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Multi-view Clustering using Barycentric Coordinate Representation

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Purpose

- Work on multiple views
- Reduce a significant time loss
- Update weights of different views

Multi-view clustering

Clustering – Data analysis technique that groups similar objects together to uncover patterns and gain insights from complex datasets. e.g. KMeans

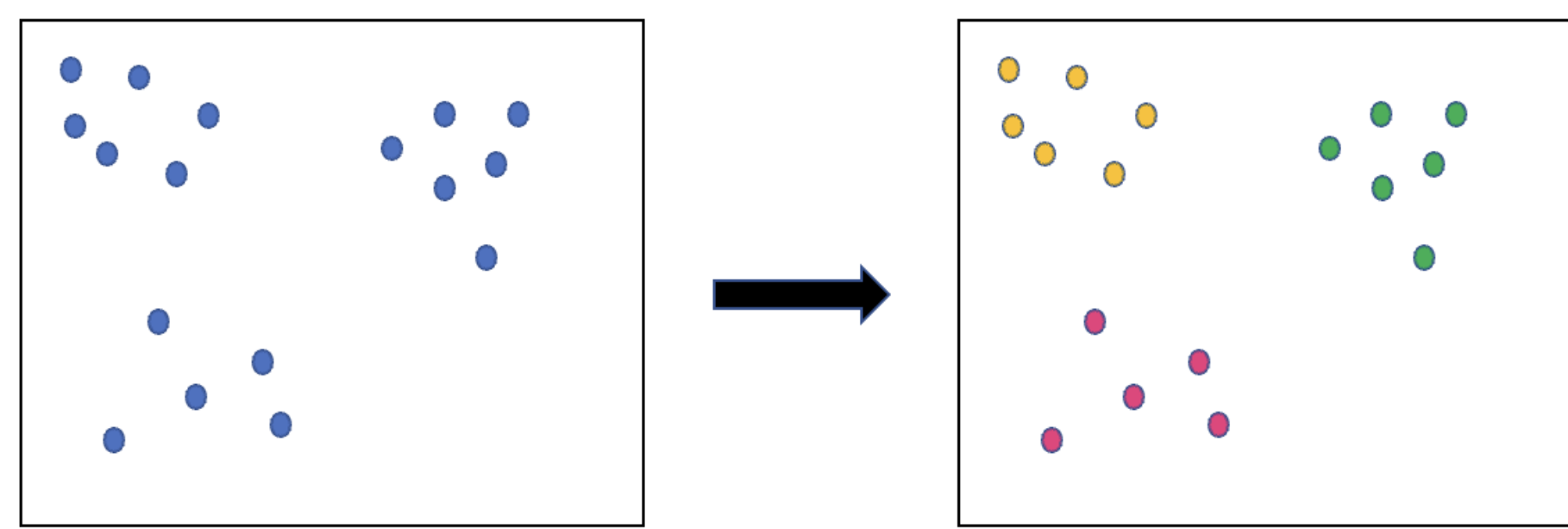


Figure 1. Example of Clustering

Multi-view data/clustering – Looking at an object or dataset from multiple perspectives. By integrating information from different views, multi-view clustering improves the accuracy and robustness of clustering algorithms, enabling a more complete understanding of the data.



Figure 2. Example of Multi-view data/clustering

RMKMC – Robust Multi-View K-means Clustering [1]

The RMKMC model aims to minimize the weighted distance between each point and its cluster centers across all views, resulting in a global communal cluster indicator matrix G . The weights of the views can be automatically updated using a single parameter to control the weight distribution.

$$\min_{C^{(v)}, G, \alpha^{(v)}} \sum_{v=1}^V (\alpha^{(v)})^\gamma \|X^{(v)} - GC^{(v)}\|_{2,1}$$

BC representation

A recent research [2] proposed that a set of fixed support points are chosen among the objects of the dataset and be used as a basis for the definition of a representation space, in order to find barycentric coordinates (BC) of data points in that space, then apply prototype-based clustering on them.

Illustration:

- triangle : $(\lambda_1 + \lambda_2 + \lambda_3) * X = \lambda_1 * A + \lambda_2 * B + \lambda_3 * C$
- p-vertices : $(\lambda_1 + \dots + \lambda_p) * X = \lambda_1 * S^1 + \dots + \lambda_p * S^p$

where $(\lambda_1, \dots, \lambda_p)$ is called **barycentric coordinate representation** with respect to the **support points** (S^1, \dots, S^p) .

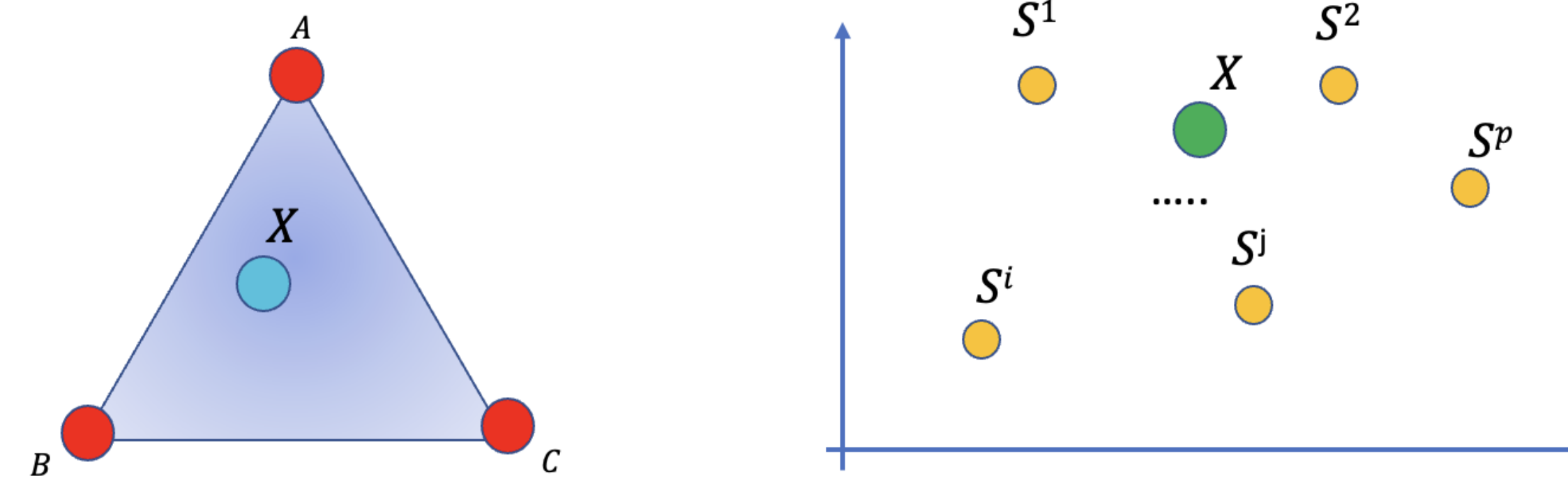


Figure 3. Define barycentric coordinate from triangle to p-vertices

Normalized barycentric coordinates:

$$X = \frac{\lambda_1 * S^1 + \dots + \lambda_p * S^p}{\lambda_1 + \dots + \lambda_p} = \sum_{i=1}^p \beta_i S^i \text{ with } \sum_{i=1}^p \beta_i = 1$$

Finding β :

$$A = \begin{pmatrix} d(s^1, s^1) - d(s^2, s^1) & \dots & d(s^1, s^p) - d(s^2, s^p) \\ \dots & \dots & \dots \\ d(s^1, s^1) - d(s^p, s^1) & \dots & d(s^1, s^p) - d(s^p, s^p) \\ 1 & \dots & 1 \end{pmatrix}, M^n = \begin{pmatrix} d(x^n, s^1) - d(x^n, s^2) \\ \dots \\ d(x^n, s^1) - d(x^n, s^p) \\ 1 \end{pmatrix}$$

$$A * \beta^n = M^n \Rightarrow \beta^n = A^{-1} * M^n$$

Distance d^2 between X and a cluster center μ :

$$d^2(x^n, \mu^k) = -\frac{1}{2}(\beta^n - \beta^k)^T * D_s * (\beta^n - \beta^k),$$

where D_s is the dissimilarity matrix between the support points.

References

- Xiao Cai, Feiping Nie, and Heng Huang. Multi-view k-means clustering on big data. In *Twenty-Third International Joint conference on artificial intelligence*, 2013.
- Parisa Rastin, Guénaél Cabanes, Basarab Matei, Younès Bennani, and Jean-Marc Marty. A new sparse representation learning of complex data: Application to dynamic clustering of web navigation. *Pattern Recognition*, 91:291–307, 2019.

BCmvlearn

Objective function:

$$J = \min_{\mu^{(v)}, G, \alpha^{(v)}} \sum_{v=1}^V (\alpha^{(v)})^\gamma \sum_{n=1}^N d^2((x^n)^{(v)}, \mu^{(v)} G_n^T) = \min_{(\beta^\mu)^{(v)}, G, \alpha^{(v)}} -\frac{1}{2} \sum_{v=1}^V (\alpha^{(v)})^\gamma H^{(v)}$$

where $H^{(v)} = \sum_{n=1}^N \Phi_n^T D_s^{(v)} \Phi_n$ with $\Phi_n = (\beta^n)^{(v)} - (\beta^\mu)^{(v)} G_n^T$

Optimization:

- Updating $(\beta^\mu)^{(v)}$: $(\beta^\mu)^{(v)} = \sum_{n=1}^N (\beta^n)^{(v)} (\sum_{n=1}^N G_n^T G_n)^{-1}$
- Updating G :

$$i = \underset{k \in \{1, \dots, K\}}{\operatorname{argmin}} \left\{ -\frac{1}{2} \sum_{v=1}^V (\alpha^{(v)})^\gamma \Psi_k^T D_s^{(v)} \Psi_k \right\}$$

where $\Psi_k = (\beta^n)^{(v)} - (\beta^\mu)^{(v)} G_{ni} = 1$ and $G_{nj} = 0$ where $j \in \{1, \dots, k\}, i \neq j$

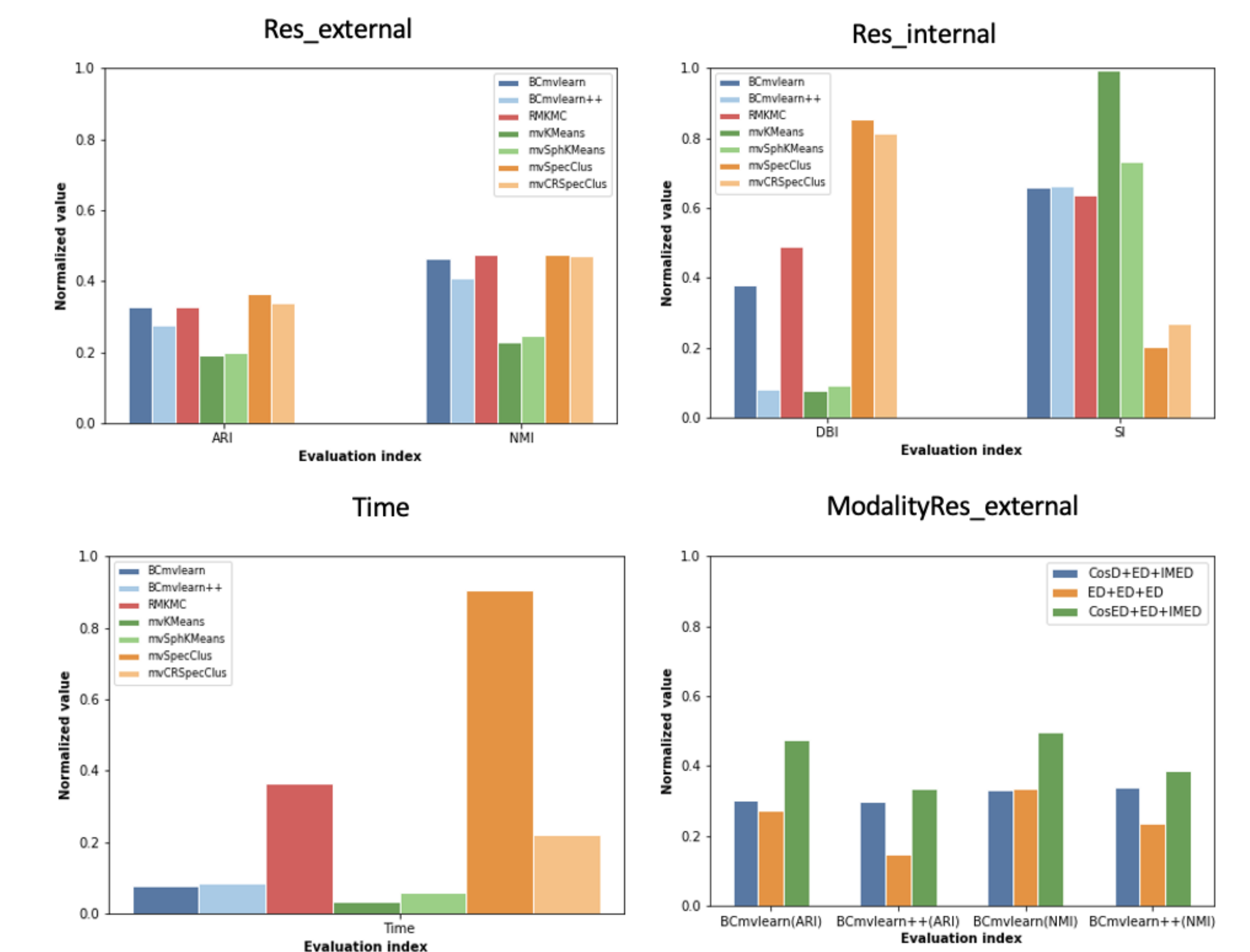
- Updating $\alpha^{(v)}$:

$$\alpha^{(v)} = \frac{(\gamma H^{(v)})^{\frac{1}{1-\gamma}}}{\sum_{v=1}^V (\gamma H^{(v)})^{\frac{1}{1-\gamma}}}$$

Alternative version:

BCmvlearn++ improves initialization by avoiding poor center placement.

Experiment Results



The experimental results on different evaluation metrics show that the proposed approach is competitive with other state-of-the-art multi-view algorithms in terms of quality and time complexity. And also could handle different distance metrics for application to multimodal clustering.