# Deep Hashing Network for Unsupervised Domain Adaptation

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IEEE Computer Vision and Pattern Recognition, Honolulu, 2017

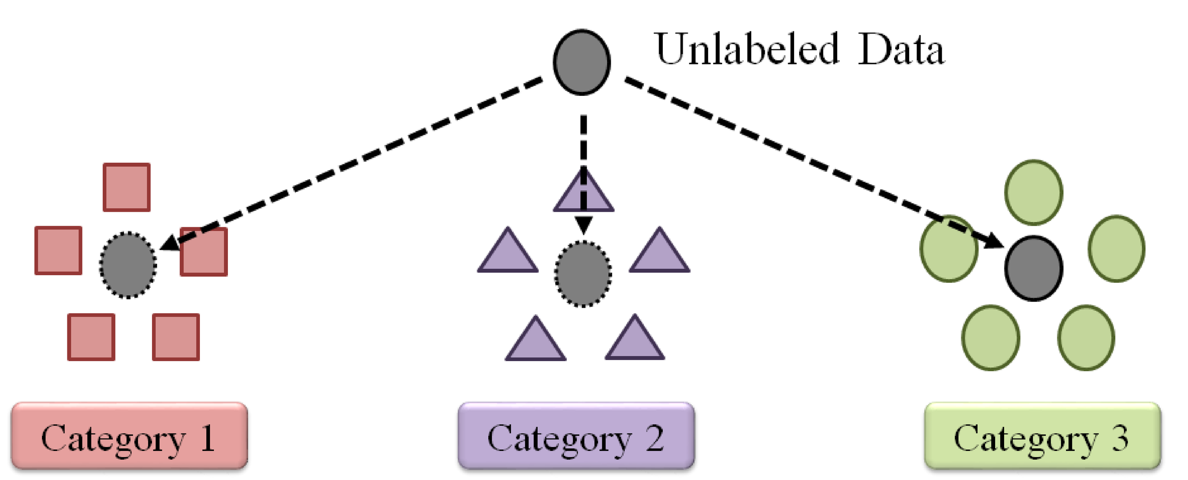
## Outline

In the absence of labeled data, domain adaptation algorithms leverage labeled data from a source domain to train a classifier for a target domain. We present a Domain Adaptive Hashing (DAH) network that exploits labeled source data and unlabeled target data to learn hash codes to classify the target data. The objectives of the DAH are:

- ✓ Supervised hash loss for source. Samples from same class have similar hash codes ('category sensitive' hashing).
- ✓ Unsupervised entropy loss for unlabeled target. A target hash code aligns with only one source category.
- ✓ Maximum Mean Discrepancy loss which aligns the source and target distributions.

## Motivation

- To measure average similarity of unlabeled data with K-Nearest Neighbors from each category




Similarity comparison with K-Nearest Neighbors

- But, neighbor search is brute force in $\mathbb{R}^d$ for large $d$
- Category based hashing reduces search space with 'category sensitive' property
- Hamming distance for hash values $\boldsymbol{h}_i$ and $\boldsymbol{h}_j$ where $\boldsymbol{h}_i, \boldsymbol{h}_j \in \{-1,+1\}^d$ is :

$$\mathrm{dist}_H(\boldsymbol{h}_i, \boldsymbol{h}_j) = \frac{1}{2}(d - \boldsymbol{h}_i^\top \boldsymbol{h}_j)$$

- Therefore, similarity between $\boldsymbol{h}_i$ and $\boldsymbol{h}_j$ is :

$$\langle \boldsymbol{h}_i, \boldsymbol{h}_j \rangle$$

- Apply similarity definition to train a deep hashing network

## Domain Adaptive Hashing (DAH)

Source $\mathcal{D}_s = \{\boldsymbol{x}_i^s, y_i^s\}_{i=1}^{n_s}$ Target $\mathcal{D}_t = \{\boldsymbol{x}_i^t\}_{i=1}^{n_t}$ $y_i^* \in Y := \{1, \dots, C\}$

### Supervised Hash Loss

Similarity $\mathcal{S} = \{s_{ij}\}^{n_s \times n_s}$, $s_{ij} \in \{0,1\}$ Hash vectors $\mathbf{H} = \{\boldsymbol{h}_i\}_{i=1}^{n_s}$, $\boldsymbol{h}_i \in \{-1,+1\}^d$

$$p(s_{ij}|\boldsymbol{h}_i, \boldsymbol{h}_j) = \begin{cases} \sigma(\boldsymbol{h}_i^\top \boldsymbol{h}_j), & s_{ij} = 1 \\ 1 - \sigma(\boldsymbol{h}_i^\top \boldsymbol{h}_j), & s_{ij} = 0, \end{cases} \qquad \sigma(x) = \frac{1}{1+e^{-x}}$$

$$\min_{\mathbf{H}} \mathcal{L}(\mathbf{H}) = -\log p(\mathcal{S}|\mathbf{H}) \qquad \text{Relaxing} \quad \boldsymbol{h}_i \implies \boldsymbol{u}_i \in \mathbb{R}^d, \quad \mathcal{U}_s = \{\boldsymbol{u}_i\}_{i=1}^{n_s}$$

$$\min_{\mathcal{U}_s} \mathcal{L}(\mathcal{U}_s) = -\sum_{s_{ij} \in \mathcal{S}} \Big( s_{ij} \boldsymbol{u}_i^\top \boldsymbol{u}_j - \log\big(1 + \exp(\boldsymbol{u}_i^\top \boldsymbol{u}_j)\big)\Big) + \sum_{i=1}^{n_s} \big|\big|\boldsymbol{u}_i - \mathrm{sgn}(\boldsymbol{u}_i)\big|\big|_2^2. \quad (1)$$

### Maximum Mean Discrepancy Loss

Fully connected layer outputs: $\mathcal{U}_s^l = \{\boldsymbol{u}_i^{s,l}\}_{i=1}^{n_s}$ and $\mathcal{U}_t^l = \{\boldsymbol{u}_i^{t,l}\}_{i=1}^{n_t}$

$$\mathcal{M}(\mathcal{U}_s, \mathcal{U}_t) = \sum_{l \in \mathcal{F}} \Big|\Big| \mathbb{E}[\phi(\boldsymbol{u}^{s,l})] - \mathbb{E}[\phi(\boldsymbol{u}^{t,l})] \Big|\Big|_{\mathcal{H}_k}^2 \quad (2)$$

### Unsupervised Entropy Loss

Given target output $\boldsymbol{u}_i^t$, $K$ source outputs $\{\boldsymbol{u}_k^{s_j}\}_{k=1}^K$ of class $j$

$$p_{ij} = \frac{\sum_{k=1}^K \exp(\boldsymbol{u}_i^{t\top} \boldsymbol{u}_k^{s_j})}{\sum_{l=1}^C \sum_{k=1}^K \exp(\boldsymbol{u}_i^{t\top} \boldsymbol{u}_k^{s_l})} \qquad \text{probability of assigning } \boldsymbol{u}_i^t \text{ to class } j$$

$$\mathcal{H}(\mathcal{U}_s, \mathcal{U}_t) = -\frac{1}{n_t} \sum_{i=1}^{n_t} \sum_{j=1}^{C} p_{ij} \log(p_{ij}) \quad (3)$$

From (1), (2) and (3)

$$\min_{\mathcal{U}} \mathcal{J} = \mathcal{L}(\mathcal{U}_s) + \gamma \mathcal{M}(\mathcal{U}_s, \mathcal{U}_t) + \eta \mathcal{H}(\mathcal{U}_s, \mathcal{U}_t)$$

## Introducing Office-Home Dataset

https://hemanthdv.github.io/officehome-dataset/


Dataset consists of images of everyday objects organized into 4 domains; `Art`: paintings, sketches and/or artistic depictions, `Clipart`: clipart images, `Product`: images without background and `Real-World`: regular images captured with a camera. Figure displays examples from 16 of the 65 categories. Dataset has around 15000 images.

## DAH Network

- Supervised Hash Loss for Source Data
- Maximum Mean Discrepancy (MMD) Loss
- Unsupervised Entropy Loss for Target Data

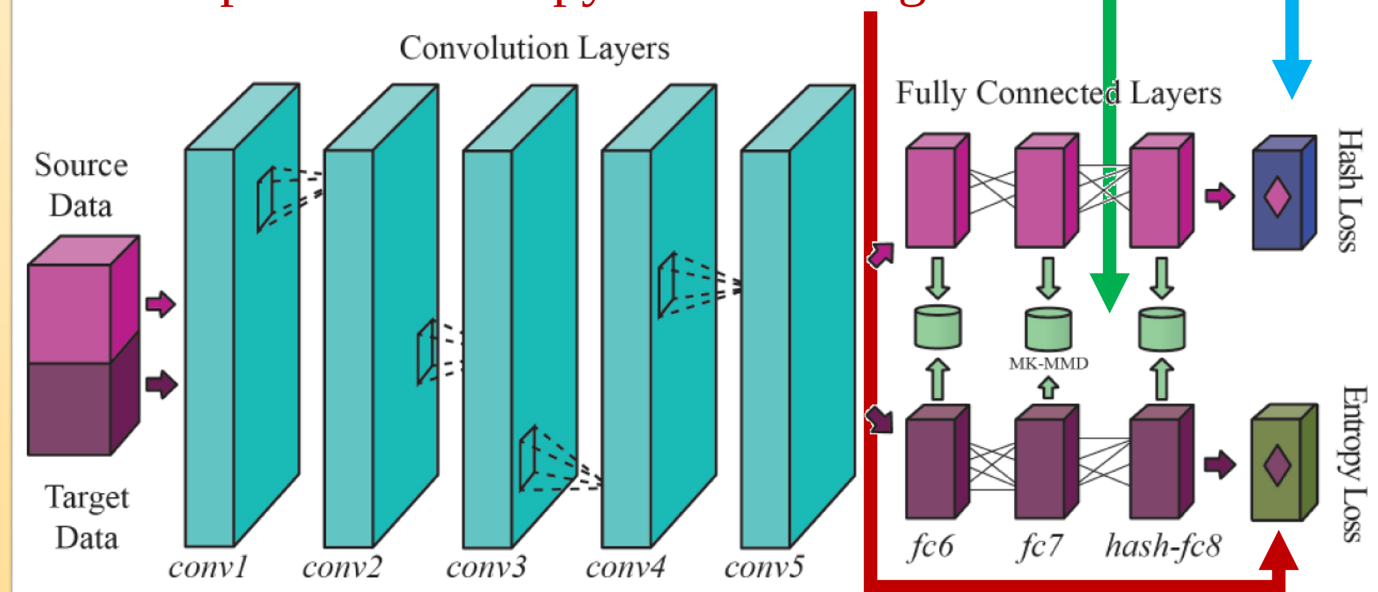



**Figure**: The Domain Adaptive Hash (DAH) network based on fine-tuning VGG-F (AlexNet) network. The MultiKernel-MMD loss aligns source and target feature distributions. The *hash-fc8* layer outputs hash vectors in *d* dimensions. The supervised hash loss estimates unique hash values for each category. The unsupervised entropy loss aligns a target hash value with one source category.

## Experiments

**Table**: Recognition accuracies (%) for domain adaptation experiments on the Office-Home dataset. {`Art` (**Ar**), `Clipart` (**Cl**), `Product` (**Pr**), `Real-World` (**Rw**)}. **Ar->Cl** implies **Ar** is source and **Cl** is target. *d*=64.

| Expt. | Ar→Cl | Ar→Pr | Ar→Rw | Cl→Ar | Cl→Pr | Cl→Rw |
|---|---|---|---|---|---|---|
| GFK | 21.60 | 31.72 | 38.83 | 21.63 | 34.94 | 34.20 |
| TCA | 19.93 | 32.08 | 35.71 | 19.00 | 31.36 | 31.74 |
| CORAL | 27.10 | 36.16 | 44.32 | 26.08 | 40.03 | 40.33 |
| JDA | 25.34 | 35.98 | 42.94 | 24.52 | 40.19 | 40.90 |
| DAN | 30.66 | 42.17 | 54.13 | 32.83 | 47.59 | 49.78 |
| DANN | 33.33 | 42.96 | 54.42 | 32.26 | 49.13 | 49.76 |
| DAH-e | 29.23 | 35.71 | 48.29 | 33.79 | 48.23 | 47.49 |
| DAH | 31.64 | 40.75 | 51.73 | 34.69 | 51.93 | 52.79 |

| Expt. | Pr→Ar | Pr→Cl | Pr→Rw | Rw→Ar | Rw→Cl | Rw→Pr |
|---|---|---|---|---|---|---|
| GFK | 24.52 | 25.73 | 42.92 | 32.88 | 28.96 | 50.89 |
| TCA | 21.92 | 23.64 | 42.12 | 30.74 | 27.15 | 48.68 |
| CORAL | 27.77 | 30.54 | 50.61 | 38.48 | 36.36 | 57.11 |
| JDA | 25.96 | 32.72 | 49.25 | 35.10 | 35.35 | 55.35 |
| DAN | 29.07 | 34.05 | 56.70 | 43.58 | 38.25 | 62.73 |
| DANN | 30.49 | 38.14 | 56.76 | 44.71 | 42.66 | 64.65 |
| DAH-e | 29.87 | 38.76 | 55.63 | 41.16 | 44.99 | 59.07 |
| DAH | 29.91 | 39.63 | 60.71 | 44.99 | 45.13 | 62.54 |

## References

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Acknowledgements: Center for Cognitive Ubiquitous Computing (CUbiC) at ASU and the National Science Foundation (NSF)