INTERNATIONAL SYMPOSIUM ON INTELLIGENT SIGNAL PROCESSING AND COMMUNICATION SYSTEMS (ISPACS) 2021

DAH: Domain Adapted Deep Image Hashing

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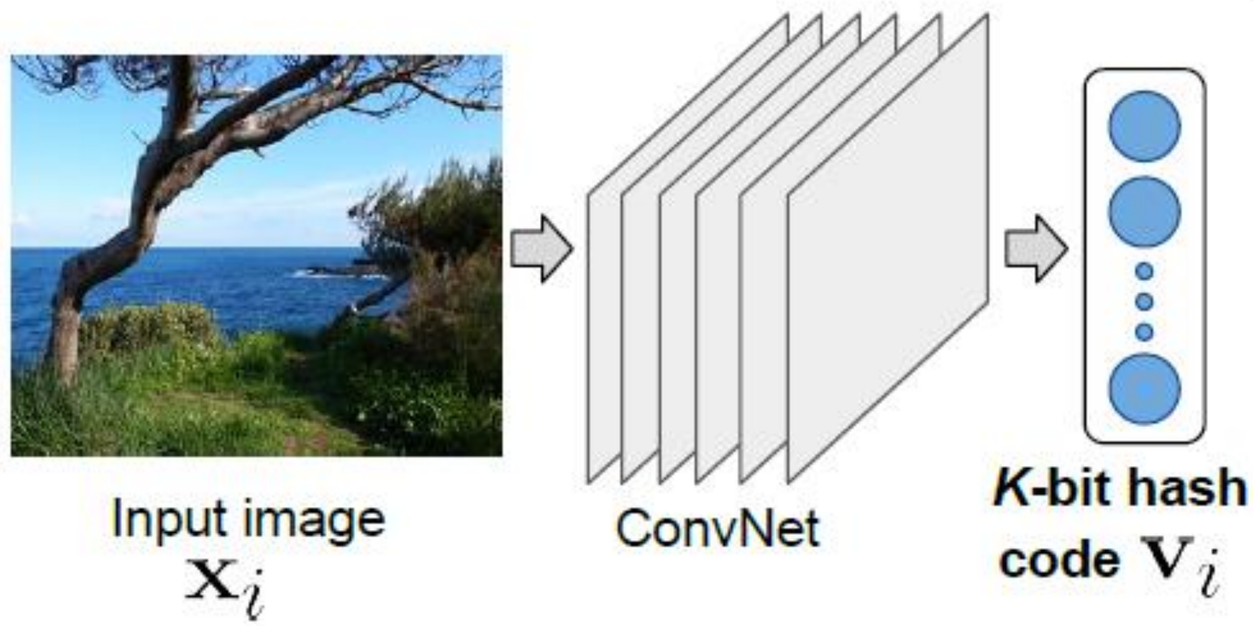
Deep Image Hashing

Hashing techniques construct a mapping from images to binary codes, with an aim to preserve semantic similarity of samples in the Hamming space.



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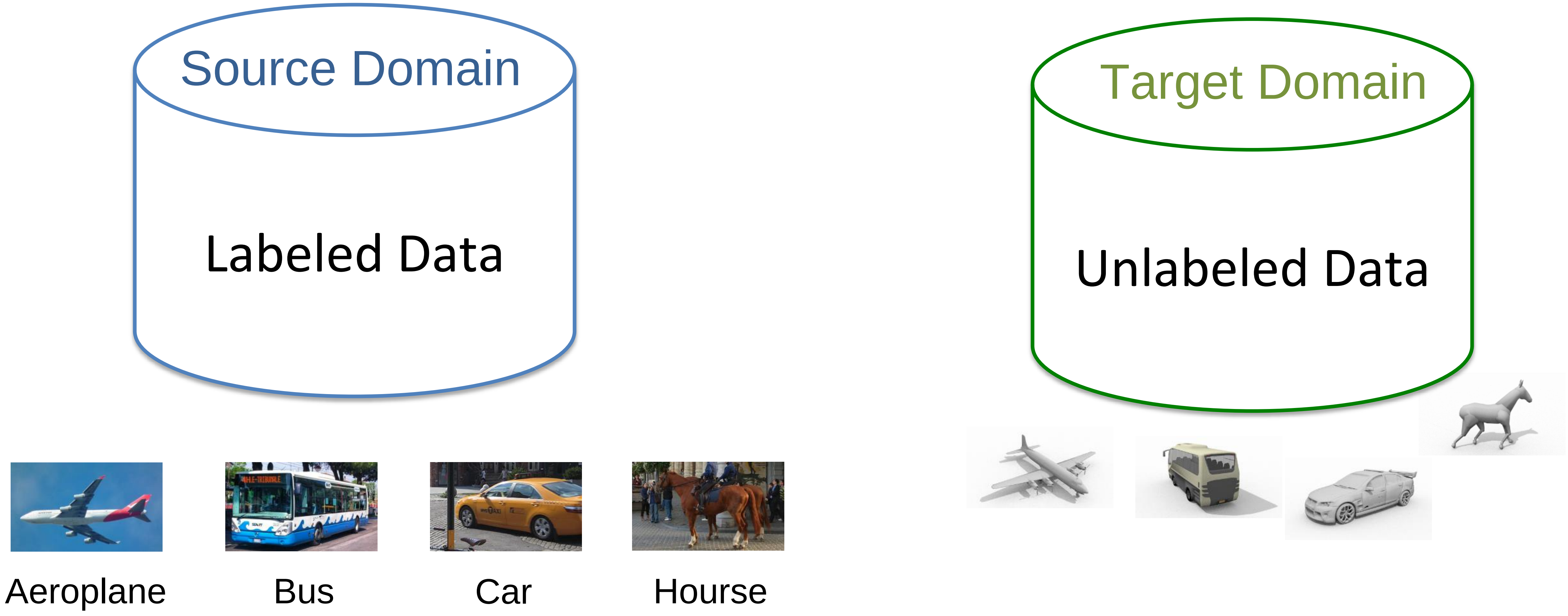
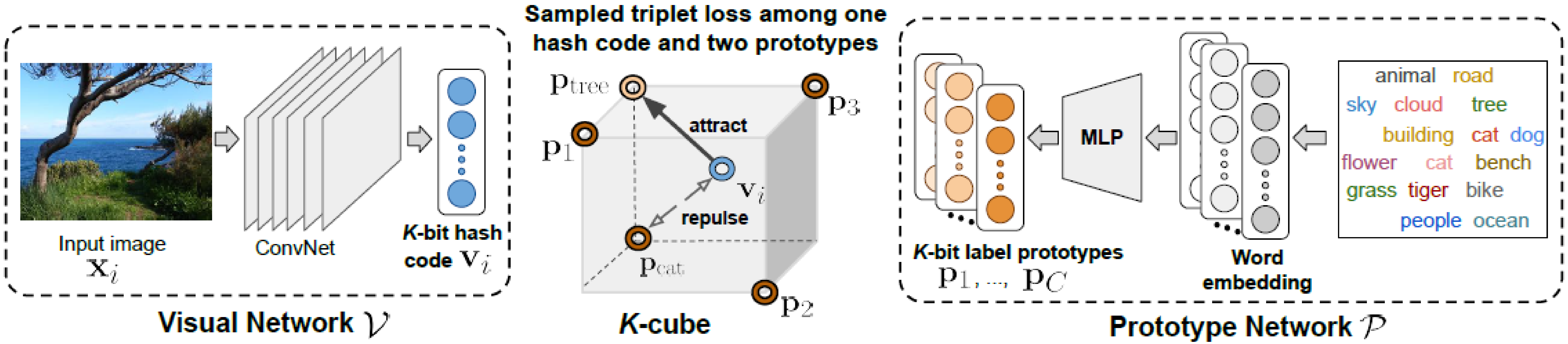
Domain Adapted Image Hashing

A hashing model is trained with labeled source domain data and unlabeled target domain data. It is expected to perform well on both domains.



Base Model: SemanticHash (*IEEE TAI* 2021)

- A *supervised* deep hashing model
- May not be applicable for cross-domain scenario



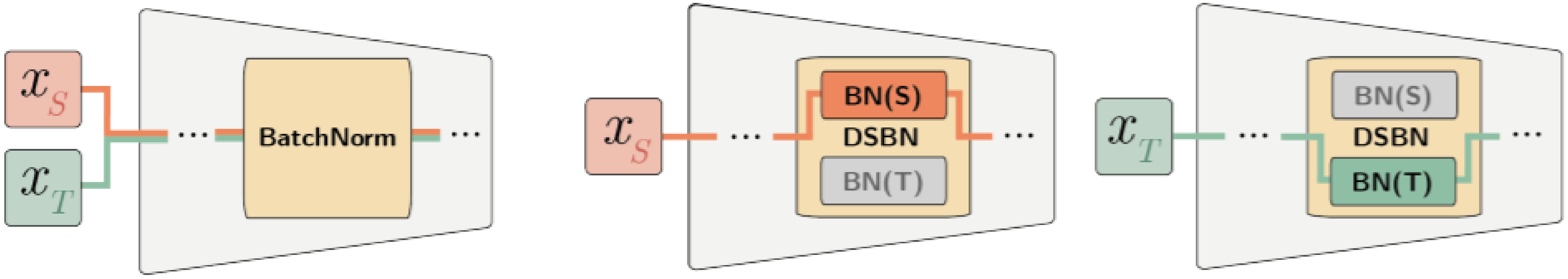
Cheng-Hao Tu, Huei-Fang Yang, Shih-Min Yang, Mei-Chen Yeh and Chu-Song Chen, "SemanticHash: Hash Coding via Semantics-guided Label Prototype Learning," *IEEE Transactions on Artificial Intelligence* (*TAI*), 2(1), 42-57, 2021.

Domain Adapted Hashing

- We address the domain shift problem in image hashing by *unsupervised domain adaptation*.
- We enhance the generalization capability of SemanticHash by domain-specific batch normalization (DSBN) and the center loss.

Domain-Specific Batch Normalization (DSBN)

DSBN adapts to both domains by specializing batch normalization layers in convolutional neural networks while allowing them to share all other model parameters.

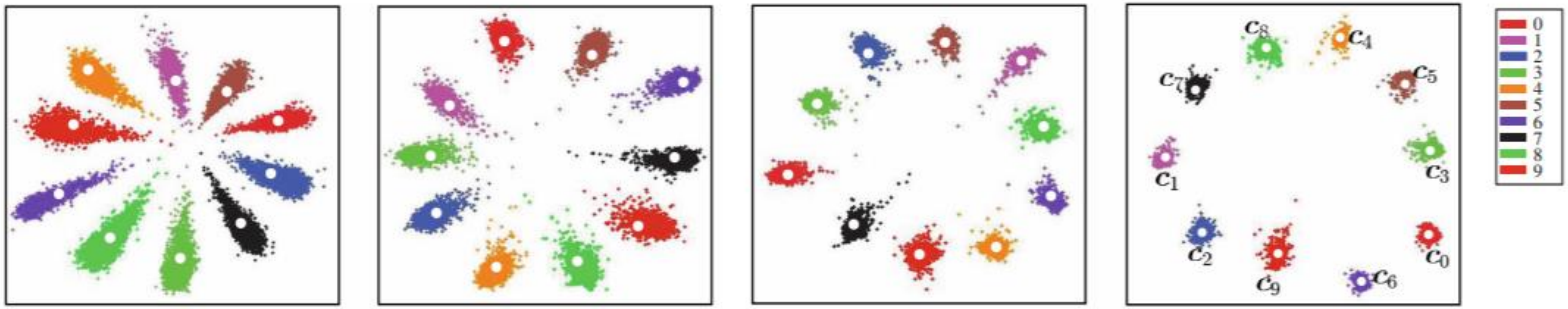


(a) Batch Normalization (b) Domain-Specific Batch Normalization

Woong-Gi Chang, Tackgeun You, Seonguk Seo, Suha Kwak, Bohyung Han, "Domain-Specific Batch Normalization for Unsupervised Domain Adaptation," *IEEE Conference on Computer Vision and Pattern Recognition* (*CVPR*), 2019.

Center Loss

Using the center loss encourages the separation of inter-class data distributions and at the same time reduce intra-class data variations.



(a) $\lambda = 0.001$ (b) $\lambda = 0.01$ (c) $\lambda = 0.1$ (d) $\lambda = 1$

Yandong Wen, Kaipeng Zhang, Zhifeng Li, and Yu Qiao, "A Discriminative Feature Learning Approach for Deep Face Recognition," *European Conference on Computer Vision* (*ECCV*), 2016.

Center Loss (Cont.)

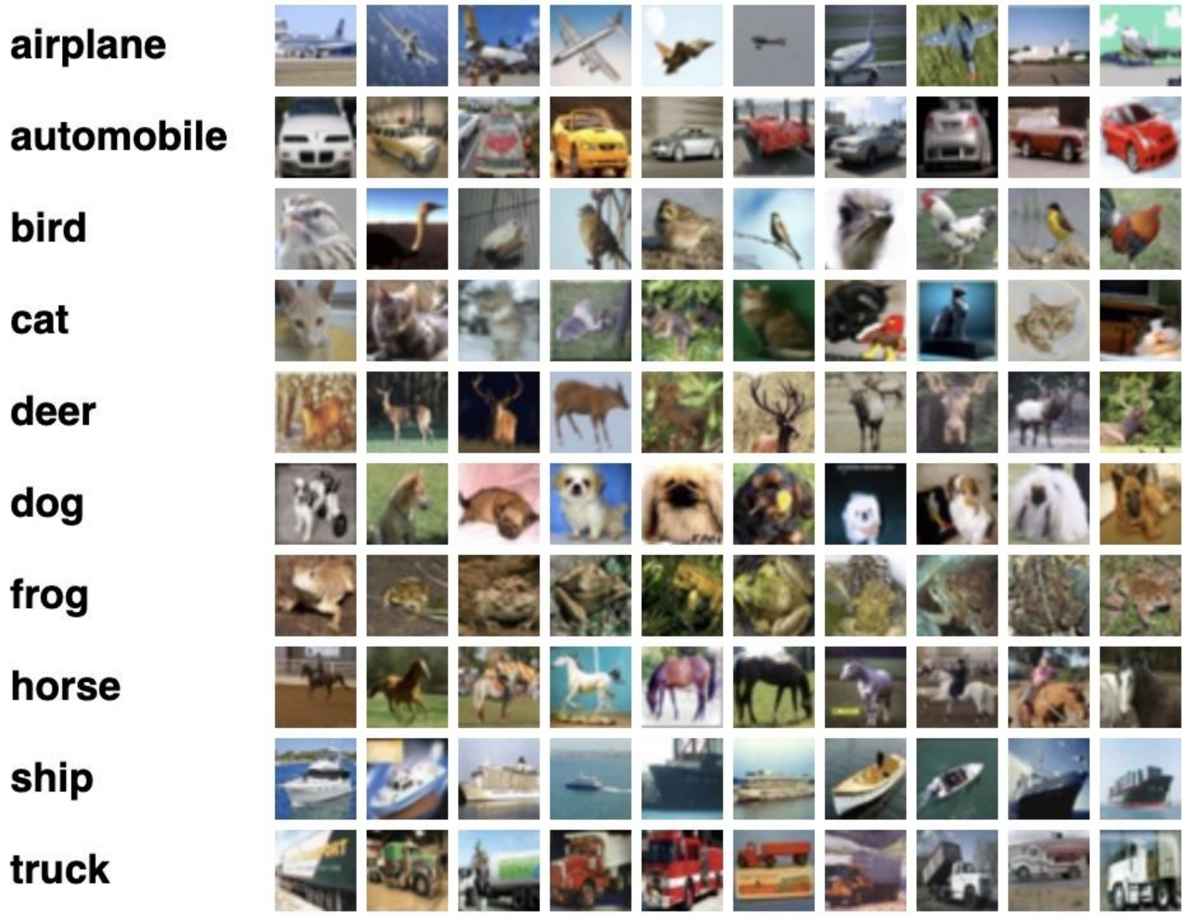
- Define the labels as the center points
- Compute a loss for an training instance by calculating the distance from this image to its ground truth (for source domain) and estimated (for target domain) label
- Total loss:

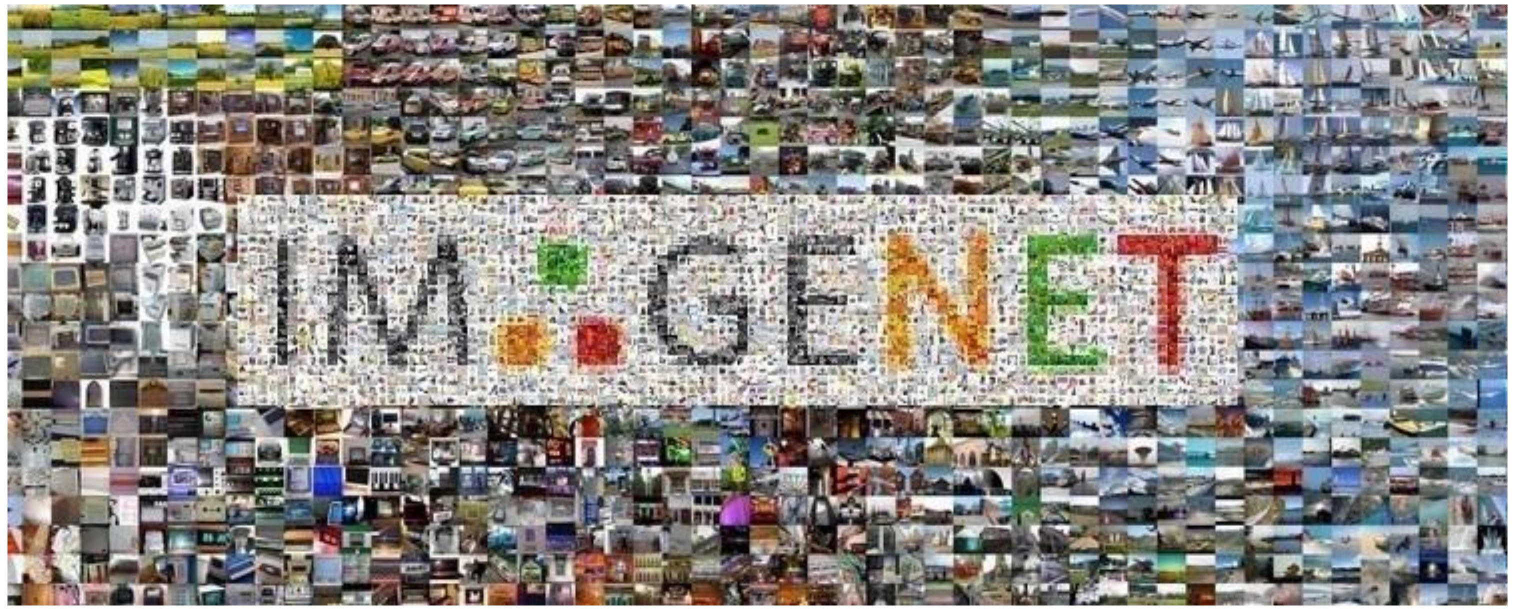
$$L = L_{CE} + \lambda L_C:$$

$$-\sum_{i=1}^{m} y_i \log_2(p_i) + \frac{\lambda}{2}\sum_{i=1}^{m} \|x_i - c_{y_i}\|^2$$

Datasets and Experimental Settings

- CIFAR10 (Source Domain)
- ImageNet (Target Domain)
- We only used the ImageNet images whose labels also appear in CIFAR10.





Result (Cross-Dataset Evaluation)

	SemanticHash	Ours (DAH)
mAP	0.3267	**0.3558**

- With the proposed domain adaptation techniques, the accuracy slightly improved.
- The benefit of using center loss is not fully realized because the pseudo labels may not be correct when training DAH.

Result (Performance Disparity between Settings)

	CIFAR10	ImageNet
mAP	0.7122	0.3558
	Traditional setting	Cross-dataset setting

- Observe a performance disparity between the traditional (both domains: CIFAR10) and the cross-dataset (source: CIFAR10, target: ImageNet) settings.

Result (Hyper Parameter λ in Final Loss)

$L = L_{CE} + \lambda L_C$:

$$-\sum_{i=1}^{m} y_i \log_2(p_i) + \frac{\lambda}{2}\sum_{i=1}^{m} \|x_i - c_{y_i}\|^2$$

		0.5	1	2
Traditional setting	CIFAR10	**0.7219**	0.7122	0.7080
Cross-dataset setting	ImageNet	0.3399	**0.3558**	0.3188

- Setting a small λ value achieved the best performance in the traditional setting.
- The best performance in the cross-dataset setting was obtained when λ was set to 1.

1. Introduction
2. Approach
3. Experiments
4. Conclusion

Conclusions

- We present DAH, an end-to-end trainable deep architecture, for cross-domain hash code learning.
- With the usage of unlabeled target domain images, we apply ***unsupervised domain adaptation techniques*** to train the deep image hashing model.
- DAH outperforms SemanticHash in a cross-dataset evaluation.
- A future direction is to obtain reliable supervisory similarity signals by distilling data pairs with confident semantic similarity relationships.

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