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Discriminative metric learning for multi-view graph partitioning

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A B S T R A C T

In recent years, multi-view graph partitioning has attracted more and more attention, but most efforts have been made to develop graph partitioning approaches directly in the original topological structure. In many real-world applications, graph may contain noisy links and the distance metric may not be so discriminative for revealing cluster structure. This paper addresses the problem of discriminative metric learning for multi-view graph partitioning. In particular, we propose a novel method called *Multi-view DML* (abbr. of Multi-view Discriminative Metric Learning) to transform the metric space in the original graph into a more discriminative metric space, in which better graph partitioning results will be obtained. We envision the multi-view graph as an adaptive dynamic system, where both the intra-view connections and the inter-view couplings are interplayed to gradually update the relation metric among nodes. On the one hand, the inter-view coupling will be influenced by the intra-view connection between two nodes. On the other hand, the inter-view coupling will also affect the intra-view connection. Such interplay eventually makes the whole graph reach a steady state which has a stronger cluster structure than the original graph. Extensive experiments are conducted on both synthetic and real-world graphs to confirm that the proposed method is able to learn more discriminative metric.

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1. Introduction

Recently, a huge amount of graphs have been generated such as social networks, citation networks and collaboration networks, where the nodes represent the objects in the world and the edges (connections) represent the relationship (interaction) among the objects [1–4]. The weight of an edge represents the interaction strength between the connected nodes [5]. These graphs may exhibit some cluster structure where nodes in the same cluster are more similar than nodes belonging to different clusters. Discovering the cluster structure not only reveals the graph properties but also has a number of real world applications, such as information influence analysis in social network, market segmentation in product market analysis, customer recommendation in online shopping platform, etc [4]. To achieve this goal, many graph partitioning[1] algorithms have been developed, such as *permanence* [6], *weighted conductance* [7], *modularity* [8,9], *PageRank centrality* [10], *cut-ratio* [11], *normalized cut* [12], and *distance dynamics* [13].

As the rapid development of the web technology, in particular in the social network, there emerge some multi-view graphs [14]. For instance, in social network, it is often the case that each user has various accounts in different social platforms which are coupled by some common bonds, e.g. Email address. Each platform is taken as a view in the social network. It is possible for a user to behave slightly differently in various views and the social behaviours in different views may influence each other, which means that the inter-view coupling should be taken into account for discovering the relationship among nodes in the same view [15]. In two different views, when a user in one view is more similar to itself in another view (i.e., more similar linkage structure and interaction strength), the strength of the inter-view coupling between this pair of views is stronger [16]. Due to the complex interplay between the intra-view connection and the inter-view coupling, multi-view graph partitioning encounters more challenges than that in single-view graph. Although some methods have been developed for multi-view graph partitioning [14,17,18], most of them are only based on the original topological structure without learning more discriminative metric space.

In real-world applications, the cluster structure in the original graph would not be quite clear and would further weaken due to the noisy links [19,20]. For example, in the same university, two users u and v from different departments may know each other.

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[1] In the literature of data mining research, graph partitioning is also called community detection in network where "community" has the same meaning of "cluster", i.e. a set of similar nodes. In this paper, we will use network and graph, community and cluster alternatively.

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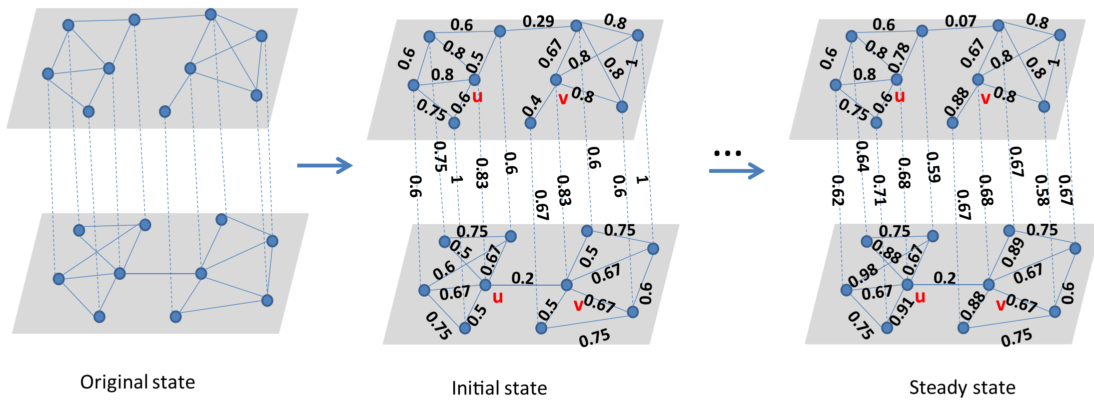

Fig. 1. Illustration of the three states of a two-view graph.

In unweighted graph, they are connected by an edge. However, it is possible that the graph partitioning algorithm assigns these two nodes into the same cluster, i.e. the same department, which is obviously wrong according to the ground-truth. Although recently, some efforts have been made to metric learning in graph so as to enhance the discriminability of cluster structure [13,19,21], they are limited to the single-view graph and there is still a lack of such work on the multi-view graph. The main challenge lies in the mutual influences between the intra-view connection and the inter-view coupling.

In this paper, we propose a new method called *Multi-view DML* (abbr. of Multi-view Discriminative Metric Learning) to address the discriminative metric learning for multi-view graph partitioning. The basic idea is to envision the given multi-view graph as a dynamic system, where three types of states are involved. The first one is the *original state*, which represents the original graph, i.e. the input of our algorithm. Jaccard similarity is utilized to transform the original state into the *initial state*. From the initial state, the intra-view connection strength and the inter-view coupling strength will be gradually updated by the proposed strategies, leading to the *steady state* which is taken as output. Therefore, the main idea of our approach has two steps: 1) Initialization. The intra-view connection strength and the inter-view coupling strength are initialized by the proposed transformation based on Jaccard similarity. 2) Update procedure. Different strategies are used to update the two types of strengths of the multi-view graph in an interplay manner. For the intra-view connection strength, three types of inter-view coupling adjusted influence from *directly linked nodes*, *common neighbors* and *exclusive neighbors* are all taken into account. On the other hand, the update of the inter-view coupling strength of one node between two views takes into account the interplay of both the intra-view connections associated with the node and the inter-view couplings related with its neighbors. The update procedure continues until convergence, in which the more discriminative metric (i.e. the intra-view connections and the inter-view couplings) will be obtained.

For illustration, Fig. 1 shows the three states of a two-view graph. (a) is the original multi-view graph describing the linking information of all the nodes in two different views and is used as the input of our algorithm. (b) presents the initial social relationship among nodes after transformation based on Jaccard similarity. (c) is the steady state of this two-view graph, which is taken as the output and provides more discriminative metric for graph partitioning.

The proposed method addresses a specific problem in multi-view clustering, which belongs to a more general field of multi-view learning. Compared with the existing metric learning methods for single-view graphs, apart from inheriting the advantages of the method in [13], the proposed Multi-view DML method for the first time provides a strategy for studying the interplay between the intra-view connection and the inter-view coupling, which would be helpful in the research of many multi-view graph analysis tasks.

The rest of the paper will be organized as follows. In Section 2, we briefly review the related work. Section 3 describes our model in detail, and in Section 4, extensive experiments are conducted to demonstrate the effectiveness of our algorithm. We finally conclude our paper in Section 5.

2. Related work

Recently, some methods have been developed for multi-view graph partitioning [14,17,18,22–25]. One of the earliest methods is [14], which presents a framework of node cluster quality evaluators that allows studying the cluster structure of multi-view graphs. In a more general manner, Zhang et al. [17] combine the information from various views and extend modularity into the multi-view weighted signed version, where the extended modularity is used for measuring the quality of dividing a graph into clusters. Higher value of the extended modularity indicates better division and higher separability of graph structure. In [18], Li et al. propose a model for multi-view weighted graph partitioning based on permanence [6]. In [22], multi-view modularity optimization has been applied to analyze the Los Angeles Police Department field interview card data set. It combines the information of two views, i.e. geographic and social information about stops to find clusters. Hu et al. [23] use multi-view modularity combining graphs and image data for graph partitioning. In [24], the graph is time-dependent and the temporal clusters to be discovered consist of nodes across multiple snapshots. A measure of partition distance called *estrangement* is proposed to find meaningful temporal clusters at various degrees of temporal smoothness in real-world graphs. Although the above methods work well in some relatively simple multi-view graphs, when handling complex multi-view graphs with less obvious cluster structure, their performance may degenerate seriously. One remedy is to enhance the discriminability before performing graph partitioning.

In the single-view graph case, some efforts have been made in enhancing the discriminability of cluster structure [13,19,21,26–31]. For instance, Yang et al. [28] propose a boosting framework for preserving both visual and semantic similarities for image retrieval systems. Yeung and Chang [29] propose an extension of RCA using both positive and negative equivalent constraints. In [30], the distance metric is learned for addressing the text line segmentation problem. In [31], an adaptive Semi-supervised Clustering Kernel Method based on Metric learning (SCKMM) is proposed to solve

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