Out-of-label Suppression Discriminative Dictionary Learning with Cluster Regularization

Xiudong Wang (wang-xd14@tsinghua.edu.cn) and Yuantao Gu (gyt@tsinghua.edu.cn)

Dept. EE, Tsinghua Univ., Beijing, China

Introduction

- Dictionary learning (DL) is an important research topic
- Sparse representation improves robustness
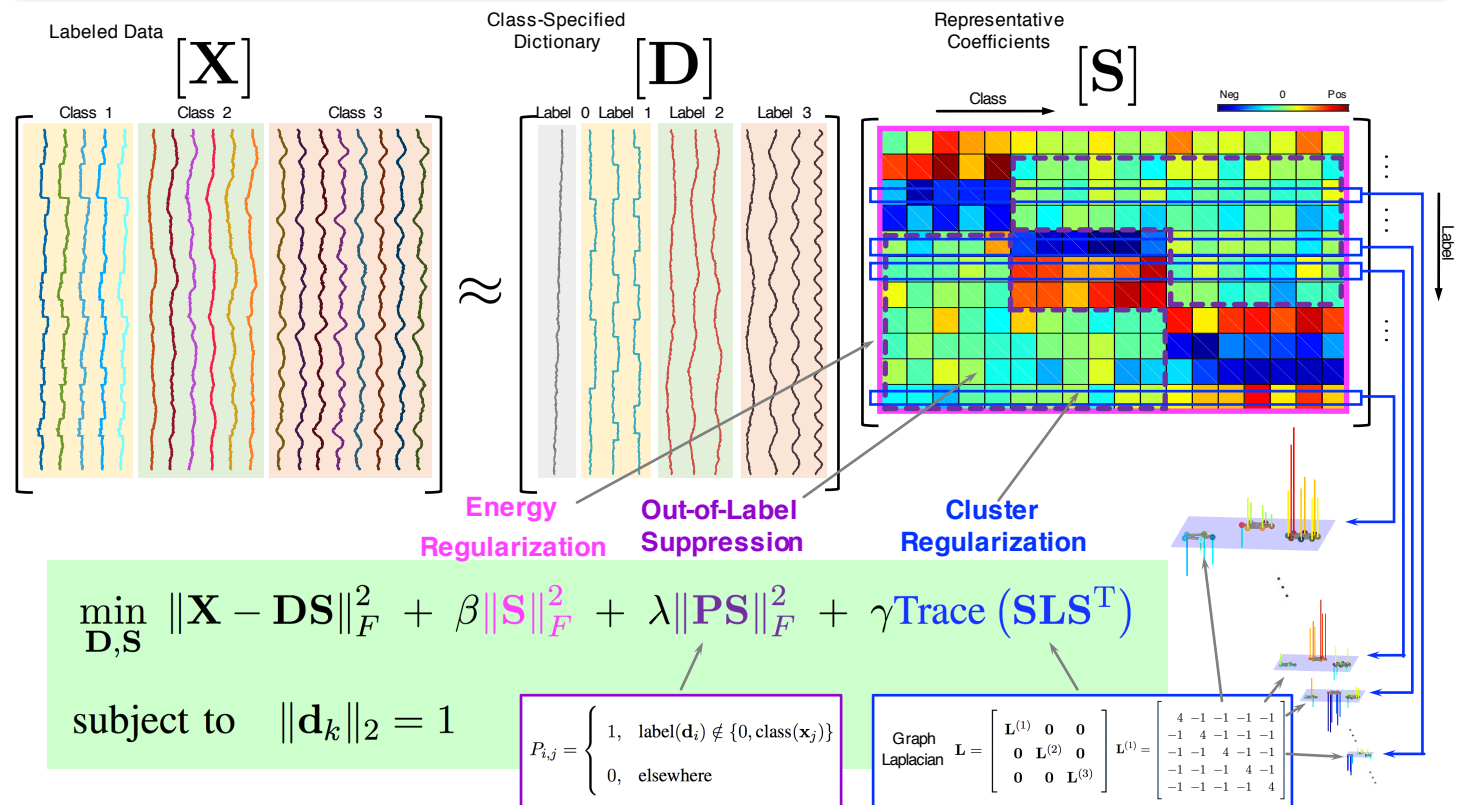- We propose a supervised DL method for classification

Motivation

- Traditional DL inserts sparseness measures (ℓ_0 or ℓ_1-norm) into the cost function to induce sparse representation
- Sparseness measures are usually non-smooth or even discontinuous, hence the iterative solving method can be time-consuming
- In supervised DL, the discriminative characteristics among sub-dictionaries and representative coefficients are not well exploited

Contribution

- Out-of-Label suppression and Cluster regularization are proposed
- The learned discriminative dictionary is ready for classification
- Analytical solution is obtained for sub-problems due to the use of ℓ_2-norm regularization

The Proposed Model

Labeled Data $[\mathbf{X}]$ — Class 1, Class 2, Class 3

Class-Specified Dictionary $[\mathbf{D}]$ — Label 0, Label 1, Label 2, Label 3

Representative Coefficients $[\mathbf{S}]$

$[\mathbf{X}] \approx [\mathbf{D}][\mathbf{S}]$

Energy Regularization — Out-of-Label Suppression — Cluster Regularization

$$\min_{\mathbf{D},\mathbf{S}} \|\mathbf{X}-\mathbf{DS}\|_F^2 + \beta\|\mathbf{S}\|_F^2 + \lambda\|\mathbf{PS}\|_F^2 + \gamma\mathrm{Trace}\left(\mathbf{SLS}^\mathrm{T}\right)$$

$$\text{subject to} \quad \|\mathbf{d}_k\|_2 = 1$$

$$P_{i,j} = \begin{cases} 1, & \mathrm{label}(\mathbf{d}_i) \notin \{0, \mathrm{class}(\mathbf{x}_j)\} \\ 0, & \mathrm{elsewhere} \end{cases}$$

Graph Laplacian $\mathbf{L} = \begin{bmatrix} \mathbf{L}^{(1)} & 0 & 0 \\ 0 & \mathbf{L}^{(2)} & 0 \\ 0 & 0 & \mathbf{L}^{(3)} \end{bmatrix}$ $\mathbf{L}^{(1)} = \begin{bmatrix} 4 & -1 & -1 & -1 & -1 \\ -1 & 4 & -1 & -1 & -1 \\ -1 & -1 & 4 & -1 & -1 \\ -1 & -1 & -1 & 4 & -1 \\ -1 & -1 & -1 & -1 & 4 \end{bmatrix}$

Experimental Results

Face Recognition @ Yale Face

Method	Accuracy	Method	Accuracy
SVM	94.42±2.80	DLSI	72.70
He	88.70	LC-KSVD	73.60
SRC	74.60	Wang	89.26
Joint	84.61±4.05	COPAR	78.30
D-KSVD	73.20	FDDL	73.20
Ours(LCC)	93.65±3.26	Ours(GCC)	95.92±2.23

The effect of out-of-label suppression

The effect of cluster regularization
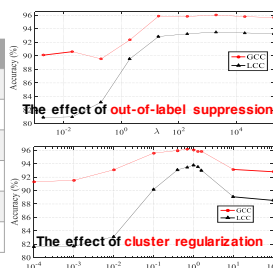
Object Recognition @ Caltech1010

Method	Accuracy	Method	Accuracy
Irani	70.64	LC-KSVD	73.60
Yang	73.20	LLC	73.44
SVM	71.98	COPAR	71.75
SRC	70.70	K-SVD	73.20
Spanias	72.40	DLSI	70.34
D-KSVD	73.00	Ours(GCC)	77.94

The effect of out-of-label suppression and cluster regularization
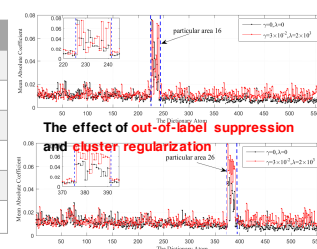
Texture Recognition @ DynTex ++

Computational Cost

Method	Train time(s)
FDDL	1279.89
COPAR	520.22
Ours(LCC)	26.92

Method	Accuracy	Method	Accuracy
SVM	90.85±0.28	Zhao	89.80
SRC	88.53	Xu	89.90
FDDL	94.21±0.42	Ghanem	63.70
kgLC-dic	92.80	kgSC-dic	93.20
K-SVD	89.31	DLSI	91.56±1.22
Joint	89.40	COPAR	94.32±0.17
D-KSVD	89.27	LC-KSVD	89.67
MCDL	90.35	Ours(LCC)	95.72±0.50