Image Hashing via Linear Discriminant Learning

Weixiang Hong*
National University of Singapore
weixiang.hong@outlook.com

Yu-Ting Chang
UC Merced
ychang39@ucmerced.edu

Haifang Qin*
Peking University
qhfpku@pku.edu.cn

Wei-Chih Hung
UC Merced
whung8@ucmerced.edu

Yi-Hsuan Tsai
NEC Labs America
wasidennis@gmail.com

Ming-Hsuan Yang
UC Merced/Google
mhyang@ucmerced.edu

1. Ablation Study on ResNet-50

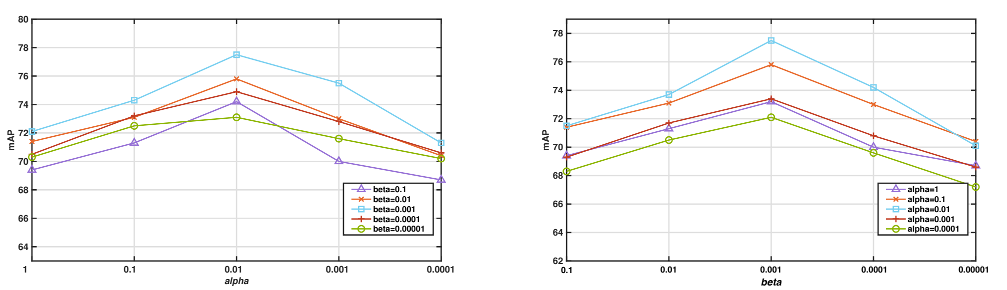
We show an ablation study on CIFAR-10 to validate the effectiveness of loss functions proposed in our method using the ResNet-50 as the backbone. In Table 1, without using the proposed inter-class loss, the performance drops significantly.

Table 1. With/Without the LDA loss using the ResNet-50 backbone on CIFAR-10.

mAP	12 bits	24 bits	32 bits	48 bits
Without Inter Loss + Intra Loss	83.1	84.5	85.6	86.3
With Inter Loss + Intra Loss	86.9	87.2	88.3	88.1

2. Sensitivity Analysis

In Figure 1, we show the sensitive analysis of the loss weights α and β on CIFAR-10. We use grid search to determine the value of hyper-parameters α and β, and fix $\alpha = 0.01$ and $\beta = 0.001$ for all the experiments.



(a) Fix β, change α.

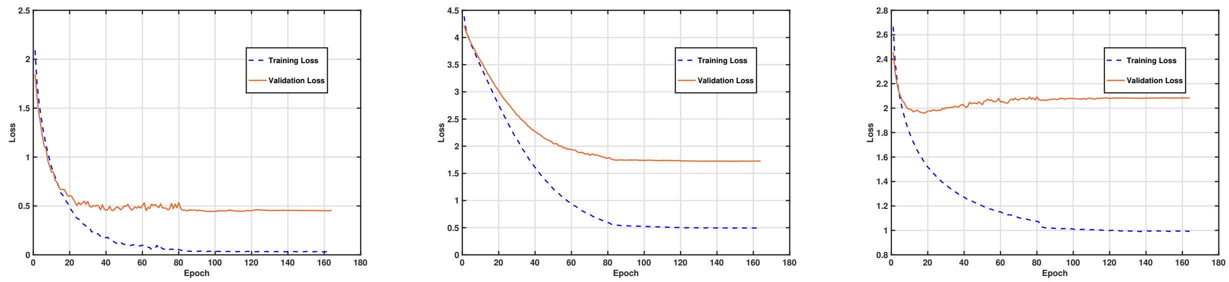
(b) Fix α, change β.

Figure 1. mAP on the CIFAR-10 dataset.

3. Implementation Details

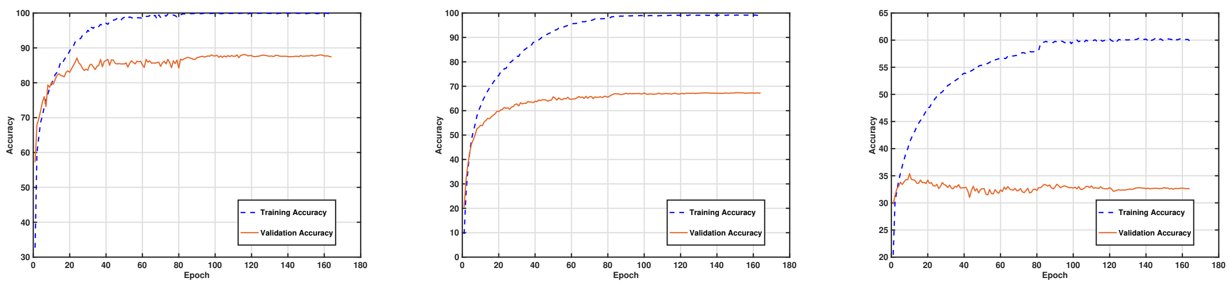
During training, we train LDH for 164 epochs and divide the learning rate by 10 at epoch 81 and 122. In addition, the train/test loss curve *w.r.t.* epoch is illustrated in Figure 2, while the change of train/test accuracy *w.r.t.* epoch is provided in Figure 3. With a single Nvidia Tesla v100 GPU, it takes around 40 minutes for training on the CIFAR-10 dataset, 6 hours on the ImageNet dataset, and 11 hours on the NUS-WIDE dataset.

*Work done at Google.



(a) CIFAR-10 dataset. (b) ImageNet dataset. (c) NUS-WIDE dataset.

Figure 2. **The train/test loss of LDH.** From left to right, we show the results from CIFAR-10, NUS-WIDE and ImageNet.



(a) CIFAR-10 dataset. (b) ImageNet dataset. (c) NUS-WIDE dataset.

Figure 3. **The train/test accuracy of LDH.** From left to right, we show the results from CIFAR-10, ImageNet and NUS-WIDE.

4. More Results and Analysis

In this section, we provide more retrieval examples in Figure 4, 5 and 6. The LDH algorithm is able to retrieve images that share the same semantic labels with the input query. In addition, we evaluate the performances of binary code using a recently proposed metric, *m*AP for unseen classes [1]. As shown in Table 2, our LDH achieves promising *m*AP for unseen classes on the CIFAR-10 dataset.

Table 2. mAP of unseen classes, with 16-bit binary code.

methods	CCA-ITQ	DHN	DPSH	HashNet	LDH (Ours)
mAP	15.4	17.9	18.5	19.8	20.4

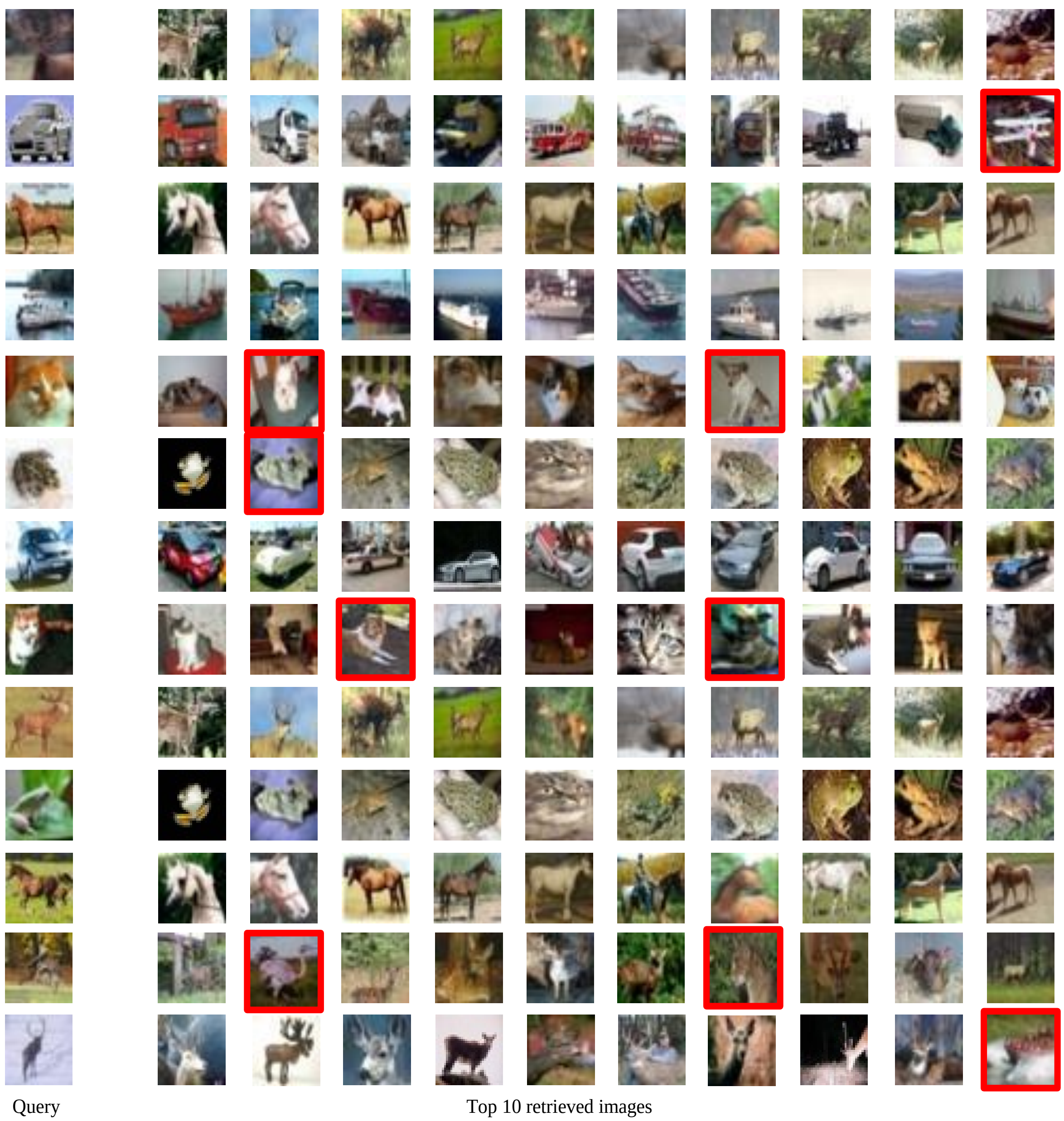


Figure 4. **Retrieval results on the CIFAR-10 dataset.** We use red rectangles to denote false positives.

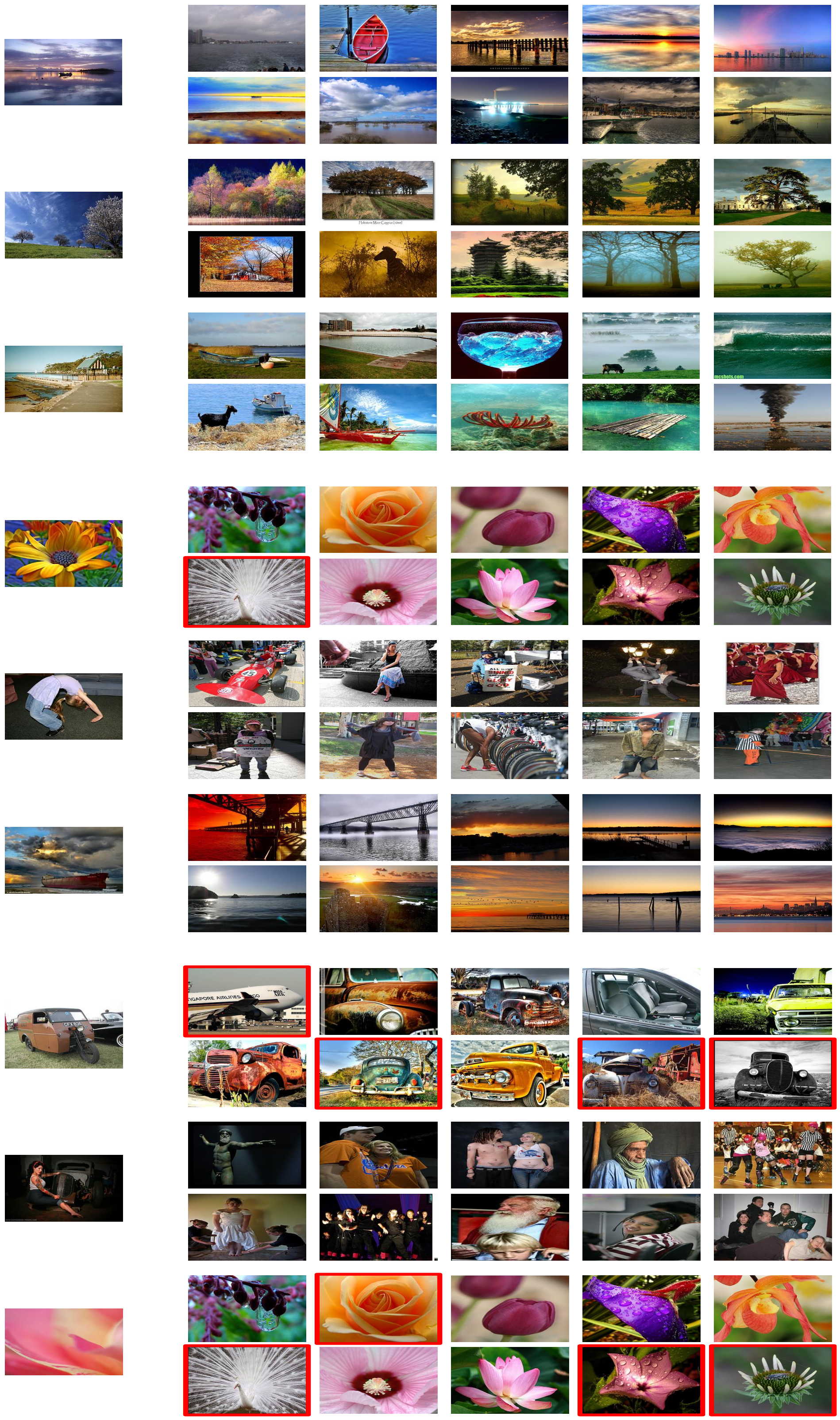


Figure 5. **Retrieval results on the NUS-WIDE dataset.** We use red rectangles to denote false positives.

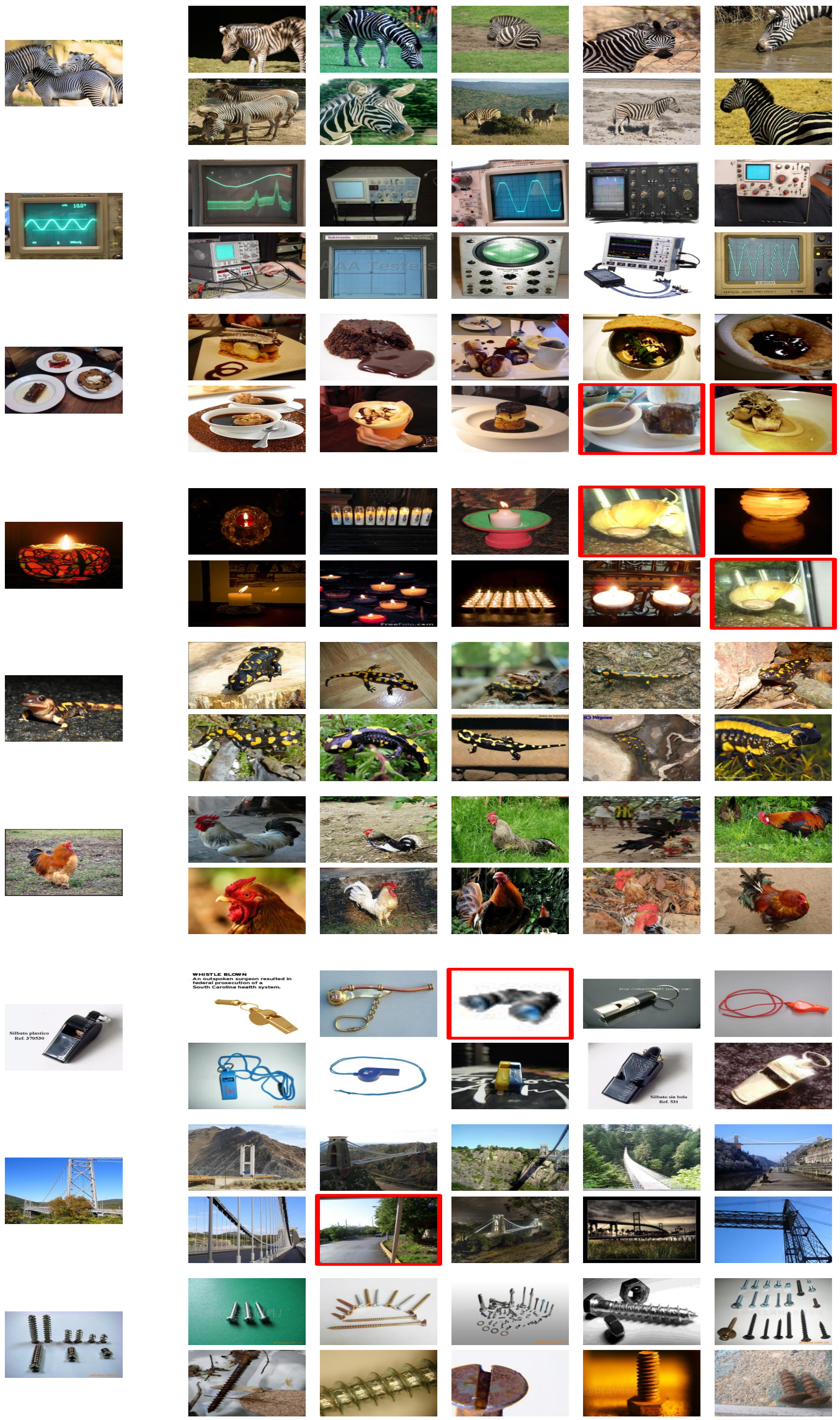


Figure 6. **Retrieval results on the ImageNet dataset.** We use red rectangles to denote false positives.

References

[1] A. Sablayrolles, M. Douze, N. Usunier, and H. Jégou. How should we evaluate supervised hashing? In *ICASSP*, 2017.