Discovering Latent Domains for Multisource Domain Adaptation

Judy Hoffman[1,2], Brian Kulis[3], Trevor Darrell[1,2], Kate Saenko[4]

[1]UC Berkeley; [2]ICSI; [3]Ohio State University; [4]University of Massachusetts, Lowell

Women in Machine Learning Workshop: December 3, 2012

Background: Object Recognition

Training Images

Background: Object Recognition

Test Image: Correct!

Background: Object Recognition

Test Image: Incorrect

Background: Domain Adaptation

- Domain adaptation helps bridge performance gap when test data is drawn from different distribution (domain) than training data.

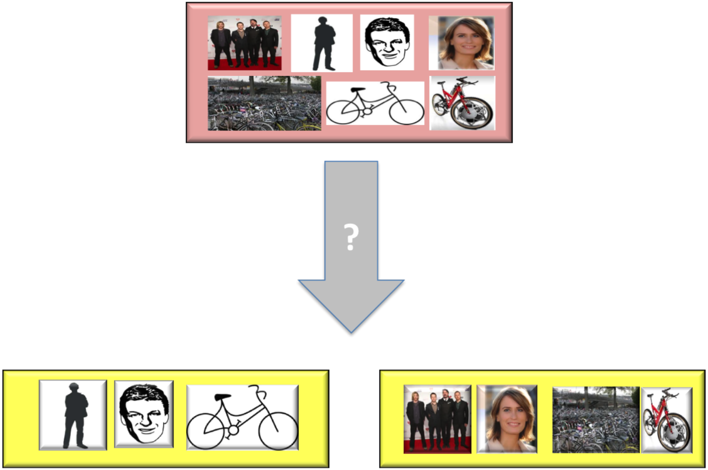
Background: Domain Adaptation

- Domain adaptation helps bridge performance gap when test data is drawn from different distribution (domain) than training data.
- Previous Methods Include
  - Feature Transformation Techniques: Saenko (ECCV 2010), Kulis (CVPR 2011), Gopalan (ICCV 2011), Gong (CVPR 2012), ...
  - Parameter Adaptation Techniques: Yang (ACM Multimedia 2007), Duan (CVPR 2009), Bergamo (NIPS 2010), Ayatar (ICCV 2011), ...

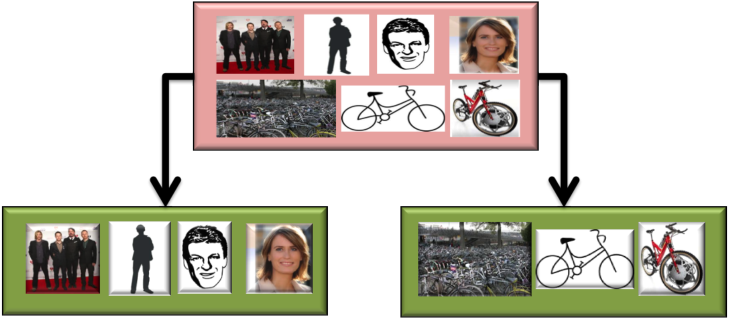
Background: Domain Adaptation

- Domain adaptation helps bridge performance gap when test data is drawn from different distribution (domain) than training data.
- Previous Methods Include
  - Feature Transformation Techniques: Saenko (ECCV 2010), Kulis (CVPR 2011), Gopalan (ICCV 2011), Gong (CVPR 2012), ...
  - Parameter Adaptation Techniques: Yang (ACM Multimedia 2007), Duan (CVPR 2009), Bergamo (NIPS 2010), Ayatar (ICCV 2011), ...
- **All** previous methods require datasets separated into **homogeneous domains**

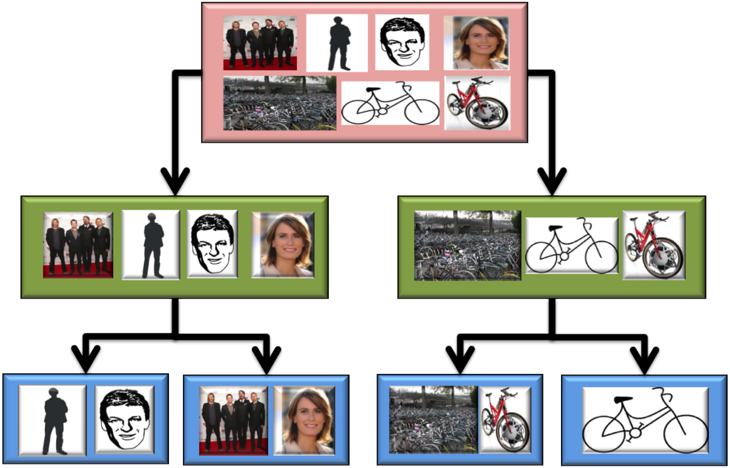
Goal: Separate heterogeneous data into homogeneous domains



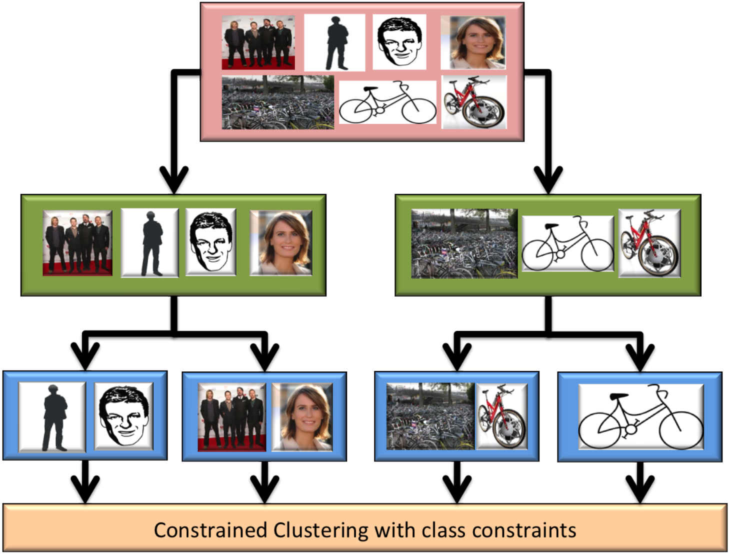
Method 1/4: Separate by category label



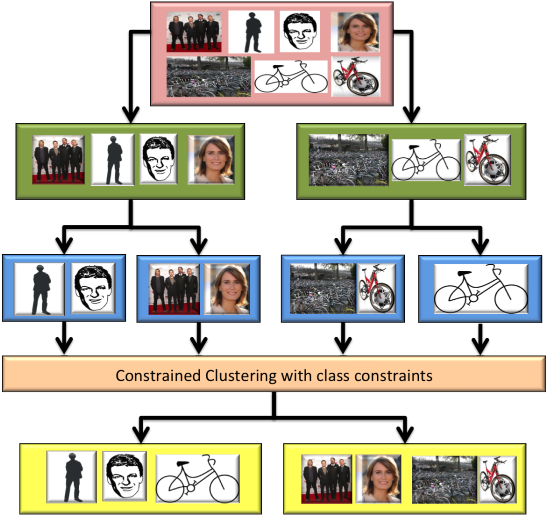
Method 2/4: Cluster each category independently



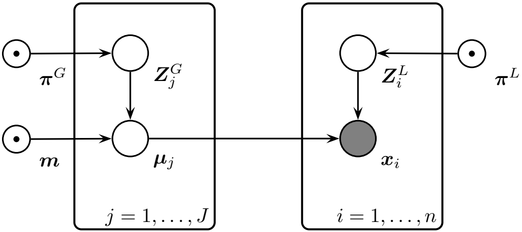
Method 3/4: Constrained clustering algorithm



Method 4/4: Iterate steps (2-3) - Output domains



Hierarchical Gaussian Mixture Model



- **x** feature vector (with known label y)
- μ mean of local cluster
- Z^L assignments for local clusters
- Z^G assignments for global clusters
- **m** mean of global cluster

Optimization Formulation

$$
\begin{aligned}
\min_{\mathbf{Z}^G,\mathbf{Z}^L,\boldsymbol{\mu},\mathbf{m}} \quad & \sum_{i=1}^{n}\sum_{j=1}^{J}\mathbf{Z}^L_{ij}(x_i-\mu_j)^2+\sum_{j=1}^{J}\sum_{k=1}^{S}\mathbf{Z}^G_{jk}(\mu_j-\mathbf{m}_k)^2 \\
\text{subject to:} \quad & \forall j,k: \;\; \mathbf{Z}^G_{jk}\in\{0,1\}, \quad \forall i,j: \;\; \mathbf{Z}^L_{ij}\in\{0,1\} \\
& \forall j: \;\; \sum_{k=1}^{S}\mathbf{Z}^G_{jk}=1, \quad \forall i: \;\; \sum_{j=1}^{J}\mathbf{Z}^L_{ij}=1
\end{aligned}
$$

Optimization Formulation

$$\min_{\mathbf{Z}^G,\mathbf{Z}^L,\boldsymbol{\mu},\mathbf{m}} \quad \sum_{i=1}^{n}\sum_{j=1}^{J}\mathbf{Z}^L_{ij}(x_i-\mu_j)^2+\sum_{j=1}^{J}\sum_{k=1}^{S}\mathbf{Z}^G_{jk}(\mu_j-\mathbf{m}_k)^2$$

subject to:

$$\forall j,k:\ \ \mathbf{Z}^G_{jk}\in\{0,1\},\quad \forall i,j:\ \ \mathbf{Z}^L_{ij}\in\{0,1\}$$

$$\forall j:\ \ \sum_{k=1}^{S}\mathbf{Z}^G_{jk}=1,\quad \forall i:\ \ \sum_{j=1}^{J}\mathbf{Z}^L_{ij}=1$$

$$\forall j:\ \ \sum_{i=1}^{n}\mathbb{I}(y_i\neq \mathrm{label}(j))\mathbf{Z}^L_{ij}=0$$

category separated

Optimization Formulation

$$\min_{\mathbf{Z}^G,\mathbf{Z}^L,\boldsymbol{\mu},\mathbf{m}} \quad \sum_{i=1}^{n}\sum_{j=1}^{J}\mathbf{Z}^L_{ij}(x_i-\mu_j)^2+\sum_{j=1}^{J}\sum_{k=1}^{S}\mathbf{Z}^G_{jk}(\mu_j-\mathbf{m}_k)^2$$

subject to: $\forall j,k: \ \mathbf{Z}^G_{jk}\in\{0,1\}, \quad \forall i,j: \ \mathbf{Z}^L_{ij}\in\{0,1\}$

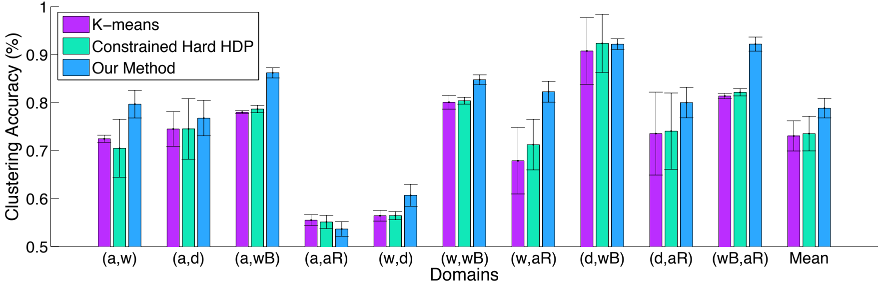
$$\forall j: \ \sum_{k=1}^{S}\mathbf{Z}^G_{jk}=1, \quad \forall i: \ \sum_{j=1}^{J}\mathbf{Z}^L_{ij}=1$$

$$\forall j: \ \sum_{i=1}^{n}\mathbb{I}(y_i\neq \text{label}(j))\mathbf{Z}^L_{ij}=0$$ category separated

$$\forall k: \ \sum_{c=1}^{K}\sum_{j=1}^{J}\mathbb{I}(\text{label}(j)=c)\mathbf{Z}^G_{jk}=1$$ do-not-link

Results

- *Office* dataset with three known domains: `amazon`(a), `webcam`(w), `dslr`(d)
- 31 Categories, 10-20 images per category



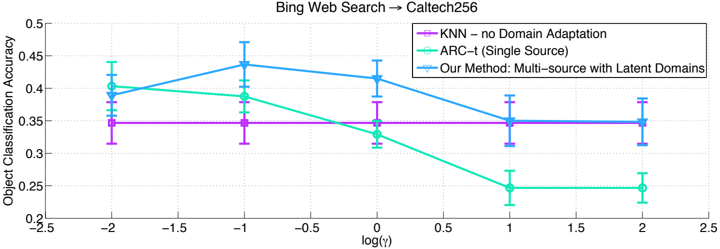
Results

- *Bing* web search data set. Heterogeneous and weakly-labeled data.
- 30 Categories, 50 Images per Category, Set Number of Domains $= 3$

(a) "Cartoon Images" (b) "Cluttered Scenes" (c) "Product Images"

Results

- *Bing* web search data set. Heterogeneous and weakly-labeled data.
- 30 Categories, 50 Images per Category, Set Number of Domains = 3



J. Hoffman, B. Kulis, T. Darrell, K. Saenko. "Discovering Latent Domains for Multisource Domain Adaptation." European Conference in Computer Vision (ECCV), 2012.

Conclusion

- Domain adaptation algorithms can bridge the performance gap when train and test data are drawn from different domains.

Conclusion

- Domain adaptation algorithms can bridge the performance gap when train and test data are drawn from different domains.
- Current multisource adaptation methods require known domain labels.

Conclusion

- Domain adaptation algorithms can bridge the performance gap when train and test data are drawn from different domains.
- Current multisource adaptation methods require known domain labels.
- Using a constrained hierarchical gaussian mixture model we are able to learn latent domain labels.

Conclusion

- Domain adaptation algorithms can bridge the performance gap when train and test data are drawn from different domains.
- Current multisource adaptation methods require known domain labels.
- Using a constrained hierarchical gaussian mixture model we are able to learn latent domain labels.
- See our EECV paper for more details and our full multisource domain adaptation algorithm.

Conclusion

- Domain adaptation algorithms can bridge the performance gap when train and test data are drawn from different domains.
- Current multisource adaptation methods require known domain labels.
- Using a constrained hierarchical gaussian mixture model we are able to learn latent domain labels.
- See our EECV paper for more details and our full multisource domain adaptation algorithm.

Thank you!