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Class centroid alignment based domain adaptation for classification of remote sensing images☆

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ABSTRACT

A new unsupervised domain adaptation algorithm based on class centroid alignment (CCA) is proposed for classification of remote sensing images. The approach aims to align the class centroids of two domains by moving the target domain samples toward source domain, with the moving direction equaling to the difference of the associated class centroids between two domains. After moving, the data distributions become similar and the classifier trained in source domain can be used to predict the changed target domain data. Since there lacks labeled information in target domain, the class centroids and moving directions are estimated based on the predicted results. Moreover, better moving directions can be determined by preserving the local similarity in the changed target domain, resulted in neighborhood based CCA (NCCA) method. Experiments with Hyperion, AVIRIS, and NCALM hyperspectral images and Worldview-2 multispectral images demonstrated the effectiveness of applying CCA and NCCA in reality.

1. Introduction

For remote sensing images, labeled instances are often difficultly, costly, or time consuming to obtain. Suppose we have had abundant labeled information from a previous image, it would be beneficial to reuse this labeled information for classification of a new image that is temporal to the previous one [1,2]. However, it will be problematic if we directly use the existing labeled data of the previous image, since the spectral characteristics may vary significantly in the new image due to the changed vegetation composition, soil moisture, topography, illumination conditions, and the angle of the sun [3]. Therefore, domain adaptation is necessary for solving the problem [4].

For classification of remote sensing images, domain adaptation methods are mainly categorized as feature based methods and instance based methods. Feature based methods, such as manifold alignment [5,6], maximum mean discrepancy [7], kernel based methods [8], and transfer component analysis [9] have been successfully applied to remote sensing images. They aim to find a feature space where data distributions of source and target images become the same. Thus, the labeled information of the source image can be used for classification of the target image. Instance based methods for remote sensing image classification include domain adaptation support vector machine (SVM) [10], manifold regularization kernel machine [11], the binary hierarchical classifier [12], graph matching [13], feature matching [14], and network analysis [15]. These methods classify the target domain image in the original data space by exploring semi-labeled data in target domain or finding the correspondences between two domains.

The algorithms of instance-based domain adaptation [16–18] can further be divided into two categories. The first one aims to gradually adjust the classifier to accommodate the distribution of target domain. For example, cross domain SVM [16], domain adaptation SVM [10], adaptive SVM [17], transferred adaboost [18], and manifold regularization kernel machine [11]. Cross domain SVM searches neighbors from the source support vectors for each labeled point in target image, and these neighbors are combined with the target domain labeled data to learn a new classifier. Adaptive SVM learns the classifier by averaging of the source classifier and the new discriminant function learned from the target image. Transferred adaboost utilizes the prediction errors on target training samples to increase the prediction ability of the “good” source training data while reduces that of the “bad” ones. All the three approaches require labeled data in target image. Differently, domain adaptation SVM and manifold regularization kernel machine approaches suppose that training data are only available in source domain; they selects semi-labeled samples in target image to help training a better classifier. The second one aims to adjust the distribution of source domain or target domain, thus both domains could share the same classifier. Julien Rebetez and

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Devis Tuia [15] proposed a method to search the correspondence between source and target domains based on network analysis. Then a matching between two domains was determined by preserving the geometrical and topological information of the graphs constructed from the two domains. Devis Tuia [13] obtained a match between two domains via graph matching algorithm, where each cluster centroid in one domain moves onto the most related cluster centroid in the other domain, with the constraint of preserving the local and global structure. The algorithms of the first type are generally time-consuming since the iterative training is required, while the latter algorithms aim to match the distributions between domains and only the classifier trained by source domain data is used, thus the computational cost is desirable. The proposed method in this paper belongs to the second type.

A good strategy to achieve domain adaptation is to adjust the data distributions of different domains to be similar, and therefore the classifier trained in source domain can be directly used to predict the target domain data. In this paper, we reduce the differences between two domains by moving the target domain data toward the source domain. If the moving direction is correct, the data distributions of the two domains will become similar. Since centroid can represent the averaging spectral property of a class, the difference of centroids is able to characterize the spectral drift of the class. Therefore, we determine the moving direction based on the difference of the class centroids between two domains. If a target domain sample belongs to one class, the sample will move with the direction equaling to centroid difference of this class. As a result, the class centroids of two domains will be aligned and two distributions become similar. This is the idea of our domain adaptation approach, and we call it class centroid alignment (CCA) approach. CCA assumes that the class centroids of target domain data are known as priors, so that the difference of class centroids between two domains can be accurately calculated; moreover, CCA requires to know the label information of each target domain sample, so that the correct moving direction can be determined. However, there lacks target domain labeled information in reality. Therefore we estimate the target class centroids based on the predicted labels, and calculate the centroid difference of each class between two domains based on estimated centroids. For each sample in target domain, its moving direction is determined by the centroid difference of its predicted class.

In CCA, the moving direction of a sample is only determined by its own predicted label. As a result, the relationships between points in target domain may be changed after moving (Two neighboring points that belong to the same class may become different if they move in different directions). In order to maintain the local similarity in target domain after moving, local neighborhood needs to be taken into account to calculate the moving direction. Therefore, neighborhood based CCA (NCCA) approach is proposed. NCCA may further improve the performance of CCA, since better moving directions may be obtained by considering more predictions in neighborhood. It is worth noting that the algorithm is conducted in an unsupervised manner since it does not require any prior information in target domain.

The proposed approach has the following properties: (1) CCA and NCCA approaches have low computational cost. Compared to the approaches that gradually update the classifier to target domain data [11,16–18], the proposed methods only train one classifier using source domain data; compared to many feature based approaches that require to perform eigen-decomposition of large scale Laplacian matrix or kernel matrix[5–7,9], CCA and NCCA methods align the two domains in the original spectral space by moving the target domain data toward source domain, and the computation of aligning the two domains only involves vector-vector addition and subtraction. (2) CCA and NCCA methods do not require label information in target domain and can achieve labor free classification. (3) NCCA approach considers the neighborhood information and preserves the local property of target domain data after the moving.

The rest of the paper is organized as follows. Section 2 describes domain adaptation problem. Section 3 presents the proposed CCA and NCCA algorithms. Experimental results are discussed in Section 4, and conclusions are summarized in Section 5.

2. Domain adaptation problem

Domain adaptation approach aims at taking advantage of the available knowledge on a given source domain to develop a classifier for classification of target domain where a priori information is not available. Since the distributions of source domain and target domain are different because of spectral drift, the classification results may be not acceptable if the classifier trained by labeled data in source domain is directly used to classify target domain data. In this paper, we aim to make the distributions across two domains be similar by moving the target domain data toward the source domain, and then target domain data can be better classified by the classifier trained in source domain. The key issue of this approach is to determine the moving directions of target domain data.

Let $\mathbf{X}_s \in \mathrm{R}^{d\times N}$ denote the source domain data with class labels $\mathbf{Y}_s \in \mathrm{R}^{1\times N}$, and $\mathbf{X}_t \in \mathrm{R}^{d\times M}$ represent the target domain data without labeled information, where d represents the dimensionality of the data, N is the number of labeled points in source domain, M is the number of unlabeled points in target domain, and $\mathbf{X}_s$ and $\mathbf{X}_t$ are distributional differently but related. There are C classes in both domains denoted as $\mathbf{\Omega} = [\Omega_1,\ldots,\Omega_C]$. We use $\mathbf{X}_{ts} \in \mathrm{R}^{d\times M}$ to represent the changed target domain data after moving toward source domain. Our domain adaptation approach firstly learns a classifier from $\mathbf{X}_s$ and $\mathbf{Y}_s$, then obtains $\mathbf{X}_{ts}$ by moving the target domain data towards source domain, and finally classifies the changed target domain data $\mathbf{X}_{ts}$ by the same classifier trained in source domain. Theoretically, the classifier trained by source domain and used to classify target domain can be any effective supervised classifiers. We utilize SVM as the base classifier in this paper due to its good performance for remote sensing images. In addition, SVM is suitable for training samples with small size and high dimensionality.

3. Domain adaptation based on class centroid alignment

3.1. CCA model in ideal condition

In order to achieve similar data distributions of source and target domains, we should capture the differences between two domains. Moreover, since the spectral drift varies in different categories, the difference between each class should be measured separately. For a class, the spectral property can be represented by its centroid, which is calculated as the mean spectra of data from the class. Suppose the class centroids are denoted as $\mathbf{U}_s = [\mathbf{u}_{s1},\ldots,\mathbf{u}_{sC}]$ for source domain and $\mathbf{U}_t = [\mathbf{u}_{t1},\ldots,\mathbf{u}_{tC}]$ for target domain. The spectral drift can be characterized by the class centroid difference: $\mathbf{d}_i = \mathbf{u}_{ti} - \mathbf{u}_{si}$, $i = 1,\ldots,C$. Supposing a target domain point $\mathbf{x}_t$ belongs to class i, it moves toward source domain along with the direction of $\mathbf{d}_i$, and then becomes $\mathbf{x}_{ts} = \mathbf{x}_t - \mathbf{d}_i$. Point $\mathbf{x}_{ts}$ is supposed to be similar to the spectra of class i in source domain data and thus become adapted to the SVM classifier trained in source domain.

Fig. 1 shows an example from the Hyperion data, where source image is collected in May and target image was collected in June in Botswana (BOT) area. The data include 9 identified classes, where classes 5, 7, and 8 are used to show the procedure of CCA. Points from different domains are plotted with different colors, and the circled black dot represents the class centroid. As shown in Fig. 1(a)–(c), two bands are used to show the distribution of data