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Transfer robust sparse coding based on graph and joint distribution adaption for image representation

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A B S T R A C T

Transfer learning can transfer knowledge from a source domain to a target domain, promoting the performance of the model learned from the source data. Sparse coding can make the representation of a model more succinct and easy to manipulate. Existing transfer sparse coding methods assume the data from the source and the target domains are accurate, which can provide useful information. However, in many real applications, the data in the source and target domains may contain noise and useless information, which could severely degrade the performance of the learned model. In this paper, we propose a transfer robust sparse coding based on graph and joint distribution adaption for image representation. The noise matrix model is utilized to handle noise and useless information in the transfer sparse coding. Moreover, the differences of marginal distribution and conditional distribution are simultaneously reduced in the transfer robust sparse coding. Extensive experiments on six benchmark datasets show the proposed method can effectively deal with the noise and useless information and therefore outperforms several state-of-the-art transfer learning methods on cross-distribution domains.

1. Introduction

Image representation is one of the crucial problems in image processing and understanding. There have been many important researches on low-level representation of images, such as HOG, SIFT, and so on. But there is still a big gap between low-level representation and high-level semantic representation [1]. In order to describe the semantic information better, many machine learning methods have been employed to learn the high-level representation of images, such as principle component analysis, sparse coding, non-negative matrix factorization, low-rank representation and so on.

Traditional machine learning assumes that the labeled training data (i.e. source domain) and the unlabeled testing data (i.e. target domain) follow the same distribution. If the testing data does not have the same distribution as the training data, then traditional machine learning algorithms may fail. However, due to different environments or devices of data collections, it is pretty common that the new testing data does not follow the same distribution as the old training data, as shown in Fig. 1. So a large amount of new data need to be collected and labeled, and the model needs to be retrained, which is expensive and time consuming.

Transfer learning was proposed to deal with the above situation, where the source domain and the target domain have different distributions [2,3]. Transfer learning promotes the performance of the model learned from the source data on the target domain, which transfers the knowledge obtained from the source domain to the target domain by reducing the divergence between domains [4] or reweighing the data of the source domain. Transfer learning has been successfully applied to homogeneous or heterogenous data classification [5,6], cross-modal multimedia retrieval [7] and recommender systems [8,9]. Mingsheng Long et al. proposed a Transfer Joint Matching (TJM) and a Joint Distribution Adaption (JDA) [10,11]. TJM matches the marginal distribution and reweighs the instances across domains in the principled dimensionality reduction [10]. JDA constructs a new representation by jointly adapting the marginal and conditional distributions [11]. Peng Zhao et al. put forward a Feature-based Joint Probability Distribution and Instance-based Transfer Learning Algorithm (FJPD-ITLA) [12]. FJPD-ITLA jointly matches marginal probability distribution and conditional probability distribution. Moreover it reweighs the instances across the domains to reduce the domain difference. Mingsheng Long et al. proposed a Graph Co-Regularized Transfer Learning (GTL), which uses nonnegative matrix factorization

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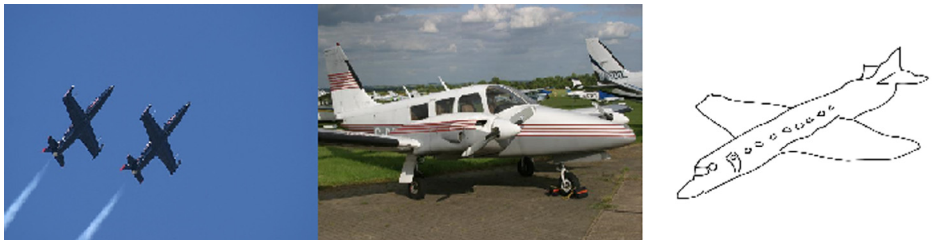

Fig. 1. Examples in domains with different distributions.

Fig. 2. The natural images existed noise information.

(NMF) and nonnegative matrix tri-factorization (NMTF) to extract common latent factors for knowledge transfer [13]. Redko Ievgen et al. proposed a Random Subspaces NMF for unsupervised transfer learning [14]. Jim Jing–Yan Wang et al. proposed the domain transfer NMF approach for data representation [15]. I-Hong Jhuo et al. presented a low-rank reconstruction method to reduce the domain distribution disparity, which transforms the visual samples in the source domain to an intermediate representation such that each transformed source sample can be linearly reconstructed by the samples of the target domain [16]. Ming Shao et al. utilized the low-rank constraint to bridge the source and the target domain in the low-dimensional space for transfer subspace learning [17]. Yuguang Yan et al. proposed a discriminative correlation subspace for heterogenous domain adaption [18].

However, the above models do not consider the sparse property, which make the representation more succinct and easy to manipulate, and facilitate an efficient content-based image indexing and retrieval. Sparse coding learns a dictionary and approximates the input data with a linear combination of just a few of the bases in the dictionary, which can find succinct representation and capture the high-level semantics. Sparse coding has received more attention in many research fields, such as machine learning, signal processing and so on. Mingsheng Long et al. incorporated sparse coding into transfer learning to make the new representation robust to the distribution difference [19]. Lei Zhang et al. proposed a latent sparse domain transfer (LSDT) for domain adaption and visual categorization of heterogeneous data [20]. Yong Xu et al. proposed a transfer subspace learning method, which uses the low-rank and sparse constraints to connect the source and the target domains in the common subspace [21].

Even though the existing transfer learning methods based on sparse coding have achieved promising results, their performances are degraded severely when the data are not clean. In many real applications, there may be some noisy background or other objects in an image which will affect the training process. Moreover, there is no guarantee that all the training data are annotated accurately. As shown in Fig. 2, the markets with red squares are not useful to understand the image semantics. So many contents within the red squares can be taken as noisy information. Recently, researchers began to pay attention to this problem. Tianyi Zhou et al. developed a GoDecomposition (GoDec) to robustly estimate the low-rank part and sparse part of a matrix with noise [22]. Liu Yang et al. proposed a non-negative collective matrix factorization model to handle noise in text-to-image transfer learning [23].

To our knowledge, our work is among the first attempts to address noise or useless information in transfer sparse coding. In this paper, we propose a transfer robust sparse coding based on graph and joint distribution adaption (TRSC-GJDA). We focus on the challenging scenarios in which the labeled source domain and the unlabeled target domain are different in both marginal and conditional distributions, and there are some noise or useless information in source and target domains.

The main contributions of this paper are summarized as follows:

- The TRSC-GJDA employs a noise matrix to describe the sparsely distributed noise or useless information, and introduces the noise matrix into the transfer sparse coding. Hence it can handle the noise and useless information in the source and target domains and therefore obtain a robust substantial feature representation.
- The TRSC-GJDA integrates the conditional distribution divergence to measure the difference of domains in transfer sparse coding. The TRSC-GJDA preserves the geometric structure and simultaneously reduces the differences of marginal and conditional distributions between domains.

The rest of the paper is organized as follows. The related works are reviewed in Section 2. In Section 3, we propose the model and TRSC-GJDA algorithm. The experimental evaluations are discussed in Section 4. Finally, we conclude this paper in Section 5.

2. Related work

In order to promote the performance of transfer learning, researchers pay more attention to what to transfer [24,25], and how to transfer [26,27]. The existing transfer learning methods can be roughly categorized into four classes: instance-based transfer learning, feature-based transfer learning, parameter-based transfer learning, and relation-based transfer learning. Our work is categorized in feature-based transfer learning. Feature-based transfer learning learns a latent high-level feature representation to improve the performance of the target task significantly.

Sparse coding only uses a few active coefficients, which makes the encoding easy to interpret and reduces the computational cost.

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