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Dynamic graph fusion label propagation for semi-supervised multi-modality classification

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ABSTRACT

The key of label propagation heavily depends on how to capture the manifold structure of the data, which usually is represented by the graph. In the semi-supervised multi-modality classification, exiting methods often optimize the linear relation of multi-graph for label propagation. However, the intrinsic manifold structure is not completely revealed by the linear fusion of multi-graph because the label changes in each iterating propagation dynamically influence the fusion relation of multi-graph. In other words, the fusion relation of multi-graph should be nonlinear because of the label changes in the propagation process, and can not be precisely described by the fixed linear relation in existing methods. To evaluate this nonlinear relationship influence on the classification performance of label propagation, we propose dynamic graph fusion label propagation (DGFLP) for the semi-supervised multi-modality classification. DGFLP is able to jointly consider the relation of multi-graph and the unique distribution of each graph, and models the various relevance of multi-graph in the propagation process. Moreover, the DGFLP alternately integrates the tradition label propagation and the new model function to describe the interaction between the multi-graph and label. The DGFLP solution provides not only the classification label but also the nonlinear relation that encodes the dynamical multi-graph relationship changes in label propagation. The experimental results demonstrate that DGFLP outperforms state-of-art methods on the ORL, AR, scenes 15, Caltech 101, and Caltech 256 databases.

1. Introduction

Distance or similarity metric is a fundamental question in pattern recognition. Although p-Laplacian metric has tighter isoperimetric inequality for representing the intrinsic structure [1], it is hard work to precisely describe the manifold structure of the entire data space though the single distance metric. The graph model usually is constructed based on the distance metric. Therefore, the multi-graph fusion of the multi-modality data [2–4] has been proposed for finding the proper metric. However, the dynamic relevance between the multi-graph and the class label is seldom considered for approximating to the manifold structure of the data in classification.

In the supervised method, multi-metric learning can capture the distance metric by holding the smaller distance in multi-modality data of the same label while preserving the larger distance among multi-modality data of the different label [5–10]. In these methods, the linear relation of multi-graph is built on the label data for maximizing the divergence among the inter-class points while minimizing the divergence in the intra-class points. In addition, the relationship of multi-graph can be learning based on metric learning [11], multimodal sparse coding [12], multiview stochastic learning [13] and multi-task learning [14]. However, the relevance between the multi-graph and class label is relatively fixed because the label data does not change in the metric learning.

In the unsupervised methods, multi-view intact space learning algorithm can combine the encoded complementary information in multiple views to discover a latent intact representation of the data [15]. In addition, multi-modality structure fusion learning can exploit the correlation and interrelation of multi-structure (multi-graph based on the distance metric) without the consideration of class label for image classification [16,17], action recognition [18], shape analysis [19,20], medical image fusion [21] and infrared target recognition [22]. Another unsupervised tensor product graph diffusion can integrate multi-view by exploring high-order graph information [23,24]. In these methods, the multi-graph constructed or the intact space learned on the similarity metric of the unlabel data has nothing with class label.

In the semi-supervised learning, co-training can choose the unlabel samples with the most confidence to help multi-modality

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features for retraining to enhance the discriminability between classes [25–27]. However, co-training mostly is not graph-base method because many credible samples for classification is evaluated for retraining the classifier. Multi-graph semi-supervised learning methods propagate the class-label information within the linear fusion graph of multi-modality data for image classification [2,4], retrieval [28], protein function predication and web page classification [3]. In multi-graph label propagation, the label propagation domain in each iteration is optimized by curriculum learning, or the correlations among the different classes is considered by propagation process. In these methods, the linear relation of multi-graph is considered for classification after the iteration propagation end, and is still fixed for each label changes in the propagation.

From the above methods, we find that linear relation of multi-graph is fixed in multi-modality classification. In fact, label changes influence the linear relation construction of multi-graph in each iteration propagation, because label data is gradually increasing with the label propagation to decide the distribution structure of the data, which can be constructed by the relation of multi-graph. In other words, the relation of multi-graph dynamically wave with the label variety, because label information is an important fact to estimate the relation of multi-graph. If the bridge is build between the relation of multi-graph and the varied label data, label propagation will be more adaptable to heterogenous structure interaction in semi-supervised learning. Moreover, according to graph theory [29], this bridge is benefit to mine the relation of multi-graph for approximating the intrinsic structure of non-linearly distributed data. Therefore, there are two issues to explore the piecewise linear relation (nonlinear relation) for multi-graph in label propagation. One issue is how to describe and model the relevance between the multi-graph and label, and another is how to integrate this model into label propagation for revealing the multi-graph relation to approximate to the manifold structure of data and improve the multi-modality classification.

To settle the above issues, we propose dynamic graph fusion label propagation (DGFLP) for the semi-supervised multi-modality classification. First, we view label propagation on multi-graph as Gaussian process, which can be modeled by multivariate Gaussian distribution. Second,each graph spacial distribution can be regarded as Ising model, and then the maximization posterior probability of multi-graph under the condition of label can be estimated by Bayes theories. At last, we integrate the proposed model into label propagation by the iterative optimization. Because the linear relation of multi-graph is different with each iterative propagation and each model estimation, dynamic graph fusion can capture the change details of manifold structure of data. Fig. 1 compares label propagation with DGFLP, and demonstrates the obvious different of these methods in multi-graph fusion of multi-modality data.

The main contributions of the proposed DGFLP have three aspects: (1) it models the relevance between multi-graph and label to describe their interrelation;(2) it can obtain the nonlinear relation of multi-graph to approximate to the manifold structure; (3) it is able to incorporate multi-graph fusion into label propagation for improve the multi-modality classification. The main idea of DGFLP is shown in Fig. 1 (b).

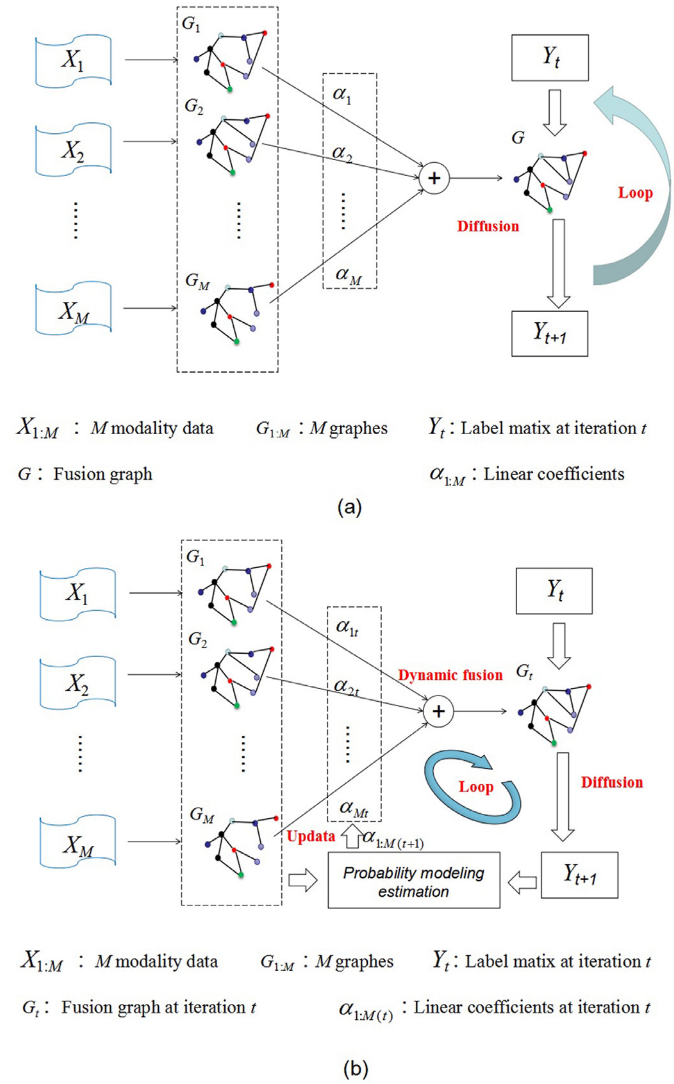

Fig. 1. The illustration flow chart comparison between label propagation in (a) and dynamic graph fusion label propagation (DGFLP) in (b) for multi-graph fusion of multi-modality data.

2. Related works

Semi-supervised learning usually supports the solution of multi-modality classification, in which multiple views /features /similarities/lables/graphes are extracted to describe the same objects (for example, images, videos and targets etc.). These methods have a common purpose, which captures the complementary relation of multi-modality data to enhance the discriminative classification by co-learning the label and unlabel data.

In recent research, many methods utilize the different way to reach the common purpose of semi-supervised multi-modality classification. The representative existing methods can be roughly divided into four categories: multi-label correlation, multi-view constraint consistency, multi-view co-training/labeling, multi-modal deep networking and multi-graph fusion [2,4,28].

First, multi-label correlation can exploit relationship between labels, and deal with the situation of the lacked data or even missing labels through manifold regularizer reducing the required labeled data [30] or dynamic propagation performing transductive learning [31]. These methods can capture the label correlation for multi-modality data in the semi-supervised learning.

Second, multi-view constraint consistency can utilize the correlation and complement derived from multiple views cues of image data, which satisfy the pair-wise view constraint [32], the global label consistency [33], the Hessian regularized logistic regression [34], the maximum entropy consensus [35], or the pseudo-label images [36]. The advantage of these methods is to find the consistency of the multi-modality data and the relation between the data and the label in the semi-supervised learning.

Third, multi-view co-training can collaborate the label rules to judge the consistency and diversity of the classifies for improving