Multiway p-spectral clustering on Grassmann manifolds

Author and Presenter:

Dimosthenis Pasadakis (Università della Svizzera italiana, Switzerland)

Co-authors:

Christie L. Alappat (Friedrich-Alexander-Universität Erlangen-Nürnberg, Germany)
Olaf Schenk (Università della Svizzera italiana, Switzerland)
Gerhard Wellein (Friedrich-Alexander-Universität Erlangen-Nürnberg, Germany)

The representantion of data in the form of graphs [1] and their separation into groups is a ubiquitous task in every scientific domain that deals with interacting or interconnected data. Spectral clustering and its nonlinear reformulations have gained a lot of attention due to their increased numerical benefits and solid mathematical background. In this talk we present a direct multiway spectral clustering algorithm in the p-norm, for $p \in (1, 2]$. The problem of computing multiple eigenvectors of the graph p-Laplacian, a nonlinear generalization of the standard graph Laplacian, is recast as an unconstrained minimization problem on a Grassmann manifold and solved with a state-of-the-art library for Riemannian optimization. The value of p is reduced in a pseudocontinuous manner, promoting sparser solution vectors that correspond to optimal graph cuts as p approaches one. Monitoring the monotonic decrease of the balanced graph cuts guarantees that we obtain the best available solution from the p-levels considered. We demonstrate the effectiveness and accuracy of our algorithm in various synthetic test-cases. Our numerical examples and comparative results with eigenvector-based clustering methods indicate that the proposed method obtains high quality clusters both in terms of balanced graph cut metrics and in terms of the accuracy of the labelling assignment. Furthermore, we will demonstrate studies for the classification of facial images and handwritten characters to showcase the applicability in real-world datasets.

References

[1] A. Eftekhari, D. Pasadakis, M. Bollhöfer, S. Scheidegger, and O. Schenk, Block-enhanced precision matrix estimation for large-scale datasets, Journal of Computational Science, Volume 53, 2021, 101389, ISSN 1877-7503, https://doi.org/10.1016/j.jocs.2021.101389.