Multiple Kernel k-means with Incomplete Kernels

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Motivation

Multiple kernel clustering (MKC) [1, 2, 3] optimally combines the multiple kernels of each sample to improve clustering performance. However, existing MKC algorithms cannot effectively handle the situation where some kernels are missing, which is common in practical applications. Figure 1 gives an illustration in clustering Alzheimer's disease (AD), where a subset of channels of many objects are absent.

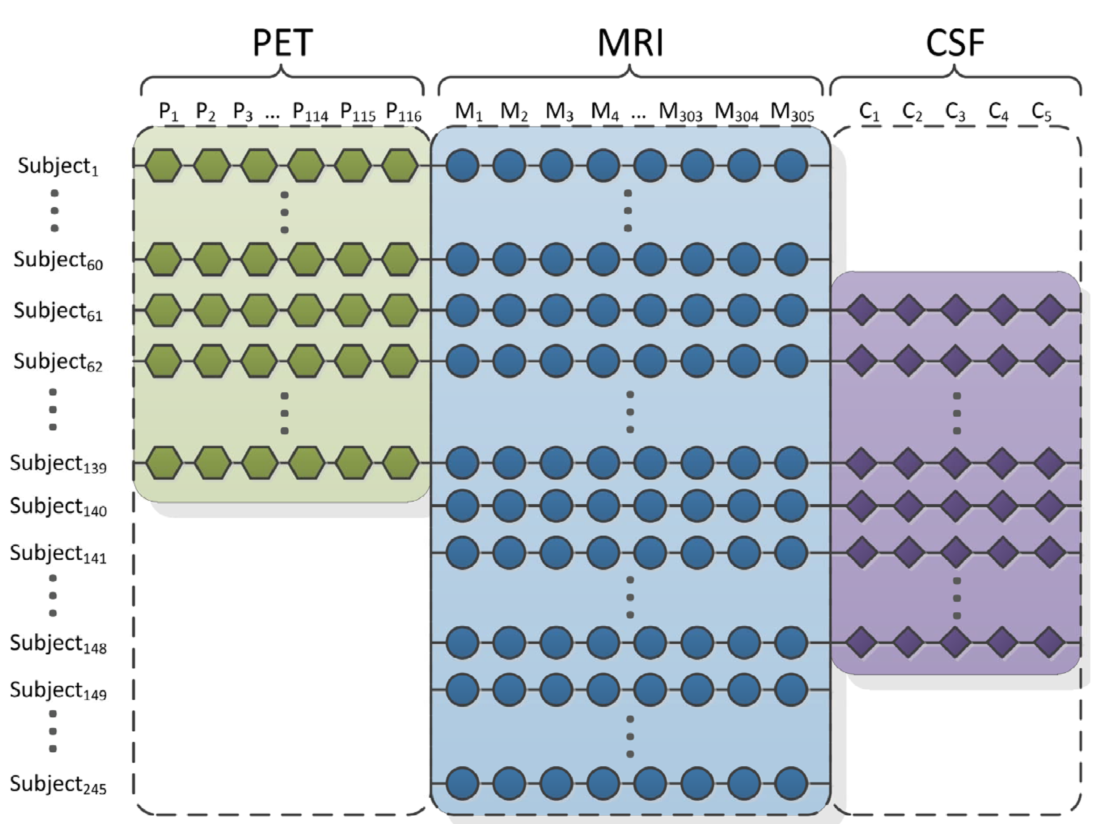

Figure 1: Each subject of AD is represented by cerebrospinal fluid (CSF), magnetic resonance imaging (MRI) and positron emission tomography (PET). However, many subjects lack a subset of measures, as marked by the white areas.

The presence of incomplete base kernels makes it difficult to utilize the information of all views for clustering. A straightforward remedy may firstly impute incomplete kernels with a filling algorithm and then perform a standard MKC algorithm with the imputed kernels. Though demonstrating promising clustering performance in various applications, the above "two-stage" algorithms share a drawback that they disconnect the processes of imputation and clustering, and this prevents the two learning processes from negotiating with each other to achieve the optimal clustering.

Proposed Algorithm

We propose an absent multiple kernel k-means algorithm that integrates imputation and clustering into a single optimization procedure. In our algorithm, the clustering result at the last iteration guides the imputation of absent kernel elements, and the latter is in turn used to conduct the subsequent clustering. By this way, the imputation and clustering processes are seamlessly connected, with the aim to achieve better clustering performance. This objective is fulfilled as in Eq.(1),

$$\begin{aligned} \min_{\mathbf{H},\,\boldsymbol{\beta},\,\{\mathbf{K}_p\}_{p=1}^m} \quad & \mathrm{Tr}\left(\mathbf{K}_{\boldsymbol{\beta}}(\mathbf{I}_n - \mathbf{H}\mathbf{H}^\top)\right) \\ s.t. \quad & \mathbf{H} \in \mathbb{R}^{n\times k},\ \mathbf{H}^\top\mathbf{H} = \mathbf{I}_k, \\ & \boldsymbol{\beta}^\top \mathbf{1}_m = 1,\ \beta_p \geq 0, \\ & \mathbf{K}_p(\mathbf{s}_p, \mathbf{s}_p) = \mathbf{K}_p^{(cc)},\ \mathbf{K}_p \succeq 0,\ \forall p, \end{aligned} \tag{1}$$

Note that the constraint $\mathbf{K}_p(\mathbf{s}_p,\mathbf{s}_p) = \mathbf{K}_p^{(cc)}$ is imposed to ensure that $\mathbf{K}_p$ maintains the known entries during the course.

Conclusions

While MKC algorithms have recently demonstrated promising performance in various applications, they are not able to effectively handle the scenario where base kernels are incomplete. This paper proposes to jointly optimize the kernel imputation and clustering to address this issue. It makes these two learning procedures seamlessly integrated to achieve better clustering. The proposed algorithm effectively solves the resultant optimization problem, and it demonstrates well improved clustering performance via extensive experiments on benchmark data sets, especially when the missing ratio is high. In the future, we plan to further improve the clustering performance by considering the correlations of different base kernels [4]

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Partial Experimental Results