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A Unified Framework for Distance-Aware Domain Adaptation

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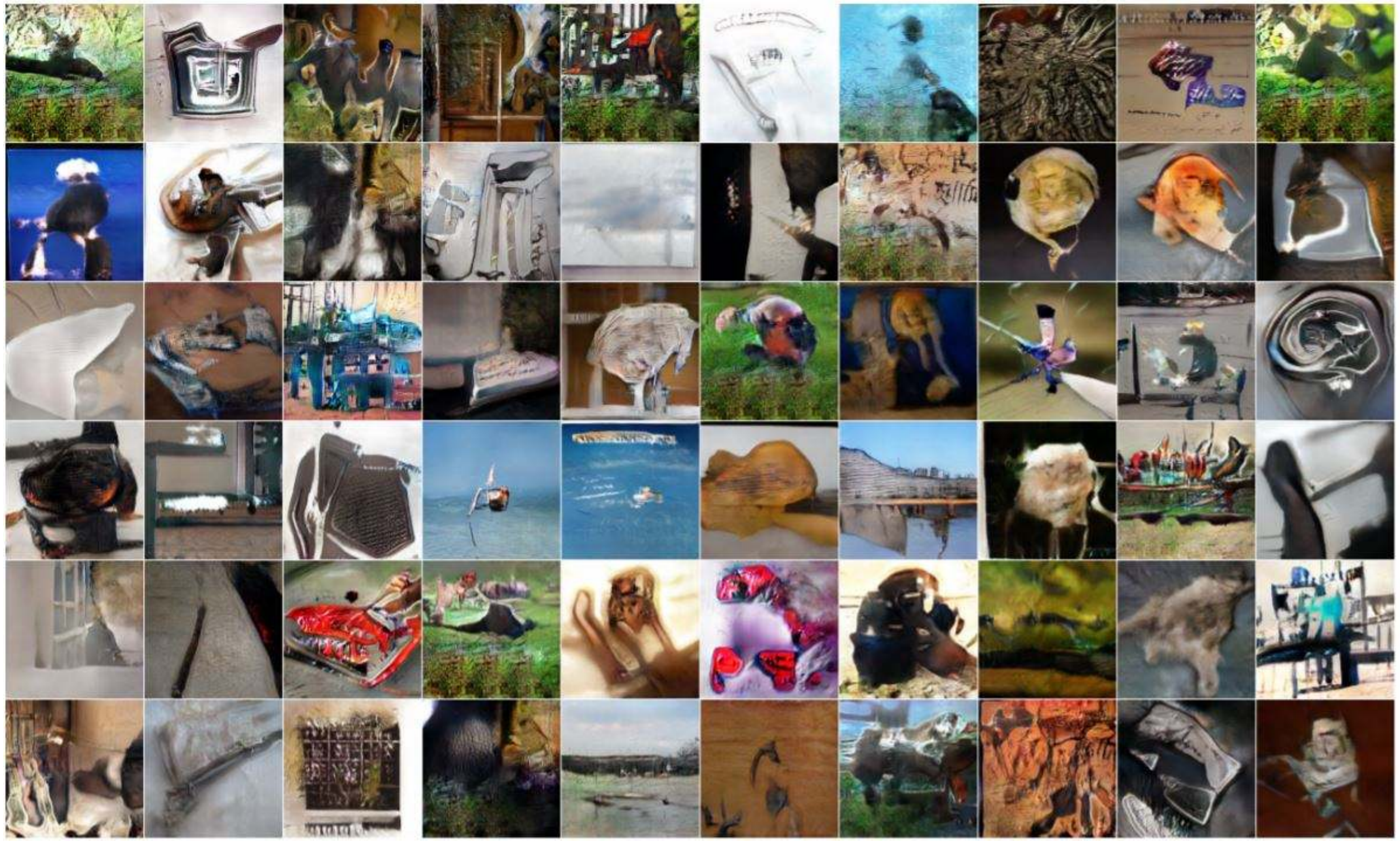
Motivation

Why we need Domain adaptation (DA) ?

- Labeling a huge amount of training data is expensive and time consuming.



Motivation

Why we need Domain adaptation (DA) ?

- Labeling a huge amount of training data is expensive and time consuming.
- Directly generalizing the models trained on a labeled source domain to another related but unlabeled target domain may often not perform well.

Mismatch

Source domain

Target domain

Proposed Method

Cross-Domain Distance

$$\min \left\| \frac{1}{n_s} \sum_{i=1}^{n_s} A^T x_i - \frac{1}{n_t} \sum_{j=1}^{n_t} A^T x_j \right\|^2$$

$$\min \sum_{c=1}^{C} \left\| \frac{1}{n_s^{(c)}} \sum_{x_i \in X_s^{(c)}} A^T x_i - \frac{1}{n_t^{(c)}} \sum_{x_j \in X_t^{(c)}} A^T x_j \right\|^2$$

JDA
[Long et al, ICCV'13]

$$\max \sum_{c=1}^{C} \left\| \frac{1}{n_s^{(c)}} \sum_{x_i \in D_s^{(c)}} A^T x_i - \frac{1}{\sum_{r \in \{\{1 \ldots C\}-\{c\}\}} n_t^{(r)}} \sum_{x_j \in D_t^{(r)}} A^T x_j \right\|^2$$

$$\max \sum_{c=1}^{C} \left\| \frac{1}{n_t^{(c)}} \sum_{x_i \in D_t^{(c)}} A^T x_i - \frac{1}{\sum_{r \in \{\{1 \ldots C\}-\{c\}\}} n_s^{(r)}} \sum_{x_j \in D_s^{(r)}} A^T x_j \right\|^2$$

repulsive force distance

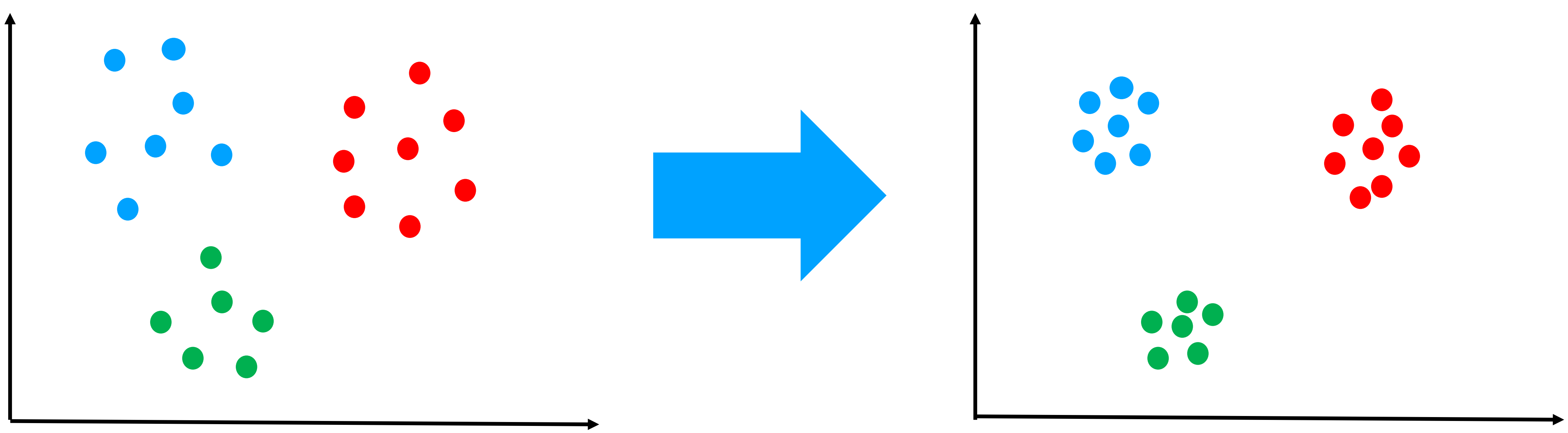
Proposed Method

Intra-class Distance

$$\min \sum_{c=1}^{C} \sum_{i=1}^{n_s^c} \left\| A^T y_s^{ci} \left(x_s^i - \mu_{s,c} \right) \right\|^2$$

$$\min \sum_{c=1}^{C} \sum_{i=1}^{n_t^c} \left\| A^T y_t^{ci} \left(x_t^i - \mu_{t,c} \right) \right\|^2$$

increase the compactness of both domains



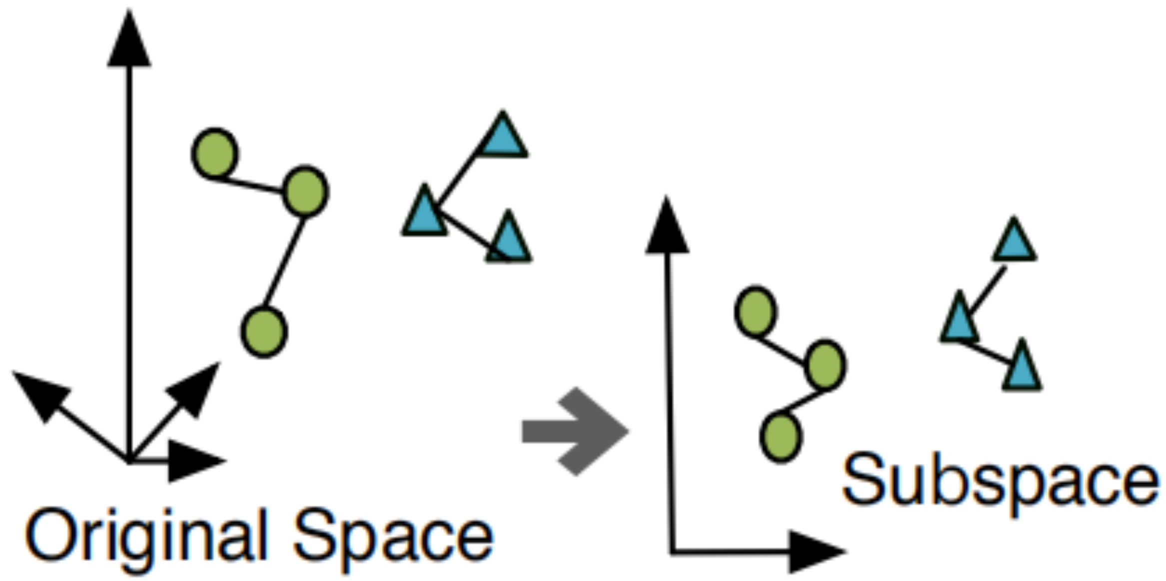
Proposed Method

Second-Order Statistics Distance

$$\min \operatorname{tr}\left(A^T X_s H_s X_s^T A - A^T X_t H_t X_t^T A\right)$$

Laplacian Regularization

$$\min \operatorname{tr}\left(A^T X L X^T A\right)$$

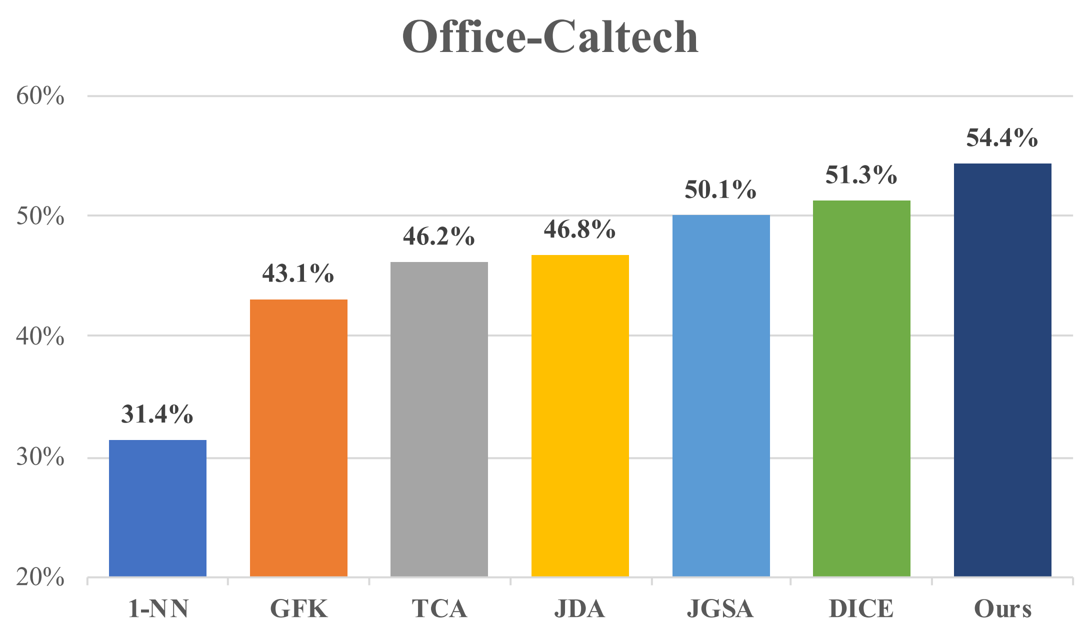


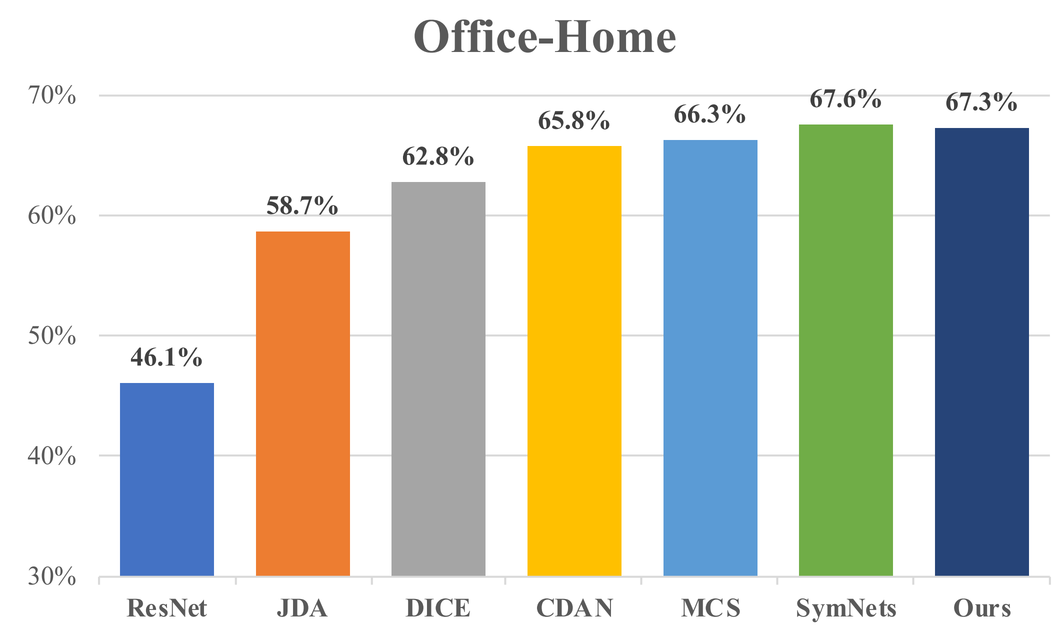
Experiments

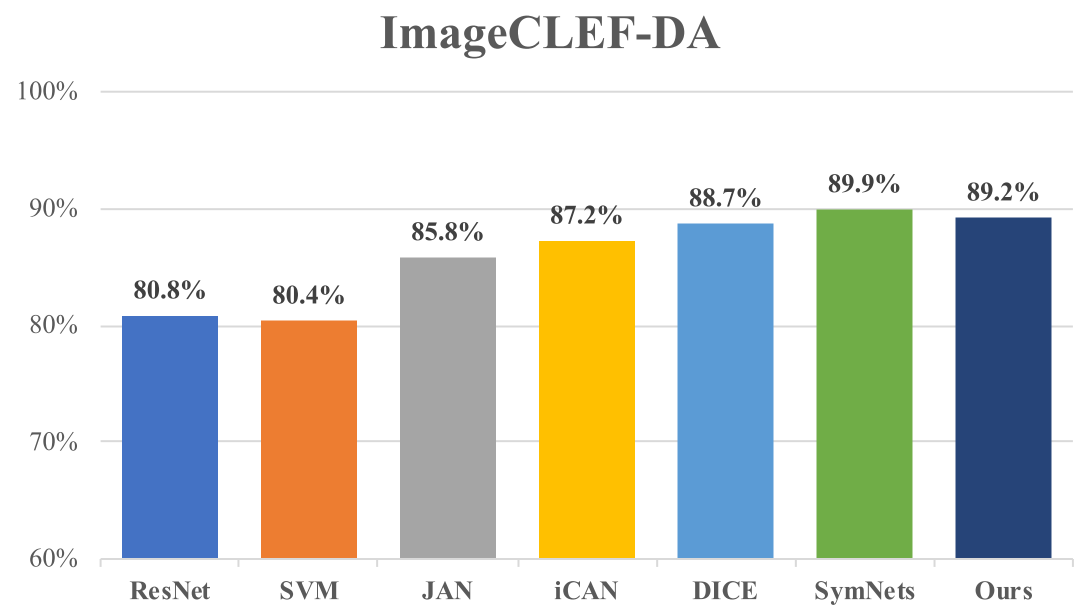
- Office31 + Caltech (Indoor Images, 4 domains)
- ImageCLEF-DA (Natural Images, 3 domains)
- Office-Home (Everyday Objects Images, 4 domains)

Features: SURF800, DeCAF6 and ResNet-50

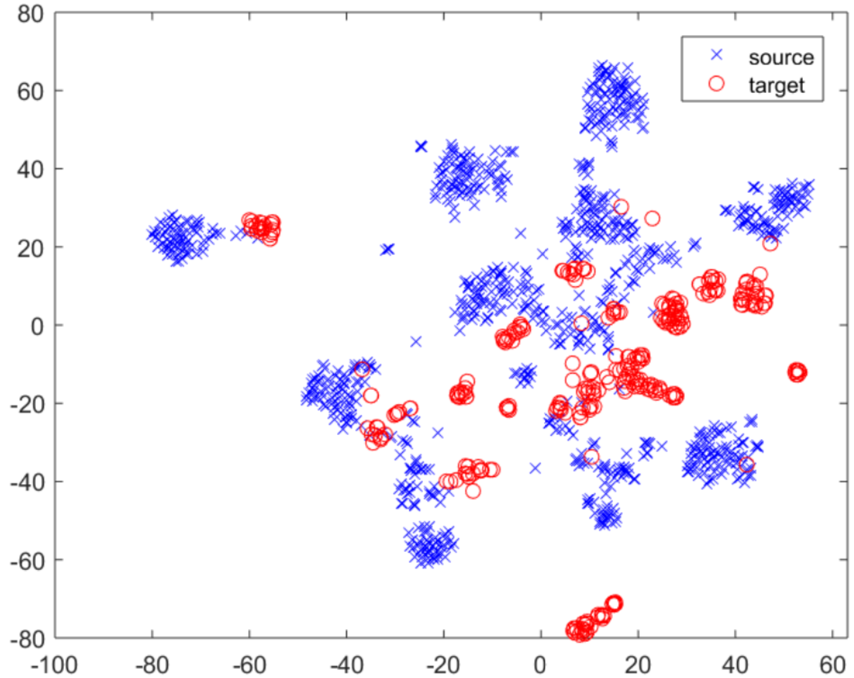
Results and Discussions



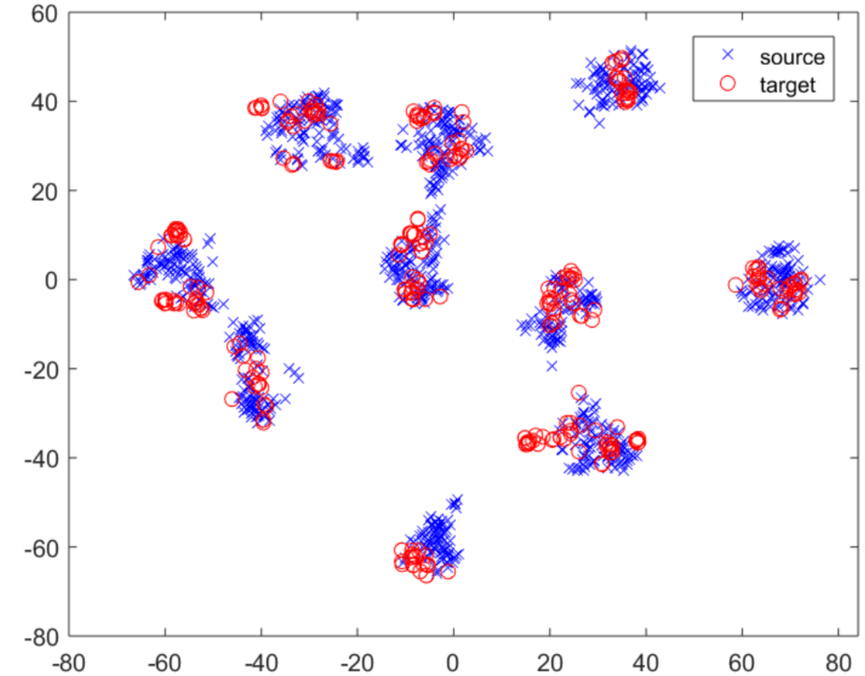




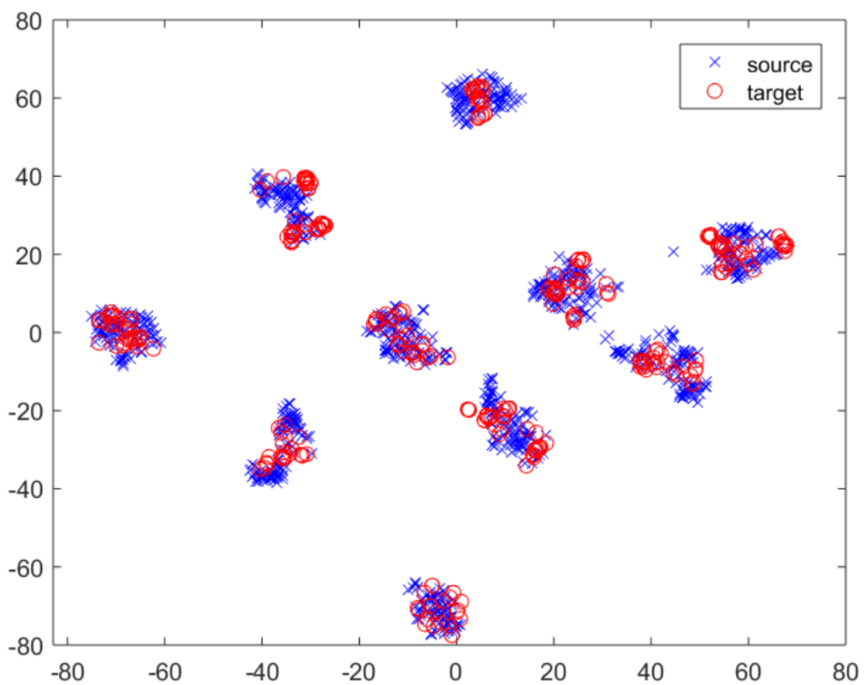
t-SNE



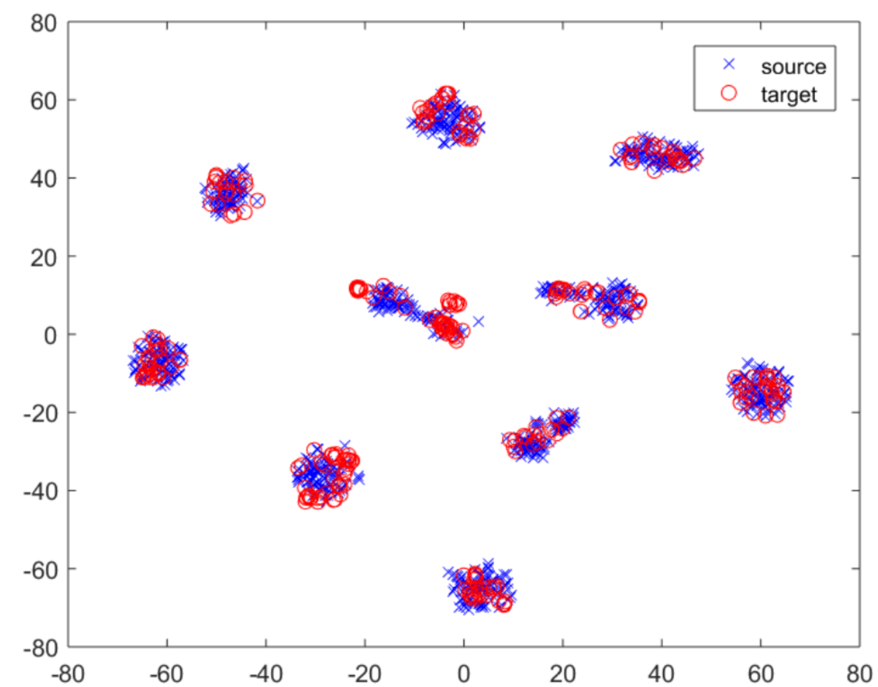
No adaptation



JDA



DICE



Ours

Summary

In this paper, we proposed a novel domain adaptation framework, which learns a feature projection to map the source domain and the target domain into a latent space. After projection to the latent space,

- Cross-domain distance is minimized.
- Intra-class distance is decreased and inter-class distance is increased simultaneously to ensure domain-invariant.
- Manifold structure of data are still maintained with the geometry property can be further exploited.
- The difference of variance between two domains are minimized to explore more hidden data.

Thank you.