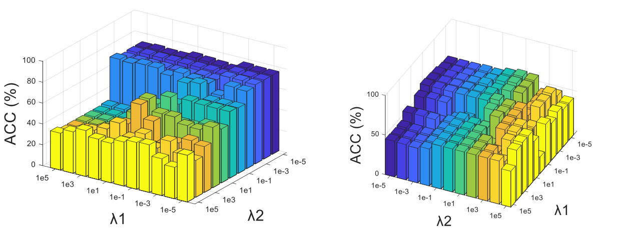
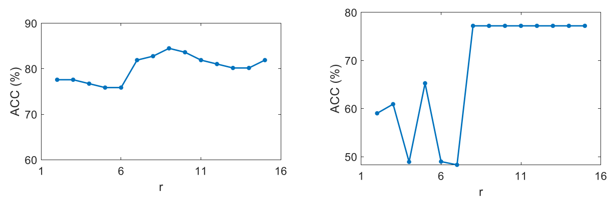
Supplementary material



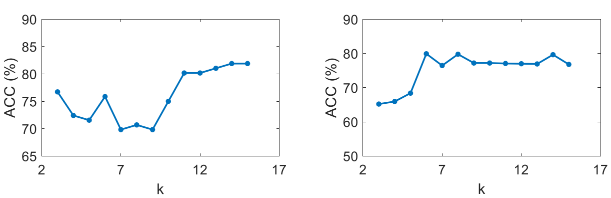
(a) BBCSport (b) Caltech7

Figure 1. The clustering ACC of the proposed method with respect to parameters λ_1 and λ_2 on the (a) BBCSport dataset and (b) Caltech7 dataset with 30% missing views.



(a) BBCSport (b) Caltech7

Figure 2. The clustering ACC of the proposed method with respect to parameter r on the (a) BBCSport dataset and (b) Caltech7 dataset with 30% missing views.



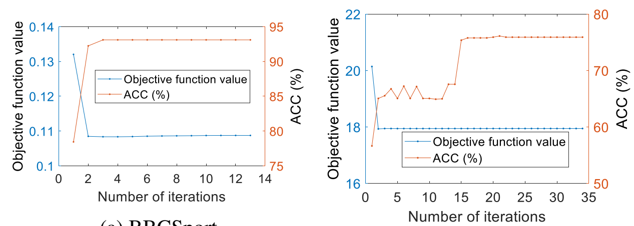
(a) BBCSport (b) Caltech7

Figure 3. The clustering ACC of the proposed method with respect to the nearest neighbor number k of the initialized graphs on the (a) BBCSport dataset and (b) Caltech7 dataset with 30% missing views.

1. Additional experiments

1.1. Parameter analysis

As far as we know, penalty parameter selection is still an open problem for machine learning models. In this subsection, we conduct several experiments on the BBCSport and Caltech7 datasets with 30% missing views to analyze the penalty parameters used in our model.



(a) BBCSport (b) Caltech7

Figure 4. Objective function value and ACC of the proposed method on the (a) BBCsport dataset and (b) Caltech7 dataset with 10% missing views *w.r.t.* each iteration.

Parameters λ_1 and λ_2: Fig. 1 shows the clustering ACC of the proposed method with respect to different parameters λ_1 and λ_2 on the two incomplete multi-view datasets. We can observe that: 1) on the BBCSport dataset, a relatively better performance can be obtained when parameter λ_2 is relatively small. 2) On the Caltech7 dataset, it seems that when λ_2 locates in a relatively large value area such as $[0.1, 10^5]$ and $\lambda_1 \leq 0.1\lambda_2$, the proposed method can obtain a relatively good performance. Considering that a relatively large parameter λ_2 is beneficial to guarantee the exactly c block structures of the graph while a too large λ_2 will lead to the ignoring of structural information of the initialized graphs, selecting a reasonable parameter λ_2 is very important. In our method, according to the experimental results, we recommend 0.1 for λ_2 and variable $\lambda_1 \leq 0.1\lambda_2$.

Parameter r: Fig. 2 shows the ACC of the proposed method with respect to r on the two incomplete multi-view datasets. It is easy to observe that the proposed method can obtain a satisfied clustering performance when r is selected from $[7, 15]$ on the BBCSport dataset and $[8, 15]$ on the Caltech7 dataset. These observations demonstrate that the proposed method is flexible in selecting parameter r.

Parameter nearest neighbor number k: Fig. 3 shows the relationship of ACC and nearest neighbor number k of the proposed method on the two incomplete multi-view datasets. We can find that when k is selected from $[11, 15]$ on the BBCSport dataset and $[6, 15]$ on the Caltech7 dataset, our method can obtain a relatively stable and good clustering ACC. So, we suggest setting the nearest neighbor number k as 15, especially for the large-scale datasets with a small cluster number.

1.2. Convergence analysis

Theoretical aspect: Alternating iterative optimization algorithm is adopted to optimize the proposed learning model, in which a complex optimization problem is divided into three sub-problems with closed-form solutions. According to the alternating iterative optimization, the objective function values of the model will decrease after updating each variable by solving the corresponding subproblem. So the objective function value monotonically decreases during the iteration in solving these three variables. In addition, combining that the objective function value has a lower bound of 0, our model will finally converge to a stable value after a few iterations with the alternating iterative optimization.

Experimental aspect: We also conduct experiments on the BBCSport and Caltech7 datasets with 10% missing views to validate the convergence property of the proposed method. The experimental results are shown in Fig. 4. We can find that the convergence property are well verified from the observed monotonically decreasing curve of the objective function.