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A framework of uniform contribution embedding of data

Yuelong Li [a,b,c,*,1], Yan Jin [a], Jianming Wang [a], Zhitao Xiao [d], Lei Geng [d]

[a] School of Computer Science and Software Engineering, Tianjin Polytechnic University, Tianjin, 300387, PR China
[b] Department of Computer Science, University of York, York YO10 5GH, UK
[c] Tianjin Key Laboratory of Intelligence Computing and Novel Software Technology, Tianjin University of Technology, Tianjin 300384, PR China
[d] School of Electronics and Information Engineering, Tianjin Polytechnic University, Tianjin 300387, PR China

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ABSTRACT

In the scenario of big data, incorporating multiple attribute descriptions of the same subject (i.e., so-called multi-view data analysis) and the developing effective data visualization techniques have been one of the most important topics in the computer vision and machine learning community. In this paper, a multiple view source attributes embedding framework is proposed that can assemble various object attributes together and embed them into a low dimensional space to realize visual data structure demonstration. Classical sole attribute data embedding approaches such as MDS and SHE can be utilized under this framework. The core idea of this framework is to achieve a uniform contribution merging, which means every source attribute will contribute equally to the final embedded output. The underlying reason for this idea is that now that an attribute is input as a source and no prior weight is given beforehand, it should be treated equally. The most exciting advantage of this strategy is that it can avoid prejudice caused by major attributes (exerting due to their evident quantity advantage), which may lead the minor attributes be ignored. In addition, we propose a simple iterating algorithm to implement this framework, and plenty of experiments are conducted under diverse source attribute configurations to validate its effectiveness.

1. Introduction

Attribute is a description and measurement to certain characteristics of an object. It can be asserted that the full set of all attributes defines an object. Thus, the relationships of objects can be expressed and described by the dissimilarities of corresponding attributes. While, the attribute dissimilarity matrix is a common utilized approach to quantitatively measure these relationships. It is well-known that this kind of matrix can be utilized to represent each arbitrary pairwise relationship, such as physical distance, class label difference, appearance similarity, gender distinction, and so forth. As to the specific form, dissimilarity matrix is flexible: its entry value can be continuous or discrete (e.g., the description of whether two samples have the same class label); it can be learned automatically or labeled manually; it can be symmetric or dissymmetric (depending on the specific metric). Due to its significant function, in the past dozens of years, dissimilarity description and especially the dissimilarity matrix have been extensively explored and researched in the fields of pattern recognition, machine learning, computer vision, and so forth. And till now, related techniques have been utilized in tremendous research topics such as face classification [1–7], image segmentation [8], action recognition [9,10], object matching [8], kinship verification [11], and so on [12–19].

On the other hand, nowadays, in the fields of computer vision and visualization, the research of data visualization and graphical presentation receives more and more attentions. In this area, the visual demonstration of spatial structures of high dimensional data set is of great value to both theoretical researches and practical applications. While, the two dimensional dissimilarity matrix is a direct reflection to the mutual spatial relationships of a group of high dimensional data points in certain aspect. Furthermore, some dissimilarity matrices can be acquired even without the original high dimensional data, e.g., in kernel approaches [20–23], the point coordinates in the original extremely high dimensional kernel space are generally unacquirable. Thus, how to directly embed an attribute dissimilarity matrix into low dimensional visual space to graphically demonstrate underlying data structures becomes an interesting research topic. In the past few decades, a large number of effective approaches have been worked out. MDS [24] tries to preserve original Euclidean distance information during embedding. SHE [25] is a spherical surface embedding approach and emphasizes the preservation of the non-distance

* Corresponding author.
E-mail addresses: liyuelong@pku.edu.cn, liyuelong@tjpu.edu.cn (Y. Li).
[1] Institution a and c contribute equally to this work.

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Fig. 1. Three different types of human description attributes.

information of dissimilarity matrix. Isomap [26] pays attention to the underlying data manifold. SNE [27], t-SNE [28], and HSSNE [29] explore data embedding from the view of statistical data distribution. Through exploiting the local symmetries of linear reconstruction, LLE [30] could approximate the ground truth nonlinear data manifold structure. Hessian LLE [31] introduces the local isometry of Reimannian manifold into data embedding. SPE [32] is a stochastic data structure approximation approach. As to the quantitative objective of those embedding approaches, in a word, it is to minimize the difference between source dissimilarity matrix (which may be defined totally distinctly by different approaches) and that calculated according to embedded points, to optimally demonstrate the genuine data spatial relationships in low dimensional visual space.

In this paper, rather than continue to explore pre-mentioned single dissimilarity input matrix based embedding techniques, we mainly focus on the merging of multiple arbitrary types of dissimilarities that describe the same object group and corresponding multiple input sources based data embedding. Nowadays, accompanied with the amazing development of information acquirement and processing techniques, more and more aspects and views of a target object can be explored and disclosed. As an example, Fig. 1 shows three distinct types of attributes that describe human beings. Clearly, each attribute shown in this figure provides a description to a specific aspect of human, no matter it is an attribute of the appearance, high understanding level, or image description features.

Thus, how to incorporate various kinds of input attribute dissimilarities into a unified relationship description becomes a practical research topic. Fig. 2 shows an example of the value to merge distinct attributes for visual presentation. From these figures,[2] it can be observed that the class label information effectively highlights the relationships of intra-class.

[2] It can be observed on the two SHE figures, especially on the lower right one, some balls that describe the location of data points are occluded and hence could not be intactly displayed. That is because the SHE algorithm cannot always perfectly embed points onto a spherical surface, and hence sometimes there are tiny deviations on a portion of points.

As to the merging of source attribute dissimilarities, how to design a reasonable criterion is the most critical problem. After setting a reliable merging objective, the left works are only to propose a specific algorithm to implement this criterion. These works are relatively simple, because unlike most of pattern recognition and machine learning problems where precious raw data have to be divided into independent training and evaluating subsets to ensure the generalized ability of proposed approach, however, as to data embedding, all source data can be utilized to the training procedure to achieve an optimal embedding. Moreover, generally, data visualization research pays less attention to computing complexity and time costs. These good news seem to be exciting, right? But unfortunately, a perfect merging criterion is hardly achievable.

Intuitively, if there are more than one source attribute inputs, the best choice is to let the users determine their merging weights according to their relative significance, because the users are the most appropriate experts who really understand the underlying nature of source data. However, this solution is infeasible under most of circumstances. For one thing, no each user is good at quantizing the significance of various characteristics and features of objects, and this requirement to users usually seems boring and less user-friendly. For another, clearly, relying on manual settings will seriously degrade the application value and robustness of an algorithm. Furthermore, when the number of source attributes becomes huge, manual setting is absolutely a disaster with extremely low accuracy. Therefore, designing a reliable objective merging criterion is necessary. However, at a first glance, it seems that there is no answer to this question which satisfies every requirement. Since there will be only one merged comprehensive dissimilarity output, if some attributes are assigned bigger weights, the significance of others will be unavoidably weaken. And though it seems plausible to rely on the common information reflected by the majority of source attributes, there is also an old saying that the truth often lies in the hands of a few. For example, in some extremely challenging datasets of facial images (such as LFW [34]), compared with tremendous possible image feature descriptors, the class label information may be minor (as to the similarity of the constructed attribute dissimilarity matrix with that of other descriptions), but