Supervised Transfer Sparse Coding

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Abstract

This work relaxes the transfer learning problem introducing a supervised approach. We demosntrate that

- A small number of labeled data in the target domain can leverage the classification accuracy of the transfer sparse coding methods [1, 2].
- We propose a unified framework named supervised transfer sparse coding (STSC) which employs a supervised model to guide the way the transfer sparse coding is performed.

Introduction

Domain transfer learning techniques often assume that labels for the objects in the target domain are unavailable.

Common assumptions:

- Training set consists of objects from the source domain which are entirely labeled.
- Testing set consists of objects from the target domain which are all unlabeled.
- Learning and classification is semi-supervised.

We relax these assumtions and study the following setting.

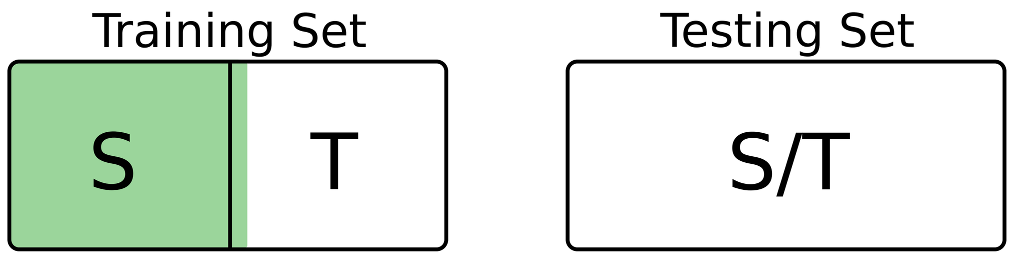

Figure 1 : The training and testing layouts under the study.

In our setting (Figure 1):

- Training set consists of objects from both domains:
  - Training objects from the source domain are entirely labeled.
  - Training objects from the target domain are almost unlabeled, i.e., a small fraction of them can be labeled.
- Testing objects are all unlabeled.
- The domains of testing objects regarded as unknown.
- Learning and classification is supervised.

Applications

The proposed setting is natural in applications that inherently deal with multi-domain mixed datasets:

- Classification of images in social networks and media – a natively multi-domain task: Objects usually appear on a variety of backgrounds forming essentially multi-domain sets.

- Bilingual speech and text recognition, important for bilingual countries or international congresses.

In order to effectively learn robust representations of the data under the new setting, we further propose a unified framework: **Supervised Transfer Sparse Coding (STSC)**, which simultaneously

1. optimizes the sparse representation,
2. performs domain transfer,
3. learns a classification model that guides 1 and 2.

The principal difference between the well established transfer sparse coding (TSC) [1] and the proposed STSC approach is illustrated by Figure 2:

- The merged domain by TSC is difficult to classify.
- In STSC, SVM decision boundaries regularize the way the domains are merged, and the resulting unified domain is much easier to be classified.

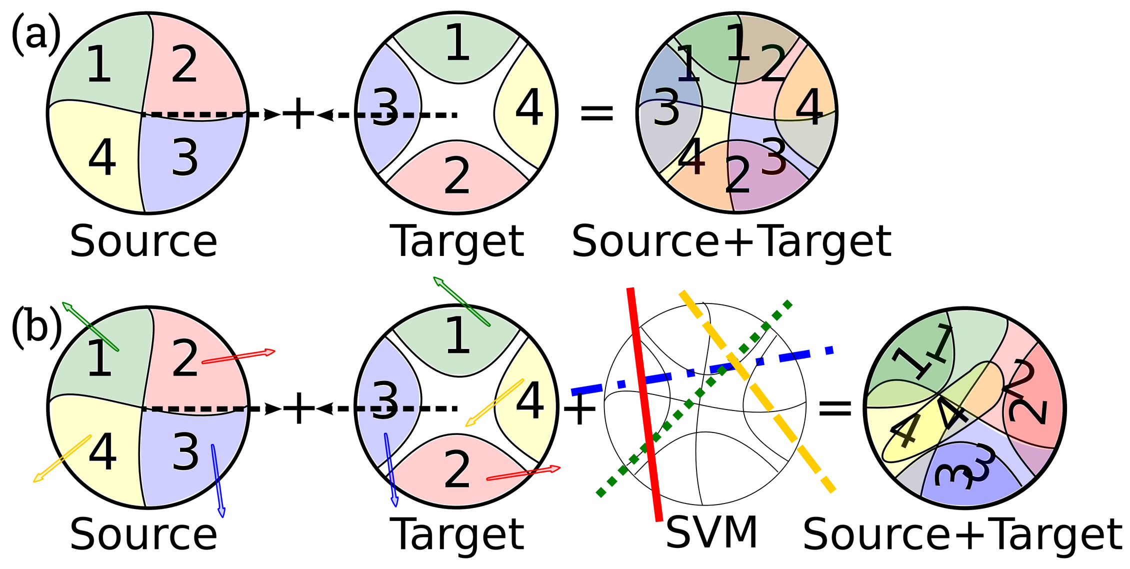

Figure 2 : (a) Illustration of TSC. (b) Illustration of STSC. The supervised learning component assists the domains to be transferred in a better manner.

The STSC Approach

Supervised transfer sparse coding (STSC) consists of three components: sparse coding, domain transfer, and supervised transfer correction via a multi-calss SVM-term.

$$\min_{U,V,W} \left\{ \overbrace{\|\mathbf{X}-\mathbf{UV}\|_F^2 + \lambda \sum_{i=1}^{N} \|\mathbf{v}_i\|_1}^{\text{sparse coding}} + \overbrace{\mathrm{Tr}\left(\mathbf{V}\tilde{\mathbf{M}}\mathbf{V}^\top\right)}^{\text{transfer \& geometry}} + \underbrace{\kappa\left(\frac{1}{2}\|\mathbf{W}\|_F^2 + c\mathbf{1}^\top \Xi \mathbf{1}\right)}_{\text{multi-class SVM}} \right\}$$

$$\text{s.t. } \|\mathbf{u}_k\|_2^2 \le 1,\ k = 1, \cdots, K,\quad \mathbb{1} - \Xi \preceq \mathbf{Y} \circ (\mathbf{W}^\top \mathbf{V} + \mathbf{B}),\ \Xi \succeq 0, \tag{1}$$

where $\mathbf{X}$ is the original training data, $\mathbf{U}$ is the dictionary, $\mathbf{V}$ is the sparse code (*the rest of the notation see in* [4]).

Three-Step Optimization

In order to solve the problem (1), we propose the following tree-step optimization algorithm.

1. **Sparse Codes Learning** is done by optimizing

$$\min_{\mathbf{V}} \left\{ \|\mathbf{X}-\mathbf{UV}\|_F^2 + \lambda \sum_{i=1}^{N} \|\mathbf{v}_i\|_1 + \mathrm{Tr}\left(\mathbf{V}\left(\tilde{\mathbf{M}} - \frac{1}{2}\Psi\right)\mathbf{V}^\top\right) \right\}.$$

via a modified feature-sign algorithm [2].

2. **Dictionary Learning** is performed by solving

$$\max_{\nu} \min_{\mathbf{U}} \left\{ \|\mathbf{X}-\mathbf{UV}\|_F^2 + \sum_{k=1}^{K} \nu_k \left(\|\mathbf{u}_k\|_2^2 - 1\right) \right\}$$
$$\text{s.t. } \nu \succeq 0,$$

using the algorithm proposed by Lee et al. [3].

3. **SVM Learning**

$$\min_{\Gamma} \left\{ \frac{1}{2}\mathrm{Tr}\left(\mathbf{V}\Psi\mathbf{V}^\top\right) - \mathbf{1}^\top \Gamma \mathbf{1} \right\}$$
$$\text{s.t. } (\Gamma \circ \mathbf{Y})\,\mathbf{1} = 0,$$
$$0 \preceq \Gamma \preceq \kappa\, c,$$

which is a convex quadratic programming problem.

STSC Algorithm

Input: $\mathbf{X}$ – training data, $\mathcal{Y}$ – labels.
Input: $\alpha, \mu, \kappa, \lambda, c, \mathtt{iter\_num}$ – parameters.

1. Build the MMD matrix $\mathbf{M}$, Graph-Laplacian matrix $\mathbf{L}$, and label matrix $\mathbf{Y}$ for the labeled objects.
2. $\mathbf{U} \leftarrow$ uniform random matrix; zero mean columns.
3. $\Gamma \leftarrow 0$, $\Psi \leftarrow 0$.
4. **for** $t = 1, \cdots, \mathtt{iter\_num}$ **do**
5. Find $\mathbf{V}$ by solving **Sparse Codes Learning**.
6. Find $\mathbf{U}$ by solving **Dictionary Learning**.
7. Find Γ and compute Ψ by **learning SVM**.

Output: $\mathbf{U}$ – dictionary, $\mathbf{V}$ – sparse codes.

Results and Discussion

Below results justify our assumptions showing that:

1. A small number of labeled data can significantly improve classification accuracy after TSC.
2. The proposed STSC is able to further improve the performance of the classification (Figure 4).

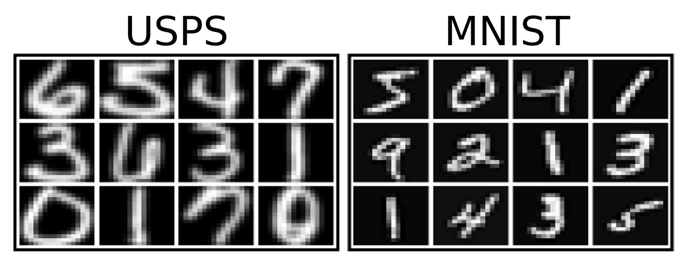

Figure 3 : Examples from the USPS and MNIST datasets.

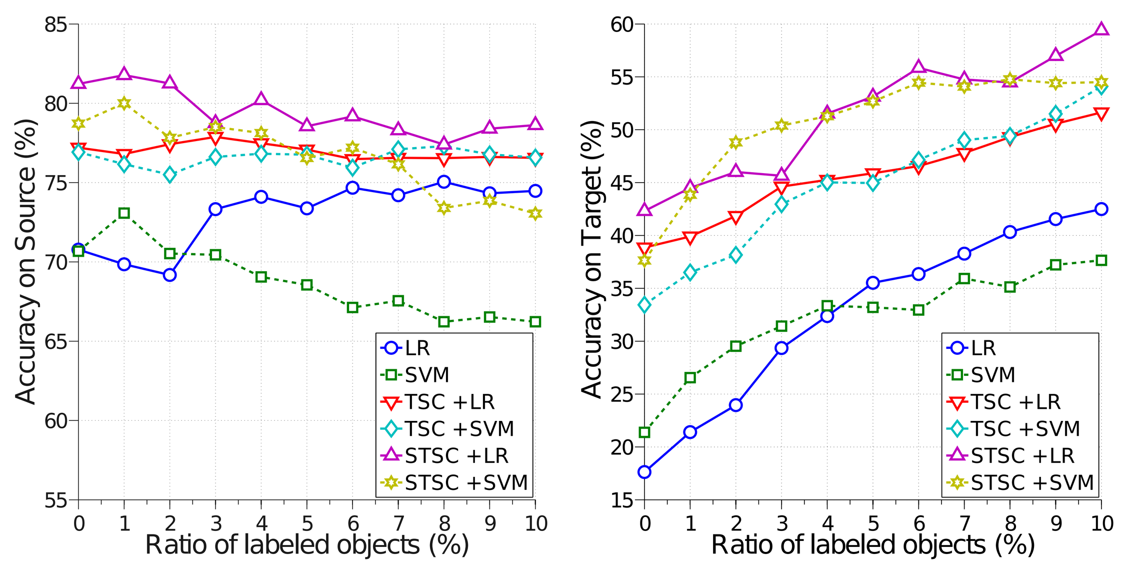

Figure 4 : Classification accuracies LR and SVM on the source and target domains of after applying TSC, STSC, or no coding. The dataset: USPS – MNIST.

Dataset	USPS–MNIST	USPS–MADBase	Caltech–Amazon
LR	35.5 ± 0.8	24.1 ± 3.0	39.7 ± 1.9
SVM	33.2 ± 1.5	19.3 ± 4.2	34.6 ± 3.7
TSC+LR	45.8 ± 1.8	24.1 ± 3.8	38.3 ± 2.1
TSC+SVM	44.9 ± 2.4	22.9 ± 4.3	32.5 ± 1.6
STSC+SVM	52.6 ± 3.8	24.0 ± 4.8	41.5 ± 2.5
STSC+LR	$\mathbf{53.1} \pm \mathbf{2.2}$	$\mathbf{31.0} \pm \mathbf{3.5}$	$\mathbf{43.0} \pm \mathbf{2.1}$

Table 1 : Classification accuracy on the target domain of the test set (5% labeled target objects in the training set).

Conclusions

- We reformulated the transfer learning problem and introduced a novel relaxed cross-domain setting.
- We demonstrated that a small number of labeled objects from the target domain can significantly improve transfer sparse coding performance.
- We proposed a *supervised* transfer sparse coding (STSC) framework and showed that simultaneous optimization of sparse representations, domain transfer, and supervised classification yields better discriminative representations.

Acknowledgments

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