UNSUPERVISED DOMAIN ADAPTATION WITH JOINT SUPERVISED SPARSE CODING AND DISCRIMINATIVE REGULARIZATION TERM

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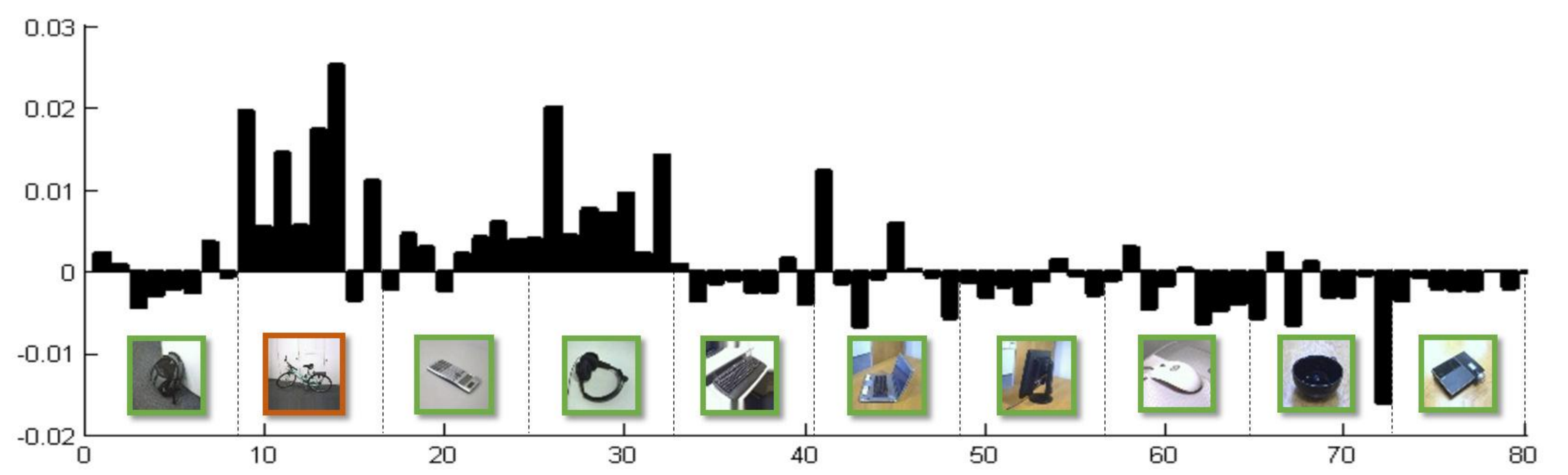
Introduction

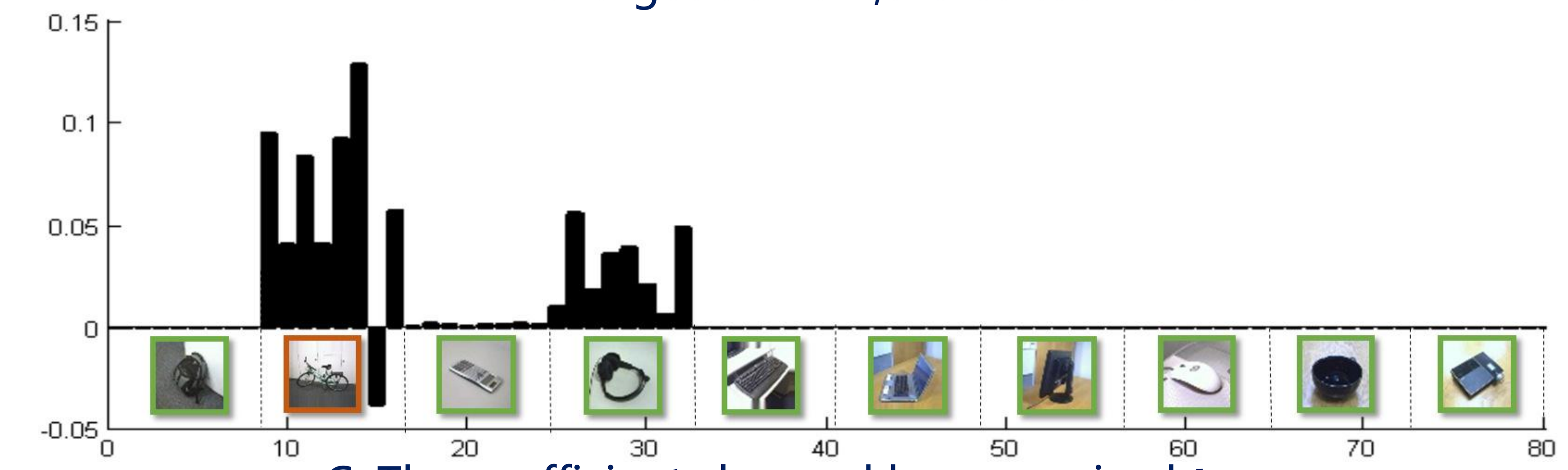
Situation:

- Source and target data are from different distributions.
- Unsupervised domain adaptation: no labels are available in target domain.



A. The coefficients learned by unsupervised $l_{2,1}$ norm

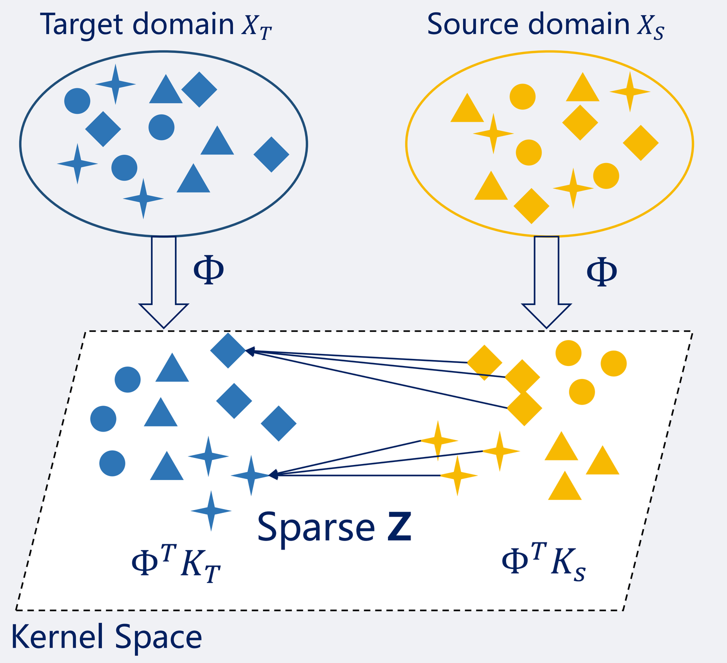
B. Target domain,the Caltech 256



C. The coefficients learned by supervised $l_{2,1}$ norm

Methods

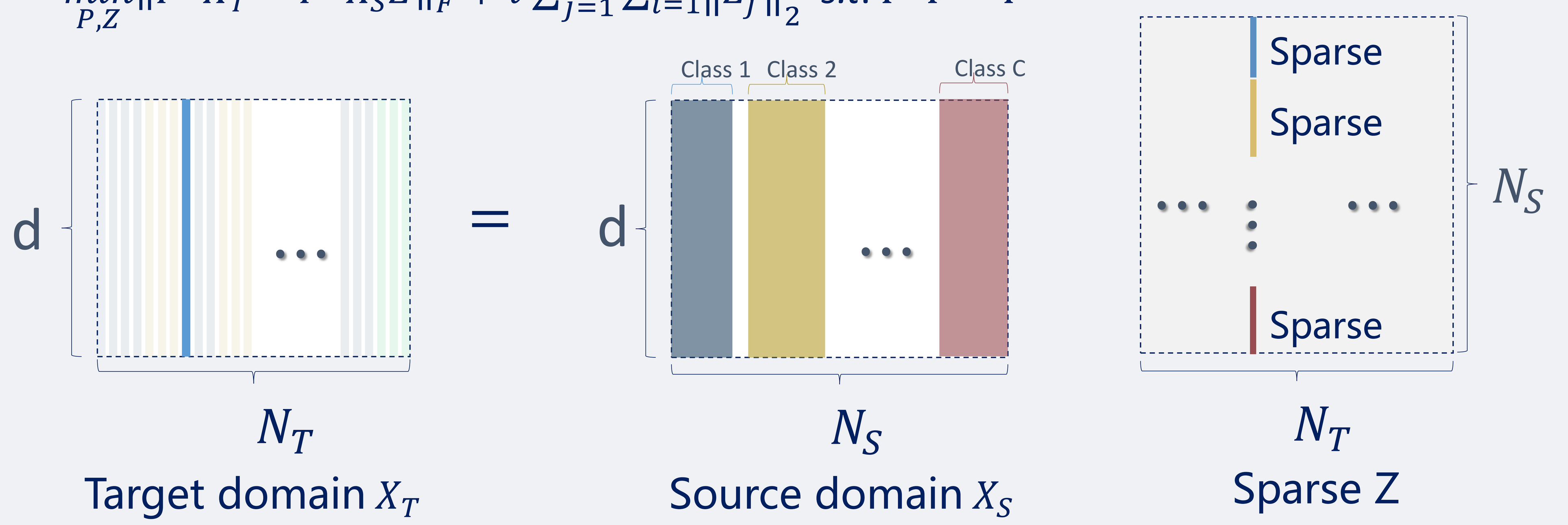
Motivation: Represent target domain using source domain data as much of the same class as possible.



Key points:

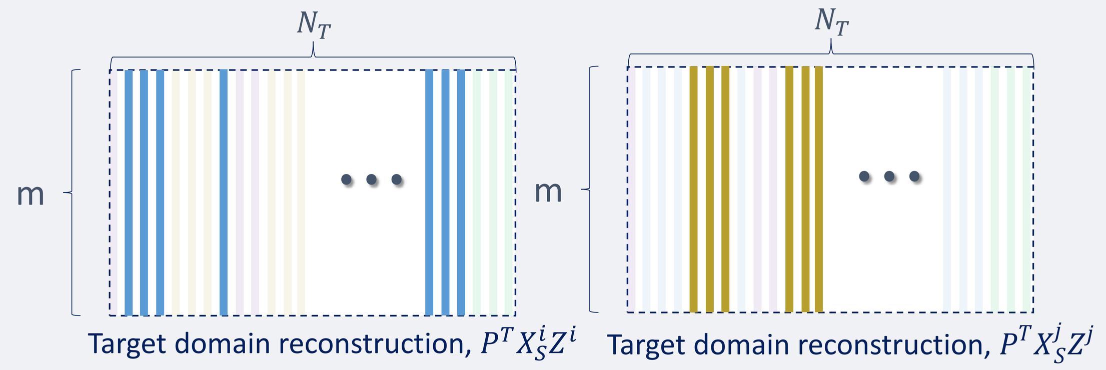
- Restrict the coefficients from the same class to be similar while forcing the ones from different classes to be sparse through supervised $l_{2,1}$ norm.

$$\min_{P,Z} \|P^T X_T - P^T X_S Z\|_F^2 + \tau \sum_{j=1}^{N_T} \sum_{i=1}^{C} \|Z_j^i\|_2 \quad s.t.\ \mathrm{P^T P = I}$$



- Enforce the target domain reconstruction differences from different source classes to be maximized.

$$\max_{P,Z} \|P^T X_S^i Z^i - P^T X_S^j Z^j\|_F^2$$



- Kernelized, $P = \varphi(X)\Phi$, where $X = [X_S, X_T]$,$\mathrm{K} = \varphi(X)^T\varphi(X)$,$K_S = \varphi(X)^T\varphi(X_S)$, $K_T = \varphi(X)^T\varphi(X_T)$

$$\min_{\Phi,Z} \|\Phi^T K_T - \Phi^T K_S Z\|_F^2 + \tau \sum_{j=1}^{N_T} \sum_{i=1}^{C} \|Z_j^i\|_2 - \gamma \sum_{i,j}^{C} \|\Phi^T X_S^i Z^i - \Phi^T X_S^j Z^j\|_2$$
$$s.t.\ \Phi^\mathrm{T} \mathrm{K} \Phi = \mathrm{I_M}$$

Results

- **Data** The 4DA database consists of four datasets including A (Amazon), W (Webcam), D (DSLR) and C (Caltech-256)
- **Methods**
  - **LTSL** Discriminative transfer subspace learning via low-rank and sparse representation,2016.
  - **TSL** Generalized transfer subspace learning through low-rank constraint, 2014.
  - **LSDT** Latent sparse domain transfer learning for visual adaptation,2016.
- **Experiments**

12 combinations of each two domains, and 20 random splits of data are used

4DA SURF	LTSL(LDA)+RLS	LTSL(LDA)+KNN	TSL_LRSR+RLS	TSL_LRSR+KNN	LSDT	DDA
A→C	22.4±0.6	17.6±0.8	37.2±0.4	36.9±0.3	38.6±0.3	**39.7±0.3**
A→W	25.7±0.9	31.8±1.1	33.2±0.6	32.8±0.6	37.6±0.5	**38.3±0.5**
A→D	25±1.1	29.5±0.9	34.5±0.8	33.6±0.8	39.2±0.5	**40.5±0.6**
C→A	31.3±0.8	31.8±0.8	34.9±0.5	34.6±0.4	38.4±0.5	**39.5±0.5**
C→W	28.8±1.1	**40.5±1.1**	29.3±1	28.9±1	33.6±1.2	35.1±1.3
C→D	34.6±1.2	38.1±1.4	33.4±0.9	33.5±0.9	39.3±0.7	**40.6±0.8**
D→A	31.1±0.5	32.7±0.9	31.9±0.3	31.5±0.4	35.3±0.3	**36.1±0.2**
D→C	27±0.4	23.6±0.5	30.2±0.2	29.9±0.3	32.8±0.2	**33.2±0.2**
D→W	58.4±0.8	49.1±1.2	72.5±0.5	72.2±0.5	76.7±0.4	**78.2±0.4**
W→A	32.7±0.7	34.8±1	32.3±0.5	32±0.5	36.7±0.3	**37.5±0.3**
W→C	27.6±0.8	23.6±0.8	29.4±0.3	28.9±0.3	32.8±0.3	**33.4±0.3**
W→D	55.5±0.8	49.4±1.4	63.9±0.9	63.4±0.9	68±0.7	**69.3±0.8**

Conclusions

- **E**liminate the distribution mismatch between domains by joint supervised sparse coding and discriminative regularization term are used.
- **U**nsupervised and merely depends on the labels of source domain.
- **I**mprove the generalization capacity of classifier learned on the learned common subspace

Reference

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