International Journal of Trend in Scientific Research and Development (IJTSRD)
Volume 4 Issue 2, February 2020 Available Online: www.ijtsrd.com e-ISSN: 2456 – 6470

# Artificial Bee Colony Based Multiview Clustering (ABC-MVC) for Graph Structure Fusion in Benchmark Datasets

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**ABSTRACT**

Combining data from several information sources has become a significant research area in classification by several scientific applications. Many of the recent work make use of kernels or graphs in order to combine varied categories of features, which normally presume one weight for one category of features. These algorithms don't consider the correlation of graph structure between multiple views, and the clustering results highly based on the value of predefined affinity graphs. Artificial Bee Colony is combined to Multi-view Clustering (ABC-MVC) model in order to combine each and every one of features and learn the weight for each feature with respect to each cluster separately by new joint structured sparsity-inducing norms. It also solves the issue of MVC by seamlessly combining the graph structures of varied views in order to completely make use of the geometric property of underlying data structure. ABC-MVC model is based on the presumption with the purpose of intrinsic underlying graph structure would assign related connected part in each graph toward the similar group. Implementation results shows that the proposed ABC-MVC model gets improved clustering accuracy than the other conventional methods such as Graph Structure Fusion (GSF) and Multiview Clustering with Graph Learning (MVGL). The results are implemented to Caltech-101 and Columbia Object Image Library (COIL-20) with respect to clustering accuracy (ACC), Normalized Mutual Information (NMI), and Adjusted Rand Index (ARI)

***How to cite this paper:*** N. Kamalraj "Artificial Bee Colony Based Multiview Clustering (ABC-MVC) for Graph Structure Fusion in Benchmark Datasets" Published in International Journal of Trend in Scientific Research and Development (ijtsrd), ISSN: 2456-6470, Volume-4 | Issue-2, February 2020, pp.969-674, URL: www.ijtsrd.com/papers/ijtsrd30170.pdf

IJTSRD30170



***KEYWORDS:*** *Multiview Clustering, Artificial Bee Colony (ABC), Multi-view Clustering (MVC), and graph structure*

## 1. INRODUCTION

Several issues in classification include datasets by several views where observations are denoted via several sources of features. Since the diverse samples include varied and partly self-determining data, the multi-view learning is helpful by means of decreasing the noise, in addition by increasing statistical consequence and leveraging the interactions and correlations among datasets in order to get additionally refined and higher-level data, which is also named as data fusion.

Noticeably, integrating the data included in several views is able to bring huge profit designed for data clustering [1-3]. The large amount simple method toward make use of the data of each and everyone views is to concatenate the dataset features of every view jointly and subsequently carry out the conventional clustering methods. On the other hand, such a technique be deficient in the capability in the direction of differentiate the dissimilar consequence of varied views.

Many works have been performed for solving this issue of multi view clustering in the recent years. Those methods have been categorized into two major types such as multi-view semi-supervised (e.g. co-training and co-EM [4] and unsupervised learning (e.g. multi-view clustering [5] algorithms. It is generally make use of several redundant views toward successfully learn from unlabeled information via equally training a set of classifiers described in every view, with the presumption with the purpose of multi-view features known the class are conditionally self-determining.

The major aim of these methods is to group a set of data objects related some criteria, such with the purpose of same data objects are clustered into the similar group, and dissimilar objects are grouped into some clusters. On the other hand, in some real-world applications, the independence presumption of the feature sets is not fine satisfied, such with the purpose of these methods might not successfully work [6].

In traditional algorithms, graphs are generally created in order to integrate varied features related to different categories of descriptions. A graph is generally created in order to find the association among samples, and the graph structure is also determined with the affinity matrix [7]–[8]. Results of the conventional graph-based algorithms are hugely computed with the value of the predefined graph [9-10]. They focus on how in the direction of increase the similarity among samples and how towards stability the weights of diverse views however disregard the geometric property of the graph construction. Artificial Bee Colony is combined to Multi-view Clustering (ABC-MVC) model in order to combine each and every one of features and learn the weight for each feature with respect to each cluster separately by new joint structured sparsity-inducing norms. It also solves the issue of MVC by seamlessly combining the graph structures of varied views in order to completely make use of the geometric property of underlying data structure.

## 2. LITERATURE REVIEW

Cleuziou et al [11] introduced a new clustering method for grouping of multi-view data. Here the data objects are represented by some sets of features. It is used to investigate a data for grouping patterns with the purpose of carry out a consensus among the patterns from varied views. This need in order to combine data from every view via carryout a fusion step with the purpose of detects the agreement among the views and handles the conflicts.

Kumar and Daumé [12] introduced a spectral clustering method for the multi-view setting have access toward multiple views of the data, every of which be able to be separately used for grouping. It is essence of co-training, which is previously a extensively used design in semi-supervised learning. This result is compared to traditional algorithms on synthetic and real-world datasets in the direction of show the effectiveness of the proposed spectral clustering.

Wang et al [13] proposed a novel MVC model toward integrate each and every one features and learn the weight for each feature with respect to each group independently by joint structured sparsity-inducing norms. The proposed MVC framework permits us not only in the direction of carry out clustering tasks, however also to handle with categorization steps via an addition when the labeling data is obtainable. Implemented MVC new data fusion method in order to five generally used multi-view data sets designed for together clustering and classification. In each and every one experimental result, method obviously performs better than the other clustering algorithms.

Liu et al [14] proposed a novel Nonnegative Matrix Factorization (NMF) depending on MVC. It is used for investigating a factorization with the purpose of obtains correct clustering results on varied views of data. The major aim of this work is to create a joint matrix factorization step by constraint with the purpose of pushes clustering results of every view towards a usual consensus as alternate of fixing it straightforwardly.

Eaton et al [15] proposed a MVC depending on constrained clustering with the purpose of be able to operate by means of an imperfect mapping. Known a set of pairwise constraints in every view, constrained clustering broadcast these constraints by a local similarity measure toward those samples with the purpose of be able to be mapped in the direction of the other views, permitting the propagated constraints toward be reassigned across views by means of the partial mapping. It makes use of co-EM toward iteratively approximation the propagation in each view depending on the present clustering algorithm, transfer the constraints across views, and subsequently revise the clustering algorithm.

de Carvalho et al [16] proposed a fuzzy partition and a vector of medoids designed for every fuzzy cluster in addition to study a relevance weight designed for every dissimilarity matrix by means of optimizing an objective function. These relevance weights modify at every iteration of the fuzzy partition algorithm which is varied from one group to another group. Furthermore, some algorithms used for taking the fuzzy partition and fuzzy groups presented by this algorithm is also clearly discussed. Some samples shows the results and value of the proposed algorithm.

Wang and Chen [17] introduced a MinimaxFCM approach via minimax optimization depending on Fuzzy c means. In this algorithm, consensus clustering results are created depending on minimax optimization here the maximum disagreements of varied weighted views are reduced. In addition, the weight of every view is able to be learned automatically in the clustering step. Additionally, there is simply one parameter toward be set besides the fuzzifier. Results demonstrate that the proposed MinimaxFCM algorithm works better than the other MVC methods with respect to accuracy and error.

Yang and Wang [18] studied a detailed review of MVC methods, gives a classification related to the methods and standards concerned, and categorizes these methods into five major types such as co-training style algorithms, multi-kernel learning, multiview graph clustering, multi-view subspace clustering, and multi-task multi-view clustering. From this multi-view graph clustering is again divided into graph, network, and spectral methods. Multi-view subspace clustering is categorized into subspace learning, and non-negative matrix factorization. Additionally, it lists a number of publically accessible multi-view datasets. Generally, this work serves as an initial text and review for MVC.

Zhan et al [19] handled the issues of MVC by seamlessly combining the graph structures of varied views in the direction of completely develop the geometric property of fundamental data structure. The proposed method is based on the statement with the purpose of the essential fundamental graph structure would assign related connected part in every graph toward the similar group. Varied graphs beginning multiple views are combined via the use of Hadamard product because several views are generally jointly disclosing the similar underlying structure across varied views. Particularly, the graphs are combined into a new one and the formation of the global graph is adaptively tuned via a new objective function consequently with the purpose of the no. of parts of the graph is accurately identical toward the no. of groups. It is worth noting with the aim straightforwardly get group indicators from the graph itself not including the stage additional graph-cut. Results demonstrate with this algorithm gets improved clustering results when compared to other methods.

## 3. PROPOSED METHODOLOGY

Artificial Bee Colony is combined to Multi-view Clustering (ABC-MVC) model in order to combine each and every one of features and learn the weight for each feature with respect to each cluster separately by new joint structured sparsity-inducing norms. It also solves the issue of MVC by seamlessly combining the graph structures of varied views in order to completely make use of the geometric property of underlying data structure. ABC-MVC model is based on the presumption with the purpose of intrinsic underlying graph structure would assign related connected part in each graph toward the similar group. Implementation results shows that the proposed ABC-MVC model gets improved clustering accuracy than the other conventional methods such as Graph Structure Fusion (GSF) and Multiview Clustering with Graph Learning (MVGL). Figure 1 with the purpose of different graphs created from several views are merged into an intrinsic graph A.

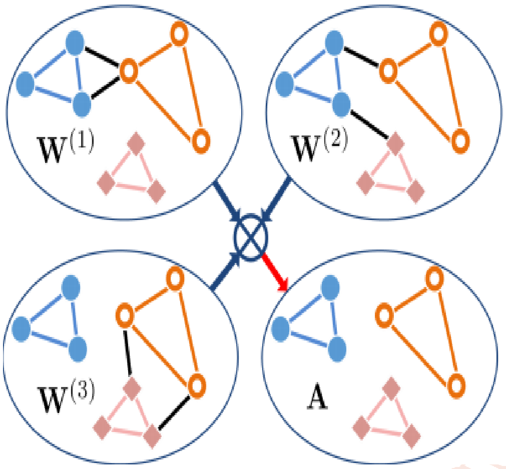


**Figure1. Schematic diagram of graph structure fusion**

### 3.1. Model formulation

Let us presume that the data matrix is denoted as $X = [X_1, X_2, \ldots, X_{n_c}] = [x_1, x_2, \ldots, x_n] \in R^{d \times n}$, where $X_c$ is represented as the data matrix related to the $c^{th}$ group, $x_i$ is represented as a data point, n is the no. of data points, dis denoted as the dimension, and $n_c$ is represented as a no. of clusters. In graph-based multiview learning algorithms, datapoints are generally denoted as vertices in an undirected graph W by weighted edges depicting the pairwise association of instances. For two instances $x_i$ and $x_j$ , their similarity $w_{ij}$ is generally allocated to a huge weight when their distance $\left|\left|x_i - x_j\right|\right|^2$ is small. If assign k neighbors in order to the $j^{th}$ data points, the $j^{th}$ row$w_j$ of W has k no. of nonzero parts, i.e., there are k no. of vertices related towards the $j^{th}$ vertex in the graph.

By multiview data, varied affinity matrices $W^{(v)}$ ($v \in [1, n_v]$) are created via the use of a k-Nearest Neighbor (k-NN) graph in this work, where $n_v$ is denoted as the total no.of views and v is denoted as the view index. In multiple graphs, varied similarity measures are well captured over the equal set of vertices. Purpose is with the intention of different graphs are integrated into a complete graph by the computation of $n_c$ no. of parts consequently with the purpose of vertices in every connected part of the graph are partitioned into one group. To detect the intrinsic structure shared via varied views, the Hadamard product is utilized in order to conserve the general edges in multiple graphs. Hadamard product is used to fuse each and every one of the affinity matrices W(v)into one affinity graph A by equation(1)

$$A = \prod_{v=1}^{n_v} W^{(v)} \qquad (1)$$

Here, $\prod$ is denoted as the Hadamard product of a sequence. In the Figure 1, the usual edges in varied graphs are preserved in the graph A and the connected parts change to three. If we sum up these graphs part-wisely, the graph A has only one connected part. However, by multiplying them part wisely, an intrinsic structure is attaining in Figure 1. It can be seen from Figure 1 with the purpose of the graph A has exactly three connected parts. Known a fused affinity matrix A, similarity matrix S can be learned with the purpose of the related graph has exactly $n_c$ connected parts.

If the similarity matrix $S \geq 0$, whose Laplacian matrix L assures towards a theorem: The number $n_c$ of connected parts of the graph S is similar toward the multiplicity of zero as an eigenvalue of its Laplacian matrix L. From the Fan's theorem able to be compute an objective function in equation (2),

$$\sum_{c=1}^{n_c} \lambda_c = \min_U a_1 a_2 \langle UU^T, L\rangle \; s.t \; U \in R^{n_c * n_c}, U^T U = I \; (2)$$

where $\langle .,. \rangle$ is represented as the Frobenius inner multiplication of two matrices, $a_1 a_2$ is denoted as the regularization parameters computed by the optimization algorithm. $Tr(.)$ is represented as the trace operator $, U^T = [u_1, u_2, \ldots, u_n], L = D - \frac{S^T + S}{2}$is denoted as the Laplacian matrix, $I \in R^{n_c * n_c}$is denoted as the identity matrix, D is denoted as a diagonal matrix and its parts are column sums of $\frac{S^T + S}{2}$.

### 3.2. Artificial Bee Colony (ABC)

Artificial Bee Colony (ABC) algorithm is used for optimization of the clustering function. In equation (2), ABC algorithm optimizes the parameters of$a_1 a_2$ which simulates the intellectual foraging actions of honey bee swarms [20]. In ABC algorithm, optimization is performed depending on three major types of bees: employed, onlookers and scouts [21]. In this ABC optimization, location of the dataset points of a food source denotes an optimal solution to the clustering and the nearest amount of a food source related to the quality (clustering accuracy) of the related clustering formation. The amount of the employed bees is similar to the number of possible tuning of the regularization parameters in the dataset. At the initial stage, a randomly distributed initial datapoints (food source positions) is created. After that, the dataset is subjected to repeat the cycles of the search processes of the employed, onlooker, and scout bees, correspondingly. An employed bee gives changes on the source position of the current data points or instances in her memory for finding correct parameters and finds a new food source clustering solution. Given that the nectar amount of the new selected data point is higher accuracy when compared to earlier parameters, the bee memorizes the new parameters value with their location forgets the old one. Else she keeps the location of the one in her memory. After each and every one of the employed bees total the investigate procedure; they share the location data of the sources by the onlookers on the dance area. Each onlooker computes the nectar data taken from each and every one of the employed bees and subsequently finds a food source based on the nectar amounts of sources. In the employed bee, she produces changes on the source location of the cluster parameters for better clustering in her memory and checks its nectar amount. Given with the purpose of its nectar data point with highest clustering than with the purpose of the recent accuracy, the bee memorizes the new location of parameters and forgets the old parameter values. The sources abandoned are described and new parameters of the clusters are randomly produced to be changed the abandoned ones by scout's bees.

Each employed bee gives new regularization parameters in the neighborhood of the parameter optimization in the objective function in its memory by equation (3)

$$V_i = X_i + (X_i - X_k) \times \phi \qquad (3)$$

where k is denoted as the integer near to me, $k \neq i$, and $\phi$is a random real number in [−1, 1]. Related to the fitness of $X_i$, compute the probability value $P_i$byequation (4) and (5).

$$P_i = \frac{fit_i}{\sum_{i=1}^{n} fit_i} \qquad (4)$$

$$fit_i = \begin{cases} \frac{1}{1+f_i} iff_i \geq 0 \\ 1 + abs(f_i) iff_i < 0 \end{cases} \qquad (5)$$

The selection of scout bee is calculated by equation (6):

$$chance_k = \frac{nectar_k^{\alpha}}{\sum_{i=1}^{N} nectar_i^{\alpha}} \qquad (6)$$

where $nectar_k$ is denoted as the no.of nectar in the food source k, $\sum_{i=1}^{N} nectar_i$is denoted as the total amount of nectars around the hive. The no. of soldiers for scout bee is computed by equation (7):

$$Soldiers_i = \beta \times \left(\frac{P_i^{\mu}}{H^{\mu}}\right) + \gamma \qquad (7)$$

where percentage of soldiers chosen for i^th scout bee is denoted by $Soldiers_i$. $P_i^{\mu}$is denoted as the preference i^th scout bee is $p_i$.Number of each and every one of the scout bees is denoted by H. μ is constant. Trapping in local minima is avoided by this method.

## 4. EXPERIMENTAL SETUP

In this section two benchmark datasets are used for MVC analysis. The results of these datasets are implemented to three clustering methods such as MVGL, GSF and proposed ABC-MVC algorithm.

### 4.1. Caltech-101

Caltech-101 includes of 101 categories by 8677 images. For implementation, seven classes and 1474 images are chosen to measure the results of the clustering methods. For these images six features are extracted and used for implementation. Those features are Gabor by dimension 48, wavelet-moment by dimension 40, CENsus TRansform hISTogram (CENTRIST) by dimension 254, Histogram of Oriented Gradient (HOG) by dimension 1948, GIST by dimension 512, and Local Binary Patterns (LBP) by dimension 982.

### 4.2. COIL-20

COIL-20 dataset is from the Columbia Object Image Library and includes 1440 images of 20 objects. Each class includes 72 images. For those images three major features are extracted. Those features are intensity by dimension 1024, LBP by dimension 3304, and Gabor by dimension 6750.

### 4.3. Evaluation results

Three measures are used to assess the performance of clustering methods. Those metrics are Clustering Accuracy (ACC), Normalized Mutual Information (NMI), and adjusted rand index (ARI). These three metrics are mostly used, and they are able to be computed via comparing the obtained label of each instance by the ground-truth given in benchmark datasets. For these three metrics, the larger value denotes the improved clustering results (See table 1).

**TABLE1. CLUSTERING METRICS EVALUATION VS CLUSTERING METHODS**

| Metrics | Methods | DATASETS | |
|---|---|---|---|
| | | Caltech-101 | COIL-20 |
| ACC (%) | MVGL | 72.36 | 90.21 |
| | GSF | 83.62 | 92.46 |
| | ABC-MVC | 92.59 | 94.89 |
| NMI (%) | MVGL | 62.82 | 91.56 |
| | GSF | 71.25 | 94.76 |
| | ABC-MVC | 81.69 | 97.28 |
| ARI (%) | MVGL | 56.43 | 91.38 |
| | GSF | 78.91 | 93.64 |
| | ABC-MVC | 90.37 | 96.85 |

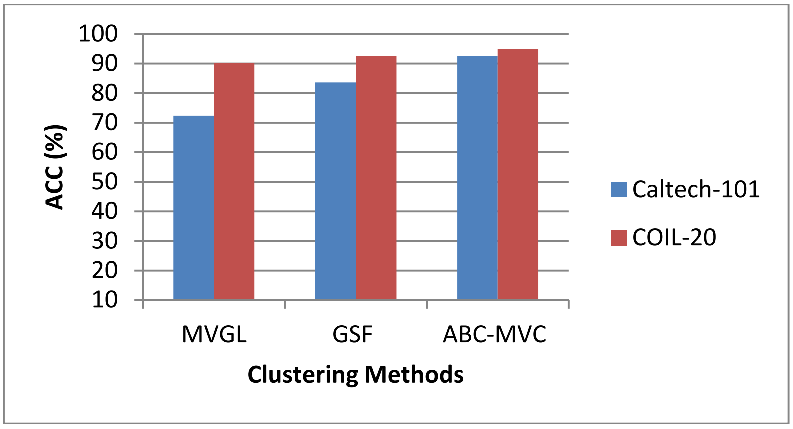


**FIGURE2. ACC RESULTS COMPARISON FOR CLUSTERING METHODS**

Figure 2 shows the performance comparison results of three clustering methods such as MVGL, GSF, and proposed ABC-MVC with respect to clustering accuracy. The results are measured to benchmark datasets such as Caltech-101 and COIL-20. The method like MVGL, GSF, and proposed ABC-MVC gives higher accuracy results of 72.36%, 83.62% and 92.59% for Caltech-101 dataset.

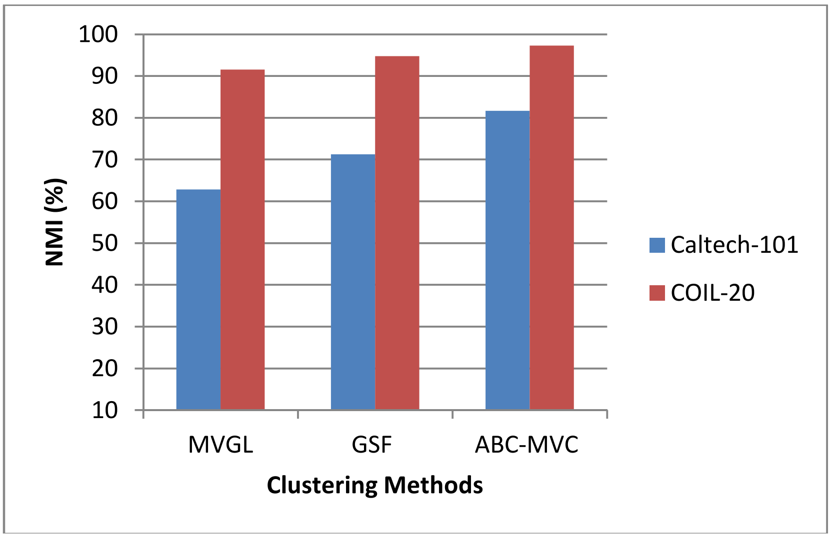


**FIGURE3. NMI RESULTS COMPARISON FOR CLUSTERING METHODS**

Figure 3 shows the performance comparison results of three clustering methods such as MVGL, GSF, and proposed ABC-MVC with respect to NMI. The NMI results are measured to benchmark datasets such as Caltech-101 and COIL-20. The methods like MVGL, GSF, and proposed ABC-MVC gives higher NMI results of 62.82%, 71.25% and 81.69% for Caltech-101 dataset.

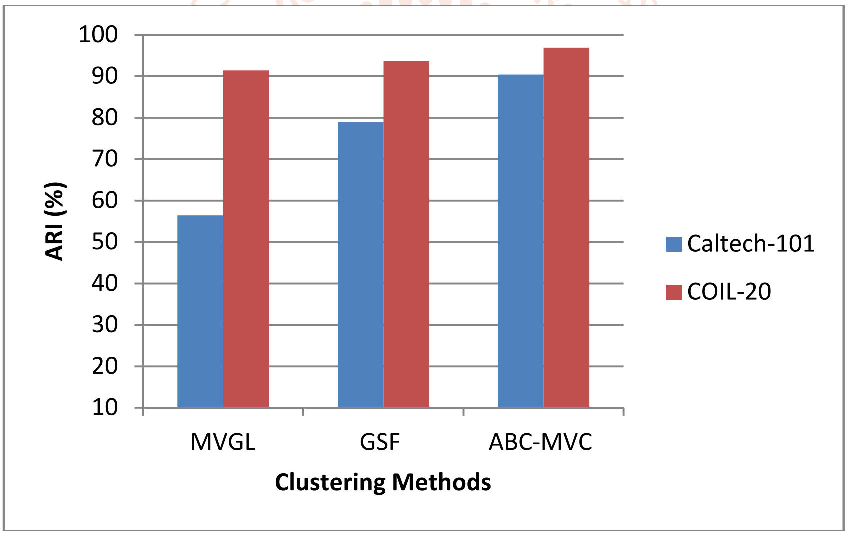


**FIGURE4. ARI RESULTS COMPARISON FOR CLUSTERING METHODS**

Figure 4 shows the performance comparison results of three clustering methods such as MVGL, GSF, and proposed ABC-MVC with respect to ARI. The ARI results are measured to benchmark datasets such as Caltech-101 and COIL-20. The methods like MVGL, GSF, and proposed ABC-MVC gives higher ARI results of 56.43%, 78.91%, and 90.37% for Caltech-101 dataset. The methods provide higher results for all metrics for COIL-20 dataset when compared to Caltech-101 dataset. The method like MVGL, GSF, and proposed ABC-MVC gives higher accuracy results of 90.21%, 92.46% and 94.89% for Caltech-101 dataset (See Figure 2). The methods like MVGL, GSF, and proposed ABC-MVC gives higher NMI results of 91.56%, 94.76% and 97.28% for Caltech-101 dataset (See Figure 3). The methods like MVGL, GSF, and proposed ABC-MVC gives higher ARI results of 91.38%, 93.64% and 96.85% for Caltech-101 dataset (See Figure 4).

## 5. CONCLUSION AND FUTURE WORK

Integrating multiview features for clustering is a fundamental issue in data. Many works have been performed for solving this issue of multi view clustering in the recent years. In traditional algorithms, graphs are generally created in order to integrate varied features related to different categories of descriptions. In this work, a novel Artificial Bee Colony is combined to Multi-view Clustering (ABC-MVC) is performed depending on graph structure fusion, which learns a global graph by means of exact $n_c$ related parts reflecting cluster indicators. ABC-MVC proposed a model in order to combine each and every one of features and learn the weight for each feature with respect to each cluster separately by new joint structured sparsity-inducing norms. It also solves the issue of MVC by seamlessly combining the graph structures of varied views in order to completely make use of the geometric property of underlying data structure. ABC-MVC model is based on the presumption with the purpose of intrinsic underlying graph structure would assign related connected part in each graph toward the similar group. A result shows that the proposed ABC-MVC model gets an improved clustering accuracy when compared to other conventional methods such as Graph Structure Fusion (GSF) and Multiview Clustering with Graph Learning (MVGL). In the future work, other optimization methods such as bat algorithm, firefly algorithm introduced in order to provide towards optimize it.

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