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# Multi-source adaptation embedding with feature selection by exploiting correlation information

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ABSTRACT

While feature selection has recently received much research attention, less or limited effort has been made on improving the performance of feature selection by leveraging the shared knowledge from other related domains. Besides, multi-source adaptation embedding by exploiting the correlation information among domain features and distributions has long been largely unaddressed. To this end, we propose in this paper a robust **M**ulti-source **A**daptation **E**mbedding framework with **F**eature **S**election (MAEFS) by exploiting the correlation information via joint $l_{2,1}$-norm and trace-norm regularization, and apply it to cross-domain visual recognition. Specifically, to uncover cross-domain invariant subspaces by minimizing the distribution discrepancy between source and target domains, instead of evaluating the importance of each feature individually, MAEFS selects features in a collaborated mode for considering the correlation information among features. Furthermore, multiple feature selection functions for different source adaptation objects are simultaneously learned in a joint framework, which enables MAEFS to utilize the correlated knowledge among multiple source domains via trace-norm regularization, thus facilitating domain invariant embedding. Besides, by employing graph embedding and sparse regression scheme via $l_{2,1}$-norm minimization, MAEFS can preserve the original geometrical structure information as well as be robust to some noises or outliers existed in domains. Finally, an efficient iterative algorithm is proposed to optimize MAEFS, whose convergence is theoretically guaranteed. Comprehensive experimental evidence on a large number of visual datasets verifies the effectiveness of the proposed framework.


## 1. Introduction

The generalization error bound of the traditional machine learning techniques is guaranteed by the statistical learning theory only under a common hypothesis that both training and testing data are sampled from an identical probability distribution [2–5]. With the advent of the era of big data, however, one witnesses an exponential growth of heterogeneous visual data generated from different application fields, which has brought a compelling requirement for those traditional learning models to generalize well across different distribution domains. For this end, domain adaptation learning (DAL) [6,7], which is a newly proposed fundamental machine learning methodology for cross-domain learning tasks, has been proposed to classify target domain by using some other related source/auxiliary domain(s) with even different distributions. In DAL, there usually exist two distinct types of domains [1,6]: one from a source domain and the other from a target domain of interest. The source domain usually contains a large amount of labeled data such that a classifier can be reliably constructed, and the target domain contains a large amount of unlabeled data sampled from a substantially different but related distribution as that of the source domain. DAL technologies are prevalent in many real-world visual applications ranging from image annotation/classification [8–11], video concept detection [12–15], to object recognition [16–19].

To overcome the so-called negative transfer problem [20], multi-source DAL has also been put forward to learn an optimal target classifier by fusing information from multiple different source domains [21]. One of major problems in DAL is how to reduce the distribution distance between domains by a certain feature transform technique [22]. To address this problem, most existing multi-source DAL methods can be roughly organized into two categories [6]: domain invariant feature transformation learning, and domain adaptation classifier induction. The former also includes two subcategories: domain distribution distance measure learning [9,10,12,22–24] and domain adaptation shared

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subspace learning [16–19]. The domain distribution distance measure learning focuses on learning a common feature space where the domain distribution difference is explicitly reduced by minimizing some predefined distance measure criterion; while the domain adaptation shared subspace learning aims to construct a latent space by preserving some important properties of the original data, in which the distributions of the source and target domains are drawn close. The domain adaptation classifier induction intends to directly design an adaptive classifier by incorporating the adaptation of different distributions through some model regularization [13–15]. Discovering domain-invariant subspaces that enable adaptation has been an extensively studied paradigm [16–19,34–38], in which the source and target domains have the same (or similar) marginal distributions, and the posterior distributions of the labels are also the same across domains. Hence, a classifier trained on the source would likely perform well on the target. Several ways of measuring distribution similarities have been explored [16,19,23–25], and theoretical analysis shows that the performance of the classifier on the target is indeed positively correlated with those similarities. In this paper, we mainly focus on the domain adaptation shared subspace learning, also called domain adaptation embedding method, due to its particular effectiveness on multi-source DAL.

While the effectiveness and efficiency of existing multi-source adaptation embedding methods have made them of particular use in practice, unfortunately, they have to deal with some of the following inevitable problems in the big data era:

(1) How to jointly select the most effective features in the original high-dimensional visual space. Since visual data are normally represented by multiple different features, therefore inevitable to bring in irrelevant and/or redundant information in them, it is indispensable to employ feature selection to preprocess visual data so as to facilitate subsequent DAL tasks. However, no or limited efforts have been focused on multi-source adaptation embedding with joint feature selection. In other words, multi-source adaptation embedding by exploiting the correlation information among domain features has yet been unsolved.
(2) How to effectively mining the correlated knowledge contained in multiple sources. During the adaptation, most of multi-source adaptation methods typically deal with source samples separately without accounting for the correlated structures among sources, which may (either implicitly or explicitly) cause the adapted distribution to be arbitrarily scattered around and any structural information beyond single source domain may become undermined. Besides, for multi-source DAL systems, it is crucial for weight determination during learning based on the correlation and quality of source domains. Such characteristics are not yet feasible in the extant multi-source DAL methods.
(3) How to handle the error data (e.g., noises and outliers) which possibly exist in training data of domains. Since the visual training data of source domain may be randomly obtained from Internet or other open source websites, noises and outliers may abound in the training data by nature. The existing methods [16–19] blindly transform all training data including noises and particularly possible outliers into some shared subspace. This can lead to significantly distorted or corrupted models when the followed classification models are learned.

In this paper, we focus on overcoming those challenges in a unified framework. Our core idea is to model how the source and the target domains (including features and distributions) are related in order to enable multi-source adaptation embedding. Our effort centers on the theme of jointly learning multiple domain-invariant feature subspaces by sufficiently exploiting the correlation information among features as well as sources. Although some of existing works [26–31] have partially addresses the mentioned-above issues, none of them has addressed these issues in one unified framework. Instead, we will present to address all these issues in an integrated framework. Specifically, motivated by the latest mathematical advances in $l_{2,1}$-norm minimization [32], which has been explored as the rotational invariant $l_1$-norm and recently used for multi-task learning and feature selection [31–33], we propose a robust **M**ulti-source **A**daptation **E**mbedding framework with **F**eature **S**election by jointly exploiting the correlation information among both features and sources via joint $l_{2,1}$-norm and trace-norm regularization, or called MAEFS for short. In this framework, the trace-norm regularization is introduced to explore the shared information among multiple sources, and the $l_{2,1}$-norm loss function is designed to alleviate impact of noises or outliers as well as to generate row sparsity to get sparse feature selection solution. We match distributions between different domains in MAEFS by minimizing the nonparametric Maximum Mean Discrepancy (MMD) [25] in an infinite dimensional reproducing kernel Hilbert space (RKHS).

Our joint optimization framework offers several advantages in terms of generalizability and efficiency of the method. Firstly, learning separate projection matrix for each domain makes it easy to handle any changes in feature dimension and types in different source domains. It also makes the algorithm conveniently extensible to handle multiple source domains. Further, learning the low-dimensional subspace companied by sparse feature selection makes the algorithm faster, and irrelevant/redundant information in original features can be discarded before dimension reduction. Moreover, joint learning of feature selection and projections ensures that the common internal structure of data in multiple domains is extracted, which can be represented well by joint $l_{2,1}$-norm and trace-norm minimization. In sum, this paper makes the following main contributions:

(1) We present a robust multi-source adaptation embedding framework with feature selection by jointly exploiting the correlation information among features as well as sources via joint $l_{2,1}$-norm and trace-norm regularization.
(2) Instead of evaluating the importance of each feature individually, the proposed framework selects features in a collaborated mode, by which the correlation information among features is considered. Moreover, multiple feature selection functions for different source adaptation objects are simultaneously learned in a joint framework, which enables our framework to utilize the correlated knowledge of multiple source domains as auxiliary information, thus facilitating domain invariant embedding.
(3) By employing graph embedding and sparse regression scheme via $l_{2,1}$-norm minimization, our framework can preserve the original geometrical structure information as well as be robust to some noises or outliers existed in domains.
(4) We derive an efficient iterative algorithm for our framework, and rigorous convergence and computational complexity analysis of our algorithm are also given. We perform comprehensive experimental on a large number of visual datasets to verify the effectiveness and efficiency of the proposed framework.

The rest of paper is organized as follows. In Section 2, the previous related works are discussed, and the preliminaries including feature selection, domain distribution distance measure, and transfer component analysis are introduced. We present our framework and its corresponding optimal algorithm in Section 3 and Section 4, respectively. Section 5 gives discussions about the convergence of MAEFS, and connections with other related arts. Experimental re-