Revision Note

Accurate Multi-view Clustering to Seek the Cross-viewed yet Uniform Sample Assignment via Tensor Feature Matching

Yue Zhang[a], Wuxiu Quan[b], Tatsuya Akutsu[c], Li Liu[d,*], Hongmin Cai[b], Bin Zhang[e,*]

[a]*School of Computer Science, Guangdong Polytechnic Normal University, Tianhe, Guangzhou 510665, China*
[b]*School of Computer Science and Engineering, South China University of Technology, Guangzhou 510006, China*
[c]*Bioinformatics Center, Institute for Chemical Research, Kyoto University, Uji, Kyoto 611-0011, Japan*
[d]*School of Information Science and Engineering, Shandong Normal University, Changqing, Jinan 250358, China.*
[e]*Guangdong Institute of Intelligence Science and Technology, Hengqin, Zhuhai, Guangdong 519031, China*

Abstract

Multi-view clustering has become one of the popular clustering branches with data accumulation from multiple domains. Unfortunately, a large heterogeneity gap exists due to cross-view discrepancy, resulting in inaccurate sample-wise similarity estimation. Furthermore, the popular multi-view clustering methods heavily rely on sample-wise similarity measurements, which often lead to suboptimal clustering performance due to inaccurate similarity estimation across views. To tackle these challenges, this paper presents an accurate multi-view clustering method from a standpoint of inter-view feature-wise matching to bypass the inaccurate sample-wise similarity that leverages tensor feature matching for cross-viewed yet uniform sample assignment, named by multi-view clustering via tensor feature matching (MC-TFM). Specifically, our approach begins with exploring a comprehensive feature matching tensor by exploiting both intra-view and inter-view correlations among multi-view features. Subsequently, a feature matching matrix, which preserves the correlations and importance of multi-view features for guiding the cross-viewed yet uniform sample assignment, is estimated based on this tensor. Furthermore, these correlations and importance are maintained into two coded feature bases by decomposing the feature matching matrix. Finally, a sample assignment matrix is learned via jointly reconstructing the samples using the two bases further cooperating with spectral clustering. In this way, the heterogeneity gap is bridged by tensor feature matching, and the inaccurate sample-wise similarity estimation is omitted by using feature-wise matching to guide sample-wise assignment. Extensive experiments conducted on seven real-world datasets highlight the effectiveness of the cross-viewed yet uniform sample assignment, demonstrating the potential of our approach in accurate multi-view clustering tasks.

Keywords:
Multi-view clustering, Tensor feature matching, Uniform sample assignment, Multimodal, Multimedia computing, Data mining

*Corresponding author, liuli_790209@163.com (Li Liu), zhangbin@gdiist.cn (Bin Zhang)

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