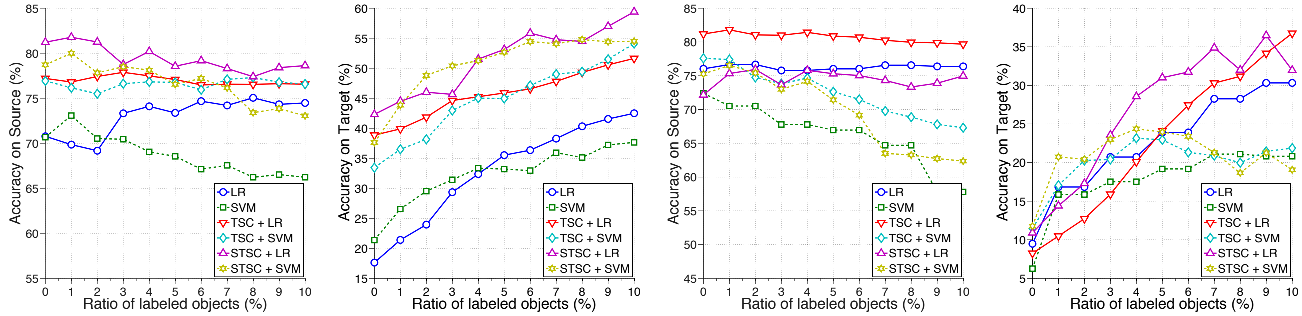

(a) USPS & MNIST. (b) USPS & MNIST. (c) USPS & MADBase. (d) USPS & MADBase.

Figure 4: Classification accuracy of STSC+LR, STSC+SVM, and the baseline methods for different ratios of labeled target domain objects in the training set. (a) Accuracy on the source domain of the testing set for USPS & MNIST; (b) accuracy on the target domain of the testing set for USPS & MNIST; (c) accuracy on the source domain of the testing set for USPS & MADBase; (d) accuracy on the target domain of the testing set for USPS & MADBase. Methods with LR classifiers are drawn as solid lines; methods with SVM classifiers are depicted as dashed lines.

Table 3: Classification accuracy on the target domain of the test set (5% labeled target domain objects in the training set). Accuracy is averaged over five resamplings of the training and testing sets. Standard deviations are also presented.

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	**53.1 ± 2.2**	**31.0 ± 3.5**	**43.0 ± 2.1**

One might doubt that the achieved performance is the merit of knowledge transfer, arguing that 10% of target subset of the training data labeled is almost enough to be able to generalize. This is indeed true: The higher the target labeled ratio, the less transfer plays role. However, our experiments explicitly suggest that for labeled ratios below 5%, transfer from the source domain is crucial: TSC+LR trained only on the labeled 2% of the training target data yields only 28% of accuracy on the testing target objects. If we train the same method with the training source domain assisting in an unsupervised fashion, the accuracy jumps up to 41%. If use STSC+LR and enable supervised correction of the transfer, we get 46% of the accuracy on the testing target domain.

5.5 Limitations

Although STSC outperforms other methods in the given setting of a relaxed supervised cross-domain transfer classification, it is important to mention that STSC's additional tuning parameter (SVM term weight κ) is sensitive in some cases. One should keep it relatively small, to make the method finally converge. Otherwise, supervised transfer correction would possibly be too large, and the three-step optimization procedure will remain oscillating without convergence. In such case, STSC will perform relatively poor in comparison with classical TSC method.

6 Conclusion and Future Work

In this paper, we demonstrate that a small number of labeled objects from the target domain can significantly improve performance of the state-of-the-art transfer sparse coding methods. We propose a supervised transfer sparse coding (STSC) framework for learning discriminative representations in a relaxed cross-domain transfer learning setting. Using STSC, we show that by simultaneously optimizing sparse representations, domain transfer, and supervised classification, learned representations can further improve the subsequent classification accuracy.

In the future, we plan to extend STSC framework with different supervised transfer correction terms based on other classifiers, e.g., logistic regression and linear discriminant analysis (LDA).

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