = augT(x), augS(x) # random views
8     hT, hS = H(xT), H(xS) # hashing, n-by-K
9
10 L = SdH(hT, hS) # loss
11 L.backward() # back-propagate
12 update(H(xS)) # Adam update
13
14 def SdH(hT, hS): #Self-distilled Hashing
15     hT = hT.detach() # stop gradient
16     hT = normalize(hT, dim=1) # l2-normalize
17     hS = normalize(hS, dim=1) # l2-normalize
18     return 1- (hT * hS).sum(dim=1).mean()

```

Algorithm 3 Entire DHD training for batch size N_B

- 1: Initialize ϵ with pretrained model weights.
- 2: Initialize H and P with Xavier initialization.
- 3: $g^+(h) = \exp\left(\frac{(h-1)^2}{2}\right)$
- 4: $g^-(h) = \exp\left(\frac{(h+1)^2}{2}\right)$

Input: Parameters of each component $\epsilon; H; P$

Input: $X_B = f(x_1; y_1); \dots; (x_{N_B}; y_{N_B})g$

- 5: for n in $1, \dots, N_B$ do

6: draw two transformations $t_{2n-1} T_T; t_{2n} T_S$

7: $x_{2n-1} = t_{2n-1}(x_n)$

8: $x_{2n} = t_{2n}(x_n)$

9: $h_{2n-1} = \tanh(H_H(E_\epsilon(x_{2n-1})))$

10: $h_{2n} = \tanh(H_H(E_\epsilon(x_{2n})))$

11: $p_{2n-1} = P_P(h_{2n-1})$

12: end for

13: $\text{SdH} L_{\text{SdH}}$ with $f h_{2n-1}; h_{2n} g_{n=1}^{N_B}$

14: $\text{HP} L_{\text{HP}}$ with $f p_{2n-1}; y_n g_{n=1}^{N_B}$

15: $\text{bce-Q} L_{\text{bce-Q}}$ with $g^+; g^-; f h_{2n-1} g_{n=1}^{N_B}$

16: $E; H \quad E; H \quad \frac{\partial \text{SdH}}{\partial E; H} + \frac{\partial \text{HP}}{\partial E; H} + \frac{\partial \text{BCE-Q}}{\partial E; H}$

17: $P \quad P \quad \frac{\partial \text{HP}}{\partial P}$

Output: Updated $\epsilon; H; P$

B. Experimental Setting

B.a. More Details on Implementation

The pretrained model weights of AlexNet [8] and ResNet [6] are from Torchvision¹. Especially for transformer backbones, we adopt base pretrained model weights as: ViT [3] with vit_base_patch16_224, DeiT [12] with deit_base_distilled_patch16_224 and SwinT [10] with swin_base_patch4_window7_224, from timm² open source library respectively. In order to fit in to deep encoders, we crop the center of the dataset images to the size of 224 × 224 after augmentation for training, while cropping without augmentation for test.

There may be performance differences in the retrieval results of existing methods [1, 2, 4, 9, 13–15] depending on the implementation setups, but we set the same training strategy as: Adam optimizer [7], learning rate schedule [11] with warm-up for the first 10 epochs, and reducing the learning rate of the deep encoder by 1/20, for a fair comparison. Batch size is set to 128 as default, however, we adjust it as a half for pair-wise learning approaches [1, 2] for stable learning, and as a quarter when training transformers, in order to fit in NVIDIA 3090 RTX 24GB GPUs. Other conditions for training are adopted with defaults proposed in each method.

B.b. Dataset Configuration and Statistics

During dataset preparation, we resize all images to 256 × 256. Figure A shows how distributed each category is in the training sets of retrieval datasets.

ImageNet is a single-labeled dataset to evaluate the classification performance, which consists of over 1.2M images in the training set and 50K images in the validation set. There are 1,000 categories to be classified. However, we employ a subset of ImageNet with 100 categories, where the training set and the query set are configured by assigning single label (1/100 = 1% of total) to each image. The training set is composed of the same 130 images per category.

NUS-WIDE is a multi-labeled dataset which contains 269,648 images crawled from the Web, all annotated with at least one concept out of a total of 81. We collect images with 21 most frequent concepts to perform experiments, where the training set and the query set are arranged to have at least 500 and 100 images for each category, respectively. To be specific with training set, one image has up to 10 labels (10/21 = 48% of total), with an average of 2.94 labels (2.93/21 = 14% of total).

MS COCO is a multi-labeled dataset containing 132,218 images of 80 categories, where each image is assigned one or more semantic labels. We adopt randomly sampled 10,000 and 5,000 images for training and test, respectively. In particular for training set, one image has up to 15 labels (15/80 = 19% of total), with an average of 2.94 labels (2.94/80 = 4% of total).

B.c. Deformation Setup

Following the experimental setup in [5] to investigate the quality of image embeddings, we use the imgaug³ library to evaluate the deep hashing model performance when unseen transformation (deformation) is given. Experimental results are reported in Table 5 of the main paper.

- Cutout: each input image is randomly filled by two grayish pixels that are 20% of the image size.
- Dropout: $p \times 100\%$ of pixels are dropped from each image where $p = \text{ftj}0 < t < 0:01g$.
- Zoom-in: each input image is transformed by zoom-in at scale of 50%.
- Zoom-out: each input image is transformed by zoom-out at scale of 200%.
- Rotation: each input image is rotated at a randomly sampled degree where $d = \text{ftj} 30 < t < 30 g$.
- Shearing: each input image is sheared at a randomly sampled degree where $d = \text{ftj} 30 < t < 30 g$.
- Gaussian Noise: noise is sampled once per pixel from a normal distribution with $\text{std} = \text{ftj}0 < t < 25:5g$ and added to each image.

(a) ImageNet

(b) NUS-WIDE

(c) MS COCO

Figure A. Number of images per category in the training set.

¹<https://pytorch.org/vision>

²<https://github.com/rwightman/pytorch-image-models>

³<https://github.com/aleju/imgaug>

	ImageNets _T = 0:5			NUS-WIDE _{sT} = 0:5			MS COCO _{sT} = 0:5		
Hyper-parameter	16-bit	32-bit	64-bit	16-bit	32-bit	64-bit	16-bit	32-bit	64-bit
= 0:2	0.864	0.891	0.901	0.791	0.825	0.840	0.818	0.868	0.888
= 0:4	0.858	0.884	0.892	0.812	0.839	0.850	0.839	0.873	0.889
= 0:6	0.858	0.881	0.887	0.820	0.839	0.850	0.829	0.866	0.878
= 0:8	0.850	0.874	0.886	0.813	0.837	0.846	0.815	0.854	0.876
= 1:0	0.856	0.871	0.882	0.817	0.836	0.845	0.809	0.854	0.872

Table A. mAP scores by varying on ResNet backbone DHD, where the setup utilized in the main paper is shown in bold.

	ImageNet = 0:2			NUS-WIDE = 0:6			MS COCO = 0:4		
Hyper-parameter	16-bit	32-bit	64-bit	16-bit	32-bit	64-bit	16-bit	32-bit	64-bit
s_T = 0:2	0.866	0.888	0.897	0.812	0.838	0.849	0.839	0.871	0.889
s _T = 0:4	0.866	0.889	0.896	0.810	0.839	0.848	0.837	0.873	0.888
s _T = 0:5	0.864	0.891	0.901	0.820	0.839	0.850	0.839	0.873	0.889
s _T = 0:6	0.860	0.885	0.895	0.817	0.839	0.849	0.834	0.871	0.886
s _T = 0:8	0.858	0.881	0.890	0.819	0.837	0.843	0.828	0.866	0.883
s _T = 1:0	0.845	0.874	0.884	0.815	0.833	0.841	0.825	0.860	0.878

Table B. mAP scores by varying on ResNet backbone DHD, where the setup utilized in the main paper is shown in bold.

	1	2		16-bit	64-bit
(1)	0.1	0.1	0.5	0.657	0.721
(2)	0.05	0.1	0.5	0.652	0.716
(3)	0.5	0.1	0.5	0.654	0.715
(4)	0.1	0.05	0.5	0.658	0.717
(5)	0.1	0.5	0.5	0.652	0.713
(6)	0.1	0.1	0.25	0.654	0.716
(7)	0.1	0.1	1.0	0.656	0.717

Table C. Ablation study on hyper-parameters of DHD on ImageNet. The setup utilized in the main paper is shown in bold.

C. Additional Experimental Results

C.a. Ablation Study on Hyper-parameters

To investigate the influences of hyper-parameters utilized in DHD, we perform retrieval experiments and show the results in Table B, A and C. Specifically, the mean Average Precision (mAP) scores are measured by varying the value of hyper-parameter to be investigated, while fixing others as defaults.

In Table A, we examine the temperature scaling parameter τ . Following the results and the observation in Sec B.b, we set the optimal τ differently to each dataset, since cross-entropy-based D_{HP} should be handled according to how the labels are distributed. The more categories to classify, the lower τ is required to get more distinct predictions.

In Table B, we explore the impact of transformation occurrences s_T . It can be seen that the performance is almost similar when s_T is less than 0.5, and the performance starts to degrade when s_T is larger than 0.5. This indicates that dividing the augmentation groups as easy teacher and difficult

student, giving teacher group to low , is effective.

In Table C (2-5), we change the balancing parameter of L_{sdH} and α_2 of L_{bce-Q} to figure out the impact of training objectives in retrieval performance. From the results with little performance difference, it can be confirmed that the proposed loss functions are not sensitive to the hyper-parameters. In Table C (6, 7), we vary the standard deviation value of the Gaussian estimators σ_{bce-Q} . The mAP scores show that providing a stricter estimator ($0:25$) tends to degrade performance, but that also did not seem to have a significant effect. From the results in Table C (8), we find out that applying LN does not change the results much.

C.b. Additional Visualized Results

Trainable Hash Proxies. We additionally visualized the pairwise cosine similarity of trainable hash proxies for all classes in each dataset in Figures B, C, D, with ResNet backbone @ 64-bit. For single label ImageNet dataset, semantically similar classes show higher similarity such as European salamander-spotted salamander and electric locomotive-passenger car. For multi-label datasets, frequency appear together in a single image show higher similarity such as oysters-plants and ocean-beach in NUS-WIDE, or baseball bat-baseball glove and truck-bus-car in MS COCO. Particularly, we observed that discriminability can still be preserved when two classes have high cosine similarity as shown in the buildings-window-vehicle case of NUS-WIDE. Here the cosine similarity of buildings-window (0.48) and window-vehicle (0.55) is high, but the cosine similarity of buildings-vehicle (0.08) is low.

Qualitative Results. In order to see whether the difficulty of transformation is really different according to β , we illustrate Figure E. For β_T , images do not significantly deviate from the original. However, for β_S , some images are distorted to the point of being hard to recognize. Figure F shows what images are actually retrieved as results when transformation is applied. We can confirm that our DHD is robust to transformation and achieves high quality results.

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Figure B. Pairwise cosine similarities of trainable hash proxies on ImageNet.

Figure C. Pairwise cosine similarities of trainable hash proxies on NUS-WIDE.

Figure D. Pairwise cosine similarities of trainable hash proxies on MS COCO.

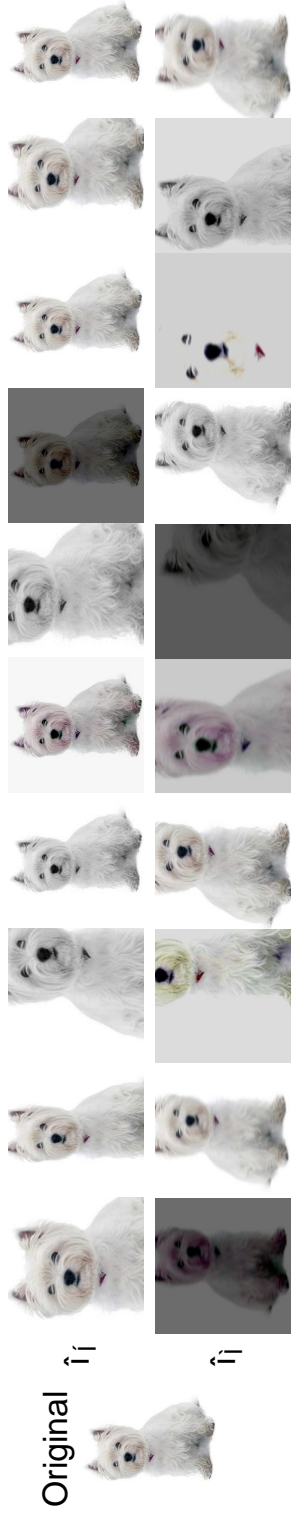


Figure E. Visualized augmentation results of different groups: weakly-transformed teacher T_T and strongly-transformed student T_S .

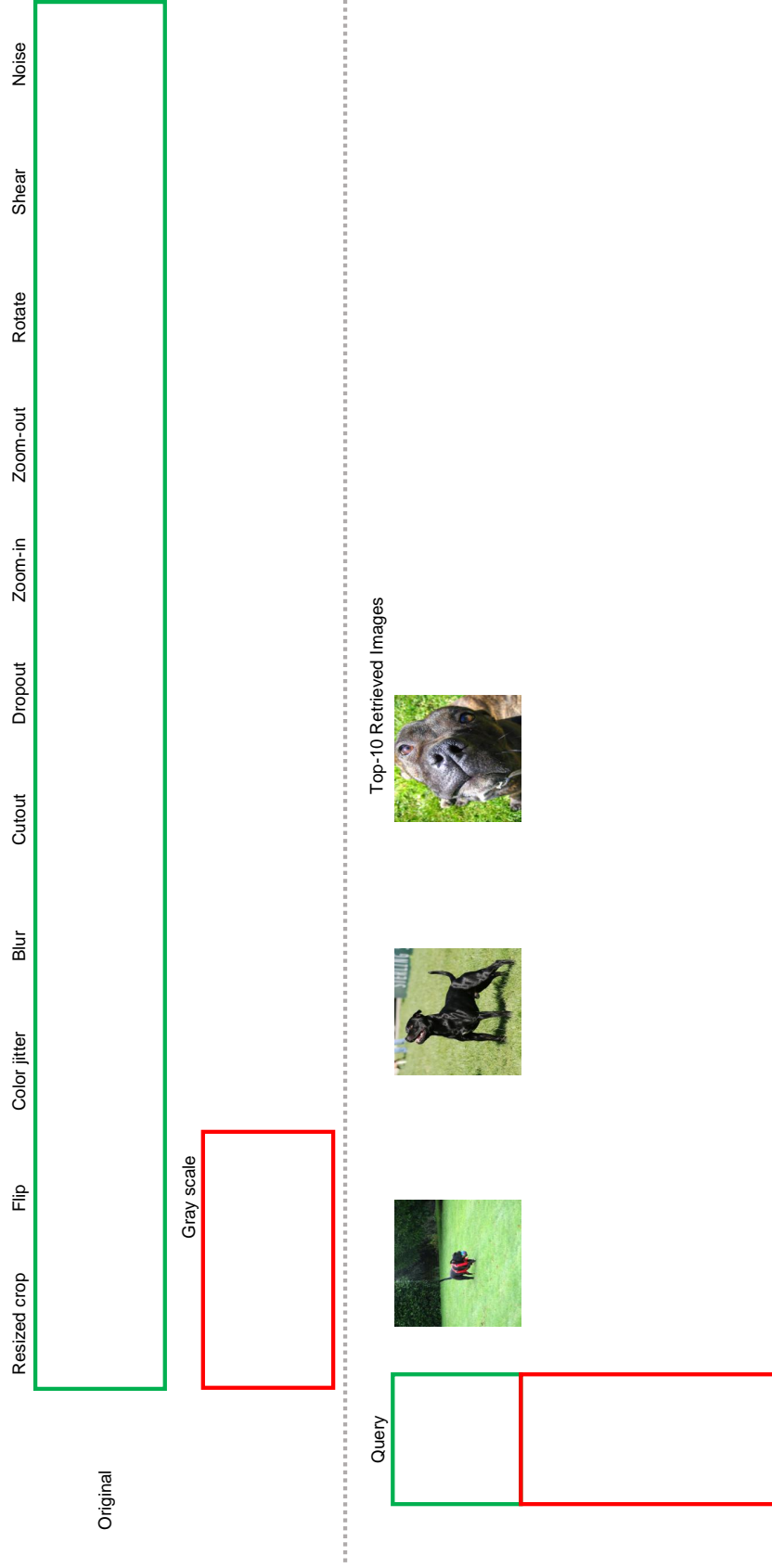


Figure F. Above: Examples of various transformations applied to the original image. The green box indicates the same search result as the original, and the red box indicates otherwise. Below: Retrieved images on ImageNet dataset. The image output from the strongly transformed T_T and the image transformed to gray scale show different retrieval results. Nevertheless, it can be seen that visually similar images of the same content are retrieved well.