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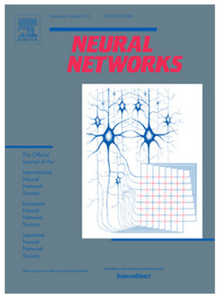

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Low-Rank and Sparse Embedding for Dimensionality Reduction

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Abstract

In this paper, we propose a robust subspace learning (SL) framework for dimensionality reduction which further extends the existing SL methods to a low-rank and sparse embedding (LRSE) framework from three aspects: overall optimum, robustness and generalization. Owing to the uses of low-rank and sparse constraints, both the global subspaces and local geometric structures of data are captured by the reconstruction coefficient matrix and at the same time the low-dimensional embedding of data are enforced to respect the low-rankness and sparsity. In this way, the reconstruction coefficient matrix learning and SL are jointly performed, which can guarantee an overall optimum. Moreover, we adopt a sparse matrix to model the noise which makes LRSE robust to the different types of noise. The combination of global subspaces and local geometric structures brings better generalization for LRSE than related methods, i.e., LRSE performs better than conventional SL methods in unsupervised and supervised scenarios, particulary in unsupervised scenario the improvement of classification accuracy is considerable. Seven specific SL methods including unsupervised and supervised methods can be derived from the proposed framework and the experiments on different data sets (including corrupted data) demonstrate the superiority of these methods over the existing, well-established SL methods. Further, we exploit experiments to provide some new insights for SL.

Index Terms

Dimensionality reduction, subspace learning, robustness, overall optimum.

I. Introduction

In many machine learning and computer vision applications, one often confronts with high-dimensional data such as face images, video frames, and text data. These data may introduce noisy and/ or redundant features owing to the high dimensionality. Dealing with such high-dimensional data is difficult due to the high computation cost and enormous memory requirements. As pointed out in [1], data points are actually sampled from a low-dimensional manifold that is embedded in a high-dimensional space. Finding a compact and informative representation of the original data is usually a critical step, which can speed up the subsequent tasks such as classification and clustering. Thus, dimensionality reduction (DR) has been commonly applied in computer vision and machine learning fields [2][3][4][5].

According to whether or not the label information are available for the training samples, DR methods can be categorized into three groups, supervised DR methods, semi-supervised DR methods, and unsupervised DR methods. The supervised DR methods commonly learn a discriminative projection by using the label information. The representative works including linear discriminant analysis (LDA)[6][7], local linear discriminant analysis framework (LLDA)[8], discriminative low-rank dictionary learning (DLR_DL) [9], locality sensitive discriminant analysis (LSDA) [10], and local discriminant embedding (LDE) [11]. In these methods, the basic criterion is to seek a discriminative projection which simultaneously maximizes the distances among the means of the classes and minimizes the distances among the data sharing the same class labels by using the Fisher's criterion [8].

However, in real-world applications, collecting high-quality labeled training data is difficult, whereas abundant unlabeled data are often easily accessible [12]. These unlabeled data are useful to promote the algorithmic performance. Thus, it is necessary to design a method that can use both labeled and unlabeled data. Semi-supervised learning is such a method which uses the data distribution and local structure of both labeled and unlabeled data and the label information of the labeled data to improve the algorithmic performance. Semi-supervised discriminant analysis (SDA), which uses the labeled data to maximize the separability between different classes and uses unlabeled data to estimate the intrinsic geometric structure of the data, is proposed to seek a discriminative projection for DR [13]. Constrained nonnegative matrix factorization for image representation (CNMF) is proposed to overcome the disadvantage of original NMF that cannot make use of the label information [14]. CNMF explicitly combines label information of the labeled samples to improve the discriminant power of the resulting matrix decomposition. Flexible manifold embedding (FME) uses label information of labeled data as well as the manifold structure of both labeled and unlabeled data to improve the performance of semi-supervised learning [15]. Semi-supervised DR using trace ratio criterion (TR-FSDA) reformulates the objective function of SDA in a trace ratio form and simultaneously

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