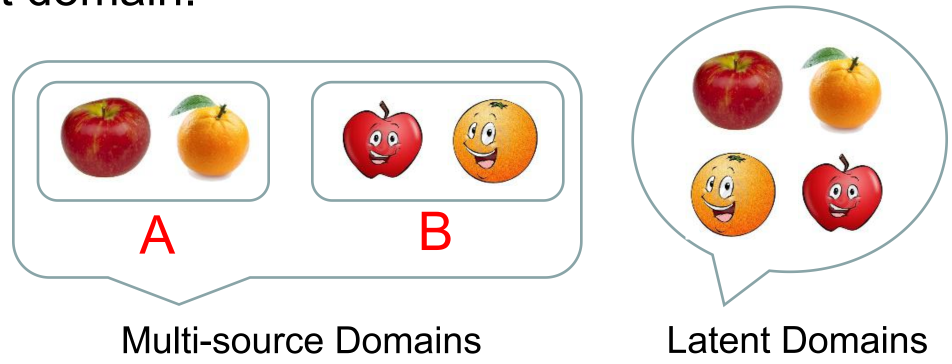
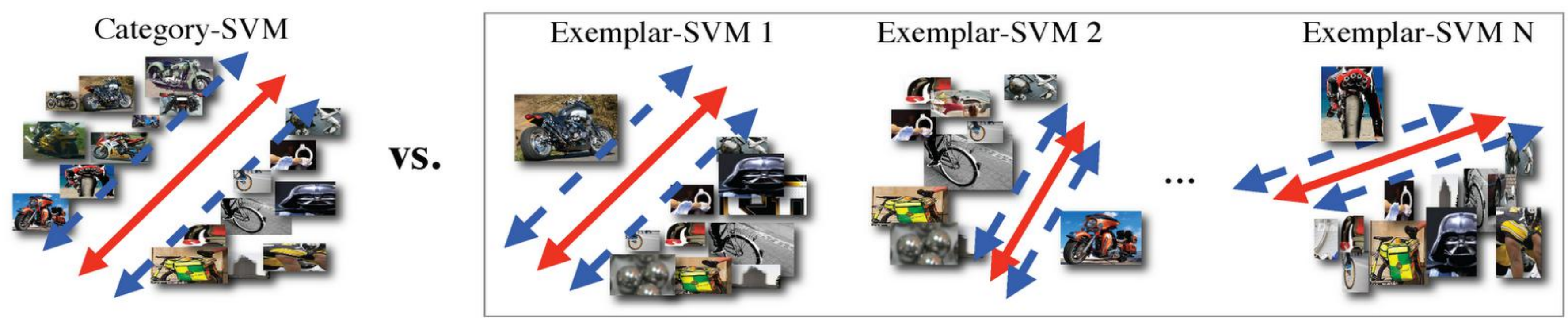
Exploiting Low-rank Structure from Latent Domains for Domain Generalization

Zheng Xu [1], Wen Li [1], Li Niu [1] and Dong Xu [1]
[1] Nanyang Technological University (NTU), Singapore

- Latent domains are characterized by different hidden factors (e.g., pose, illumination). Domain generalization is to generalize latent source domains to unknown target domain.



- Since each sample can be treated as an atomic domain, exemplar classifiers [1] can be readily incorporated into our proposed method.



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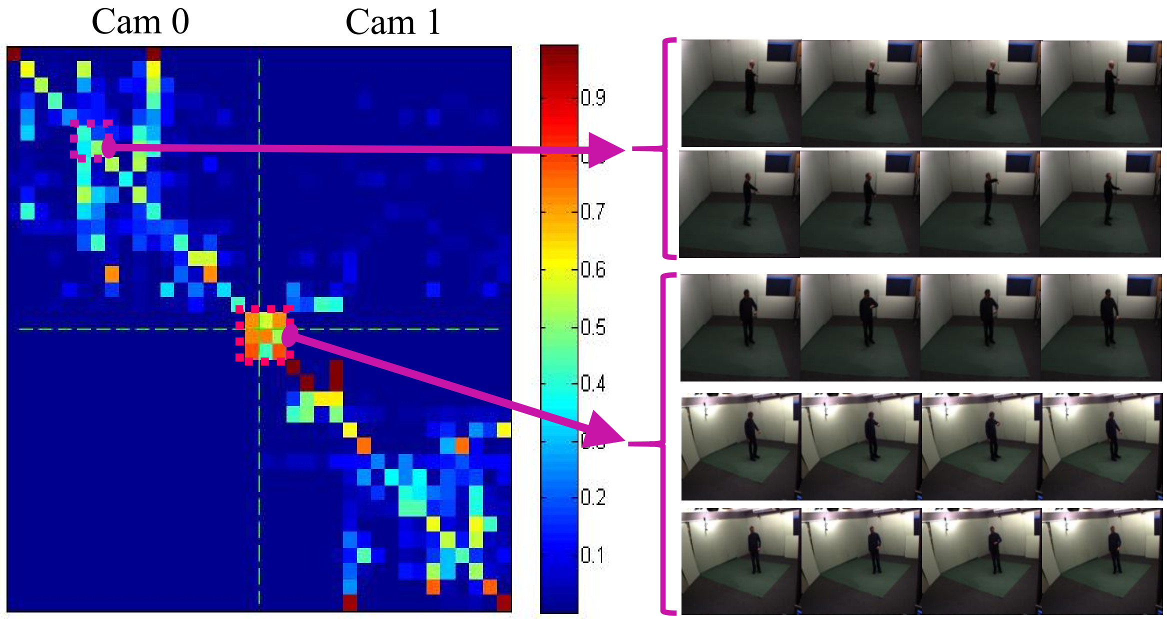
[1] Malisiewicz, T., Gupta, A., Efros, A.A.: Ensemble of exemplar-svms for object detection and beyond. In: ICCV. (2011)

➢ Low rank assumption:

Likelihood matrix is $\mathbf{G} = [g_{ij}] \in \mathbb{R}^{n \times n}$,
where each g_{ij} is the likelihood of the *i*-th positive training sample by using the *j*-th exemplar exemplar classifier.
Likelihood matrix **G** is assumed to be low-rank in ideal cases.



(a) Likelihood matrix **G** (b) Video frames

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An illustration of the likelihood matrix **G**, where we observe the block diagonal property of **G** in (a), and the frames from the videos corresponding to the two blocks with large values in **G** are also visually similar to each other in (b).

Domain Generalization

$$\min_{\mathbf{W}} J(\mathbf{W}) = \min_{\mathbf{W}} \|\mathbf{W}\|_F^2 + C_1 \sum_{i=1}^{n} l(\mathbf{w}_i, \mathbf{s}_i^+) + C_2 \sum_{i=1}^{n} \sum_{j=1}^{m} l(\mathbf{w}_i, \mathbf{s}_j^-)$$

loss on positive training samples

loss on negative training samples

$$\min_{\mathbf{W}} J(\mathbf{W}) + \lambda \|\mathbf{G}\|_*$$

use nuclear norm to approximate the rank of likelihood matrix

$$\min_{\mathbf{W},\mathbf{F}} J(\mathbf{W}) + \lambda_1 \|\mathbf{F}\|_* + \lambda_2 \|\mathbf{F} - \mathbf{G}\|_F^2$$

Optimize **W** and **F** alternatively:

- Fix W, use gradient descent to solve **F**
- Fix F, use SVT to solve **W**

introduce intermediate matrix **F** for ease of optimization

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➢ Domain Adaptation (use unlabeled target domain data)

Inspired by Domain Adaptation Machine (DAM) [2], we learn a target classifier on target domain by using prelearned exemplar classifiers.

$$\min_{\tilde{\mathbf{w}},b,\xi_i,\xi_i^*,\mathbf{f}} \quad \frac{1}{2}\|\tilde{\mathbf{w}}\|^2 + C\sum_{i=1}^{u}(\xi_i+\xi_i^*) + \frac{\lambda}{2}\Omega(\mathbf{f})$$

$$\text{s.t.} \quad \tilde{\mathbf{w}}'\phi(\mathbf{t}_i) + b - f_i \leq \epsilon + \xi_i, \quad \xi_i \geq 0$$

$$f_i - \tilde{\mathbf{w}}'\phi(\mathbf{t}_i) - b \leq \epsilon + \xi_i^*, \quad \xi_i^* \geq 0$$

intermediate variable **f**

where $\Omega(\mathbf{f}) = \sum_{j=1}^{u} \sum_{i:i\in\mathcal{T}(\mathbf{t}_j)} \tilde{v}_i \left(f_j - p(\mathbf{t}_j|\mathbf{w}_i)\right)^2$

MMD weight

prelearned exemplar classifier decision values

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[2] Duan, L., Tsang, I., Xu, D., Chua, T.: Domain adaptation from multiple sources: A domain-dependent regularization approach. T-NNLS 23(3) (2012) 504–518

Experiments: Domain Generalization

- Dataset && Features
  - Office-Caltech:
    - 4 domains: Amazon, Caltech-256, digital SLR camera and webcam
    - 4096-dim $DeCAF_6$ feature.
  - IXMAS:
    - 5 domain: five cameras from different view-points.
    - 5000-dim dense trajectories features by using K-means clustering to build a codebook with 1,000 clusters for each of the five descriptors.
- Experimental setting

We mix several domains as the source domain for training classifiers and use the remaining domains as the target domain for testing.

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Experiments: Domain Generalization

- Baselines
  - SVM
  - sub-categorization [Hoai et al. CVPR 2013]
  - undo-bias [Khosla et al. ECCV 2012]
  - discover latent domain:

    [Hoffman et al. ECCV 2012] [Gong et al. NIPS 2013]

    two methods to utilize discovered latent domains:
    - match: select the most relevant domain based on MMD
    - ensemble: use domain probabilities to re-weight decision values
  - our special case (without low-rank): exemplar classifiers

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Experiments: Domain Generalization

- Results

Recognition accuracy of domain generalization

Source	A,C	D,W	C,D,W	Cam 0,1	Cam 2,3,4	Cam 0,1,2,3
Target	D,W	A,C	A	Cam 2,3,4	Cam 0,1	Cam 4
SVM	82.68	76.06	90.73	71.70	63.83	56.61
Sub-Cate	82.61	78.65	90.75	78.11	76.90	64.04
Undo-Bias	80.49	69.98	90.98	69.03	60.56	56.84
Hoffman(Ensemble)	79.23	68.06	80.75	71.55	51.02	49.70
Hoffman(Match)	71.26	61.42	72.03	63.81	60.04	48.91
Gong(Ensemble)	84.01	77.11	91.65	75.04	68.98	57.64
Gong(Match)	80.63	76.52	90.84	71.59	60.73	55.37
E-SVMs	82.73	80.85	91.47	76.86	68.04	72.98
LRE-SVMs	84.74	81.27	92.16	79.96	80.15	74.97

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Experiments: Domain Adaptation

- Baselines

  - Domain adaptation baselines:

    1) DIP [Baktashmotlagh et al. ICCV 2013]
    2) KMM [Huang et al. NIPS 2007]
    3) GFK [Gong et al. CVPR 2012]
    4) SGF [Gopalan et al. ICCV 2011]
    5) SA [Fernando et al. ICCV 2013]

  - Discover latent domains first and then use domain adaptation methods [Hoffman et al. ECCV 2012] [Gong et al. NIPS 2013]

  - Discover latent domains first and then use DAM [Duan et al. T-NN 2012]

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Experiments: Domain Adaptation

- Results

Recognition accuracy of domain adaptation

Source	Cam 0,1	Cam 2,3,4	Cam 0,1,2,3
Target	Cam 2,3,4	Cam 0,1	Cam 4
KMM	73.92	42.22	52.57
SGF	60.37	69.04	28.66
GFK	64.87	55.53	42.16
DIP	65.20	70.03	62.92
SA	73.35	77.92	49.59
GFK Hoffman(Match)	61.33	58.77	46.62
GFK Hoffman(Ensemble)	65.32	55.01	42.09
GFK Gong(Match)	65.32	64.43	47.22
GFK Gong(Ensemble)	69.12	68.87	51.30
SA Hoffman(Match)	58.49	56.27	55.87
SA Hoffman(Ensemble)	63.01	62.05	62.69
SA Gong(Match)	66.27	67.00	63.01
SA Gong(Ensemble)	71.04	76.64	72.26
DAM Hoffman	77.92	76.99	53.76
DAM Gong	77.32	73.94	62.47
LRE-SVMs-DA	81.79	82.43	75.26

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Thanks for your attention!