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Robust Latent Regression with discriminative regularization by leveraging auxiliary knowledge

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ABSTRACT

For a domain adaptation learning problem, how to minimize the distribution mismatch between different domains is one of key challenges. In real applications, it is reasonable to obtain an optimal latent space for both domains so as to reduce the domain distribution discrepancy as much as possible. We therefore propose in this paper a Robust Latent Regression (RLR) framework with discriminative regularization by uncovering a compact and more informative latent space as well as leveraging the source domain knowledge, which learns a discriminative representation of domain data by considering the recognition task in the procedure of domain adaptation learning. On the one hand, to leverage the prior information in the source domain, RLR incorporates both the source and target classification loss functions as parts of its objective function, and simultaneously trains these two classifiers by encoding the common components of the classifier models as a low-rank regularization term, thus exploiting the discriminative information shared by different domains. On the other hand, to guarantee that the latent space is more compact and discriminative, the intrinsic geometric structure of data, and the local and global structural consistencies over labels are exploited simultaneously and incorporated into RLR. Lastly, to make our algorithm robust to the outliers and noise, we additionally introduce the $l_{2,1}$-norm into the loss function. To solve the proposed problem, an effective iterative algorithm is proposed. Extensive experiments are conducted on several visual datasets and the results show that the proposed approach achieves outstanding performance for almost all learning tasks compared with several representative algorithms.
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1. Introduction

In the classical machine learning paradigm (Gu & Sheng, 2017; Hong, Hou, Nie, et al., 2017; Xiang, Nie, Meng, et al., 2012), we usually need sufficient labeled training data to learn a classification model for classifying test data from unlabeled testing dataset that is assumed to be distributed identically with the training dataset. While supervised learning techniques have made tremendous contributions to machine learning and computer vision, their performance is often limited by the amount of labeled training data available, since labeling is expensive and time-consuming due to the great amount of human effort involved. However, the availability of large unlabeled visual data is becoming considerably easier due to the existence of low-cost consumer visual sources, and the open Internet databases such as Flickr and YouTube. Therefore, when developing a classification or retrieval algorithm using these visual data, one has to constantly deal with the different distributions of these data. Several specific examples include: recognizing objects under poor lighting conditions and poses while the algorithms are trained on other well-illuminated objects at frontal pose, detecting and segmenting an organ of interest from magnetic resonance imaging (MRI) images when available algorithms are instead optimized for computed tomography and X-ray images, recognizing and detecting human faces on infrared images while algorithms are optimized for color images, to name just a few.

In these scenarios, the distribution changes would force us rebuild the classification models in the new domain of interest, which often makes the task intellectually expensive or unpractical for many real-world applications (Pan & Yang, 2010). While exploiting the vast amount of unlabeled data directly in semi-supervised learning (SSL) is effective and valuable in its own right (Li, Liu, Tang, et al., 2015; Nie, Xu, Tsang, & Zhang, 2010; Yang et al., 2012; Zhang, Li, Zhao, et al., 2017), it is beneficial to leverage much labeled data from different but relevant data sources in hand (Bruzzone & Marconcini, 2010). For example, it is increasingly popular to enrich our limited collection of training data with those

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from the Internet. This has inspired recent research efforts into the domain adaptation learning (DAL) problems (Bruzzone & Marconcini, 2010; Patel, Gopalan, Li, & Chellappa, 2015) in computer vision and machine learning (Duan, Tsang, & Xu, 2012; Duan, Xu, & Tsang, 2012a; Geng, Tao, & Xu, 2011; Ghifary, Balduzzi, Kleijn, et al., 2017; Gong, Shi, Sha, & Grauman, 2012; Gopalan, Li, & Chellappa, 2011; Kulis, Saenko, & Darrell, 2011; Long, Wang, Ding, Pan, & Yu, 2014; Saenko, Kulis, Fritz, & Darrell, 2010; Tao, Chung, & Wang, 2012; Tao, Song, Wen, & Hu, 2017; Tao, Wen, & Hu, 2015, 2016; Yang, Yan, & Hauptmann, 2007). DAL makes use of prior knowledge in other related domains when dealing with new tasks in the given domain. In DAL, the training data and testing data are respectively from two types of domains: i.e., source domain and target domain, which generally share the same task but follow different distributions. The source domain contains sufficient labeled data for building an effective classifier, while the target domain refers broadly to a dataset containing zero or few labeled samples such that a classifier cannot be reliably built.

As well known, one key challenge in DAL is how to mitigate the distribution gap between different domains. For this end, in the literature of interest, one popular scheme is feature representation (or feature transformation) based DAL (Duan, Tsang et al., 2012; Geng et al., 2011; Ghifary et al., 2017; Gong et al., 2012; Gopalan et al., 2011; Kulis et al., 2011; Long, Wang, Ding, Pan et al., 2014; Saenko et al., 2010; Tao et al., 2012). There have been several techniques being proposed for addressing the challenge of domain adaptation by learning a common feature representation. The objective is to identify a new feature representation that is invariant across domains, in which the source and the target domain exhibit more shared characteristics. They usually separated the domain adaptation learning into two distinct steps, i.e., the first step attempts to minimize the domain gaps, and then the second step is to learn a predictive model by exploiting those transformed feature representations. While the effectiveness and efficiency of these approaches make them of particular use in practice, they also bring several new issues. The first issue is how to integrate those distinct steps into a unified framework, since the transformed features may encode less discriminative information for the sequent target learning, thus leading to an increase of the empirical loss on the labeled data. The second issue is how to effectively utilize unlabeled target data for improving the domain adaptation performance. The last but not the least issue is how to improve the robustness of the learning performance to noises which possibly exist in domains (Tao et al., 2017, 2015, 2016), since noise abound in training data by nature (Tao et al., 2017), which needs more robustness on a learning model compared to traditional DAL tasks.

To address the mentioned-above issues, we propose in this paper a novel Robust Latent Regression (RLR) framework with discriminative regularization for effective DAL by discovering a compact and more informative feature representation. In RLR, we integrate subspace learning and visual understanding into a joint learning framework by exploiting source domain knowledge as well as the correlation of different domain models. Unlike previous latent space learning models, the proposed framework learns a discriminative representation of domain data by considering the visual recognition task in DAL, which makes the uncovered representations well predict the labels of target domain. To solve the proposed problem, an effective iterative algorithm is proposed. It is worth noticing that the proposed framework is unified and any other distribution measure criterion for domain adaptation can be easily incorporated. Several distinctive features of our method are summarized as follows.

(1) Both source and target classification loss functions are incorporated into the parts of the objective function, and the labels of the unlabeled target data are simultaneously predicted.

(2) The common components of different classifier models are encoded into our method as a low-rank regularization term so as to exploit the discriminative information shared by different domains.

(3) To guarantee that the latent space is more compact and discriminative, the intrinsic geometric structure of data, and the local and global structural consistencies over labels are exploited simultaneously in our method. Besides, a constraint is further imposed on the new data representations in learning the latent space for minimizing the Maximum Mean Discrepancy (MMD) distance (Gretton, Harchaoui, Fukumizu, & Sriperumbudur, 2010) between different domains, which has been proven effective for the domain adaptation problem in the recent research (Duan, Tsang et al., 2012; Geng et al., 2011; Long, Wang, Ding, Pan et al., 2014).

(4) To make our method robust to noise, we additionally introduce the $l_{2,1}$-norm into the loss function (Li et al., 2015; Nie, Huang, Cai, & Ding, 2010; Zhang et al., 2017).

The remainder of this paper is arranged as follows. We introduce the related work in Section 2. Then we elaborate our proposed formulation in Section 3 followed by its optimization algorithm in Section 4. We present discussions in Section 5. Extensive experiments are conducted and analyzed in Section 6. Section 7 concludes this work with future work.

2. Related Work

It is assumed that visual data exist in the low-dimensional subspace (Li et al., 2015), which can provide a meaningful description of the underlying domain changes. With this viewpoint, recent years have witnessed a widespread interest in latent space (a.k.a. subspace) learning (Li et al., 2015; Zhang et al., 2017). During past decades, many latent space (a.k.a. subspace) learning methods have been widely used for classification, dimensionality reduction (Liu, Wang, & Chang, 2012; Yan, Xu, Zhang, et al., 2007; Yuan, Sun, & Lv, 2016) and visual data analysis. Nonetheless, some of them only focus on low-level features of data, which are independent of the follow-up learning tasks. With regard to the robustness issue existed in subspace learning, the framework of joint graph embedding and sparse regression for dimensionality reduction (Shi, Guo, Lai, et al., 2015) has been proposed. It can perform feature selection and latent space learning simultaneously with the $l_{2,1}$-norm regularization which is convex and could be easily optimized. Nonetheless, these methods only focus on low level features of data, which are independent of the follow-up classification tasks and ignore the high-level semantic information.

As a widely-used discriminative model, linear or nonlinear least squares regression (LSR) (Xiang et al., 2012) has been applied to many visual application systems, due to its effectiveness for data analysis as well as its completeness in statistics theory. A major drawback in this model (Nie, Xu et al., 2010; Yang et al., 2012) is its lack of robustness to noise that is naturally present in real applications. For this end, Huang, Cabral, and Torre (2016) recently developed the theory of robust regression and presented a robust discriminative LSR (DLSR) learning framework by using recent advances on low-rank decomposition. To alleviate the semantic gap in subspace learning, Li et al. (2015) try to uncover proper representations of data by integrating visual understanding and feature learning into a joint LSR framework, thus proposing a novel Robust Structured Subspace Learning (RSSL) framework by exploiting visual recognition, feature learning and feature correlation simultaneously.

In the mentioned-above schemas of semi-supervised or unsupervised LSR, however, the acquisition of sufficient training data with ground-truth labels is often expensive and time-consuming for learning a discriminative model (Pan & Yang, 2010). In this case, it would be more beneficial to sufficiently exploit other related auxiliary knowledge gained from some source domain. This has inspired recent research efforts into the domain adaptation learning

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