CLUBENCH: A CLUSTERING BENCHMARK

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ABSTRACT

Clustering is a fundamental problem in data science with a long-standing research history. Over the past few decades, numerous clustering algorithms have been developed. However, a systematic and experimental evaluation of these algorithms remains lacking and is urgently needed. To address this gap, we introduce CLUBench, a comprehensive clustering benchmark comprising 23 algorithms of diverse principles evaluated on 131 datasets across tabular, text and image data types. Our extensive experiments (174,485) yield statistically meaningful insights into the performance of various clustering methods, such as the impact of hyperparameter tuning, similarity between algorithms, and the impact of data type and dimension. Notably, we observe low-rank characteristics in cross-model performance matrices, which facilitates an efficient strategy for rapid algorithm evaluation and selection in practical applications. Additionally, we provide an easy-to-use toolbox by encapsulating the source codes from the official code repository into a unified framework, accompanied by detailed instructions. With CLUBench, researchers and practitioners can efficiently select appropriate algorithms or datasets for evaluating new datasets or proposed methods. All benchmark datasets and the toolbox are fully open-sourced and available at `https://anonymous.4open.science/r/CLUBench-ICLR2026/`.

1 INTRODUCTION

We are living in a world full of data, which serves as an approximate reflection of the physical reality. One of the basic but vital means of mining these data is to classify or group them into a set of categories for further analysis and exploration. Therefore, data clustering is ubiquitous in the real world and cluster analysis becomes a fundamental technique used in various fields, including pattern recognition, information retrieval, bioinformatics, data compression, etc. Since the 1960s, there have been systematic studies (Forgy, 1965; McQueen, 1967) concerning the clustering problem. Over the years, numerous clustering algorithms have been developed based on different observations or assumptions. Following the de facto standard taxonomy (Xu & Tian, 2015; Yin et al., 2024), the conventional clustering algorithms can be organized into five categories. The first category is partition-based clustering with classic algorithms like K-means (McQueen, 1967), K-medoids (Park & Jun, 2009) and CLARANS (Ng & Han, 2002). The second category is hierarchical clustering (Zhang et al., 1996) which constructs the hierarchical relationship among data. The third category is density-based clustering (Ester et al., 1996; Ankerst et al., 1999; Comaniciu & Meer, 2002). The fourth category is grid-based clustering (Wang et al., 1997), in which the original data space is changed into a grid structure with a definite size for clustering. The last is model-based clustering, where each cluster is assigned a particular model (e.g. GMM (Rasmussen, 1999)) and the core idea is to find the best fit between clusters and models. With the progress of deep learning techniques and especially deep unsupervised learning, many deep architectural (neural networks) clustering (DC) methods (Xie et al., 2016; Guo et al., 2017; Ji et al., 2017; Huang et al., 2020; Li et al., 2021; Cai et al., 2022; Li et al., 2023; Metaxas et al., 2023; Li et al., 2025) have been proposed in the past few years. These DC methods exhibit marked superiority when dealing with complex and high-dimensional data compared with conventional clustering algorithms.

The profusion of cluster analysis techniques, on one hand, equips us with diverse tools. On the other hand, the selection and application of such abundant means also causes confusion. In response, a few surveys and reviews (Jain et al., 1999; Xu & Wunsch, 2005; Berkhin, 2006; Xu & Tian, 2015; Min et al., 2018; Aljalbout et al., 2018; Nutakki et al., 2018; Liu et al., 2022) about clustering techniques have been introduced to organize and compare these algorithms. More recently, four clustering reviews (Yin et al., 2024; Wei et al., 2024; Zhou et al., 2024; Ren et al., 2024) are released, which further demonstrate the abundance and diversity of cluster analysis techniques again. Although the reviews provide considerable taxonomy, summarization, and comparison for these clustering techniques, they still lack a comprehensively quantified evaluation and analysis. Surprisingly, the benchmark in the literature concerning clustering techniques is quite limited and incomplete. Although there have been several attempts, such as (Javed et al., 2020; Zhou et al., 2024; Wei et al., 2024), these works, at least, have the following three limitations:

1. The benchmark datasets and clustering algorithms evaluated are quite limited (number and type), which can easily lead to a biased evaluation and conclusion.
2. The evaluation considers either conventional clustering algorithms or deep learning based clustering methods, lacking a joint and unified comparison.
3. There is a lack of a convenient and unified toolbox for the clustering methods.

In this benchmark, we attempt to address these limitations. Based on the existing work (Jeon et al., 2025) and publicly available dataset archive, we collect 131 datasets from various real-world fields and data types that cover tabular, text, and image. We evaluate these datasets on 23 clustering algorithms and provide complete experimental results, meaningful comparisons and analysis. In addition, we integrate the source codes, particularly the deep learning codes that depend on different deep learning frameworks, such as TensorFlow, PyTorch, and Caffe, into a unified framework, providing a consistent and convenient interface. Furthermore, our toolbox is easy to extend to new datasets and clustering methods. The main contributions of this benchmark are as follows.

- This benchmark provides a comprehensive evaluation for 23 clustering algorithms on 131 datasets from various fields. To a unified comparison for conventional and deep learning based clustering methods, this benchmark considers both original data samples and feature representation, particularly on image data.
- Based on these extensive results, this benchmark conduct the overall performance analysis and grouped performance comparison for investigating the potential preferences of algorithms.
- This benchmark analyzes performance similarity among algorithms and among datasets, as well as the low-rank structure of the performance matrices, to enable reliable performance prediction and rapid model selection.
- This benchmark provides a toolbox to foster the application and research of clustering techniques.

2 Related Work

2.1 Clustering Algorithms

Basically, we can divide the clustering algorithms into two categories: conventional clustering algorithms and deep clustering algorithms, depending on whether neural networks are used.

Conventional Algorithms. Conventional clustering methods typically operate on original data features through distance calculation, similarity measurement, or density estimation. They can be categorized into five groups: partition-based, hierarchical, density-based, grid-based, and model-based. Representative examples include K-means (McQueen, 1967) for partitioning, BIRCH (Zhang et al., 1996) for hierarchical clustering, DBSCAN (Ester et al., 1996) and OPTICS (Ankerst et al., 1999) for density-based clustering, STING (Wang et al., 1997) for grid-based clustering, and Gaussian Mixture Models (GMMs) (Rasmussen, 1999) for model-based clustering. Beyond these, similarity-based approaches such as affinity propagation (AP) (Frey & Dueck, 2007), spectral clustering (SepClu) (Shi & Malik, 2000; Ng et al., 2001), and subspace clustering methods (Elhamifar & Vidal, 2013; Chen et al., 2020; Fan, 2021) further expand the landscape by leveraging pairwise relations or self-expressive representations. Besides these basic algorithms, there have been many extensions, such as kernel K-means (Liu, 2022), low-rank representation (Liu et al., 2012), multi-view subspace clustering (Kang et al., 2020), federated spectral clustering (Qiao et al., 2023), etc.

Deep Clustering Algorithms. In recent years, deep clustering (Xie et al., 2016; Dilokthanakul et al., 2016; Guo et al., 2017; Ji et al., 2017; Caron et al., 2018; Han et al., 2019; Asano et al., 2019; Huang et al., 2020; Cai et al., 2022; Metaxas et al., 2023; Zhang et al., 2024; Li et al., 2025) has emerged to address the challenges of large-scale and complex structured datasets. A seminal approach is deep embedded clustering (DEC) (Xie et al., 2016), which jointly learns feature representations and cluster assignments, later extended by IDEC (Guo et al., 2017) with a reconstruction objective. Subsequent works explore diverse directions: self-expressive models combined with spectral clustering Ji et al. (2017), confidence-driven assignment (Huang et al., 2020), contrastive learning with data augmentation (Li et al., 2021), deep subspace clustering (Cai et al., 2022), diversity-aware objectives (Metaxas et al., 2023), and stability-based supervision (Li et al., 2025). These methods demonstrate the rapid evolution of deep clustering, yet systematic evaluation remains limited. There are more deep clustering algorithms and we will not detail them in this paper due to space limitations.

2.2 Existing Clustering Benchmarks and Reviews with experimental evaluation

As mentioned above, numerous conventional and deep clustering algorithms have been developed over the past few decades. Therefore, it is crucial to evaluate these methods on diverse real-world datasets and provide the community with an easy-to-use toolbox for implementation. The prior studies (Jain et al., 1999; Xu & Wunsch, 2005; Berkhin, 2006; Omran et al., 2007; Von Luxburg et al., 2010; Murtagh & Contreras, 2012; Xu & Tian, 2015; Min et al., 2018; Aljalbout et al., 2018; Nutakki et al., 2018; Javed et al., 2020; Liu et al., 2022; Yin et al., 2024; Ren et al., 2024; Zhou et al., 2024; Wei et al., 2024) have reviewed clustering algorithms. For example, Jain et al. (1999) surveys partition-based and hierarchical methods, discussing their theoretical foundations and applications, while Murtagh & Contreras (2012) focuses on hierarchical clustering and offers implementations in multiple software environments. Javed et al. (2020) benchmarks conventional methods on 112 time series datasets, whereas Zhou et al. (2024), Ren et al. (2024) and Wei et al. (2024) provide overviews of deep clustering algorithms, with Zhou et al. (2024) and Wei et al. (2024) including experimental evaluations on diverse datasets. Our CLUBench differs from these works in several key aspects. First, existing studies typically focus on specific data types or algorithms. Given the rapid development of clustering methods, a more comprehensive benchmark that covers various methods and data sets is necessary. Second, most prior benchmarks evaluate only a limited number of datasets and provide relatively simple analyses, overlooking insights that could guide further research and applications. In contrast, CLUBench offers extensive evaluations with detailed performance analysis. Finally, many existing methods are not user-friendly due to their complex implementations. CLUBench provides a unified toolbox where each algorithm can be executed with just 3 lines of code. A detailed comparison between CLUBench and other works are provided in Table 1.

Benchmark	**Coverage**			**Algorithm Type (-based)**						**Data Type**			**Resource Integration**	
	Datasets	Algo.	Metrics	Partition	Hierarchy	Density	Model	Subspace	DL	Tabular	Image	Sequence	Data	Toolbox
Javed et al. (2020)	112	8	1	✓	✓	✓	✗	✗	✗	✗	✗	✓	✗	✓[1]
Zhou et al. (2024)*	4	2	1	✗	✗	✗	✗	✗	✓	✗	✓	✗	✓	✓[2]
Wei et al. (2024)*	12	26	3	✗	✗	✗	✗	✗	✓	✓	✓	✓	✗	✗
CLUBench (ours)	131	23	3	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓

[1] https://github.com/ali-javed/clusteringBenchmark
[2] https://github.com/zhoushengisnoob/OpenDeepClustering

Table 1: Comparison among CLUBench and existing related works. * marks the clustering review, where only the datasets and methods evaluated in the experiments are counted.

3 CLUBench

Cluster analysis aims to organize samples into distinct groups based on the inherent patterns and similarities within the data. The precise definition of the clustering problem for different clustering algorithms is not completely agreed upon, such as soft clustering, hard clustering, and hierarchical clustering. In this section, we give a simple mathematical description by considering only the inputs and final outputs of algorithms, based on the description in previous work (Hansen & Jaumard, 1997). More importantly, we provide a guidance map in Section 3.2, which aims to offer readers a quick overview of the topics addressed and discussed in this benchmark, and guide them to relevant sections.

3.1 Problem Description

Given a set $\mathcal{X} = \{\mathbf{x}_1, \mathbf{x}_2, \cdots, \mathbf{x}_n\}$ with n samples and each $\mathbf{x}_i \in \mathbb{R}^m$. In CLUBench, a clustering algorithm f aims to seek a K-partition of $\mathcal{X}$, $C = \{C_1, C_2, \cdots, C_K\}(K \leq n)$, such that

1. $C_i \neq \emptyset, i = 1, \ldots, K$;
2. $\bigcup_{i=1}^{K} C_i = \mathcal{X}$;
3. $C_i \cap C_j = \emptyset, i, j = 1, \ldots, K$ and $i \neq j$.

where 3 indicates all algorithms belong to hard clustering. K must be determined prior to learning for some algorithms, whereas for others it is determined during the learning process.

3.2 MAP OF CLUBENCH

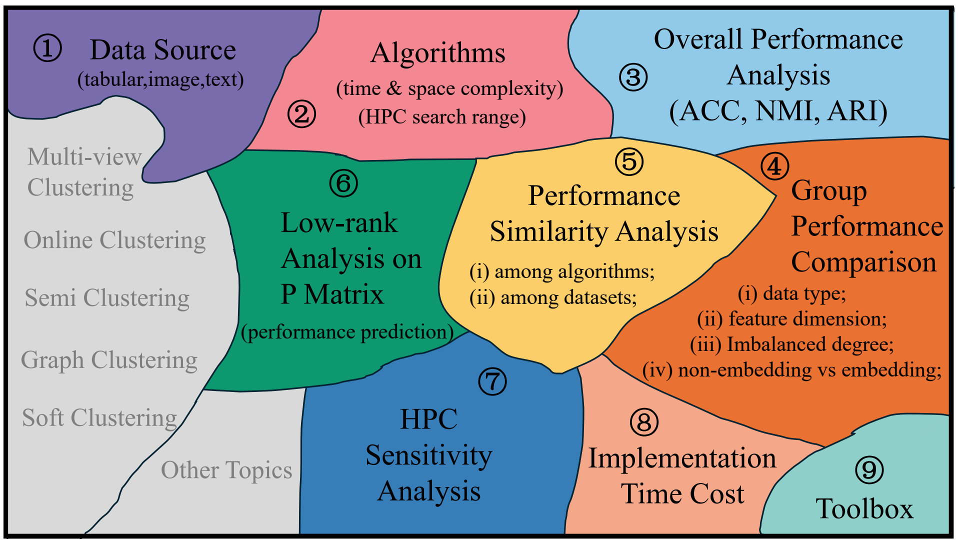


Figure 1: CLUBench MAP. Uncovered topics in CLUBench: Multi-view Clustering (Kang et al., 2020; Fang et al., 2023; Chen et al., 2023), Online Clustering (Beringer & Hüllermeier, 2006; Barbakh & Fyfe, 2008; Li et al., 2022), Semi-Clustering Basu et al. (2004); Bair (2013); Cai et al. (2023), Graph Clustering (clustering object:graph) (Schaeffer, 2007; Tian et al., 2014; Liu et al., 2023; Cai et al., 2024), Soft Clustering (Kumar & Futschik, 2007; Peters et al., 2013; Ferraro & Giordani, 2020) and possible Other Topics.

1. **Data Source**: Based on previous works (Wei et al., 2024; Zhou et al., 2024; Jeon et al., 2025) and publicly available dataset archive[1]. We gather and clean 131 benchmark datasets for clustering evaluation. The data type covers tabular, image, sequence (text) and bioinformatics data. The detailed statistics of these datasets are provided in Appendix B.1.
2. **Algorithms**: In CLUBench, we collect 23 clustering methods with (i) conventional classic algorithms including KMeans (McQueen, 1967), AggClu (Agglomerative Clustering) (Johnson, 1967), BIRCH (Zhang et al., 1996), DBSCAN (Ester et al., 1996) and SpeClu (Spectral Clustering) (Ng et al., 2001), GMM Rasmussen (1999), OPTICS (Ankerst et al., 1999), MeanShift (Comaniciu & Meer, 2002), k-PC (Agarwal & Mustafa, 2004), Affinity (Frey & Dueck, 2007), AutoSC (Fan, 2021); (ii) subspace-based algorithms like SSC (Elhamifar & Vidal, 2013), S^3COMP-C (Chen et al., 2020) and k-FSC (Fan, 2021); (iii) deep learning based clustering methods like DEC (Xie et al., 2016), IDEC (Guo et al., 2017), DSCN (Ji et al., 2017), PICA (Huang et al., 2020), ConClu(Contrastive Clustering) (Li et al., 2021), EDESC (Cai et al., 2022); (iv) the latest SOTA methods like DMICC (Li et al., 2023), DIVC (Metaxas et al., 2023) and LFSS (Li et al., 2025). More information about time and space complexity and HPC search range of the clustering algorithms evaluated is provided in Appendix B.2. Due to the extensive scope of this study, the current version of CLUBench does not include all prominent clustering algorithms, especially deep learning-based methods. We are actively integrating more methods like LRR (Liu et al., 2012), SENet (Zhang et al., 2021), P^2OT Zhang et al., 2024 and so on. In addition, since most of our datasets are single-view, multi-view clustering methods are not considered in our benchmark.
3. **Overall Performance Analysis**: First of all, we analyze the average performance (measured by ACC, Normalized Mutual Information (NMI), and Adjusted Rand Index (ARI)) of cluster-

[1] https://www.openml.org/search?type=data&status=active

ing algorithms across all 131 datasets. The detailed results are provided in Section 4.1. The complete performance results of each algorithm on each dataset are provided in Appendix D

4. **Group Performance Comparison**: To investigate the potential preferences of the clustering algorithms, we group the datasets according to four criteria: (i) data type (image, text, tabular, bioinformatics); (ii) feature dimensionality (low, middle, high); (iii) the degree of cluster imbalance; and (iv) the use of non-embedded versus embedded image data. A comparative analysis is then conducted based on these groupings in Section 4.2.
5. **Performance Similarity Analysis**: Based on the obtained performance results, a unique performance vector can be constructed for each clustering algorithm and dataset. Using these vectors, Section 4.3 analyzes the performance-based similarities among algorithms and among datasets, respectively.
6. **Low-rank Analysis on Performance Matrix**: In CLUBench, we search clustering performance for each algorithm across multiple Hyperparameter Configurations (HPC). For instance, if there are h HPCs for each clustering algorithm, a performance matrix $\mathbf{P} \in \mathbb{R}^{131\times(23h)}$ can be obtained. Under this condition, Section 4.4, analyzes the low-rank structure of $\mathbf{P}$ and constructs a matrix completion task to assess the effectiveness of performance prediction based on $\mathbf{P}$,
7. **HPC Sensitivity Analysis**: Section 4.5 compares the average performance difference between the best and worst HPC.
8. **Implementation Time Cost**: Appendix E details the average computational time (over five runs) for all algorithms.
9. **Toolbox**: To facilitate the application and research of such abundant clustering methods, we provide an easy-to-use toolbox encapsulated in Python and make it compatible with scikit-learn [2], keeping a simple usage logic. An example of calling DSCN is as follows:

```
CM = DSCN(**hpc) # hpc: dict of hyperparameter configurations.
CM.fit_predict(X) # X: data, (n_samples, dim) = X.shape.
CM.labels # predicted labels.
acc, nmi, ari, time = CM.evaluation(Y) # Y: true labels.
```

4 Experiment Results and Analysis

4.1 Overall Performance Analysis

In this section, we compare the clustering performance (measured by ACC, NMI and ARI) across all datasets. Table 2 reports the average performance of a subset of algorithms on default and best HPC (in our search range). The complete results are provided in Appendix C.1. It is worth noting that we select best performance for each dataset and then obtain best average performance in Table 2.

ConV. Algorithms	KMeans	AggClu	DBSCAN	BIRCH	GMM	SpeClu	SSC	AutoSC	k-FSC
ACC(default) **ACC(best)**	0.593 0.596 (+0.003)	0.501 0.631 (+0.130)	0.424 0.570 (+0.146)	0.592 0.619 (+0.027)	0.579 0.626 (+0.047)	0.588 **0.688** (+0.100)	0.518 0.561 (+0.043)	0.607 -	0.496 0.579 (+0.083)
NMI(default) **NMI(best)**	0.336 0.339 (+0.003)	0.178 0.366 (+0.188)	0.028 0.320 (+0.292)	0.330 0.363 (+0.033)	0.315 0.360 (+0.045)	0.318 **0.422** (+0.104)	0.200 0.232 (+0.032)	0.327 -	0.200 0.250 (+0.050)
ARI(default) **ARI(best)**	0.293 0.295 (+0.002)	0.124 0.323 (+0.199)	0.019 0.256 (+0.237)	0.272 0.316 (+0.044)	0.261 0.318 (+0.057)	0.249 **0.380** (+0.131)	0.150 0.190 (+0.040)	0.282 -	0.156 0.219 (+0.063)
Deep Algorithms	DEC	IDEC	DSCN	PICA	ConClu	EDESC	DMICC	DIVC	LFSS
ACC(default) **ACC(best)**	0.560 0.577 (+0.017)	0.550 0.603 (+0.053)	0.550 0.600 (+0.050)	0.540 0.582 (+0.042)	0.519 0.587 (+0.068)	0.557 **0.622** (+0.065)	0.543 0.593 (+0.050)	0.541 0.575 (+0.034)	0.529 0.579 (+0.050)
NMI(default) **NMI(best)**	0.290 0.309 (+0.019)	0.251 0.309 (+0.058)	0.240 0.310 (+0.070)	0.257 0.296 (+0.039)	0.257 0.321 (+0.064)	0.307 **0.367** (+0.060)	0.272 0.317 (+0.045)	0.257 0.286 (+0.029)	0.252 0.305 (+0.053)
ARI(default) **ARI(best)**	0.248 0.270 (+0.022)	0.210 0.278 (+0.068)	0.171 0.248 (+0.077)	0.220 0.259 (+0.039)	0.202 0.283 (+0.081)	0.257 **0.333** (+0.076)	0.232 0.287 (+0.055)	0.219 0.251 (+0.032)	0.212 0.275 (+0.063)

Table 2: The average clustering performance (ACC, NMI, ARI) across all datasets.

In addition, Figure 2 and Figure3 visualize the statistical performance difference and overall performance distribution difference based on ACC, NMI and ARI, respectively. Under these results, we have the following observations:

- Spectral clustering (SpeClu), as a conventional algorithm, significantly outperforms other algorithms on the average performance under the best hyperparameter configurations (HPCs),

[2] https://scikit-learn.org/stable/index.html

demonstrating its effectiveness on different data types. However, under default HPC settings, AutoSC achieves superior performance, since it is an automated machine learning algorithm.

- Moreover, most deep clustering methods, though effective on complex data such as images, do not show a significant advantage with respect to average performance compared to the conventional methods in our benchmark datasets. We attribute this to two factors: (1) tabular or data embedding lack spatial structure and augmentation strategies, making deep models designed for images less transferable; and (2) tabular features often directly capture semantic differences, so even simple metrics (e.g., Euclidean distance) remain highly effective, leaving limited room for neural representation learning to provide additional benefits.
- The performance gap between the best-performing HPC and the default HPC reflects the hyperparameter sensitivity of each method. Large gaps observed from AggClu, DBSCAN, and SpeClu indicate that these methods are particularly sensitive to hyperparameter changes.

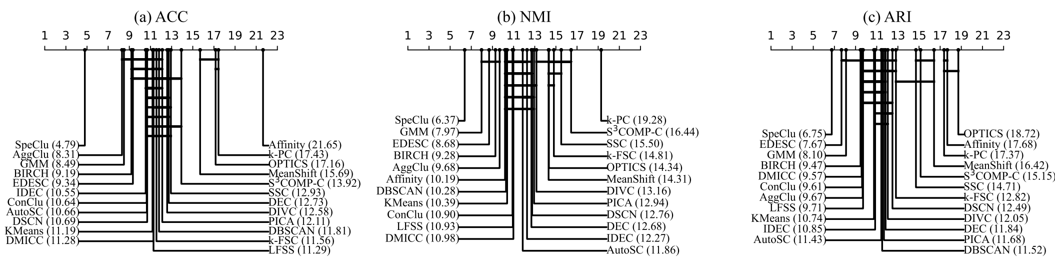


Figure 2: The CD diagram of best performance on all datasets by paired t-test. The '(value)'s are the average ranks.

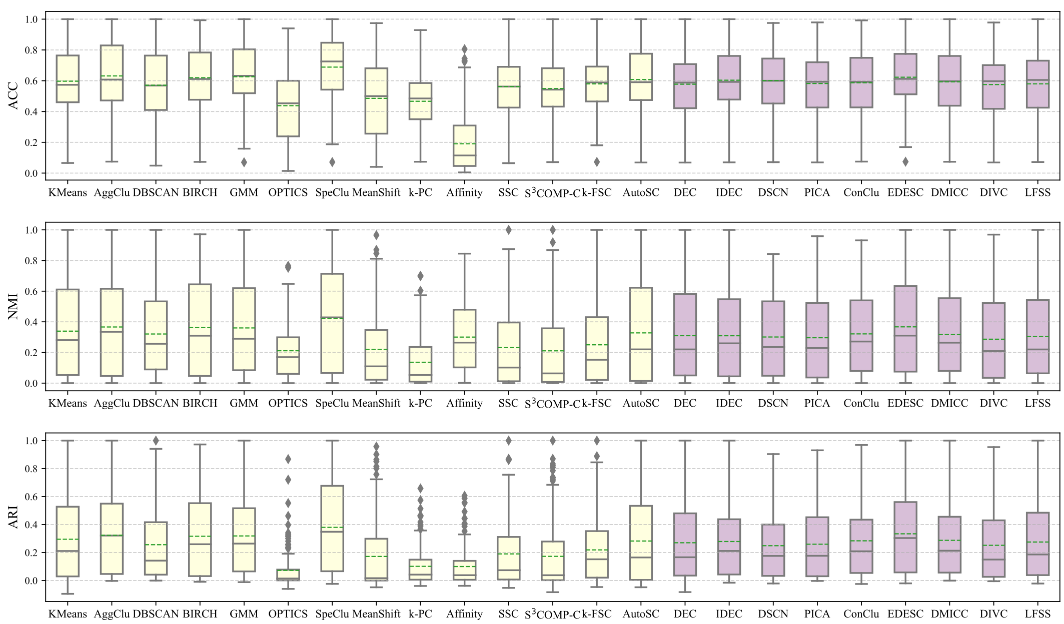


Figure 3: The statistics comparison of the performance on all datasets. The boxplots with light-yellow and purple correspond to the conventional and deep clustering algorithms, respectively. The green dash line denotes the average performance.

4.2 GROUP PERFORMANCE COMPARISON

4.2.1 ANALYSIS FROM THREE DIFFERENT PERSPECTIVES

Beyond the overall performance analysis, we group the datasets from three perspectives to uncover more specific insights: (i) data type (image, text, tabular, bioinformatics); (ii) feature dimensionality (low ($m \leq 100$), middle ($100 < m \leq 500$), high ($m > 500$)); and (iii) the degree of cluster imbalance.

In Figure 4, we visualize the average ACC rank of each algorithms on different groups. Although SpeClu consistently outperforms most methods in many scenarios, we also observe that certain methods are particularly effective in specific groups. For instance, AggClu demonstrates superior performance on highly imbalanced datasets, GMM is more effective on low-imbalance datasets, and EDESC outperforms other methods on high-dimensional datasets. More analysis on NMI and ARI performance are shown in Appendix C.4.

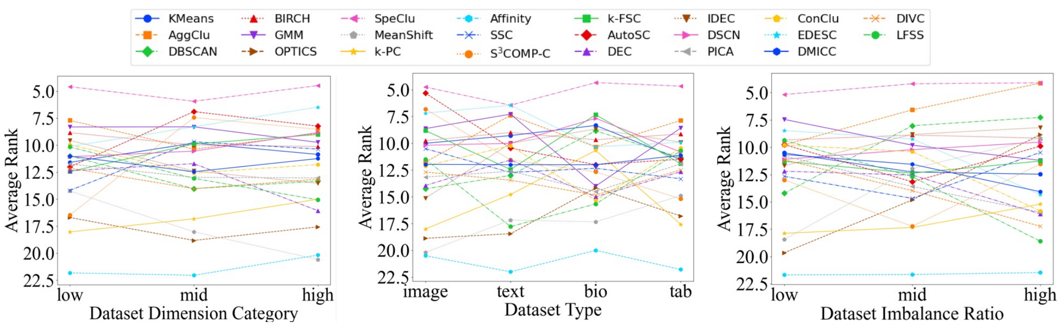


Figure 4: ACC Performance sensitivity to dataset categories across: dataset dimensionality, dataset type, and class imbalance ratio.

4.2.2 Comparison of Original and Embedded features of Image Data

Deep learning-based clustering methods generally follow one of two paradigms. Some employ an end-to-end approach, where original image samples are fed directly into CNN-based models. Others use a two-stage process, where data embeddings are first generated and then provided to an MLP-based model for clustering. To enable an extensive comparison between the two paradigms, we rewrite an MLP-based code version for each CNN-based method based on their official codebase. Here, we compare the performance difference of the two paradigms on four widely used clustering benchmark datasets: STL-10, CIFAR10, CIFAR100, and COIL20. Embeddings were extracted using CLIP Radford et al. (2021). The related results are provided in Table 3. Across nearly all methods, using CLIP features leads to substantial performance improvement. In addition, we also notice that some methods, like ConClu and LFSS, are better suited for original image data (COIL20). We also compare the performance difference between conventional and deep clustering methods with respect to the embedding data. The related results are provided in Appendix C.2.

Method	STL-10						CIFAR10						CIFAR100						COIL20					
	Original			Emb			Original			Emb			Original			Emb			Original			Emb		
	ACC	NMI	ARI	ACC	NMI	ARI	ACC	NMI	ARI	ACC	NMI	ARI	ACC	NMI	ARI	ACC	NMI	ARI	ACC	NMI	ARI	ACC	NMI	ARI
DEC	NA	NA	NA	96.70	94.14	93.63	NA	NA	NA	74.89	70.98	61.49	NA	NA	NA	42.97	60.80	27.40	NA	NA	NA	74.87	89.98	71.48
IDEC	NA	NA	NA	94.30	90.81	88.59	NA	NA	NA	55.40	52.57	38.21	NA	NA	NA	43.36	60.79	27.53	NA	NA	NA	72.56	89.35	70.95
DSCN	24.74	16.41	7.93	79.24	73.64	67.58	19.29	5.47	2.71	73.12	63.71	55.03	6.18	16.50	0.50	32.36	58.00	23.69	45.35	61.10	20.90	61.78	78.85	50.78
PICA	44.20	34.40	22.90	96.24	91.79	91.96	38.20	25.70	16.80	50.18	41.33	33.85	9.50	23.20	3.00	16.46	38.02	7.79	76.30	86.90	72.70	86.73	91.08	82.36
ConClu	47.30	36.60	26.30	82.76	78.89	72.38	44.10	31.30	21.80	62.35	56.04	46.11	11.99	27.60	3.75	12.38	32.57	4.68	82.70	81.40	71.70	55.55	68.19	43.62
EDESC	NA	NA	NA	97.47	95.07	94.87	NA	NA	NA	80.59	75.56	69.64	NA	NA	NA	44.26	61.27	29.55	NA	NA	NA	81.02	92.77	77.97
DMICC	30.10	24.30	13.50	85.04	80.83	76.30	30.40	20.50	11.70	50.90	46.05	32.13	6.80	19.70	14.60	11.46	31.88	4.67	64.50	75.20	55.60	74.20	83.67	66.98
DIVC	25.00	13.60	6.90	95.19	90.47	90.06	25.50	13.40	7.10	61.13	50.71	41.94	8.77	22.80	2.20	15.70	37.16	7.26	80.60	86.00	73.90	86.45	90.06	80.60
LFSS	38.90	30.80	18.90	68.36	52.07	47.16	39.30	27.10	17.80	41.41	26.19	19.40	13.40	28.50	4.70	32.73	44.94	17.73	83.60	86.50	76.50	75.55	84.90	69.74

Table 3: Clustering results on four image datasets using raw images (Original) vs. CLIP embeddings (Emb). The best and second-best per column are highlighted in red and orange, respectively. The 'NA' indicates the result is not available.

4.3 Performance Similarity Analysis

We construct a performance vector $\mathbf{p}$ for each algorithm and dataset. Specifically, each algorithm is characterized by a vector $\mathbf{p} \in \mathbb{R}^a$ representing its performance across all datasets with $a = 131$ in our benchmark, while each dataset is characterized by a vector $\mathbf{p} \in \mathbb{R}^b$ representing the performance of all algorithms on it with $b = 23$. Aggregating these vectors forms the performance matrices $\mathbf{P}_{acc}, \mathbf{P}_{nmi}, \mathbf{P}_{ari} \in \mathbb{R}^{a \times b}$.

4.3.1 Among Algorithms

In this section, We obtain an overall performance matrix for all methods as $\hat{\mathbf{P}} = [\mathbf{P}_{acc}^T, \mathbf{P}_{nmi}^T, \mathbf{P}_{ari}^T] \in \mathbb{R}^{b \times 3a}$. Each $\hat{\mathbf{P}}_{i,:}$ represents a performance vector for a specific method. Dimensionality reduction techniques, such as t-SNE Maaten & Hinton (2008), can then be used to visualize these performance vectors and observe performance similarities between methods. Based on Figure 5, we have the following observations. First, most deep learning algorithms cluster together, while conventional methods form two distinct clusters, indicating strong performance similarities within each group. Second, methods with similar designs are located close to each other in the visualization. For instance, subspace-based methods such as SSC, k-PC, k-FSC, and S^3COMP-C cluster together. IDEC, an extension of DEC, is positioned near DEC, and DIVC, an extension of PICA, is located close to PICA. Moreover, several deep algorithms that leverage data augmentation to construct positive and negative samples for contrastive learning, such as DIVC, PICA, LFSS, DMICC, and ConClu, form another coherent cluster. Lastly, such performance similarities provide valuable guidance for clustering research and practical applications on unseen datasets: selecting representative methods from each cluster can be far less time-consuming while remaining as effective as evaluating all.

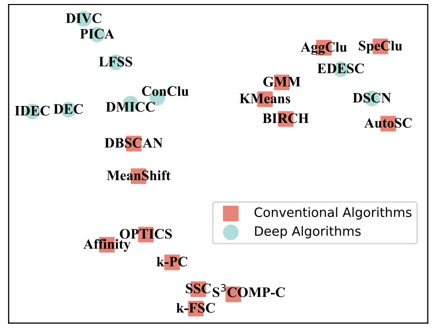
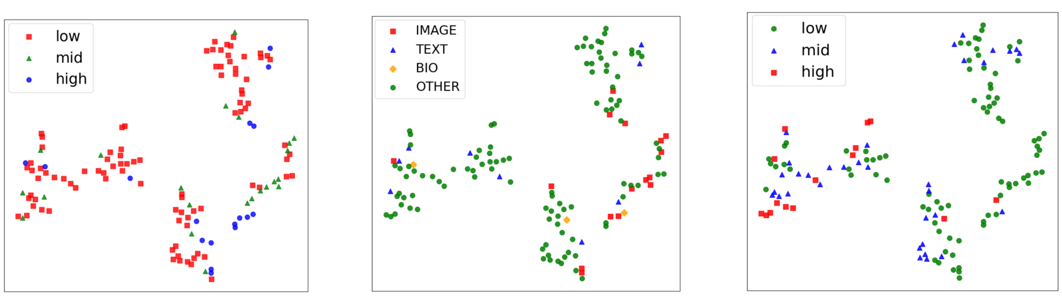


Figure 5: The t-SNE visualization results on algorithm performance vectors.

4.3.2 Among Datasets

Following the similar procedure mentioned above, we can obtain an overall performance matrix for all datasets as $\tilde{\mathbf{P}} = [\mathbf{P}_{acc}, \mathbf{P}_{nmi}, \mathbf{P}_{ari}] \in \mathbb{R}^{a \times 3b}$. Each $\tilde{\mathbf{P}}_{i,:}$ represents a performance vector for a specific dataset. Then t-SNE is utilized to obtain the visualization for each dataset. Here we divide the datasets into groups from 3 aspects: (1) data dimensionality (low, middle, high); (2) data type (image, text, bioinformatics data and other tabular datasets); (3) the degree of cluster imbalance (low, middle, high). The imbalance ratio is defined as the standard deviation of the cluster proportion distribution.

From the results in Figure 6, we observe the following: (1) With respect to dimensionality and data type, clusters are not clearly formed within groups, especially among high-dimensional datasets, suggesting that performance is not strongly related to dataset dimensionality or type. (2) In terms of cluster imbalance, most highly imbalanced datasets aggregate in a local region, which indicates that the clustering performance is easily affected by high data imbalance.



(a) Data dimensionality (b) Data type (c) Class imbalance ratio

Figure 6: The t-SNE visualization of datasets based on their performance vectors. The points are labeled according to three perspectives: data dimensionality, data type, and class imbalance ratio.

4.4 Low-Rank Analysis on Performance Matrices

To analyze the low-rank structure of the performance matrices, we conduct singular value decomposition (SVD) among the performance matrices (ACC, NMI, ARI) where each performance matrix consists of 131 rows (datasets) and 267 columns (clustering algorithms with different HPCs).

Let $\mathbf{P}_{acc}, \mathbf{P}_{nmi}, \mathbf{P}_{ari} \in \mathbb{R}^{a \times c}$ be the corresponding performance matrices and σ_i denotes the i-th singular value, where $\sigma_1 \geq \sigma_2 \geq \cdots \geq \sigma_n > 0$, a denotes the number of datasets, c denotes the number of all clustering algorithms under different hyperparameter configurations. Figure 7 presents the cumulative contribution ratio of the singular values on $\mathbf{P}_{acc}$, where the cumulative contribution ratio (ccr) is defined by $ccr(j) = (\sum_{i=1}^{j} \sigma_i)/(\sum_{i=1}^{n} \sigma_i)$. The low-rank analysis on $\mathbf{P}_{nmi}$ and $\mathbf{P}_{ari}$ is provided in Appendix C.3.

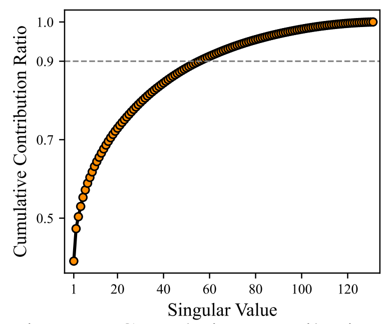


Figure 7: Cumulative contribution ratio of singular values of performance matrix $\mathbf{P}_{acc}$.

As evidenced by Figure 7, the cumulative contribution ratio of the first sixty (60/131) singular values ($ccr(60)$) exceeds 90%. This demonstrates that matrix $\mathbf{P}_{acc}$ possesses low-rank characteristics. This finding has two important implications: (1) clustering performance of novel datasets or clustering methods can be reliably predicted using only a subset of performance measurements, and (2) this property enables an efficient strategy for rapid algorithm evaluation and selection in practical applications.

To further verify the low-rank property of $\mathbf{P}_{acc}$ and the effectiveness of performance prediction, we construct the matrix completion tasks by MCAR (missing completely at random) mechanism with missing rate **mr** $\in \{0.5, 0.6, 0.7, 0.8, 0.9\}$. We use matrix factorization and non-convex optimization techniques (Candes & Recht, 2012; Chi, 2018; Fan et al., 2019) to recover the missed entries of the performance matrix $\mathbf{P}_{acc}$. The recovery results are provided in Table 4, indicating that a rapid and reliable performance prediction is available based on the performance matrix $\mathbf{P}_{acc}$.

mr	0.5	0.6	0.7	0.8	0.9
MAPE	0.1326 (0.0039)	0.1483 (0.0027)	0.1666 (0.0024)	0.1944 (0.0027)	0.2499 (0.0068)

Table 4: Recovery performance (MAPE) on the performance matrix $\mathbf{P}_{acc}$ in the setting of MCAR.

4.5 Hyperparameter Sensitivity Analysis

Figure 10 (in the Appendix) visualizes the average performance of different methods under their best- and worst-performing hyperparameter configurations. A larger gap between these two results indicates higher sensitivity to hyperparameter variation. From the Figure 10, we observe that methods such as AggClu, OPTICS, DBSCAN and SpeClu are relatively sensitive to hyperparameter changes, whereas methods like KMeans, BIRCH, and DEC are more robust. It is noteworthy, however, that the hyperparameter configuration (HPC) ranges differ across methods, and thus, the results may not provide a comprehensive measure of sensitivity.

5 Conclusions and Future Work

In this paper, we introduce CLUBench, a comprehensive clustering benchmark that evaluates 23 algorithms across 131 datasets. Based on extensive evaluation, we first conduct an overall performance analysis, which reveals that spectral clustering achieves markedly superior performance in terms of ACC, NMI, and ARI compared to other baselines. Meanwhile, deep learning-based methods do not demonstrate a general advantage over conventional algorithms. To investigate potential algorithmic preferences, we then categorize datasets according to several different criteria and observe performance variation on different kinds of datasets. Also, We utilize performance matrices to analyze similarities among datasets and algorithms, as well as their low-rank structure for a reliable performance prediction and rapid model selection. Within CLUBench, clustering performance is evaluated for each algorithm across multiple hyperparameter configurations, allowing us to assess sensitivity to hyperparameter choices within the specified search ranges. More importantly, we provide an easy-to-use toolbox to facilitate further research and application of these clustering techniques.

CLUBench can be easily extended to aggregate more clustering algorithms and new datasets. We will further consider more data types like graph and those uncovered topics like multi-view clustering, graph clustering, online clustering and so on in the future.

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A EXPERIMENTAL COVERAGE

The experimental coverage of CLUBench are summarized in Table 5.

# Datasets	# Algorithms	# HPCs	# Exp. Repeat	# Exp. Total	Metrics
131	23	276	5	174,885(131 × 276 × 5)	ACC, NMI, ARI, Time (second)

Table 5: The experimental coverage of CLUBench.

Datasets. Based on previous works (Wei et al., 2024; Zhou et al., 2024; Jeon et al., 2025) and publicly available dataset archive[3]. We gather and clean 131 benchmark datasets for clustering evaluation. The detailed statistics of these datasets are provided in Table 6, 7. The data type covers tabular, image and sequence (text), where the original samples and feature representations of image datasets are both used for two kind of comparisons: 1) the performance difference between conventional clustering algorithms and deep learning based methods; 2) the performance difference between DC methods.

Algorithms. In CLUBench, we have collected 23 clustering methods with (i) conventional classic algorithms like KMeans (McQueen, 1967), AggClu (Agglomerative Clustering) (Johnson, 1967), DB-SCAN (Ester et al., 1996), BIRCH (Zhang et al., 1996), GMM Rasmussen (1999), OPTICS (Ankerst et al., 1999), Spectral Clustering (SpeClu) (Ng et al., 2001), MeanShift (Comaniciu & Meer, 2002), k-PC (Agarwal & Mustafa, 2004), Affinity (Frey & Dueck, 2007),AutoSC (Fan, 2021); (ii) subspace-based algorithms like SSC Elhamifar & Vidal (2013), S^3COMP-C (Chen et al., 2020),k-FSC (Fan, 2021); (iii) deep learning based clustering methods like DEC (Xie et al., 2016), IDEC (Guo et al., 2017), DSCN (Ji et al., 2017), PICA (Huang et al., 2020), ConClu(Contrastive Clustering) (Li et al., 2021), EDESC (Cai et al., 2022); (iv) the latest SOTA methods like DMICC (Li et al., 2023), DIVC (Metaxas et al., 2023) and LFSS (Li et al., 2025). For the deep methods with CNN-architecture, we retain the original architecture for raw image data while adapt a new version with MLP-architecture for evaluation on embedded image, tabular and text data.

Evaluation. In CLUBench, we use three evaluation metrics ACC (Clustering Accuracy), NMI (Normalized Mututal Information), and ARI (Adjusted Rand Index) to quantifiably analyze the performance among the clustering methods. In addition, the average computational time (over five runs) of each algorithm is provided in Appendix E. Although not all experiments were conducted on the same hardware platform, these time records still provide valuable practical reference.

B DETAILED INFORMATION ON ALGORITHMS AND DATASETS

B.1 DATASETS

To control the scale of the experiments, we have undersampled the datasets with sample size $n \geq 10,000$ to 10000 samples and removed the extreme clusters (outliers to some extent) with $r_i \leq 0.05$ ($r_i := \frac{\#\ i\text{th cluster}}{\#\ \text{maximal cluster}}$).

We details the statistics of all datasets used in Table 6, Table 7, where we give two ratios $r_{mm} := \frac{\#\ \text{minimal cluster}}{\#\ \text{maximal cluster}}$ and $r_{ma} := \frac{\#\ \text{minimal cluster}}{\#\ \text{all samples}}$ to reflect the biggest difference of sample size between clusters. Moreover, we give an imbalance factor (IR) to measure the imbalance ratio of a dataset. Suppose we have a dataset containing K classes, then we define: $p_i = \frac{\#\ \text{ith class}}{\sum_{j=1}^{K}\#\ \text{jth class}}$. Then the imbalance factor is defined as the standard deviation of the class proportion distribution $\{p_i\}_{i=1}^{K}$.

[3] https://www.openml.org/search?type=data&status=active

Datasets	Type	Samples	Dimension	Classes	$\mathrm{r_{mm}}$	$\mathrm{r_{ma}}$	IR
[1] echocardiogram	tabular	61	10	2	0.386	0.279	0.221
[2] skillcraft1_master_table_dataset	tabular	3303	18	6	0.206	0.051	0.071
[3] breast_cancer_wisconsin_original	tabular	683	9	2	0.538	0.350	0.150
[4] smoker_condition	tabular	1012	7	2	0.656	0.396	0.104
[5] glass_identification	tabular	214	9	6	0.118	0.042	0.127
[6] statlog_image_segmentation	tabular	2310	19	7	1.000	0.143	0.000
[7] planning_relax	tabular	182	12	2	0.400	0.286	0.214
[8] customer_classification	tabular	1000	11	4	0.772	0.217	0.025
[9] pima_indians_diabetes_database	tabular	768	8	2	0.536	0.349	0.151
[10] mobile_price_classification	tabular	2000	20	4	1.000	0.250	0.000
[11] spambase	tabular	4601	57	2	0.650	0.394	0.106
[12] rice_seed_gonen_jasmine	tabular	9999	10	2	0.821	0.451	0.049
[13] heart_attack_analysis_prediction_dataset	tabular	303	13	2	0.836	0.455	0.045
[14] user_knowledge_modeling	tabular	258	5	4	0.273	0.093	0.098
[15] world12d	tabular	150	12	5	0.190	0.053	0.088
[16] pumpkin_seeds	tabular	2500	12	2	0.923	0.480	0.020
[17] iris	tabular	150	4	3	1.000	0.333	0.000
[18] wine	tabular	178	13	3	0.676	0.270	0.053
[19] letter_recognition	tabular	9992	16	26	0.904	0.037	0.001
[20] mammographic_mass	tabular	830	5	2	0.944	0.486	0.014
[21] breast_tissue	tabular	106	9	6	0.636	0.132	0.028
[22] hepatitis	tabular	80	19	2	0.194	0.163	0.338
[23] predicting_pulsar_star	tabular	9273	8	2	0.101	0.092	0.408
[24] breast_cancer_wisconsin_prognostic	tabular	569	30	2	0.594	0.373	0.127
[25] wireless_indoor_localization	tabular	2000	7	4	1.000	0.250	0.000
[26] date_fruit	tabular	898	34	7	0.319	0.072	0.062
[27] zoo	tabular	101	16	7	0.098	0.040	0.118
[28] htru2	tabular	9999	8	2	0.101	0.092	0.408
[29] ionosphere	tabular	351	34	2	0.560	0.359	0.141
[30] music_genre_classification	tabular	1000	26	10	1.000	0.100	0.000
[31] spectf_heart	tabular	80	44	2	1.000	0.500	0.000
[32] rice_dataset_cammeo_and_osmancik	tabular	3810	7	2	0.748	0.428	0.072
[33] ph_recognition	tabular	653	3	15	0.864	0.058	0.002
[34] banknote_authentication	tabular	1372	4	2	0.801	0.445	0.055
[35] wine_quality	tabular	4873	11	5	0.074	0.033	0.160
[36] cardiovascular_study	tabular	2927	15	2	0.179	0.152	0.348
[37] statlog_german_credit	tabular	1000	24	2	0.429	0.300	0.200
[38] boston	tabular	154	13	3	0.371	0.169	0.121
[39] seismic_bumps	tabular	646	24	2	0.071	0.067	0.433
[40] dry_bean	tabular	9997	16	7	0.147	0.038	0.065
[41] credit_risk_classification	tabular	976	11	2	0.239	0.193	0.307
[42] epileptic_seizure_recognition	tabular	5750	178	5	1.000	0.200	0.000
[43] website_phishing	tabular	1353	9	3	0.147	0.076	0.188
[44] optical_recognition_of_handwritten_digits	tabular	3823	64	10	0.967	0.098	0.001
[45] siberian_weather_stats	tabular	1407	11	7	0.073	0.024	0.122
[46] orbit_classification_for_prediction_nasa	tabular	1722	11	3	0.065	0.056	0.371
[47] magic_gamma_telescope	tabular	9999	10	2	0.542	0.352	0.148
[48] raisin	tabular	900	7	2	1.000	0.500	0.000
[49] patient_treatment_classification	tabular	4412	10	2	0.679	0.404	0.096
[50] fetal_health_classification	tabular	2126	21	3	0.106	0.083	0.316
[51] dermatology	tabular	358	34	6	0.180	0.056	0.373
[52] secom	tabular	1567	590	2	0.071	0.066	0.000
[53] paris_housing_classification	tabular	10000	17	2	0.145	0.127	0.053
[54] seeds	tabular	210	7	3	1.000	0.333	0.275
[55] wine_customer	tabular	178	13	3	0.676	0.270	0.000
[56] crowdsourced_mapping	tabular	9997	28	4	0.060	0.043	0.212
[57] durum_wheat_features	tabular	9000	236	3	1.000	0.333	0.093
[58] classification_in_asteroseismology	tabular	1001	3	2	0.404	0.288	0.063
[59] birds_bones_and_living_habits	tabular	413	10	6	0.185	0.056	0.000
[60] microbes	tabular	9995	24	10	0.082	0.020	0.097
[61] image_segmentation	tabular	210	19	7	1.000	0.143	0.440
[62] water_quality	tabular	2011	9	2	0.676	0.403	0.235
[63] insurance_company_benchmark	tabular	5822	85	2	0.064	0.060	0.115
[64] harbermans_survival	tabular	306	3	2	0.360	0.265	0.175
[65] yeast	tabular	1459	8	8	0.065	0.021	0.132

Table 6: Statistics of datasets (1-65).

Datasets	Type	Samples	Dimension	Classes	$\mathrm{r_{mm}}$	$\mathrm{r_{ma}}$	IR
[66] heart_disease	tabular	297	13	5	0.081	0.044	0.004
[67] ecoli	tabular	327	7	5	0.140	0.061	0.052
[68] extyaleb	tabular	319	30	5	0.954	0.194	0.171
[69] breast_cancer_coimbra	tabular	116	9	2	0.812	0.448	0.061
[70] student_grade	tabular	395	29	2	0.491	0.329	0.234
[71] human_stress_detection	tabular	2001	3	3	0.634	0.250	0.004
[72] fraud_detection_bank	tabular	9999	112	2	0.362	0.266	0.031
[73] pen_based_recognition_of_handwritten_digits	tabular	7494	16	10	0.922	0.096	0.000
[74] diabetic_retinopathy_debrecen	tabular	1151	19	2	0.884	0.469	0.026
[75] pistachio	tabular	2148	28	2	0.744	0.426	0.262
[76] turkish_music_emotion	tabular	400	50	4	1.000	0.250	0.000
[77] parkinsons	tabular	195	22	2	0.327	0.246	0.000
[78] weather	tabular	365	192	7	0.603	0.121	0.148
[79] blood_transfusion_service_center	tabular	748	4	2	0.312	0.238	0.004
[80] mfeat-karhunen	tabular	2000	64	10	1.000	0.100	0.039
[81] mfeat-factors	tabular	2000	216	10	1.000	0.100	0.116
[82] wall-robot-navigation	tabular	5456	24	4	0.149	0.060	0.007
[83] Waveform	tabular	5000	21	3	0.971	0.329	0.053
[84] gas-drift	tabular	10000	128	6	0.546	0.118	0.005
[85] mfeat-morphological	tabular	2000	6	10	1.000	0.100	0.000
[86] JapaneseVowels	tabular	9961	14	9	0.485	0.079	0.124
[87] rmftsa_sleepdata	tabular	1024	2	4	0.233	0.092	0.337
[88] first-order-theorem-proving	tabular	6118	51	6	0.190	0.079	0.062
[89] gina_prior2	tabular	3468	784	10	0.822	0.091	0.153
[90] fabert	tabular	8237	800	7	0.261	0.061	0.064
[91] dilbert	tabular	10000	2000	5	0.934	0.191	0.000
[92] synthetic_control	tabular	600	60	6	1.000	0.167	0.009
[93] Drug Consumption	tabular	1749	12	4	0.261	0.113	0.053
[94] shuttle	tabular	10000	9	2	0.195	0.163	0.005
[95] tr45.wc	tabular	676	8261	9	0.113	0.027	0.000
[96] steel-plates-fault	tabular	1941	33	2	0.531	0.347	0.000
[97] fbis.wc	tabular	2196	2000	11	0.128	0.030	0.000
[98] mfeat-fourier	tabular	2000	76	10	1.000	0.100	0.000
[99] vehicle	tabular	846	18	4	0.913	0.235	0.000
[100] micro-mass	tabular	360	1300	10	1.000	0.100	0.000
[101] ISOLET	tabular	7797	617	26	0.993	0.038	0.000
[102] poker-hand	tabular	10000	10	2	0.843	0.457	0.000
[103] tamilnadu-electricity	tabular	10000	2	20	0.480	0.030	0.000
[104] mnist64	image	1082	64	6	0.967	0.164	0.000
[105] MNIST_CLIP$^+$	image	9996	512	10	0.801	0.090	0.000
[106] fashion_mnist	image	3000	784	10	1.000	0.100	0.001
[107] FashionMNIST_CLIP$^+$	image	10000	512	10	1.000	0.100	0.038
[108] cifar10	image	3250	1024	10	1.000	0.100	0.021
[109] CIFAR10_CLIP$^+$	image	10000	512	10	1.000	0.100	0.153
[110] coil20*	image	1440	400	20	1.000	0.050	0.062
[111] COIL20_CLIP$^+$	image	1440	512	20	1.000	0.050	0.000
[112] labeled_faces_in_the_wild	image	2200	5828	2	1.000	0.500	0.006
[113] flickr_material_database	image	997	1536	10	0.990	0.099	0.053
[114] street_view_house_numbers	image	732	1024	10	0.341	0.064	0.000
[115] har	image	735	561	6	0.702	0.135	0.006
[116] Indian_pines	image	8858	220	5	0.121	0.055	0.000
[117] satellite_image	image	6435	36	6	0.408	0.097	0.000
[118] olivetti_faces	image	400	4096	40	1.000	0.025	0.000
[119] cnae9	text	1080	856	9	1.000	0.111	0.000
[120] imdb	text	3250	700	2	1.000	0.500	0.000
[121] hate_speech	text	3221	100	3	0.075	0.058	0.000
[122] sentiment_labeld_sentences	text	2748	200	2	0.983	0.496	0.000
[123] sms_spam_collection	text	835	500	2	0.155	0.134	0.000
[124] wos	text	9997	4096	7	0.223	0.069	0.000
[125] enron	text	9999	4096	2	0.990	0.497	0.315
[126] reuters	text	6576	4096	3	0.562	0.243	0.004
[127] 20newsgroups	text	9991	4096	20	0.612	0.033	0.366
[128] Mouse_retina	tabular (BioInfo)	8352	6198	5	0.054	0.043	0.073
[129] Campbell	tabular(BioInfo)	9993	26774	14	0.052	0.024	0.003
[130] PCam	image	4000	27648	2	0.977	0.494	0.302
[131] Baron Human	tabular (BioInfo)	8451	20125	9	0.069	0.020	0.111

Table 7: Statistics of datasets (66-131).

B.2 Clustering Algorithms

B.2.1 Analysis of Time and Space Complexity

In this section, we detail the time and space complexity of the algorithms evaluated in Table 8. Note that the reported time complexity for iteratively optimized algorithms refers to that of a single iteration. The notations used in Table 8 are defined as follows.

- n: data size.
- m: feature dimension.
- k: number of clusters.
- ρ: proportion of nonzero entries.
- $\tilde{m}$: $\max\{m, h\}$ where h is maximal latent dimension of neural networks.
- θ: number of parameters of neural networks.
- p: dimension of output from encoder.
- n_b: batch size.
- d: dimension of subspace.
- $\tilde{p}$: $\max\{m, p\}$.
- Q: number of combinations of hyperparameters.

Methods	**Time Complexity**	**Space Complexity**
KMeans (McQueen, 1967)	$\mathcal{O}(kmn)$	$\mathcal{O}(nm + km)$
AggClu (Agglomerative Clustering) (Johnson, 1967)	$\mathcal{O}(n^3)$	$\mathcal{O}(n^2)$
DBSCAN (Ester et al., 1996)	$\mathcal{O}(n \log n)$	$\mathcal{O}(n^2)$
BIRCH (Zhang et al., 1996)	$\mathcal{O}(mn)$	$\mathcal{O}(mn)$
GMM Rasmussen (1999)	$\mathcal{O}(nkm^2)$	$\mathcal{O}(nm + km^2)$
OPTICS (Ankerst et al., 1999)	$\mathcal{O}(n^2)$	$\mathcal{O}(n)$
SpeClu (Ng et al., 2001)	$\mathcal{O}(mn^2)$	$\mathcal{O}(n^2)$
MeanShift (Comaniciu & Meer, 2002)	$\mathcal{O}(n^2)$	$\mathcal{O}(nm)$
k-PC (Agarwal & Mustafa, 2004)	$\mathcal{O}(dmn + kdm^2 + m^2n)$	$\mathcal{O}(mn + kmd)$
Affinity (Frey & Dueck, 2007)	$\mathcal{O}(n^2)$	$\mathcal{O}(n^2)$
SSC (Elhamifar & Vidal, 2013)	$\mathcal{O}(mn^2)$	$\mathcal{O}(mn + \rho n^2)$
S^3COMP-C (Chen et al., 2020)	$\mathcal{O}(m\rho n^3)$	$\mathcal{O}(mn + \rho n^2)$
k-FSC (Fan, 2021))	$\mathcal{O}(kdmn)$	$\mathcal{O}(mn + kmd + kdn)$
AutoSC (Fan, 2021)	$\mathcal{O}(Q(k+m)n^2)$	$\mathcal{O}(mn + n^2)$
DEC (Xie et al., 2016)	$\mathcal{O}(\tilde{m}^2 n + knp)$	$\mathcal{O}(\theta + knp + \tilde{m}n)$
IDEC (Guo et al., 2017)	$\mathcal{O}(\tilde{m}^2 n + knp)$	$\mathcal{O}(\theta + knp + \tilde{m}n)$
DSCN (Ji et al., 2017)	$\mathcal{O}(\tilde{m}^2 n + n^2 p)$	$\mathcal{O}(\theta + n^2 + \tilde{m}n)$
PICA (Huang et al., 2020)	$\mathcal{O}(k^2 n_b + \tilde{m}^2 n_b)$	$\mathcal{O}(\theta + \tilde{m}n + k^2)$
ConClu(Contrastive Clustering) (Li et al., 2021)	$\mathcal{O}(\tilde{m}^2 n + n^2 \tilde{m})$	$\mathcal{O}(\theta + \tilde{m}n_b + n_b^2)$
EDESC (Cai et al., 2022)	$\mathcal{O}(kdpn + \tilde{m}\tilde{p}n)$	$\mathcal{O}(\theta + \tilde{m}n + kn + kpd)$
DMICC (Li et al., 2023)	$\mathcal{O}(\tilde{m}^2 n + n^2 \tilde{m})$	$\mathcal{O}(\theta + p^2 + n_b^2 + n_b\tilde{m})$
DIVC (Metaxas et al., 2023)	$\mathcal{O}(k^2 n_b + \tilde{m}^2 n_b)$	$\mathcal{O}(\theta + \tilde{m}n + k^2)$
LFSS (Li et al., 2025)	$\mathcal{O}(\tilde{m}^2 n + n^2 p)$	$\mathcal{O}(\theta + n_b^2 + n_b\tilde{m})$

Table 8: Time and space complexity.

B.2.2 The Search Range of Hyperparameter Configuration (HPC)

To obtain valid performance on all algorithms evaluated in CLUBench, we adjust the hyperparameter configurations (HPC) and search for the best performance for each clustering algorithm. The detailed search range of HPC is provided in the Table 9. It is worth noting that, in Table 9, each value of 'eps' in DBSCAN denotes a multiplier. In implementation, we use the average distance among samples as an 'eps_base' to control the argument in a reasonable range. For a dataset $\mathcal{X} = \{\mathbf{x}_1, \mathbf{x}_2, \cdots, \mathbf{x}_n\}$, we have

$$\text{eps} \leftarrow \text{eps} \times \text{eps\_base},$$

$$\text{eps\_base} = \frac{1}{n(n-1)} \sum_{i=1}^{n} \sum_{j \neq i}^{n} \text{dist}(\mathbf{x}_i, \mathbf{x}_j),$$

Where $\text{dist}(\cdot, \cdot)$ denotes a distance measure that is consistent with the argument 'metric'. The same process is used for 'max_eps' in OPTICS. Similarly, for 'gamma' in SC (Spectral Clustering), we have

$$\text{gamma} \leftarrow \text{gamma} \times \text{gamma\_base},$$

$$\text{gamma\_base} = \frac{1}{2 \times \text{median}(\{\|\mathbf{x}_i - \mathbf{x}_j\|_2 \mid \mathbf{x}_i, \mathbf{x}_j \in \mathcal{X}, i \neq j\})}.$$

Algorithm	HPC (Hyperparameter Configuration)	# Total
KMeans	init ∈ {kmeans++, random}; n_init=10; max_iter=500	2
AggClu	metric ∈ {euclidean, manhattan, cosine}; linkage ∈ {average, complete, single}	9
DBSCAN	eps ∈ $\{0.001, 0.005, 0.01, 0.1, 0.2, 0.4, 0.6, 0.8, 1.0, 10.0\}$; min_sample ∈ $\{3, 5, 10\}$; metric ∈ {euclidean, manhattan, cosine}	90
BIRCH	threshold ∈ $\{0.3, 0.5, 0.7, 0.9\}$; branching_factor ∈ $\{30, 50, 70\}$	12
GMM	covariance_type ∈ {full, spherical}; init_params ∈ {kmeans, kmeans++, random}	6
OPTICS	min_sample ∈ $\{3, 5, 7\}$; max_eps ∈ $\{0.01, 0.1, 1.0, 10.0\}$; metric ∈ {euclidean, manhattan, cosine};	36
SpeClu	affinity=knn; $k = \{3, 5, 10, 20, 30, 50\}$ affinity=rbf; gamma ∈ $\{0.1, 0.5, 1.0, 5.0, 10.0\}$	11
MeaShift	bandwidth ∈ $\{0.1, 0.3, 0.5, 0.7\}$; min_bin_freq ∈ $\{1, 3\}$	8
k-PC	init_type=k-means; d ∈ $\{5, 10, 20, 30, 50\}$	5
Affinity	damping ∈ $\{0.6, 0.7, 0.8, 0.9\}$; max_iter∈ $\{200, 500\}$; affinity=euclidean	8
SSC	lambda $= \{100.0, 10.0, 1.0, 0.01\}$	4
S^3COMP-C	delta ∈ $\{0.1, 0.3\}$; lambda ∈ $\{0.1, 0.3, 0.5\}$	6
k-FSC	$d \in \{5, 10, 20\}$; lambda $= \{0.01, 0.1, 0.3, 0.5\}$	12
AutoSC	Auto Hyperparameters Search	NA
DEC	lr= $1e^{-3}$; hidden_dims ∈ $\{64, 32, 16\}$	3
IDEC	lr= $1e^{-4}$; hidden_dims ∈ $\{64, 32, 16\}$; gamma ∈ $\{0.01, 0.1\}$	6
DSCN	lr= $1e^{-3}$; hidden_dims ∈ $\{64, 32, 16\}$; dim_subspace ∈ $\{10, 20\}$	6
PICA	lr= $1e^{-3}$; lamda ∈ $\{0.1, 0.5, 1\}$	3
ConClu	lr= $1e^{-4}$; instance_tempature ∈ $\{0.1, 0.5, 1.0\}$; cluster_tempature ∈ $\{0.1, 0.5, 1\}$	9
EDESC	lr= $1e^{-3}$; beta ∈ $\{0.1, 1, 10\}$; d ∈ $\{1, 5, 10\}$	9
DMICC	lr= $1e^{-3}$; lamda1 ∈ $\{1e^{-3}, 1e^{-4}\}$; lamda2 ∈ $\{1e^{-3}, 1e^{-4}\}$ hidden_dims ∈ $\{64, 32, 16\}$	12
DIVC	lr= $1e^{-3}$; lamda ∈ $\{0.1, 0.5, 1\}$	3
LFSS	lr= $1e^{-3}$; hidden_dims ∈ $\{64, 32, 16\}$; lamda_da ∈ $\{0.1, 0.5\}$; temp $= 0.5$	6

Table 9: The search range of hyperparameter configurations.

C More Experimental Analysis and Results

C.1 Best Average Performance of each Algorithms

In this subsection, we provide complete average performance results (best) of different methods over 131 datasets. The results are shown in Table 10. SpeClu (Spectral Clustering) significantly outperforms other algorithms on the average performance under the best hyperparameter configurations (HPCs), demonstrating its effectiveness on different data types. Most deep clustering methods do not show a significant advantage with respect to average performance compared to the conventional methods in our benchmark datasets.

Algorithms	KMeans	AggClu	DBSCAN	BIRCH	GMM	OPTICS	SpeClu	MeanShift	k-PC	Affinity	SSC	S^3COMP-C
ACC(default)	0.593	0.501	0.424	0.592	0.579	0.278	0.588	0.432	0.447	0.158	0.518	0.518
ACC(best)	0.596	0.631	0.570	0.619	0.626	0.437	**0.688**	0.485	0.466	0.190	0.561	0.549
NMI(default)	0.336	0.178	0.028	0.330	0.315	0.199	0.318	0.118	0.122	0.300	0.200	0.186
NMI(best)	0.339	0.366	0.320	0.363	0.360	0.211	**0.422**	0.220	0.136	0.300	0.232	0.210
ARI(default)	0.293	0.124	0.019	0.272	0.261	0.017	0.249	0.080	0.084	0.095	0.150	0.142
ARI(best)	0.295	0.323	0.256	0.316	0.318	0.072	**0.380**	0.171	0.101	0.099	0.190	0.172
Algorithms	k-FSC	AutoSC	DEC	IDEC	DSCN	PICA	ConClu	EDESC	DMICC	DIVC	LFSS	–
ACC(default)	0.496	0.607	0.560	0.550	0.550	0.540	0.519	0.557	0.543	0.541	0.529	–
ACC(best)	0.579	-	0.577	0.603	0.600	0.582	0.587	0.622	0.593	0.575	0.579	–
NMI(default)	0.200	0.327	0.290	0.251	0.240	0.257	0.257	0.307	0.272	0.257	0.252	–
NMI(best)	0.250	-	0.309	0.309	0.310	0.296	0.321	0.367	0.317	0.286	0.305	–
ARI(default)	0.156	0.282	0.248	0.210	0.171	0.220	0.202	0.257	0.232	0.219	0.212	–
ARI(best)	0.219	-	0.270	0.278	0.248	0.259	0.283	0.333	0.287	0.251	0.275	–

Table 10: The average clustering performance among all datasets.

C.2 Comparison between Conventional and Deep algorithms based on Embedded Image Data

Table 11 reports the performance of different methods on CLIP-embedded datasets. Interestingly, conventional algorithms such as K-means and SpeClu (Spectral Clustering) outperform several deep methods, demonstrating that strong conventional approaches can be highly effective when combined with a powerful pre-trained feature extractor like CLIP.

Algorithms	**STL-10**			**CIFAR10**			**CIFAR100**			**COIL20**		
	ACC	NMI	ARI	ACC	NMI	ARI	ACC	NMI	ARI	ACC	NMI	ARI
KMeans	98.00	95.15	95.63	71.78	66.24	55.32	47.09	62.39	31.89	80.17	93.44	77.99
AggClu	83.98	88.72	80.20	58.86	61.30	49.94	32.90	56.97	25.35	87.99	96.56	84.71
DBSCAN	36.50	48.66	21.58	14.64	10.87	0.12	7.01	16.75	0.70	84.65	94.90	82.68
BIRCH	97.06	93.92	93.60	68.85	64.69	49.06	45.73	61.53	28.36	77.71	93.33	76.60
GMM	81.52	88.34	78.44	73.01	67.70	54.07	46.13	61.57	31.17	81.64	92.06	79.25
OPTICS	13.30	13.58	0.12	10.43	10.13	0.02	6.22	11.44	0.03	32.22	52.30	5.59
SpeClu	98.60	96.51	96.93	76.71	70.71	48.68	45.70	60.61	16.53	93.06	95.40	90.51
MeanShift	10.00	0.00	0.00	10.01	0.02	0.00	1.01	0.02	0.00	5.00	0.00	0.00
Affinity	10.14	58.88	9.25	5.37	45.70	3.82	20.03	60.96	13.97	48.54	84.50	55.49
DEC	96.70	94.14	93.63	74.89	70.98	61.49	42.97	60.80	27.40	74.87	89.98	71.48
IDEC	94.30	90.81	88.59	55.40	52.57	38.21	43.36	60.79	27.53	72.56	89.35	70.95
DSCN	79.24	73.64	67.58	73.12	63.71	55.03	32.36	58.00	23.69	61.78	78.85	50.78
PICA	96.24	91.79	91.96	50.18	41.33	33.85	16.46	38.02	7.79	86.73	91.08	82.36
ConClu	82.76	78.89	72.38	62.35	56.04	46.11	12.38	32.57	4.68	55.55	68.19	43.62
EDESC	97.47	95.07	94.87	80.59	75.56	69.64	44.26	61.27	29.55	81.02	92.77	77.97
DMICC	85.04	80.83	76.30	50.90	46.05	32.13	11.46	31.88	4.67	74.20	83.67	66.98
DIVC	95.19	90.47	90.06	61.13	50.71	41.94	15.70	37.16	7.26	86.45	90.06	80.60
LFSS	68.36	52.07	47.16	41.41	26.19	19.40	32.73	44.94	17.73	75.55	84.90	69.74

Table 11: Clustering results on four image datasets using CLIP embeddings. Metrics are ACC / NMI / ARI (%). Best per column within each block (traditional vs. deep) is highlighted in red.

C.3 Low-rank analysis on NMI and ARI

We also analyze the low-rank structure on performance matrices $\mathbf{P}_{nmi}$ and $\mathbf{P}_{ari}$. As evidenced by Figure 8, the cumulative contribution ratio of the first sixty (60/131) singular values ($ccr(60)$) exceeds 90%. This demonstrates that the performance matrices possess low-rank characteristics.

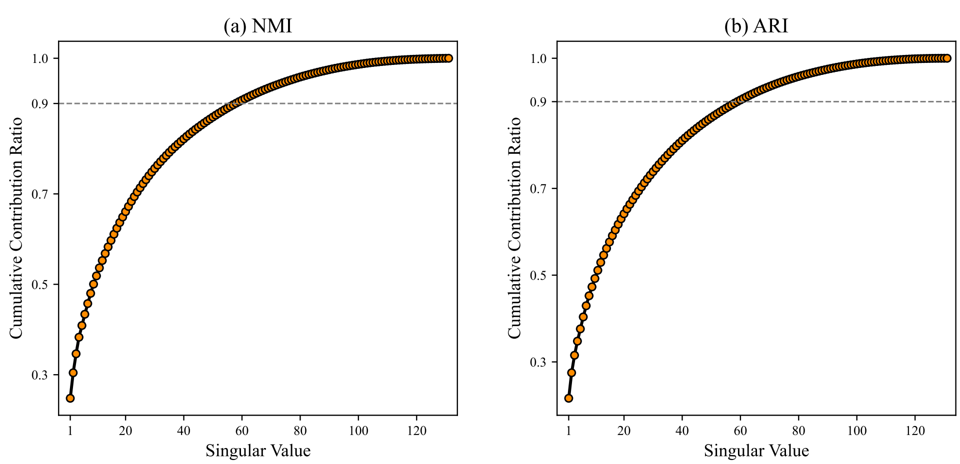

Figure 8: Cumulative contribution ratio of singular values of performance matrix $\mathbf{P}_{nmi}$ and $\mathbf{P}_{ari}$.

C.4 GROUP ANALYSIS FROM THREE DIFFERENT PERSPECTIVES

Beyond the overall performance analysis, we groups the datasets from three perspectives to uncover more specific insights: (i) data type (image, text, tabular, bioinformatics); (ii) feature dimensionality (low ($m \leq 100$), middle ($100 < m \leq 500$), high ($m > 500$); and (iii) the degree (IR B.1) of cluster imbalance (low (IR < 0.1), middle ($0.1 \leq$ IR ≤ 0.3), high (IR > 0.3)).

In Figure 9, we visualize the average rank of ACC, NMI and ARI on different groups. Although SpeClu consistently outperforms most methods in many scenarios, we also observe that certain methods are particularly effective in specific groups. For instance, AggClu demonstrates superior performance on highly imbalanced datasets, GMM is more effective on low-imbalance datasets, and EDESC outperforms other methods on high-dimensional datasets. On different data type, SpeClu shows the consistent advantages compared most baselines and AutoSC achieves superior performance on image data but inferior performance on other data types.

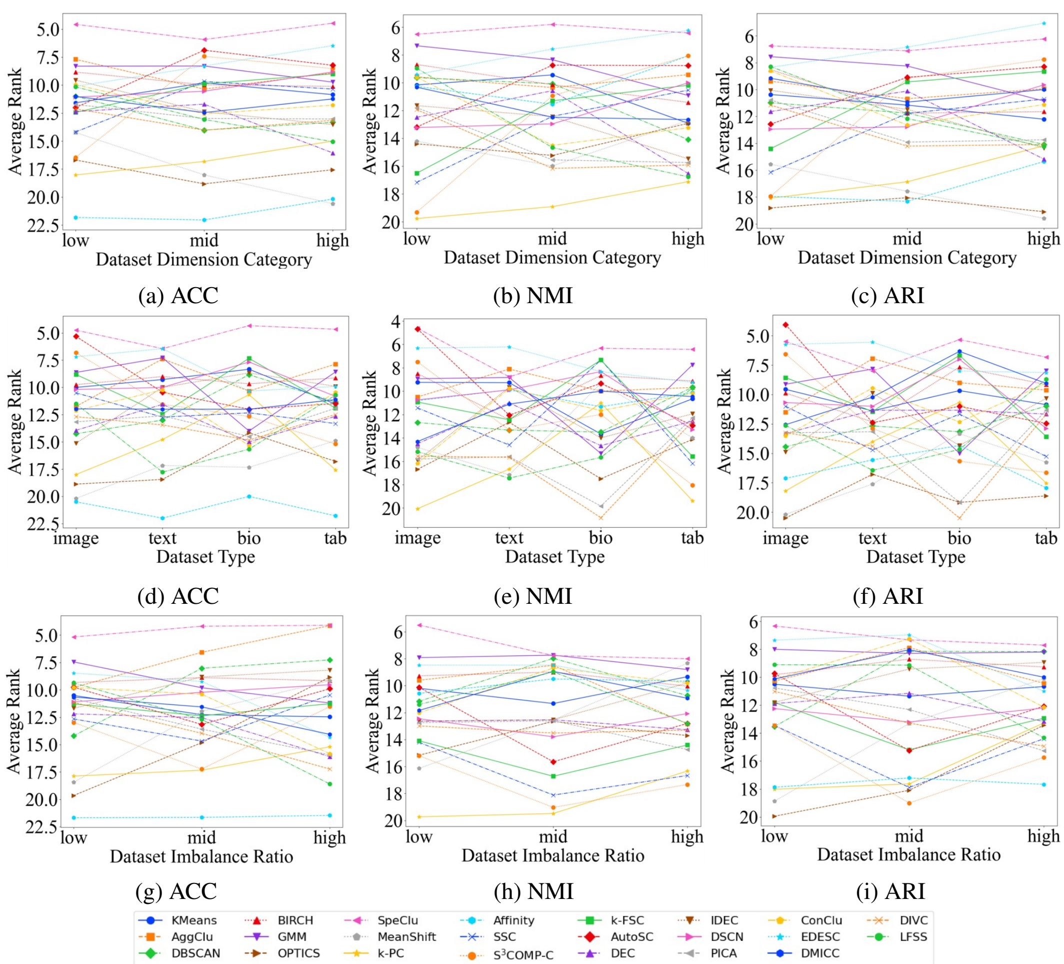

Figure 9: Performance sensitivity to dataset categories across: dataset dimensionality, dataset type, and class imbalance ratio.

C.5 HYPERPARAMETER SENSITIVITY ANALYSIS

Figure 10 visualizes the average performance of different methods under their best- and worst-performing hyperparameter configurations. A larger gap between these two results indicates higher sensitivity to hyperparameter variation. From the Figure 10, we observe that methods such as AggClu, OPTICS, DBSCAN and SpeClu are relatively sensitive to hyperparameter changes, whereas methods like K-means, BIRCH, and DEC are more robust. It is noteworthy, however, that the hyperparameter configuration (HPC) ranges differ across methods, and thus, the results may not provide a comprehensive measure of sensitivity.

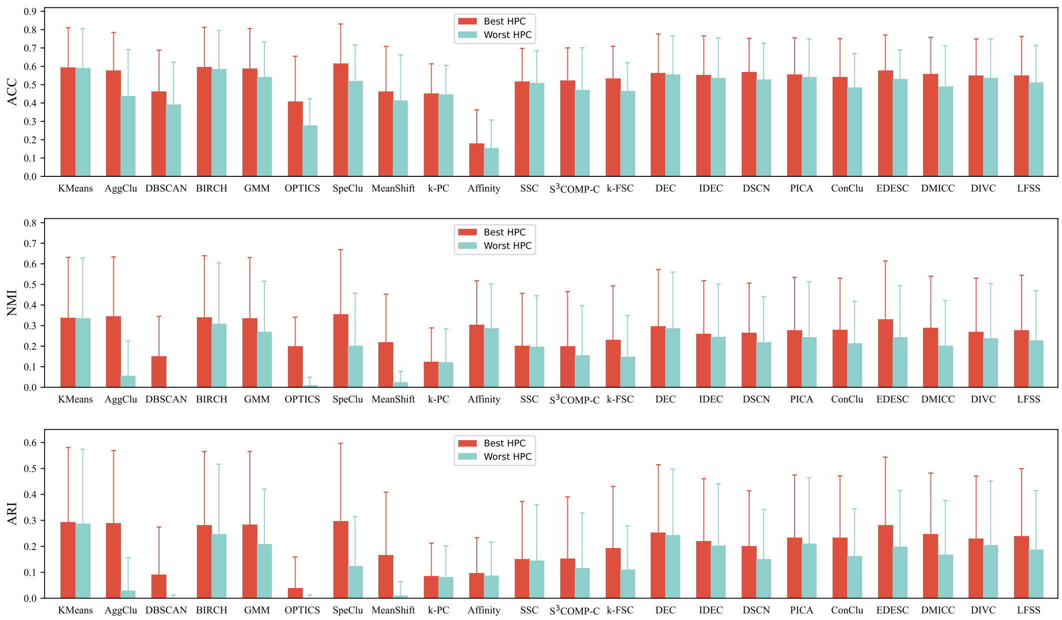

Figure 10: Performance comparison between the overall-best and overall-worst hyperparameter configurations.

D Complete Best Performance (ACC, NMI, ARI) on 131 Datasets

The detailed best performance of each method on 131 datasets are provided from Table 12 to Table 23.

Dataset Index	KMeans	AggClu	DBSCAN	BIRCH	GMM	OPTICS	SpeClu	MeanShift	k-PC	Affinity	SSC
1	0.869	0.902	0.885	0.918	0.803	0.770	0.918	0.770	0.659	0.344	0.557
2	0.322	0.304	0.263	0.324	0.325	0.219	0.316	0.249	0.224	0.033	0.240
3	0.957	0.972	0.956	0.968	0.947	0.391	0.971	0.908	0.655	0.284	0.770
4	0.988	0.991	0.977	0.993	0.993	0.938	0.993	0.937	0.598	0.100	0.600
5	0.450	0.430	0.519	0.542	0.446	0.453	0.462	0.472	0.358	0.341	0.379
6	0.572	0.509	0.466	0.552	0.610	0.174	0.548	0.516	0.487	0.212	0.732
7	0.553	0.720	0.703	0.577	0.709	0.692	0.725	0.714	0.715	0.099	0.687
8	0.328	0.320	0.286	0.333	0.336	0.254	0.334	0.279	0.294	0.046	0.292
9	0.675	0.639	0.688	0.676	0.672	0.651	0.716	0.604	0.540	0.073	0.638
10	0.297	0.316	0.213	0.299	0.295	0.235	0.304	0.250	0.276	0.023	0.290
11	0.599	0.822	0.577	0.599	0.705	0.503	0.879	0.575	0.564	0.059	0.607
12	0.977	0.970	0.863	0.967	0.981	0.512	0.974	0.974	0.552	0.044	0.573
13	0.815	0.792	0.657	0.789	0.719	0.495	0.825	0.541	0.540	0.139	0.564
14	0.458	0.632	0.415	0.562	0.600	0.357	0.567	0.407	0.350	0.194	0.330
15	0.821	0.827	0.747	0.887	0.811	0.687	0.920	0.773	0.289	0.687	0.560
16	0.797	0.820	0.546	0.847	0.865	0.455	0.808	0.597	0.520	0.048	0.584
17	0.831	0.887	0.667	0.860	0.967	0.560	0.847	0.667	0.443	0.440	0.587
18	0.967	0.927	0.843	0.938	0.961	0.506	0.983	0.601	0.483	0.309	0.809
19	0.282	0.296	0.207	0.319	0.329	0.053	0.600	0.041	0.265	0.113	0.290
20	0.798	0.778	0.702	0.516	0.759	0.478	0.794	0.720	0.574	0.516	0.524
21	0.483	0.538	0.462	0.453	0.545	0.481	0.642	0.387	0.370	0.415	0.481
22	0.770	0.825	0.850	0.800	0.810	0.750	0.838	0.662	0.690	0.312	0.800
23	0.935	0.964	0.923	0.973	0.852	0.869	0.955	0.953	0.905	0.020	0.880
24	0.908	0.942	0.800	0.923	0.940	0.587	0.942	0.615	0.564	0.121	0.707
25	0.927	0.833	0.683	0.947	0.979	0.266	0.966	0.900	0.377	0.115	0.571
26	0.743	0.739	0.664	0.776	0.751	0.222	0.788	0.640	0.317	0.278	0.578
27	0.851	0.921	0.851	0.871	0.812	0.723	0.855	0.842	0.453	0.683	0.600
28	0.938	0.924	0.920	0.969	0.851	0.878	0.965	0.922	0.916	0.018	0.929
29	0.707	0.689	0.923	0.729	0.848	0.598	0.701	0.507	0.794	0.345	0.652
30	0.358	0.340	0.324	0.370	0.366	0.146	0.481	0.269	0.217	0.188	0.320
31	0.565	0.675	0.787	0.525	0.658	0.688	0.802	0.512	0.562	0.287	0.650
32	0.913	0.888	0.798	0.897	0.910	0.507	0.919	0.904	0.646	0.047	0.590
33	0.553	0.510	0.464	0.443	0.525	0.320	0.619	0.317	0.206	0.559	0.466
34	0.559	0.792	0.898	0.686	0.644	0.541	0.683	0.573	0.609	0.090	0.637
35	0.345	0.375	0.406	0.389	0.365	0.406	0.449	0.432	0.276	0.028	0.453
36	0.687	0.841	0.818	0.677	0.819	0.817	0.831	0.808	0.610	0.022	0.830
37	0.633	0.701	0.645	0.614	0.632	0.669	0.695	0.676	0.629	0.037	0.694
38	0.710	0.961	0.851	0.812	0.779	0.604	0.955	0.545	0.522	0.338	0.649
39	0.642	0.932	0.933	0.932	0.860	0.933	0.932	0.907	0.626	0.107	0.860
40	0.785	0.526	0.569	0.778	0.833	0.189	0.752	0.441	0.391	0.071	0.502
41	0.581	0.803	0.773	0.760	0.729	0.792	0.806	0.804	0.584	0.805	0.769
42	0.249	0.257	0.399	0.238	0.404	0.329	0.308	0.202	0.279	0.038	0.350
43	0.689	0.599	0.489	0.611	0.691	0.429	0.687	0.480	0.380	0.049	0.542
44	0.645	0.733	0.494	0.654	0.643	0.108	0.795	0.116	0.518	0.112	0.793
45	0.324	0.386	0.303	0.343	0.310	0.265	0.382	0.330	0.238	0.073	0.230
46	0.439	0.858	0.818	0.674	0.590	0.764	0.840	0.857	0.374	0.031	0.420
47	0.553	0.701	0.763	0.706	0.629	0.637	0.649	0.617	0.621	0.016	0.657
48	0.769	0.829	0.556	0.844	0.788	0.461	0.813	0.557	0.622	0.084	0.524
49	0.609	0.584	0.571	0.664	0.630	0.577	0.598	0.593	0.529	0.021	0.530
50	0.644	0.782	0.718	0.701	0.671	0.739	0.768	0.732	0.493	0.044	0.778
51	0.734	0.849	0.707	0.749	0.908	0.545	0.964	0.721	0.587	0.405	0.936
52	0.926	0.932	0.894	0.932	0.869	0.916	0.923	0.875	0.662	0.035	0.900
53	0.504	0.873	0.867	0.569	0.591	0.872	0.873	0.874	0.539	0.006	0.740
54	0.919	0.924	0.700	0.910	0.922	0.424	0.933	0.776	0.433	0.367	0.733
55	0.966	0.927	0.843	0.938	0.960	0.506	0.983	0.601	0.463	0.309	0.809
56	0.494	0.488	0.773	0.401	0.492	0.738	0.566	0.723	0.371	0.032	0.788
57	0.487	0.512	0.486	0.485	0.524	0.274	0.600	0.477	0.489	0.024	0.574
58	0.913	0.904	0.890	0.852	0.906	0.615	0.941	0.838	0.681	0.330	0.680
59	0.447	0.496	0.564	0.467	0.546	0.351	0.543	0.433	0.443	0.266	0.448
60	0.194	0.238	0.243	0.213	0.285	0.242	0.368	0.242	0.171	0.036	0.248
61	0.581	0.586	0.586	0.557	0.556	0.548	0.781	0.424	0.474	0.533	0.700
62	0.517	0.597	0.594	0.561	0.585	0.597	0.597	0.599	0.521	0.020	0.542
63	0.632	0.940	0.891	0.773	0.875	0.940	0.936	0.895	0.929	0.010	0.940
64	0.524	0.739	0.716	0.742	0.667	0.729	0.739	0.654	0.690	0.732	0.562
65	0.475	0.408	0.372	0.513	0.472	0.325	0.447	0.328	0.246	0.098	0.316
66	0.378	0.589	0.542	0.404	0.437	0.424	0.613	0.559	0.284	0.128	0.293

Table 12: The ACC on datasets [1]-[66] (Part-1).

Dataset Index	S^3COMP-C	k-FSC	AutoSC	DEC	IDEC	DSCN	PICA	ConClu	EDESC	DMICC	DIVC	LFSS
1	0.659	0.587	0.836	0.928	0.925	0.774	0.836	0.869	0.830	0.866	0.803	0.918
2	0.246	0.258	0.252	0.372	0.326	0.257	0.296	0.354	0.316	0.320	0.265	0.283
3	0.583	0.704	0.635	0.969	0.618	0.927	0.970	0.974	0.975	0.970	0.971	0.969
4	0.569	0.614	0.991	0.991	0.990	0.904	0.967	0.992	0.956	0.974	0.912	0.975
5	0.357	0.450	0.439	0.488	0.490	0.464	0.436	0.505	0.448	0.464	0.449	0.472
6	0.573	0.619	0.625	0.590	0.618	0.420	0.658	0.526	0.544	0.609	0.659	0.616
7	0.682	0.696	0.692	0.576	0.579	0.723	0.521	0.555	0.570	0.576	0.537	0.577
8	0.288	0.293	0.282	0.317	0.311	0.320	0.327	0.356	0.343	0.331	0.331	0.337
9	0.560	0.664	0.572	0.697	0.716	0.611	0.654	0.701	0.642	0.691	0.663	0.677
10	0.278	0.278	0.274	0.278	0.322	0.306	0.328	0.341	0.298	0.340	0.317	0.331
11	0.574	0.660	0.579	0.551	0.548	0.600	0.606	0.720	0.876	0.699	0.606	0.601
12	0.554	0.736	0.985	0.974	0.877	0.975	0.979	0.985	0.988	0.967	0.978	0.984
13	0.545	0.625	0.706	0.709	0.721	0.738	0.751	0.825	0.751	0.791	0.769	0.752
14	0.346	0.337	0.492	0.426	0.481	0.535	0.491	0.430	0.478	0.480	0.455	0.512
15	0.575	0.673	0.747	0.787	0.788	0.677	0.795	0.867	0.744	0.817	0.799	0.873
16	0.570	0.699	0.619	0.664	0.877	0.823	0.787	0.860	0.784	0.802	0.810	0.866
17	0.460	0.613	0.813	0.916	0.881	0.599	0.821	0.853	0.819	0.844	0.825	0.880
18	0.565	0.837	0.961	0.917	0.912	0.826	0.931	0.955	0.928	0.893	0.930	0.899
19	0.251	0.303	0.328	0.203	0.578	0.375	0.257	0.178	0.309	0.206	0.260	0.316
20	0.569	0.559	0.511	0.790	0.798	0.723	0.786	0.806	0.788	0.802	0.787	0.805
21	0.477	0.485	0.613	0.504	0.496	0.406	0.623	0.594	0.543	0.615	0.617	0.632
22	0.800	0.667	0.738	0.705	0.765	0.823	0.650	0.750	0.730	0.710	0.693	0.637
23	0.542	0.908	0.876	0.799	0.947	0.702	0.711	0.792	0.844	0.824	0.699	0.699
24	0.619	0.609	0.910	0.877	0.947	0.934	0.900	0.916	0.928	0.915	0.876	0.875
25	0.496	0.721	0.825	0.777	0.802	0.737	0.962	0.966	0.824	0.906	0.957	0.905
26	0.504	0.700	0.631	0.677	0.659	0.666	0.652	0.732	0.711	0.710	0.631	0.668
27	0.390	0.657	0.564	0.691	0.764	0.574	0.798	0.713	0.828	0.814	0.749	0.693
28	0.633	0.909	0.845	0.785	0.945	0.795	0.699	0.742	0.846	0.846	0.652	0.754
29	0.521	0.885	0.527	0.904	0.893	0.621	0.723	0.741	0.791	0.720	0.730	0.769
30	0.318	0.357	0.279	0.362	0.761	0.362	0.320	0.336	0.348	0.356	0.332	0.340
31	0.560	0.647	0.750	0.638	0.642	0.585	0.770	0.800	0.695	0.748	0.740	0.762
32	0.549	0.604	0.909	0.815	0.761	0.881	0.893	0.909	0.915	0.900	0.901	0.912
33	0.473	0.486	0.560	0.565	0.546	0.470	0.635	0.565	0.468	0.573	0.616	0.629
34	0.545	0.638	0.577	0.630	0.592	0.660	0.783	0.789	0.704	0.675	0.656	0.880
35	0.382	0.411	0.451	0.301	0.623	0.411	0.442	0.389	0.428	0.348	0.392	0.303
36	0.735	0.741	0.837	0.554	0.643	0.844	0.671	0.634	0.608	0.777	0.604	0.651
37	0.691	0.577	0.692	0.663	0.697	0.676	0.593	0.613	0.592	0.596	0.545	0.589
38	0.548	0.727	0.968	0.740	0.719	0.658	0.792	0.818	0.887	0.804	0.794	0.851
39	0.868	0.917	0.918	0.932	0.932	0.923	0.562	0.641	0.730	0.722	0.559	0.684
40	0.428	0.477	0.581	0.664	0.590	0.783	0.632	0.663	0.631	0.656	0.604	0.702
41	0.801	0.662	0.760	0.613	0.635	0.769	0.557	0.622	0.612	0.601	0.577	0.663
42	0.336	0.427	0.429	0.388	0.352	0.253	0.265	0.406	0.268	0.416	0.247	0.423
43	0.524	0.524	0.492	0.679	0.669	0.663	0.566	0.730	0.738	0.676	0.597	0.618
44	0.919	0.859	0.777	0.565	0.502	0.337	0.685	0.468	0.687	0.591	0.647	0.643
45	0.263	0.332	0.244	0.294	0.308	0.327	0.245	0.318	0.330	0.257	0.303	0.274
46	0.437	0.724	0.591	0.657	0.811	0.488	0.634	0.547	0.580	0.524	0.584	0.480
47	0.530	0.589	0.537	0.568	0.723	0.557	0.577	0.576	0.609	0.643	0.639	0.620
48	0.524	0.564	0.844	0.790	0.736	0.755	0.861	0.877	0.867	0.835	0.867	0.866
49	0.528	0.596	0.521	0.622	0.640	0.612	0.600	0.603	0.595	0.614	0.609	0.677
50	0.680	0.607	0.774	0.520	0.616	0.734	0.601	0.474	0.577	0.596	0.636	0.509
51	0.879	0.915	0.955	0.821	0.803	0.820	0.798	0.704	0.830	0.836	0.692	0.849
52	0.931	0.511	0.930	0.807	0.881	0.928	0.667	0.843	0.698	0.817	0.591	0.625
53	0.830	0.821	0.630	0.588	0.838	0.630	0.633	0.568	0.606	0.761	0.723	0.605
54	0.496	0.690	0.895	0.863	0.826	0.755	0.913	0.876	0.855	0.892	0.910	0.933
55	0.571	0.837	0.961	0.901	0.925	0.866	0.915	0.972	0.911	0.899	0.927	0.949
56	0.711	0.485	0.407	0.460	0.838	0.718	0.511	0.473	0.490	0.486	0.490	0.447
57	0.353	0.580	0.346	0.721	0.587	0.597	0.812	0.787	0.669	0.807	0.749	0.809
58	0.631	0.678	0.904	0.924	0.926	0.861	0.818	0.896	0.909	0.916	0.828	0.904
59	0.451	0.426	0.458	0.473	0.481	0.484	0.453	0.523	0.534	0.465	0.459	0.479
60	0.190	0.199	0.208	0.210	0.587	0.236	0.197	0.238	0.252	0.198	0.190	0.209
61	0.463	0.641	0.605	0.538	0.551	0.541	0.643	0.467	0.568	0.583	0.656	0.610
62	0.551	0.565	0.527	0.528	0.550	0.597	0.564	0.531	0.559	0.547	0.560	0.571
63	0.940	0.655	0.934	0.564	0.808	0.929	0.842	0.814	0.753	0.761	0.767	0.568
64	0.535	0.735	0.523	0.649	0.671	0.708	0.608	0.624	0.637	0.626	0.607	0.578
65	0.282	0.344	0.407	0.417	0.442	0.449	0.364	0.339	0.461	0.358	0.366	0.371
66	0.335	0.539	0.337	0.381	0.388	0.434	0.347	0.515	0.498	0.428	0.358	0.360

Table 13: The ACC on datasets [1]-[66] (Part-2).

Dataset Index	KMeans	AggClu	DBSCAN	BIRCH	GMM	OPTICS	SpeClu	MeanShift	k-PC	Affinity	SSC
67	0.818	0.838	0.709	0.826	0.827	0.523	0.854	0.795	0.364	0.349	0.580
68	0.529	0.862	0.636	0.915	0.518	0.470	0.912	0.204	0.821	0.251	0.950
69	0.560	0.560	0.655	0.534	0.636	0.578	0.569	0.526	0.602	0.526	0.629
70	0.790	0.722	0.689	0.656	0.785	0.656	0.749	0.663	0.517	0.081	0.668
71	0.823	0.799	0.646	0.832	0.796	0.146	0.977	0.472	0.414	0.151	0.523
72	0.734	0.734	0.679	0.734	0.723	0.704	0.745	0.686	0.729	0.040	0.739
73	0.722	0.580	0.695	0.754	0.739	0.083	0.798	0.216	0.601	0.122	0.760
74	0.545	0.534	0.599	0.533	0.597	0.520	0.560	0.520	0.532	0.064	0.574
75	0.759	0.846	0.527	0.804	0.688	0.573	0.789	0.568	0.533	0.041	0.572
76	0.574	0.608	0.412	0.595	0.560	0.270	0.627	0.263	0.389	0.142	0.455
77	0.579	0.703	0.733	0.682	0.630	0.805	0.851	0.713	0.615	0.723	0.708
78	1.000	1.000	1.000	0.989	1.000	0.542	1.000	0.967	0.307	0.600	1.000
79	0.679	0.767	0.763	0.767	0.666	0.571	0.765	0.767	0.762	0.131	0.666
80	0.746	0.626	0.416	0.718	0.706	0.122	0.768	0.100	0.580	0.130	0.680
81	0.719	0.606	0.447	0.774	0.789	0.127	0.931	0.124	0.305	0.193	0.937
82	0.418	0.426	0.415	0.456	0.432	0.361	0.477	0.409	0.360	0.049	0.410
83	0.504	0.601	0.440	0.678	0.837	0.320	0.507	0.339	0.343	0.032	0.342
84	0.370	0.431	0.267	0.388	0.519	0.147	0.539	0.276	0.392	0.111	0.383
85	0.641	0.498	0.558	0.488	0.614	0.085	0.833	0.552	0.373	0.479	0.463
86	0.378	0.466	0.313	0.438	0.537	0.090	0.780	0.162	0.422	0.054	0.480
87	0.351	0.414	0.418	0.365	0.379	0.259	0.375	0.389	0.359	0.253	0.320
88	0.284	0.420	0.422	0.383	0.264	0.282	0.412	0.403	0.332	0.157	0.380
89	0.482	0.515	0.244	0.592	0.490	0.101	0.455	0.126	0.356	0.082	0.480
90	0.236	0.230	0.160	0.227	0.243	0.184	0.241	0.220	0.212	0.037	0.217
91	0.343	0.325	0.334	0.356	0.371	0.178	0.471	0.205	0.377	0.045	0.412
92	0.657	0.575	0.667	0.575	0.727	0.458	0.817	0.402	0.303	0.368	0.383
93	0.300	0.435	0.431	0.362	0.364	0.428	0.432	0.430	0.310	0.030	0.285
94	0.855	0.924	0.915	0.837	0.852	0.806	0.814	0.892	0.832	0.058	0.583
95	0.230	0.334	0.241	0.214	0.248	0.228	0.348	0.163	0.208	0.188	0.377
96	0.510	0.654	0.655	0.653	0.608	0.653	0.632	0.653	0.603	0.079	0.529
97	0.252	0.323	0.350	0.260	0.274	0.216	0.444	0.168	0.252	0.203	0.239
98	0.556	0.432	0.314	0.558	0.561	0.118	0.583	0.113	0.391	0.122	0.458
99	0.361	0.407	0.408	0.430	0.419	0.336	0.411	0.400	0.350	0.144	0.402
100	0.486	0.661	0.514	0.556	0.519	0.353	0.773	0.150	0.238	0.325	0.669
101	0.548	0.407	0.127	0.589	0.554	0.054	0.533	0.046	0.485	0.132	0.572
102	0.504	0.543	0.550	0.531	0.526	0.543	0.542	0.543	0.503	0.004	0.534
103	0.066	0.074	0.049	0.073	0.070	0.014	0.072	0.072	0.074	0.018	0.064
104	0.870	0.653	0.700	0.966	0.804	0.389	0.958	0.175	0.486	0.147	0.879
105	0.573	0.521	0.318	0.543	0.539	0.106	0.781	0.116	0.424	0.060	0.664
106	0.476	0.417	0.236	0.468	0.571	0.115	0.552	0.146	0.449	0.131	0.524
107	0.639	0.499	0.385	0.622	0.635	0.105	0.687	0.101	0.485	0.063	0.553
108	0.211	0.194	0.149	0.204	0.225	0.108	0.204	0.110	0.136	0.064	0.216
109	0.718	0.589	0.146	0.689	0.730	0.104	0.767	0.100	0.590	0.054	0.715
110	0.651	0.478	0.823	0.664	0.658	0.365	0.747	0.085	0.266	0.344	0.633
111	0.802	0.880	0.847	0.777	0.816	0.322	0.931	0.050	0.532	0.485	0.397
112	0.523	0.520	0.516	0.544	0.533	0.471	0.527	0.481	0.511	0.043	0.503
113	0.320	0.309	0.161	0.326	0.325	0.130	0.774	0.101	0.196	0.221	0.483
114	0.157	0.198	0.191	0.156	0.159	0.195	0.187	0.153	0.163	0.112	0.201
115	0.531	0.479	0.358	0.552	0.530	0.335	0.528	0.350	0.263	0.317	0.418
116	0.572	0.629	0.656	0.494	0.572	0.601	0.675	0.616	0.404	0.056	0.435
117	0.679	0.554	0.523	0.703	0.702	0.209	0.674	0.653	0.505	0.141	0.540
118	0.605	0.525	0.427	0.645	0.584	0.463	0.721	0.070	0.268	0.615	0.547
119	0.244	0.609	0.322	0.116	0.284	0.140	0.572	0.107	0.378	0.266	0.735
120	0.635	0.550	0.526	0.500	0.649	0.501	0.510	0.500	0.516	0.494	0.626
121	0.680	0.780	0.781	0.767	0.585	0.606	0.771	0.773	0.588	0.076	0.729
122	0.508	0.526	0.525	0.506	0.539	0.453	0.537	0.503	0.528	0.100	0.505
123	0.876	0.940	0.891	0.892	0.867	0.715	0.872	0.800	0.626	0.744	0.861
124	0.438	0.446	0.281	0.533	0.434	0.285	0.558	0.310	0.350	0.024	0.545
125	0.957	0.940	0.518	0.962	0.957	0.448	0.915	0.500	0.643	0.010	0.504
126	0.531	0.861	0.506	0.538	0.771	0.390	0.721	0.432	0.488	0.032	0.431
127	0.159	0.145	0.074	0.166	0.160	0.062	0.441	0.055	0.332	0.050	0.309
128	0.913	0.830	0.833	0.926	0.891	0.838	0.847	0.770	0.573	0.310	0.285
129	0.462	0.403	0.457	0.388	0.214	0.457	0.490	0.418	0.428	0.195	0.253
130	0.556	0.578	0.601	0.608	0.567	0.504	0.614	0.458	0.518	0.153	0.518
131	0.438	0.453	0.325	0.488	0.361	0.311	0.542	0.267	0.637	0.318	0.910

Table 14: The ACC on datasets [67]-[131] (Part-1).

Dataset Index	S^{3}COMP-C	k-FSC	AutoSC	DEC	IDEC	DSCN	PICA	ConClu	EDESC	DMICC	DIVC	LFSS
67	0.435	0.591	0.596	0.801	0.798	0.746	0.626	0.716	0.782	0.703	0.620	0.661
68	0.927	0.909	0.972	0.749	0.759	0.896	0.503	0.370	0.668	0.464	0.482	0.470
69	0.653	0.612	0.552	0.534	0.536	0.634	0.583	0.647	0.595	0.579	0.579	0.707
70	0.669	0.617	0.684	0.682	0.661	0.711	0.738	0.770	0.727	0.797	0.704	0.696
71	0.506	0.421	0.526	0.800	0.812	0.742	0.589	0.915	0.744	0.806	0.488	0.914
72	0.755	0.735	0.743	0.594	0.739	0.736	0.678	0.600	0.793	0.710	0.649	0.650
73	0.456	0.804	0.883	0.702	0.586	0.694	0.689	0.607	0.706	0.637	0.699	0.790
74	0.519	0.551	0.507	0.569	0.739	0.543	0.560	0.599	0.573	0.579	0.566	0.616
75	0.595	0.623	0.604	0.707	0.586	0.790	0.795	0.802	0.695	0.717	0.803	0.727
76	0.323	0.521	0.300	0.553	0.566	0.511	0.486	0.482	0.577	0.538	0.482	0.512
77	0.685	0.749	0.723	0.651	0.720	0.760	0.709	0.703	0.704	0.670	0.693	0.733
78	1.000	1.000	1.000	1.000	1.000	0.734	0.970	0.860	1.000	1.000	0.977	1.000
79	0.645	0.762	0.742	0.673	0.760	0.738	0.593	0.592	0.625	0.641	0.586	0.628
80	0.732	0.927	0.683	0.782	1.000	0.826	0.536	0.385	0.753	0.468	0.488	0.414
81	0.849	0.897	0.939	0.677	0.560	0.909	0.689	0.555	0.720	0.731	0.691	0.685
82	0.401	0.390	0.406	0.403	0.425	0.412	0.412	0.432	0.429	0.399	0.403	0.358
83	0.348	0.407	0.501	0.641	0.615	0.515	0.676	0.654	0.608	0.597	0.690	0.527
84	0.381	0.479	0.238	0.341	0.328	0.390	0.488	0.461	0.544	0.447	0.402	0.642
85	0.458	0.543	0.636	0.642	0.642	0.504	0.638	0.652	0.579	0.613	0.643	0.650
86	0.426	0.490	0.799	0.352	0.384	0.740	0.390	0.368	0.523	0.278	0.389	0.453
87	0.297	0.408	0.371	0.351	0.378	0.395	0.374	0.459	0.414	0.376	0.374	0.369
88	0.373	0.281	0.372	0.315	0.302	0.394	0.417	0.325	0.301	0.304	0.417	0.303
89	0.542	0.469	0.574	0.314	0.307	0.260	0.427	0.357	0.488	0.401	0.418	0.322
90	0.252	0.205	0.301	0.200	0.217	0.237	0.234	0.213	0.210	0.211	0.228	0.187
91	0.331	0.382	0.302	0.315	0.368	0.394	0.205	0.355	0.380	0.354	0.205	0.370
92	0.443	0.482	0.575	0.615	0.638	0.626	0.795	0.732	0.601	0.809	0.886	0.887
93	0.310	0.434	0.383	0.340	0.344	0.426	0.366	0.373	0.369	0.328	0.357	0.332
94	0.738	0.812	0.531	0.702	0.856	0.846	0.696	0.778	0.734	0.796	0.661	0.711
95	0.780	0.514	0.265	0.227	0.233	0.266	0.302	0.263	0.401	0.289	0.301	0.210
96	0.519	0.691	0.616	0.529	0.547	0.585	0.581	0.556	0.613	0.640	0.601	0.676
97	0.515	0.546	0.362	0.256	0.242	0.300	0.317	0.389	0.529	0.358	0.307	0.210
98	0.520	0.631	0.566	0.567	0.533	0.586	0.490	0.429	0.539	0.467	0.500	0.445
99	0.347	0.375	0.506	0.412	0.392	0.406	0.402	0.424	0.388	0.397	0.400	0.427
100	0.761	0.443	0.703	0.396	0.454	0.507	0.625	0.589	0.636	0.553	0.586	0.358
101	0.490	0.578	0.502	0.458	0.377	0.446	0.364	0.292	0.565	0.360	0.366	0.417
102	0.538	0.521	0.510	0.513	0.544	0.519	0.519	0.508	0.516	0.529	0.514	0.520
103	0.071	0.073	0.069	0.068	0.070	0.071	0.069	0.075	0.074	0.074	0.069	0.072
104	0.942	0.949	0.792	0.586	0.474	0.606	0.778	0.616	0.841	0.795	0.790	0.735
105	0.790	0.888	0.804	0.613	0.467	0.756	0.249	0.452	0.780	0.491	0.226	0.456
106	0.613	0.591	0.585	0.437	0.501	0.542	0.509	0.516	0.508	0.509	0.489	0.492
107	0.655	0.677	0.649	0.635	0.549	0.598	0.423	0.627	0.673	0.552	0.421	0.601
108	0.197	0.202	0.252	0.167	0.169	0.244	0.187	0.218	0.209	0.210	0.191	0.197
109	0.865	0.792	0.835	0.749	0.554	0.731	0.502	0.624	0.806	0.509	0.611	0.546
110	0.700	0.692	0.748	0.614	0.597	0.528	0.677	0.404	0.628	0.574	0.647	0.617
111	0.842	0.680	0.916	0.749	0.726	0.618	0.867	0.556	0.810	0.742	0.865	0.756
112	0.509	0.515	0.535	0.522	0.522	0.520	0.515	0.521	0.546	0.531	0.515	0.526
113	0.615	0.496	0.612	0.175	0.188	0.394	0.308	0.244	0.453	0.265	0.326	0.217
114	0.249	0.181	0.180	0.155	0.155	0.181	0.163	0.175	0.169	0.163	0.164	0.176
115	0.565	0.362	0.596	0.574	0.541	0.536	0.495	0.540	0.555	0.531	0.513	0.600
116	0.344	0.396	0.382	0.483	0.600	0.586	0.410	0.593	0.567	0.526	0.442	0.546
117	0.452	0.619	0.668	0.590	0.556	0.651	0.698	0.727	0.769	0.710	0.718	0.752
118	0.691	0.462	0.823	0.391	0.403	0.455	0.478	0.320	0.438	0.424	0.480	0.502
119	0.744	0.613	0.384	0.226	0.198	0.565	0.331	0.254	0.596	0.331	0.329	0.232
120	0.506	0.580	0.501	0.587	0.570	0.561	0.580	0.647	0.688	0.576	0.586	0.539
121	0.691	0.405	0.729	0.498	0.403	0.753	0.717	0.606	0.451	0.559	0.653	0.468
122	0.511	0.548	0.526	0.519	0.549	0.525	0.529	0.531	0.536	0.540	0.526	0.519
123	0.861	0.619	0.820	0.894	0.938	0.856	0.643	0.757	0.792	0.729	0.666	0.588
124	0.606	0.509	0.573	0.470	0.389	0.445	0.327	0.415	0.577	0.369	0.310	0.265
125	0.505	0.734	0.510	0.898	0.959	0.525	0.885	0.878	0.977	0.890	0.906	0.820
126	0.700	0.566	0.433	0.696	0.710	0.655	0.576	0.748	0.883	0.726	0.537	0.496
127	0.282	0.364	0.334	0.101	0.133	0.225	0.123	0.132	0.204	0.129	0.100	0.129
128	0.733	0.230	0.993	0.579	0.592	0.910	0.804	0.830	0.904	0.695	0.804	0.338
129	0.261	0.434	0.394	0.184	0.580	0.429	0.425	0.233	0.386	0.260	0.413	0.127
130	0.511	0.589	0.522	0.631	0.617	0.551	0.529	0.538	0.554	0.610	0.529	0.664
131	0.833	0.540	0.594	0.222	0.217	0.818	0.299	0.359	0.648	0.332	0.299	0.172

Table 15: The ACC on datasets [67]-[131] (Part-2).

Dataset Index	KMeans	AggClu	DBSCAN	BIRCH	GMM	OPTICS	SpeClu	MeanShift	k-PC	Affinity	SSC
1	0.388	0.598	0.449	0.640	0.423	0.255	0.640	0.309	0.012	0.284	0.026
2	0.143	0.134	0.118	0.128	0.131	0.117	0.128	0.075	0.036	0.134	0.040
3	0.731	0.814	0.764	0.784	0.733	0.191	0.802	0.695	0.020	0.334	0.190
4	0.906	0.925	0.882	0.939	0.939	0.758	0.939	0.763	0.018	0.303	0.060
5	0.305	0.392	0.454	0.458	0.361	0.309	0.347	0.479	0.151	0.390	0.233
6	0.603	0.459	0.558	0.623	0.612	0.374	0.566	0.526	0.398	0.566	0.642
7	0.003	0.022	0.011	0.001	0.027	0.026	0.042	0.000	0.010	0.024	0.001
8	0.021	0.022	0.042	0.024	0.023	0.049	0.020	0.021	0.009	0.074	0.006
9	0.063	0.042	0.068	0.090	0.131	0.002	0.133	0.066	0.001	0.081	0.002
10	0.008	0.027	0.092	0.008	0.008	0.077	0.009	0.000	0.004	0.095	0.004
11	0.010	0.322	0.100	0.010	0.179	0.150	0.563	0.053	0.014	0.147	0.002
12	0.857	0.816	0.673	0.795	0.879	0.076	0.844	0.846	0.001	0.241	0.023
13	0.327	0.270	0.182	0.282	0.149	0.185	0.357	0.109	0.010	0.172	0.007
14	0.215	0.373	0.293	0.314	0.425	0.214	0.310	0.103	0.033	0.323	0.040
15	0.773	0.719	0.678	0.809	0.766	0.576	0.842	0.720	0.041	0.697	0.421
16	0.279	0.335	0.157	0.388	0.428	0.113	0.294	0.126	0.000	0.159	0.023
17	0.657	0.763	0.734	0.738	0.900	0.536	0.673	0.734	0.089	0.547	0.280
18	0.879	0.787	0.608	0.808	0.855	0.253	0.928	0.502	0.099	0.504	0.462
19	0.376	0.406	0.487	0.442	0.470	0.434	0.720	0.000	0.343	0.578	0.380
20	0.293	0.247	0.215	0.002	0.217	0.068	0.285	0.237	0.025	0.002	0.004
21	0.531	0.610	0.515	0.536	0.545	0.446	0.532	0.464	0.242	0.502	0.372
22	0.160	0.223	0.091	0.229	0.227	0.201	0.242	0.207	0.015	0.162	0.015
23	0.397	0.577	0.329	0.642	0.257	0.089	0.475	0.529	0.236	0.087	0.208
24	0.546	0.682	0.534	0.629	0.661	0.136	0.708	0.277	0.023	0.267	0.139
25	0.804	0.740	0.533	0.866	0.924	0.215	0.908	0.784	0.120	0.472	0.264
26	0.702	0.683	0.621	0.751	0.749	0.260	0.791	0.576	0.113	0.562	0.647
27	0.847	0.909	0.847	0.857	0.845	0.765	0.824	0.869	0.320	0.627	0.630
28	0.406	0.368	0.294	0.600	0.256	0.074	0.586	0.400	0.286	0.084	0.334
29	0.125	0.100	0.592	0.151	0.418	0.076	0.126	0.296	0.242	0.234	0.018
30	0.315	0.296	0.256	0.343	0.302	0.261	0.454	0.254	0.085	0.356	0.230
31	0.101	0.186	0.268	0.044	0.156	0.174	0.448	0.158	0.020	0.121	0.076
32	0.569	0.488	0.434	0.520	0.562	0.086	0.594	0.553	0.060	0.193	0.019
33	0.604	0.613	0.595	0.604	0.605	0.546	0.624	0.566	0.202	0.617	0.466
34	0.011	0.259	0.698	0.213	0.093	0.022	0.190	0.100	0.036	0.301	0.048
35	0.051	0.085	0.125	0.069	0.053	0.124	0.050	0.045	0.028	0.108	0.006
36	0.027	0.013	0.032	0.029	0.034	0.015	0.019	0.039	0.000	0.026	0.010
37	0.011	0.004	0.030	0.006	0.006	0.037	0.005	0.011	0.003	0.046	0.001
38	0.470	0.842	0.614	0.700	0.571	0.447	0.822	0.384	0.119	0.473	0.227
39	0.003	0.001	0.000	0.001	0.012	0.000	0.001	0.007	0.003	0.029	0.010
40	0.714	0.586	0.525	0.709	0.739	0.235	0.724	0.433	0.246	0.459	0.399
41	0.004	0.000	0.016	0.000	0.000	0.020	0.001	0.004	0.001	0.001	0.000
42	0.111	0.154	0.352	0.177	0.272	0.244	0.140	0.236	0.081	0.176	0.140
43	0.239	0.159	0.148	0.111	0.245	0.119	0.203	0.044	0.008	0.209	0.102
44	0.648	0.745	0.599	0.717	0.638	0.302	0.832	0.046	0.475	0.580	0.812
45	0.097	0.087	0.095	0.088	0.097	0.143	0.076	0.056	0.050	0.156	0.044
46	0.084	0.017	0.044	0.107	0.106	0.065	0.006	0.000	0.004	0.084	0.010
47	0.002	0.120	0.185	0.131	0.027	0.018	0.001	0.101	0.016	0.077	0.029
48	0.339	0.367	0.294	0.377	0.374	0.107	0.392	0.138	0.048	0.173	0.002
49	0.030	0.021	0.059	0.060	0.038	0.054	0.003	0.002	0.002	0.054	0.010
50	0.202	0.041	0.154	0.234	0.201	0.159	0.263	0.171	0.032	0.159	0.133
51	0.864	0.905	0.791	0.869	0.903	0.487	0.927	0.812	0.518	0.664	0.857
52	0.007	0.003	0.026	0.003	0.010	0.011	0.016	0.053	0.001	0.029	0.000
53	0.000	0.000	0.032	0.009	0.070	0.039	0.000	0.000	0.011	0.080	0.000
54	0.728	0.746	0.534	0.750	0.739	0.293	0.763	0.624	0.077	0.519	0.320
55	0.876	0.787	0.608	0.808	0.858	0.253	0.928	0.502	0.090	0.504	0.462
56	0.245	0.265	0.270	0.353	0.325	0.096	0.446	0.000	0.071	0.214	0.199
57	0.521	0.479	0.469	0.514	0.520	0.227	0.537	0.491	0.085	0.317	0.320
58	0.604	0.582	0.550	0.374	0.586	0.229	0.658	0.531	0.004	0.320	0.020
59	0.281	0.262	0.381	0.254	0.417	0.294	0.445	0.302	0.163	0.337	0.211
60	0.070	0.046	0.338	0.078	0.145	0.336	0.259	0.054	0.030	0.259	0.015
61	0.654	0.566	0.629	0.608	0.607	0.612	0.709	0.531	0.386	0.661	0.603
62	0.001	0.002	0.011	0.001	0.012	0.001	0.001	0.005	0.002	0.036	0.005
63	0.013	0.002	0.016	0.014	0.005	0.000	0.003	0.027	0.009	0.019	0.000
64	0.001	0.025	0.067	0.040	0.070	0.001	0.015	0.060	0.010	0.008	0.006
65	0.292	0.230	0.136	0.297	0.290	0.125	0.284	0.098	0.071	0.248	0.132
66	0.213	0.234	0.229	0.164	0.144	0.144	0.326	0.127	0.023	0.210	0.033

Table 16: The NMI on datasets [1]-[66] (Part-1).

Dataset Index	S^3COMP-C	k-FSC	AutoSC	DEC	IDEC	DSCN	PICA	ConClu	EDESC	DMICC	DIVC	LFSS
1	0.013	0.203	0.368	0.645	0.639	0.193	0.442	0.414	0.403	0.415	0.312	0.640
2	0.027	0.059	0.073	0.180	0.133	0.095	0.121	0.175	0.151	0.161	0.067	0.109
3	0.025	0.123	0.010	0.789	0.617	0.653	0.798	0.834	0.832	0.804	0.803	0.815
4	0.024	0.038	0.924	0.921	0.916	0.677	0.811	0.932	0.796	0.838	0.669	0.841
5	0.141	0.298	0.360	0.347	0.338	0.340	0.330	0.417	0.326	0.347	0.341	0.396
6	0.417	0.524	0.623	0.603	0.617	0.414	0.622	0.519	0.555	0.565	0.609	0.559
7	0.005	0.003	0.008	0.001	0.002	0.030	0.001	0.002	0.003	0.004	0.002	0.013
8	0.006	0.006	0.008	0.018	0.017	0.017	0.023	0.031	0.026	0.031	0.022	0.028
9	0.003	0.013	0.001	0.098	0.101	0.086	0.084	0.135	0.080	0.096	0.093	0.102
10	0.004	0.005	0.004	0.006	0.034	0.020	0.025	0.040	0.015	0.041	0.023	0.042
11	0.022	0.063	0.021	0.010	0.001	0.009	0.000	0.145	0.471	0.133	0.000	0.041
12	0.011	0.186	0.891	0.843	0.547	0.842	0.858	0.887	0.906	0.801	0.854	0.882
13	0.014	0.043	0.197	0.154	0.162	0.213	0.197	0.329	0.197	0.260	0.221	0.189
14	0.035	0.073	0.293	0.197	0.302	0.275	0.264	0.190	0.189	0.215	0.192	0.336
15	0.325	0.530	0.626	0.715	0.714	0.535	0.758	0.772	0.660	0.751	0.750	0.832
16	0.018	0.117	0.081	0.112	0.547	0.330	0.277	0.415	0.301	0.289	0.303	0.432
17	0.063	0.220	0.620	0.797	0.736	0.413	0.624	0.732	0.635	0.718	0.630	0.716
18	0.214	0.533	0.861	0.752	0.737	0.568	0.791	0.839	0.804	0.724	0.805	0.716
19	0.245	0.331	0.449	0.274	0.027	0.485	0.329	0.238	0.391	0.264	0.341	0.385
20	0.014	0.021	0.005	0.269	0.287	0.188	0.252	0.290	0.267	0.296	0.263	0.290
21	0.304	0.347	0.526	0.552	0.535	0.330	0.523	0.529	0.579	0.546	0.543	0.576
22	0.015	0.111	0.140	0.120	0.120	0.123	0.148	0.223	0.197	0.149	0.206	0.141
23	0.015	0.259	0.246	0.205	0.426	0.108	0.099	0.213	0.250	0.258	0.144	0.146
24	0.005	0.050	0.554	0.491	0.426	0.639	0.528	0.570	0.634	0.573	0.456	0.471
25	0.162	0.438	0.658	0.631	0.598	0.739	0.879	0.887	0.700	0.767	0.873	0.764
26	0.448	0.620	0.640	0.632	0.615	0.593	0.621	0.625	0.669	0.640	0.604	0.656
27	0.434	0.674	0.654	0.670	0.728	0.455	0.746	0.671	0.824	0.825	0.702	0.702
28	0.013	0.251	0.210	0.200	0.405	0.108	0.082	0.176	0.283	0.266	0.112	0.161
29	0.091	0.465	0.113	0.529	0.508	0.040	0.171	0.250	0.251	0.160	0.190	0.254
30	0.178	0.229	0.164	0.291	0.330	0.285	0.271	0.260	0.274	0.277	0.271	0.276
31	0.015	0.067	0.242	0.072	0.088	0.081	0.229	0.300	0.159	0.225	0.203	0.220
32	0.007	0.032	0.555	0.377	0.330	0.494	0.523	0.556	0.586	0.531	0.550	0.565
33	0.464	0.495	0.622	0.599	0.608	0.559	0.635	0.638	0.568	0.613	0.634	0.647
34	0.005	0.071	0.026	0.072	0.032	0.235	0.288	0.256	0.173	0.120	0.121	0.503
35	0.005	0.002	0.009	0.049	0.012	0.032	0.014	0.061	0.057	0.053	0.035	0.064
36	0.000	0.000	0.007	0.007	0.017	0.007	0.008	0.030	0.016	0.022	0.017	0.030
37	0.006	0.004	0.000	0.000	0.001	0.006	0.027	0.021	0.020	0.014	0.009	0.019
38	0.148	0.373	0.859	0.455	0.430	0.361	0.545	0.559	0.672	0.563	0.582	0.622
39	0.004	0.005	0.004	0.001	0.001	0.003	0.012	0.036	0.020	0.007	0.012	0.004
40	0.261	0.344	0.469	0.583	0.501	0.637	0.583	0.610	0.550	0.616	0.538	0.661
41	0.000	0.000	0.000	0.003	0.003	0.000	0.002	0.004	0.003	0.003	0.005	0.006
42	0.110	0.181	0.220	0.266	0.278	0.103	0.021	0.228	0.097	0.244	0.014	0.247
43	0.013	0.048	0.018	0.220	0.202	0.222	0.228	0.279	0.243	0.269	0.224	0.210
44	0.840	0.793	0.777	0.539	0.464	0.396	0.618	0.399	0.697	0.525	0.565	0.542
45	0.026	0.009	0.070	0.076	0.083	0.057	0.079	0.069	0.058	0.082	0.029	0.090
46	0.001	0.011	0.064	0.149	0.136	0.088	0.060	0.118	0.054	0.086	0.068	0.081
47	0.013	0.010	0.001	0.012	0.131	0.013	0.037	0.008	0.039	0.068	0.062	0.054
48	0.003	0.018	0.393	0.335	0.256	0.295	0.423	0.463	0.439	0.399	0.436	0.436
49	0.001	0.000	0.002	0.036	0.039	0.021	0.031	0.028	0.024	0.029	0.040	0.090
50	0.114	0.130	0.011	0.123	0.167	0.069	0.099	0.135	0.143	0.166	0.066	0.161
51	0.752	0.817	0.910	0.845	0.847	0.705	0.847	0.675	0.892	0.788	0.737	0.703
52	0.001	0.001	0.001	0.004	0.011	0.005	0.003	0.000	0.001	0.009	0.004	0.003
53	0.028	0.001	0.138	0.094	0.064	0.147	0.034	0.092	0.035	0.000	0.021	0.036
54	0.090	0.285	0.679	0.640	0.600	0.450	0.726	0.657	0.657	0.709	0.714	0.767
55	0.207	0.533	0.861	0.710	0.746	0.652	0.775	0.897	0.809	0.719	0.780	0.807
56	0.010	0.179	0.252	0.186	0.064	0.195	0.162	0.243	0.319	0.213	0.182	0.184
57	0.015	0.233	0.010	0.527	0.464	0.469	0.513	0.473	0.454	0.525	0.451	0.511
58	0.002	0.015	0.554	0.613	0.631	0.400	0.327	0.562	0.590	0.608	0.351	0.582
59	0.243	0.166	0.328	0.257	0.261	0.271	0.261	0.289	0.290	0.271	0.269	0.288
60	0.020	0.019	0.043	0.085	0.464	0.077	0.077	0.077	0.079	0.087	0.081	0.084
61	0.394	0.583	0.568	0.588	0.609	0.490	0.617	0.551	0.594	0.595	0.604	0.603
62	0.001	0.011	0.001	0.001	0.003	0.008	0.000	0.001	0.005	0.004	0.002	0.011
63	0.001	0.002	0.011	0.007	0.007	0.007	0.003	0.002	0.001	0.000	0.005	0.004
64	0.005	0.007	0.000	0.032	0.033	0.036	0.022	0.073	0.045	0.028	0.007	0.017
65	0.090	0.152	0.217	0.241	0.260	0.202	0.219	0.189	0.221	0.237	0.224	0.237
66	0.023	0.033	0.166	0.176	0.154	0.182	0.199	0.231	0.235	0.196	0.209	0.164

Table 17: The NMI on datasets [1]-[66] (Part-2).

Dataset Index	KMeans	AggClu	DBSCAN	BIRCH	GMM	OPTICS	SpeClu	MeanShift	k-PC	Affinity	SSC
67	0.675	0.725	0.634	0.707	0.697	0.354	0.696	0.702	0.125	0.533	0.330
68	0.424	0.750	0.561	0.805	0.409	0.402	0.820	0.000	0.700	0.564	0.860
69	0.019	0.019	0.089	0.027	0.107	0.122	0.092	0.038	0.045	0.065	0.041
70	0.220	0.093	0.040	0.203	0.200	0.056	0.290	0.075	0.021	0.124	0.017
71	0.700	0.725	0.494	0.712	0.710	0.477	0.918	0.619	0.017	0.475	0.148
72	0.000	0.000	0.110	0.000	0.061	0.068	0.033	0.120	0.000	0.097	0.008
73	0.705	0.672	0.733	0.782	0.708	0.325	0.817	0.252	0.573	0.614	0.760
74	0.007	0.007	0.032	0.006	0.048	0.027	0.010	0.028	0.003	0.047	0.013
75	0.247	0.378	0.090	0.309	0.118	0.034	0.335	0.008	0.002	0.147	0.011
76	0.318	0.338	0.168	0.360	0.306	0.200	0.429	0.115	0.055	0.277	0.124
77	0.108	0.260	0.225	0.242	0.115	0.285	0.293	0.031	0.014	0.024	0.051
78	1.000	1.000	1.000	0.971	1.000	0.648	1.000	0.966	0.236	0.831	1.000
79	0.009	0.021	0.024	0.021	0.002	0.026	0.012	0.032	0.003	0.074	0.002
80	0.665	0.675	0.504	0.732	0.680	0.296	0.802	0.000	0.532	0.578	0.810
81	0.714	0.711	0.651	0.789	0.727	0.325	0.874	0.050	0.244	0.637	0.874
82	0.095	0.155	0.174	0.118	0.109	0.152	0.128	0.004	0.063	0.227	0.054
83	0.365	0.324	0.213	0.391	0.511	0.056	0.370	0.000	0.000	0.223	0.000
84	0.213	0.329	0.352	0.292	0.360	0.365	0.486	0.259	0.165	0.456	0.199
85	0.683	0.649	0.614	0.582	0.642	0.370	0.847	0.627	0.383	0.611	0.393
86	0.373	0.424	0.489	0.534	0.621	0.360	0.807	0.000	0.325	0.494	0.420
87	0.034	0.046	0.031	0.046	0.051	0.104	0.051	0.015	0.008	0.063	0.020
88	0.039	0.008	0.054	0.022	0.054	0.160	0.016	0.042	0.021	0.164	0.040
89	0.437	0.548	0.342	0.567	0.448	0.270	0.562	0.155	0.280	0.480	0.530
90	0.041	0.015	0.177	0.015	0.018	0.191	0.026	0.104	0.036	0.289	0.026
91	0.082	0.158	0.155	0.145	0.166	0.222	0.382	0.003	0.139	0.327	0.195
92	0.768	0.801	0.852	0.801	0.788	0.625	0.797	0.678	0.346	0.684	0.266
93	0.010	0.006	0.009	0.010	0.009	0.007	0.006	0.012	0.004	0.050	0.002
94	0.187	0.543	0.483	0.000	0.158	0.050	0.373	0.292	0.000	0.182	0.020
95	0.039	0.238	0.185	0.047	0.076	0.243	0.259	0.306	0.054	0.205	0.282
96	0.087	0.002	0.014	0.001	0.092	0.000	0.035	0.001	0.014	0.214	0.089
97	0.108	0.231	0.139	0.073	0.139	0.241	0.354	0.216	0.115	0.335	0.016
98	0.526	0.488	0.376	0.550	0.547	0.295	0.645	0.045	0.384	0.509	0.486
99	0.112	0.182	0.257	0.152	0.221	0.184	0.210	0.200	0.053	0.255	0.137
100	0.609	0.745	0.645	0.675	0.628	0.518	0.783	0.251	0.130	0.618	0.703
101	0.709	0.636	0.210	0.744	0.713	0.195	0.748	0.030	0.603	0.607	0.664
102	0.000	0.000	0.003	0.001	0.000	0.000	0.000	0.000	0.000	0.011	0.001
103	0.006	0.007	0.195	0.003	0.006	0.256	0.007	0.002	0.006	0.290	0.002
104	0.767	0.736	0.702	0.933	0.749	0.454	0.915	0.041	0.334	0.591	0.787
105	0.522	0.511	0.329	0.574	0.506	0.170	0.787	0.012	0.326	0.506	0.631
106	0.518	0.531	0.270	0.518	0.514	0.197	0.582	0.200	0.409	0.478	0.557
107	0.667	0.618	0.469	0.659	0.666	0.140	0.717	0.005	0.456	0.462	0.598
108	0.072	0.061	0.063	0.068	0.094	0.023	0.068	0.114	0.012	0.115	0.081
109	0.662	0.613	0.109	0.647	0.677	0.101	0.707	0.000	0.509	0.457	0.625
110	0.772	0.688	0.917	0.805	0.784	0.538	0.869	0.098	0.358	0.745	0.795
111	0.934	0.966	0.949	0.933	0.921	0.523	0.954	0.000	0.698	0.845	0.658
112	0.002	0.002	0.008	0.006	0.003	0.055	0.002	0.054	0.000	0.021	0.000
113	0.235	0.245	0.075	0.264	0.249	0.088	0.735	0.163	0.056	0.436	0.385
114	0.032	0.036	0.009	0.027	0.029	0.050	0.022	0.163	0.029	0.095	0.076
115	0.539	0.503	0.533	0.615	0.536	0.421	0.691	0.523	0.061	0.520	0.413
116	0.472	0.565	0.612	0.456	0.473	0.469	0.600	0.479	0.208	0.270	0.001
117	0.613	0.458	0.494	0.624	0.607	0.190	0.638	0.610	0.310	0.458	0.398
118	0.787	0.768	0.676	0.818	0.769	0.753	0.885	0.174	0.499	0.821	0.739
119	0.222	0.620	0.361	0.014	0.272	0.393	0.585	0.295	0.231	0.439	0.669
120	0.054	0.007	0.002	0.000	0.077	0.002	0.000	0.000	0.001	0.016	0.046
121	0.018	0.044	0.044	0.001	0.006	0.120	0.042	0.001	0.009	0.079	0.046
122	0.007	0.005	0.005	0.001	0.010	0.040	0.036	0.010	0.002	0.062	0.001
123	0.088	0.491	0.280	0.215	0.043	0.106	0.056	0.224	0.019	0.216	0.002
124	0.314	0.354	0.171	0.352	0.314	0.096	0.391	0.000	0.173	0.277	0.351
125	0.784	0.723	0.175	0.773	0.784	0.107	0.657	0.023	0.093	0.170	0.007
126	0.284	0.568	0.140	0.374	0.479	0.180	0.539	0.001	0.094	0.264	0.002
127	0.136	0.128	0.030	0.148	0.136	0.056	0.525	0.059	0.297	0.265	0.296
128	0.664	0.538	0.521	0.685	0.618	0.473	0.283	0.434	0.042	0.306	0.105
129	0.280	0.154	0.022	0.294	0.071	0.022	0.440	0.260	0.424	0.222	0.307
130	0.010	0.033	0.081	0.070	0.015	0.019	0.063	0.108	0.001	0.062	0.018
131	0.294	0.523	0.095	0.430	0.151	0.044	0.449	0.242	0.510	0.300	0.813

Table 18: The NMI on datasets [67]-[131] (Part-1).

Dataset Index	S^3COMP-C	k-FSC	AutoSC	DEC	IDEC	DSCN	PICA	ConClu	EDESC	DMICC	DIVC	LFSS
67	0.254	0.306	0.526	0.649	0.644	0.532	0.558	0.560	0.653	0.562	0.570	0.586
68	0.837	0.776	0.927	0.581	0.609	0.824	0.300	0.183	0.555	0.245	0.281	0.244
69	0.071	0.053	0.007	0.067	0.069	0.076	0.026	0.081	0.046	0.040	0.023	0.122
70	0.005	0.033	0.016	0.051	0.037	0.088	0.213	0.271	0.174	0.306	0.160	0.163
71	0.090	0.060	0.399	0.662	0.678	0.571	0.291	0.791	0.625	0.685	0.142	0.765
72	0.047	0.110	0.017	0.030	0.067	0.008	0.075	0.026	0.169	0.061	0.072	0.046
73	0.389	0.731	0.830	0.678	0.588	0.691	0.644	0.577	0.716	0.588	0.653	0.713
74	0.000	0.019	0.004	0.013	0.067	0.009	0.012	0.032	0.017	0.022	0.014	0.040
75	0.018	0.029	0.016	0.166	0.588	0.299	0.278	0.292	0.144	0.176	0.308	0.151
76	0.046	0.188	0.034	0.253	0.012	0.253	0.189	0.206	0.310	0.245	0.213	0.184
77	0.003	0.003	0.016	0.069	0.054	0.087	0.232	0.260	0.238	0.210	0.219	0.145
78	1.000	1.000	1.000	1.000	1.000	0.724	0.959	0.921	1.000	1.000	0.969	1.000
79	0.009	0.003	0.005	0.003	0.007	0.015	0.034	0.073	0.053	0.035	0.035	0.038
80	0.768	0.850	0.781	0.719	1.000	0.793	0.447	0.285	0.732	0.364	0.412	0.284
81	0.795	0.840	0.889	0.671	0.573	0.829	0.608	0.515	0.758	0.641	0.618	0.621
82	0.004	0.066	0.017	0.096	0.087	0.069	0.111	0.110	0.098	0.092	0.101	0.091
83	0.001	0.061	0.370	0.337	0.253	0.183	0.407	0.403	0.376	0.336	0.366	0.334
84	0.165	0.279	0.041	0.161	0.147	0.271	0.337	0.280	0.406	0.285	0.206	0.472
85	0.376	0.541	0.653	0.662	0.652	0.580	0.646	0.625	0.609	0.642	0.652	0.675
86	0.294	0.393	0.818	0.287	0.342	0.652	0.325	0.298	0.526	0.185	0.347	0.352
87	0.017	0.010	0.026	0.040	0.043	0.039	0.045	0.043	0.037	0.055	0.040	0.051
88	0.026	0.042	0.038	0.033	0.045	0.033	0.000	0.038	0.033	0.034	0.000	0.060
89	0.546	0.416	0.570	0.227	0.206	0.267	0.356	0.271	0.446	0.327	0.350	0.175
90	0.102	0.040	0.074	0.019	0.016	0.013	0.000	0.011	0.044	0.012	0.005	0.007
91	0.188	0.175	0.124	0.069	0.149	0.164	0.000	0.179	0.166	0.102	0.000	0.120
92	0.340	0.581	0.728	0.711	0.680	0.614	0.853	0.728	0.715	0.782	0.830	0.813
93	0.001	0.002	0.005	0.006	0.003	0.007	0.004	0.012	0.008	0.006	0.003	0.009
94	0.029	0.112	0.000	0.088	0.169	0.209	0.239	0.277	0.246	0.222	0.195	0.243
95	0.645	0.408	0.110	0.061	0.064	0.117	0.197	0.182	0.289	0.158	0.198	0.064
96	0.104	0.228	0.025	0.005	0.018	0.038	0.068	0.030	0.052	0.078	0.034	0.097
97	0.467	0.496	0.317	0.102	0.071	0.149	0.287	0.212	0.480	0.303	0.269	0.063
98	0.523	0.536	0.606	0.541	0.495	0.572	0.432	0.375	0.505	0.410	0.432	0.329
99	0.049	0.088	0.300	0.131	0.119	0.185	0.136	0.126	0.142	0.118	0.124	0.162
100	0.782	0.423	0.758	0.424	0.482	0.553	0.691	0.637	0.747	0.620	0.663	0.292
101	0.678	0.677	0.708	0.623	0.543	0.657	0.463	0.430	0.705	0.484	0.461	0.444
102	0.000	0.001	0.000	0.000	0.001	0.000	0.000	0.000	0.000	0.000	0.000	0.000
103	0.006	0.006	0.005	0.006	0.006	0.006	0.006	0.005	0.006	0.007	0.007	0.006
104	0.868	0.894	0.791	0.534	0.343	0.646	0.679	0.490	0.774	0.666	0.694	0.542
105	0.779	0.779	0.807	0.568	0.379	0.706	0.157	0.362	0.740	0.395	0.121	0.331
106	0.609	0.535	0.627	0.431	0.477	0.521	0.464	0.439	0.554	0.471	0.447	0.458
107	0.671	0.653	0.683	0.661	0.563	0.599	0.353	0.590	0.673	0.541	0.358	0.479
108	0.070	0.078	0.114	0.037	0.042	0.095	0.057	0.066	0.071	0.067	0.058	0.057
109	0.753	0.669	0.724	0.710	0.526	0.637	0.413	0.560	0.756	0.460	0.507	0.354
110	0.800	0.812	0.864	0.738	0.731	0.684	0.754	0.565	0.756	0.687	0.726	0.677
111	0.919	0.755	0.964	0.900	0.894	0.789	0.911	0.682	0.928	0.837	0.901	0.849
112	0.001	0.001	0.004	0.002	0.002	0.004	0.001	0.001	0.007	0.003	0.001	0.002
113	0.537	0.366	0.505	0.050	0.072	0.323	0.233	0.165	0.404	0.154	0.244	0.072
114	0.115	0.056	0.053	0.030	0.028	0.039	0.036	0.026	0.038	0.034	0.038	0.039
115	0.524	0.279	0.610	0.580	0.554	0.520	0.438	0.496	0.583	0.512	0.465	0.504
116	0.102	0.207	0.339	0.404	0.441	0.447	0.335	0.475	0.466	0.449	0.290	0.433
117	0.263	0.441	0.615	0.443	0.402	0.488	0.560	0.584	0.668	0.590	0.582	0.619
118	0.826	0.671	0.913	0.630	0.647	0.678	0.693	0.583	0.702	0.661	0.691	0.703
119	0.688	0.491	0.252	0.127	0.101	0.493	0.188	0.126	0.469	0.198	0.221	0.082
120	0.001	0.021	0.001	0.033	0.020	0.020	0.021	0.063	0.107	0.022	0.026	0.004
121	0.024	0.035	0.046	0.005	0.007	0.057	0.002	0.031	0.005	0.026	0.010	0.004
122	0.005	0.008	0.004	0.001	0.010	0.011	0.005	0.003	0.005	0.009	0.005	0.001
123	0.002	0.009	0.009	0.337	0.465	0.026	0.136	0.229	0.177	0.094	0.089	0.104
124	0.410	0.362	0.430	0.388	0.284	0.337	0.040	0.310	0.421	0.282	0.000	0.082
125	0.007	0.168	0.012	0.630	0.788	0.029	0.569	0.466	0.860	0.593	0.602	0.334
126	0.376	0.133	0.001	0.405	0.391	0.283	0.215	0.409	0.674	0.391	0.153	0.084
127	0.282	0.320	0.344	0.062	0.109	0.215	0.086	0.101	0.206	0.096	0.057	0.083
128	0.257	0.018	0.940	0.394	0.331	0.706	0.000	0.567	0.712	0.440	0.000	0.220
129	0.128	0.401	0.442	0.039	0.042	0.363	0.054	0.324	0.388	0.304	0.041	0.014
130	0.008	0.025	0.001	0.065	0.071	0.009	0.003	0.004	0.014	0.047	0.003	0.079
131	0.697	0.520	0.669	0.067	0.031	0.742	0.000	0.462	0.600	0.330	0.000	0.023

Table 19: The NMI on datasets [67]-[131] (Part-2).

Dataset Index	KMeans	AggClu	DBSCAN	BIRCH	GMM	OPTICS	SpeClu	MeanShift	k-PC	Affinity	SSC
1	0.526	0.636	0.589	0.690	0.398	0.281	0.690	0.330	-0.001	0.147	-0.003
2	0.079	0.088	0.046	0.098	0.082	0.006	0.074	0.002	0.013	0.006	0.010
3	0.833	0.891	0.831	0.874	0.799	-0.021	0.885	0.815	0.043	0.200	0.270
4	0.953	0.965	0.941	0.972	0.972	0.868	0.972	0.851	0.034	0.053	0.030
5	0.163	0.199	0.302	0.282	0.190	0.084	0.220	0.288	0.098	0.142	0.115
6	0.469	0.362	0.278	0.473	0.492	0.024	0.369	0.357	0.327	0.192	0.550
7	0.004	0.016	0.045	0.002	0.084	0.017	0.033	0.000	0.005	-0.004	-0.012
8	0.015	0.008	0.007	0.018	0.020	0.000	0.015	-0.002	0.005	0.005	0.002
9	0.115	0.074	0.129	0.122	0.117	0.006	0.184	0.082	0.002	0.015	0.013
10	0.006	0.012	0.002	0.006	0.006	0.000	0.007	0.000	0.002	0.005	0.002
11	-0.005	0.414	0.076	-0.005	0.185	0.062	0.574	-0.006	-0.017	0.009	0.001
12	0.910	0.884	0.731	0.873	0.927	-0.001	0.897	0.902	0.003	0.020	0.021
13	0.393	0.339	0.186	0.331	0.190	0.025	0.421	0.051	0.008	0.040	0.012
14	0.157	0.302	0.189	0.283	0.364	0.034	0.256	0.037	0.013	0.089	0.030
15	0.756	0.698	0.654	0.814	0.745	0.461	0.850	0.683	0.000	0.588	0.340
16	0.354	0.408	0.121	0.482	0.532	0.004	0.379	0.060	0.000	0.017	0.028
17	0.616	0.718	0.568	0.672	0.904	0.341	0.641	0.568	0.039	0.353	0.249
18	0.901	0.785	0.556	0.819	0.879	0.088	0.947	0.401	0.063	0.245	0.501
19	0.151	0.137	0.027	0.188	0.179	0.003	0.502	0.000	0.146	0.097	0.140
20	0.353	0.309	0.283	0.000	0.267	-0.000	0.345	0.293	0.032	0.000	0.001
21	0.300	0.388	0.286	0.284	0.355	0.228	0.410	0.159	0.132	0.223	0.170
22	0.241	0.352	0.100	0.312	0.328	0.192	0.382	0.270	0.015	0.051	-0.051
23	0.598	0.709	0.553	0.797	0.362	0.097	0.675	0.682	0.457	0.003	0.406
24	0.664	0.780	0.585	0.714	0.774	0.048	0.779	0.316	0.014	0.053	0.169
25	0.818	0.693	0.341	0.867	0.944	0.007	0.914	0.802	0.084	0.093	0.240
26	0.686	0.686	0.560	0.742	0.738	0.018	0.739	0.493	0.068	0.247	0.535
27	0.804	0.950	0.918	0.925	0.745	0.553	0.784	0.864	0.135	0.556	0.420
28	0.610	0.559	0.510	0.778	0.358	0.080	0.724	0.542	0.513	0.002	0.564
29	0.168	0.140	0.713	0.207	0.504	-0.009	0.159	0.341	0.322	0.118	0.018
30	0.176	0.165	0.142	0.195	0.177	0.006	0.301	0.091	0.046	0.107	0.120
31	0.015	0.115	0.322	0.001	0.124	0.133	0.419	0.042	0.009	0.019	0.079
32	0.682	0.601	0.578	0.630	0.673	0.005	0.703	0.677	0.086	0.019	0.032
33	0.388	0.382	0.307	0.371	0.368	0.130	0.418	0.304	0.083	0.402	0.284
34	0.013	0.341	0.800	0.132	0.083	-0.005	0.128	0.120	0.049	0.051	0.074
35	0.038	0.059	0.004	0.057	0.032	0.004	0.007	0.005	0.016	0.004	0.003
36	0.078	0.052	0.116	0.076	0.132	0.046	0.082	0.105	0.002	0.001	0.040
37	0.039	0.003	0.063	0.028	-0.011	0.001	0.020	0.010	0.022	0.002	0.011
38	0.424	0.883	0.563	0.637	0.528	0.254	0.867	0.265	0.085	0.210	0.206
39	-0.016	-0.003	0.000	-0.003	0.039	0.000	-0.003	-0.008	0.014	0.004	-0.050
40	0.668	0.363	0.324	0.639	0.690	0.011	0.631	0.267	0.165	0.060	0.329
41	-0.018	0.004	0.043	-0.009	-0.009	0.028	-0.002	0.005	0.009	0.002	-0.002
42	0.023	0.027	0.194	0.030	0.179	0.079	0.087	0.078	0.058	0.008	0.120
43	0.329	0.181	0.135	0.149	0.336	-0.036	0.292	-0.000	0.006	0.020	0.006
44	0.510	0.621	0.379	0.554	0.502	0.003	0.721	0.000	0.358	0.103	0.697
45	0.038	0.059	0.022	0.021	0.033	0.010	0.028	0.013	0.017	0.009	0.009
46	0.011	0.041	0.067	0.108	0.050	0.074	-0.024	-0.001	0.002	0.002	-0.010
47	0.008	0.100	0.261	0.111	0.060	-0.005	0.001	0.148	0.046	0.003	0.077
48	0.288	0.432	0.278	0.474	0.331	0.013	0.392	0.055	0.059	0.029	0.001
49	0.047	0.028	0.023	0.096	0.065	0.017	0.003	0.001	0.002	0.003	0.000
50	0.188	0.041	0.188	0.266	0.231	0.153	0.392	0.181	-0.039	0.006	0.316
51	0.704	0.844	0.643	0.711	0.875	0.236	0.934	0.658	0.390	0.330	0.861
52	0.033	0.013	0.079	0.013	0.067	0.048	0.069	0.085	0.009	0.000	0.040
53	-0.000	-0.000	0.024	0.013	0.023	0.042	-0.001	0.000	0.007	0.001	-0.010
54	0.773	0.789	0.480	0.758	0.779	0.062	0.811	0.621	0.056	0.299	0.360
55	0.897	0.785	0.556	0.819	0.877	0.088	0.947	0.401	0.056	0.245	0.501
56	0.131	0.227	0.235	0.198	0.152	0.077	0.305	0.000	0.024	0.004	0.307
57	0.355	0.363	0.346	0.347	0.383	0.024	0.404	0.331	0.099	0.015	0.304
58	0.678	0.649	0.619	0.448	0.655	0.239	0.773	0.624	0.017	0.204	0.070
59	0.242	0.214	0.310	0.208	0.394	0.036	0.321	0.183	0.155	0.163	0.224
60	0.026	0.012	0.100	0.033	0.081	0.098	0.180	0.001	0.012	0.011	0.004
61	0.469	0.421	0.381	0.401	0.416	0.331	0.604	0.238	0.273	0.443	0.471
62	0.001	0.007	0.028	0.005	0.026	0.000	0.000	0.002	0.002	0.002	0.006
63	0.025	0.004	0.071	0.061	0.048	0.000	0.019	0.044	0.061	0.000	0.010
64	-0.001	0.069	0.150	0.105	0.104	0.006	0.012	0.174	0.016	0.030	0.011
65	0.211	0.134	0.046	0.231	0.209	0.024	0.178	0.029	0.026	0.029	0.065
66	0.166	0.331	0.282	0.147	0.115	0.020	0.423	0.126	0.008	0.039	0.012

Table 20: The ARI on datasets [1]-[66] (Part-1).

Dataset Index	S^3COMP-C	k-FSC	AutoSC	DEC	IDEC	DSCN	PICA	ConClu	EDESC	DMICC	DIVC	LFSS
1	-0.038	-0.009	0.441	0.723	0.713	0.237	0.446	0.530	0.445	0.521	0.361	0.690
2	0.019	0.030	0.038	0.108	0.087	0.041	0.070	0.123	0.093	0.104	0.038	0.079
3	0.026	0.165	-0.012	0.879	0.504	0.730	0.882	0.897	0.901	0.883	0.885	0.880
4	0.019	0.051	0.965	0.962	0.958	0.727	0.875	0.969	0.842	0.900	0.716	0.903
5	0.089	0.205	0.232	0.188	0.189	0.198	0.192	0.259	0.180	0.213	0.212	0.239
6	0.349	0.442	0.530	0.480	0.504	0.215	0.519	0.385	0.422	0.459	0.508	0.468
7	0.028	0.012	0.045	0.001	0.009	0.032	-0.003	0.003	0.003	0.002	-0.005	0.018
8	0.003	0.004	0.001	0.013	0.010	0.014	0.018	0.026	0.023	0.026	0.019	0.024
9	0.001	0.036	0.008	0.151	0.175	0.026	0.106	0.160	0.090	0.141	0.107	0.124
10	0.002	0.003	0.002	0.003	0.027	0.012	0.023	0.034	0.011	0.036	0.020	0.037
11	-0.018	0.101	-0.016	0.010	-0.002	-0.003	0.000	0.194	0.565	0.179	0.000	0.040
12	0.016	0.221	0.940	0.900	0.586	0.903	0.918	0.940	0.951	0.872	0.915	0.936
13	0.011	0.059	0.167	0.201	0.207	0.241	0.253	0.421	0.260	0.337	0.289	0.252
14	0.022	0.039	0.215	0.127	0.211	0.209	0.186	0.103	0.155	0.167	0.144	0.222
15	0.291	0.527	0.602	0.688	0.696	0.477	0.749	0.791	0.638	0.746	0.744	0.827
16	0.022	0.157	0.055	0.141	0.586	0.419	0.351	0.518	0.380	0.368	0.387	0.537
17	0.052	0.175	0.584	0.789	0.703	0.318	0.592	0.662	0.595	0.683	0.600	0.701
18	0.193	0.564	0.884	0.765	0.754	0.550	0.806	0.867	0.801	0.719	0.802	0.712
19	0.082	0.154	0.165	0.087	0.030	0.079	0.132	0.086	0.172	0.093	0.139	0.176
20	0.018	0.014	0.000	0.336	0.355	0.214	0.326	0.374	0.331	0.364	0.328	0.371
21	0.177	0.198	0.392	0.285	0.265	0.173	0.397	0.376	0.403	0.424	0.396	0.443
22	-0.048	0.103	0.198	0.157	0.192	0.197	0.086	0.227	0.193	0.185	0.140	0.069
23	0.007	0.482	0.425	0.259	0.615	0.104	0.072	0.250	0.372	0.366	0.132	0.126
24	-0.006	0.045	0.672	0.570	0.615	0.752	0.641	0.690	0.736	0.690	0.567	0.562
25	0.161	0.434	0.640	0.594	0.567	0.655	0.904	0.913	0.678	0.784	0.891	0.772
26	0.374	0.638	0.567	0.575	0.562	0.564	0.571	0.612	0.626	0.647	0.534	0.614
27	0.142	0.533	0.423	0.566	0.676	0.371	0.694	0.639	0.838	0.761	0.669	0.549
28	0.036	0.475	0.353	0.244	0.595	0.149	0.062	0.177	0.395	0.395	0.078	0.187
29	-0.041	0.591	-0.033	0.647	0.613	0.057	0.201	0.229	0.345	0.192	0.215	0.288
30	0.119	0.163	0.077	0.172	0.285	0.170	0.144	0.153	0.168	0.175	0.153	0.157
31	0.008	0.078	0.242	0.073	0.086	0.029	0.287	0.352	0.176	0.260	0.242	0.267
32	0.010	0.043	0.668	0.400	0.285	0.582	0.618	0.670	0.689	0.639	0.644	0.677
33	0.277	0.302	0.412	0.382	0.391	0.321	0.446	0.433	0.336	0.407	0.440	0.450
34	0.008	0.075	0.013	0.094	0.043	0.128	0.345	0.334	0.204	0.161	0.150	0.576
35	0.004	-0.001	0.005	0.031	0.045	0.017	0.009	0.048	0.043	0.033	0.030	0.041
36	-0.008	0.003	0.050	0.018	0.051	0.029	0.016	0.053	0.039	0.094	0.024	0.062
37	0.025	0.013	0.001	-0.000	0.004	0.018	0.035	0.045	0.034	0.032	0.009	0.030
38	0.110	0.343	0.904	0.468	0.430	0.330	0.521	0.553	0.689	0.547	0.555	0.594
39	0.000	-0.025	-0.023	-0.003	-0.003	-0.011	0.002	0.043	0.050	0.019	0.007	-0.021
40	0.198	0.245	0.299	0.481	0.423	0.581	0.459	0.507	0.479	0.519	0.420	0.557
41	0.000	-0.001	-0.009	-0.005	-0.016	-0.005	-0.002	0.023	0.013	-0.001	0.006	0.038
42	0.084	0.143	0.164	0.150	0.128	0.013	0.017	0.193	0.059	0.206	0.010	0.208
43	0.001	0.028	-0.014	0.303	0.278	0.271	0.245	0.382	0.335	0.327	0.269	0.275
44	0.833	0.752	0.671	0.403	0.317	0.145	0.537	0.278	0.573	0.414	0.470	0.454
45	0.003	-0.001	0.018	0.020	0.022	0.003	0.024	0.036	0.028	0.025	0.010	0.028
46	-0.004	-0.046	0.088	0.106	0.231	0.036	0.022	0.044	-0.020	0.049	0.030	0.022
47	-0.000	0.027	0.004	0.019	0.153	-0.012	0.041	0.020	0.056	0.094	0.088	0.058
48	0.003	0.020	0.474	0.339	0.235	0.288	0.522	0.567	0.539	0.452	0.539	0.534
49	0.003	0.000	0.001	0.058	0.072	0.040	0.041	0.042	0.037	0.054	0.053	0.124
50	0.212	0.152	0.006	0.072	0.175	0.103	0.078	0.053	0.135	0.178	0.057	0.119
51	0.785	0.824	0.921	0.778	0.747	0.677	0.753	0.670	0.830	0.768	0.621	0.701
52	0.001	0.000	-0.006	0.039	0.071	0.028	-0.000	-0.005	0.001	0.055	0.003	0.013
53	0.119	0.014	0.068	0.032	0.187	0.067	0.043	0.015	0.024	-0.001	0.017	0.038
54	0.090	0.285	0.720	0.646	0.592	0.465	0.762	0.681	0.678	0.721	0.756	0.813
55	0.191	0.564	0.884	0.723	0.787	0.646	0.778	0.917	0.819	0.727	0.791	0.848
56	0.013	0.159	0.131	0.111	0.187	0.166	0.117	0.198	0.247	0.146	0.125	0.141
57	0.001	0.225	0.000	0.479	0.372	0.358	0.542	0.488	0.400	0.528	0.467	0.543
58	-0.016	0.062	0.649	0.714	0.724	0.495	0.360	0.624	0.666	0.687	0.392	0.649
59	0.249	0.159	0.252	0.239	0.224	0.230	0.252	0.287	0.289	0.276	0.242	0.282
60	0.009	0.004	0.007	0.035	0.372	0.033	0.032	0.025	0.040	0.036	0.033	0.037
61	0.258	0.475	0.412	0.396	0.423	0.324	0.488	0.362	0.429	0.440	0.482	0.478
62	0.002	0.017	0.002	0.003	0.008	0.018	0.002	0.003	0.008	0.005	0.008	0.019
63	0.005	0.015	0.063	0.008	0.043	0.042	0.006	-0.025	-0.007	0.003	0.009	0.007
64	0.002	0.000	-0.002	0.075	0.086	0.066	0.043	0.059	0.078	0.055	0.008	0.021
65	0.044	0.083	0.148	0.144	0.164	0.119	0.124	0.099	0.146	0.130	0.124	0.127
66	0.012	0.018	0.059	0.145	0.155	0.145	0.131	0.271	0.222	0.190	0.138	0.102

Table 21: The ARI on datasets [1]-[66] (Part-2).

Dataset Index	KMeans	AggClu	DBSCAN	BIRCH	GMM	OPTICS	SpeClu	MeanShift	k-PC	Affinity	SSC
67	0.724	0.766	0.644	0.741	0.739	0.150	0.748	0.723	0.057	0.242	0.210
68	0.197	0.657	0.359	0.793	0.168	0.114	0.781	0.000	0.658	0.181	0.870
69	0.006	0.004	0.088	-0.006	0.066	0.074	0.016	-0.008	0.042	0.003	0.058
70	0.327	0.175	0.095	0.086	0.296	0.014	0.246	0.063	-0.018	0.018	0.053
71	0.620	0.610	0.416	0.634	0.603	0.135	0.934	0.438	0.010	0.139	0.105
72	0.000	0.000	0.215	0.000	0.151	0.048	0.049	0.165	-0.002	0.001	0.016
73	0.582	0.481	0.603	0.645	0.566	0.002	0.686	0.091	0.465	0.125	0.670
74	0.007	0.001	0.039	0.003	0.037	0.003	0.013	-0.002	0.005	0.005	0.021
75	0.269	0.479	0.004	0.368	0.140	0.012	0.334	-0.003	0.004	0.013	0.020
76	0.286	0.322	0.156	0.331	0.264	0.009	0.403	0.003	0.047	0.063	0.093
77	-0.095	0.160	0.323	0.127	0.065	0.398	0.408	-0.048	-0.028	-0.038	0.127
78	1.000	1.000	1.000	0.971	1.000	0.314	1.000	0.957	0.153	0.606	1.000
79	0.051	0.031	0.022	0.031	0.020	-0.060	0.021	0.056	0.000	0.011	-0.022
80	0.564	0.553	0.244	0.632	0.582	0.004	0.687	0.000	0.399	0.115	0.670
81	0.617	0.546	0.445	0.685	0.630	0.004	0.858	0.001	0.189	0.193	0.865
82	0.052	0.074	0.061	0.065	0.071	0.021	0.076	0.001	0.027	0.012	-0.011
83	0.254	0.312	0.115	0.337	0.575	-0.000	0.252	0.000	-0.000	0.014	-0.000
84	0.078	0.148	0.074	0.114	0.270	0.023	0.200	0.013	0.113	0.061	0.072
85	0.550	0.434	0.418	0.398	0.506	0.010	0.765	0.457	0.271	0.445	0.276
86	0.214	0.208	0.227	0.313	0.440	0.005	0.689	0.000	0.220	0.044	0.270
87	0.033	0.062	0.029	0.046	0.048	-0.003	0.051	0.015	-0.001	0.040	0.010
88	0.009	0.002	0.022	0.016	0.021	-0.018	0.003	0.017	0.033	0.050	0.010
89	0.315	0.400	0.057	0.429	0.322	0.001	0.314	0.003	0.175	0.063	0.350
90	0.003	0.005	0.011	-0.003	0.005	0.016	0.002	0.001	0.030	0.017	-0.006
91	0.052	0.083	0.100	0.090	0.097	0.014	0.278	0.000	0.128	0.019	0.174
92	0.620	0.616	0.682	0.616	0.662	0.300	0.696	0.416	0.163	0.387	0.184
93	0.008	0.002	0.008	0.023	0.020	0.003	0.000	0.005	0.004	0.002	0.001
94	0.368	0.676	0.624	0.001	0.305	0.007	0.367	0.480	-0.002	0.012	0.026
95	-0.004	0.057	0.012	-0.009	-0.001	0.005	0.131	-0.002	0.017	-0.012	0.173
96	-0.038	0.001	0.018	-0.000	0.054	0.000	-0.005	-0.000	0.032	0.023	-0.053
97	-0.003	0.018	0.086	0.002	0.032	0.006	0.177	-0.017	0.057	0.067	0.004
98	0.394	0.346	0.074	0.415	0.401	0.004	0.423	0.000	0.282	0.100	0.296
99	0.075	0.111	0.076	0.122	0.135	0.023	0.116	0.097	0.040	0.066	0.098
100	0.316	0.511	0.408	0.399	0.350	0.101	0.624	0.002	0.042	0.245	0.540
101	0.473	0.363	0.007	0.502	0.476	0.001	0.454	0.000	0.367	0.120	0.459
102	-0.000	0.000	0.005	0.003	-0.000	0.000	-0.000	0.000	-0.000	0.000	0.004
103	-0.000	-0.000	-0.000	-0.000	0.000	-0.000	0.000	0.000	-0.000	-0.000	-0.000
104	0.727	0.602	0.553	0.924	0.677	0.162	0.909	0.000	0.276	0.160	0.756
105	0.400	0.339	0.103	0.376	0.345	0.000	0.678	0.000	0.248	0.050	0.472
106	0.341	0.332	0.035	0.303	0.367	0.001	0.397	0.011	0.284	0.099	0.398
107	0.525	0.429	0.172	0.497	0.519	0.000	0.554	0.000	0.341	0.049	0.451
108	0.034	0.030	0.021	0.032	0.049	0.000	0.033	0.001	0.003	0.014	0.039
109	0.553	0.499	0.001	0.491	0.541	0.000	0.487	0.000	0.418	0.038	0.535
110	0.580	0.389	0.788	0.619	0.592	0.069	0.710	0.002	0.157	0.408	0.537
111	0.780	0.847	0.827	0.766	0.793	0.056	0.905	0.000	0.464	0.555	0.371
112	0.002	0.001	0.001	0.007	0.004	0.000	0.002	-0.000	0.000	0.001	-0.000
113	0.116	0.074	0.022	0.119	0.123	0.001	0.640	-0.000	0.023	0.139	0.251
114	0.001	0.000	0.003	-0.002	-0.001	0.000	-0.003	-0.009	0.003	0.004	0.028
115	0.395	0.325	0.327	0.477	0.387	0.259	0.492	0.317	0.047	0.254	0.267
116	0.302	0.417	0.464	0.260	0.303	0.320	0.489	0.341	0.114	0.021	-0.008
117	0.529	0.387	0.346	0.551	0.514	0.012	0.521	0.533	0.290	0.100	0.328
118	0.462	0.388	0.072	0.501	0.434	0.129	0.639	0.001	0.090	0.492	0.405
119	0.041	0.470	0.060	-0.000	0.067	0.012	0.281	0.004	0.160	0.101	0.581
120	0.073	0.010	0.002	-0.000	0.099	0.000	0.000	0.000	0.001	0.004	0.063
121	-0.037	0.111	0.111	-0.001	0.002	0.073	0.111	0.004	0.006	0.005	0.037
122	0.000	0.002	0.002	0.000	0.009	0.001	0.005	0.000	0.003	0.004	0.000
123	0.110	0.686	0.478	0.259	0.068	0.024	0.064	0.361	0.045	0.301	-0.008
124	0.210	0.258	0.019	0.293	0.212	-0.006	0.314	0.000	0.122	0.009	0.283
125	0.834	0.775	0.028	0.854	0.834	0.002	0.688	0.000	0.120	0.002	0.000
126	0.197	0.634	0.137	0.194	0.488	0.057	0.484	0.000	0.103	0.011	-0.000
127	0.049	0.040	0.002	0.052	0.048	0.000	0.320	-0.000	0.182	0.019	0.158
128	0.754	0.774	0.765	0.713	0.769	0.721	0.348	0.758	0.158	0.143	0.038
129	0.347	0.170	0.058	0.278	0.055	0.058	0.322	0.118	0.209	0.024	0.102
130	0.012	0.024	0.041	0.047	0.018	-0.000	0.052	0.013	0.002	0.023	0.001
131	0.127	0.321	0.050	0.234	0.057	0.036	0.269	0.084	0.574	0.163	0.865

Table 22: The ARI on datasets [67]-[131] (Part-1).

Dataset Index	S^3COMP-C	k-FSC	AutoSC	DEC	IDEC	DSCN	PICA	ConClu	EDESC	DMICC	DIVC	LFSS
67	0.139	0.243	0.446	0.697	0.696	0.573	0.481	0.580	0.695	0.588	0.470	0.491
68	0.820	0.784	0.930	0.530	0.548	0.802	0.220	0.107	0.462	0.152	0.200	0.196
69	0.094	0.048	0.002	-0.004	-0.004	0.074	0.025	0.078	0.032	0.022	0.019	0.164
70	0.019	0.051	0.045	0.102	0.083	0.136	0.232	0.289	0.206	0.351	0.193	0.152
71	0.084	0.025	0.299	0.573	0.583	0.496	0.279	0.780	0.535	0.619	0.133	0.765
72	0.078	0.204	0.030	0.036	0.163	0.013	0.091	0.038	0.304	0.122	0.097	0.083
73	0.281	0.680	0.770	0.560	0.429	0.563	0.525	0.423	0.586	0.465	0.540	0.631
74	-0.001	0.013	-0.002	0.019	0.163	0.005	0.016	0.038	0.021	0.026	0.018	0.053
75	0.034	0.055	0.034	0.189	0.429	0.345	0.349	0.364	0.179	0.220	0.378	0.206
76	0.015	0.188	0.005	0.232	0.017	0.223	0.163	0.174	0.289	0.213	0.178	0.186
77	0.025	-0.007	-0.036	-0.082	0.002	0.139	0.171	0.160	0.162	0.109	0.146	0.205
78	1.000	1.000	1.000	1.000	1.000	0.572	0.931	0.834	1.000	1.000	0.953	1.000
79	0.033	0.000	-0.021	0.029	0.020	0.052	0.037	0.030	0.057	0.058	0.033	0.060
80	0.684	0.845	0.678	0.650	1.000	0.733	0.327	0.162	0.645	0.251	0.296	0.200
81	0.738	0.815	0.874	0.561	0.445	0.808	0.505	0.376	0.647	0.550	0.515	0.534
82	-0.003	0.052	-0.001	0.060	0.061	0.049	0.069	0.082	0.053	0.053	0.060	0.049
83	0.001	0.041	0.253	0.342	0.265	0.180	0.351	0.325	0.342	0.312	0.344	0.248
84	0.108	0.160	0.004	0.103	0.091	0.113	0.253	0.204	0.281	0.203	0.173	0.409
85	0.286	0.420	0.538	0.529	0.506	0.358	0.511	0.491	0.453	0.501	0.513	0.550
86	0.208	0.276	0.764	0.166	0.203	0.574	0.212	0.175	0.394	0.105	0.229	0.246
87	0.005	0.012	0.031	0.034	0.046	0.033	0.032	0.064	0.043	0.047	0.032	0.033
88	0.019	0.028	-0.003	0.039	0.040	0.005	0.000	0.055	0.036	0.029	0.000	0.046
89	0.423	0.299	0.443	0.141	0.129	0.072	0.244	0.177	0.332	0.220	0.239	0.137
90	0.055	0.025	0.030	0.009	0.013	0.002	0.000	0.009	0.030	0.009	0.003	0.005
91	0.159	0.134	0.064	0.048	0.109	0.096	0.000	0.124	0.152	0.078	0.000	0.099
92	0.281	0.414	0.610	0.542	0.565	0.474	0.749	0.588	0.561	0.694	0.785	0.770
93	0.001	-0.000	0.008	0.003	0.002	0.006	0.006	0.023	0.012	0.008	0.002	0.014
94	-0.083	0.266	0.002	0.117	0.269	0.268	0.153	0.287	0.235	0.293	0.112	0.173
95	0.640	0.317	0.007	-0.007	0.002	0.025	0.107	0.080	0.220	0.087	0.102	0.024
96	-0.038	0.152	-0.029	-0.000	0.003	-0.021	0.023	0.007	0.059	0.078	0.040	0.124
97	0.348	0.363	0.190	0.054	0.026	0.059	0.179	0.146	0.380	0.182	0.153	0.039
98	0.362	0.445	0.439	0.412	0.372	0.402	0.321	0.267	0.371	0.280	0.328	0.235
99	0.038	0.072	0.216	0.106	0.085	0.116	0.105	0.108	0.108	0.097	0.095	0.122
100	0.633	0.256	0.563	0.202	0.279	0.350	0.490	0.438	0.526	0.400	0.449	0.135
101	0.429	0.487	0.421	0.360	0.260	0.325	0.232	0.185	0.475	0.242	0.235	0.256
102	0.001	0.002	0.000	0.001	0.003	-0.001	0.000	0.000	0.001	0.000	0.000	0.000
103	-0.000	-0.000	0.000	-0.000	0.000	0.000	0.000	0.000	-0.000	-0.000	0.000	0.000
104	0.870	0.888	0.742	0.445	0.259	0.500	0.625	0.412	0.724	0.625	0.639	0.504
105	0.712	0.776	0.737	0.459	0.275	0.633	0.110	0.248	0.673	0.301	0.080	0.260
106	0.478	0.418	0.466	0.296	0.335	0.357	0.316	0.300	0.393	0.320	0.301	0.332
107	0.540	0.560	0.550	0.528	0.401	0.432	0.292	0.470	0.563	0.419	0.287	0.402
108	0.042	0.039	0.061	0.015	0.018	0.051	0.028	0.035	0.038	0.033	0.029	0.028
109	0.724	0.624	0.659	0.615	0.382	0.550	0.339	0.461	0.696	0.321	0.419	0.289
110	0.602	0.649	0.720	0.535	0.518	0.374	0.592	0.301	0.561	0.477	0.551	0.502
111	0.807	0.580	0.909	0.715	0.710	0.508	0.824	0.436	0.780	0.670	0.806	0.697
112	0.000	0.001	0.005	0.002	0.002	0.002	0.001	0.001	0.009	0.004	0.001	0.002
113	0.426	0.274	0.378	0.015	0.022	0.176	0.123	0.072	0.296	0.080	0.131	0.031
114	0.057	0.018	0.015	-0.000	-0.001	0.002	0.006	0.008	0.005	0.003	0.006	0.008
115	0.411	0.187	0.481	0.490	0.448	0.353	0.274	0.351	0.434	0.368	0.306	0.410
116	0.040	0.092	0.192	0.223	0.309	0.398	0.177	0.392	0.347	0.301	0.166	0.268
117	0.204	0.433	0.556	0.385	0.333	0.419	0.480	0.516	0.658	0.512	0.511	0.588
118	0.564	0.288	0.761	0.210	0.236	0.253	0.318	0.155	0.323	0.271	0.320	0.335
119	0.609	0.417	0.118	0.055	0.053	0.368	0.115	0.077	0.403	0.119	0.135	0.037
120	0.000	0.028	0.000	0.045	0.024	0.020	0.028	0.086	0.144	0.029	0.035	0.006
121	0.023	0.021	0.037	0.002	-0.005	0.088	0.006	0.033	-0.010	0.051	0.010	0.004
122	0.000	0.010	0.002	0.002	0.012	0.002	0.004	0.003	0.006	0.009	0.002	0.001
123	-0.008	-0.033	-0.048	0.511	0.645	0.015	0.081	0.233	0.276	0.046	0.068	0.029
124	0.345	0.273	0.333	0.267	0.189	0.251	0.034	0.209	0.330	0.176	0.000	0.067
125	0.000	0.222	0.000	0.677	0.842	0.011	0.630	0.573	0.909	0.626	0.666	0.410
126	0.425	0.142	0.000	0.353	0.372	0.320	0.227	0.434	0.689	0.415	0.155	0.103
127	0.140	0.202	0.180	0.016	0.034	0.044	0.029	0.032	0.094	0.031	0.020	0.029
128	0.391	0.013	0.974	0.384	0.300	0.832	0.000	0.711	0.780	0.543	0.000	0.038
129	-0.057	0.281	0.198	0.061	0.042	0.285	0.049	0.149	0.269	0.281	0.016	0.012
130	0.000	0.031	0.002	0.072	0.054	0.011	0.004	0.005	0.018	0.061	0.003	0.108
131	0.735	0.422	0.528	0.037	0.019	0.710	0.000	0.265	0.480	0.174	0.000	0.012

Table 23: The ARI on datasets [67]-[131] (Part-2).

E IMPLEMENTATION TIME COST

The average time cost (over five runs) of each method on each of the 131 datasets is provided from Table 24 to Table 27.

Dataset Index	KMeans	AggClu	DBSCAN	BIRCH	GMM	OPTICS	SpeClu	MeanShift	k-PC	Affinity	SSC
1	0.026	0.011	0.002	0.093	0.031	0.063	0.022	0.146	0.053	0.008	0.193
2	0.128	0.548	0.103	0.755	13.324	26.359	7.273	2.138	0.619	21.220	467.539
3	0.015	0.009	0.010	0.054	0.087	0.373	0.087	0.589	0.091	0.866	14.132
4	0.019	0.033	0.016	0.091	0.067	1.051	0.131	1.556	0.100	0.817	23.797
5	0.028	0.002	0.003	0.015	0.087	0.130	0.042	0.825	0.039	0.092	2.933
6	0.105	0.195	0.071	0.247	1.532	10.033	0.820	1.247	0.483	17.918	52.426
7	0.019	0.002	0.003	0.019	0.071	0.012	0.006	0.275	0.071	0.080	0.111
8	0.039	0.047	0.014	0.106	0.143	1.028	0.019	1.349	0.084	0.941	11.236
9	0.031	0.018	0.009	0.100	0.182	0.663	0.014	1.167	0.034	0.434	15.410
10	0.079	0.227	0.044	0.480	1.118	7.323	0.052	1.298	0.197	5.001	165.389
11	0.063	0.992	0.361	1.371	3.394	68.108	0.303	5.031	0.207	113.844	576.251
12	0.035	2.734	1.346	0.696	0.580	489.641	5.750	24.701	0.357	182.770	4341.151
13	0.012	0.004	0.004	0.021	0.118	0.234	0.083	0.664	0.023	0.203	0.211
14	0.021	0.003	0.003	0.009	0.185	0.179	0.011	0.404	0.075	0.243	2.764
15	0.011	0.002	0.002	0.006	0.050	0.093	0.046	0.591	0.103	0.014	1.577
16	0.031	0.151	0.065	0.252	1.350	3.978	1.407	2.664	0.183	11.275	60.462
17	0.008	0.002	0.003	0.006	0.106	0.095	0.026	0.249	0.050	0.036	0.114
18	0.010	0.001	0.003	0.009	0.082	0.023	0.030	0.602	0.019	0.017	1.830
19	0.391	3.370	1.174	3.901	36.224	642.053	2.040	13.488	3.194	398.349	4072.630
20	0.011	0.011	0.010	0.036	0.031	0.084	0.141	1.135	0.022	0.244	14.013
21	0.016	0.001	0.002	0.006	0.061	0.075	0.060	0.480	0.120	0.007	1.086
22	0.010	0.001	0.002	0.009	0.123	0.052	0.074	0.089	0.015	0.014	0.111
23	0.053	3.759	1.376	0.378	1.325	508.937	1.716	19.430	0.515	130.535	6549.695
24	0.019	0.008	0.007	0.059	0.266	0.470	0.066	0.357	0.030	0.383	1.167
25	0.030	0.062	0.047	0.161	1.423	5.119	0.379	2.035	0.083	4.050	103.367
26	0.040	0.018	0.010	0.117	1.467	0.730	0.017	0.572	0.389	0.506	3.652
27	0.018	0.001	0.002	0.007	0.136	0.064	0.006	0.099	0.108	0.014	1.025
28	0.058	4.038	1.592	0.389	1.296	629.835	6.513	22.252	0.411	148.610	8128.247
29	0.013	0.006	0.004	0.030	0.299	0.063	0.011	0.361	0.017	0.091	0.361
30	0.039	0.034	0.012	0.168	1.354	1.094	0.021	0.711	0.540	1.312	45.365
31	0.009	0.001	0.002	0.007	0.023	0.050	0.004	0.088	0.026	0.016	1.009
32	0.029	0.438	0.200	0.205	0.155	23.553	0.217	3.749	0.070	21.456	509.126
33	0.041	0.007	0.008	0.014	0.204	0.556	0.113	0.814	0.190	0.319	1.324
34	0.021	0.027	0.023	0.051	0.099	0.076	0.028	1.528	0.027	2.350	32.637
35	0.130	1.169	0.234	0.598	3.679	10.116	7.639	8.538	0.494	59.312	1020.823
36	0.052	0.283	0.104	0.279	6.197	19.390	1.818	3.917	0.154	20.445	265.634
37	0.021	0.020	0.014	0.114	0.657	0.079	0.349	0.735	0.076	1.558	8.716
38	0.013	0.001	0.003	0.018	0.147	0.105	0.034	0.463	0.031	0.017	1.569
39	0.013	0.018	0.006	0.064	0.209	0.014	0.011	0.460	0.027	0.570	16.019
40	0.107	4.453	1.105	1.702	9.063	373.295	6.126	13.241	1.532	251.236	4448.016
41	0.019	0.019	0.011	0.117	0.106	0.091	0.019	1.044	0.032	0.349	10.822
42	0.158	3.913	0.465	4.141	15.153	107.774	0.587	7.764	4.652	138.519	15475.563
43	0.035	0.060	0.025	0.090	0.169	0.305	0.028	1.207	0.046	2.642	23.565
44	0.267	0.602	0.192	1.304	10.275	39.518	1.486	3.887	0.907	36.292	1879.024
45	0.052	0.066	0.017	0.178	0.624	2.055	0.035	1.815	0.140	2.786	31.266
46	0.043	0.111	0.023	0.229	0.177	3.982	0.370	1.489	0.107	3.583	82.994
47	0.108	3.878	1.488	0.605	0.620	631.343	4.877	29.290	0.190	243.122	4868.109
48	0.020	0.012	0.010	0.041	0.138	0.338	0.175	0.844	0.020	1.156	17.422
49	0.072	0.635	0.140	1.347	2.286	3.259	5.416	5.645	0.134	90.330	455.408
50	0.059	0.092	0.046	0.256	1.636	0.732	0.910	1.682	0.130	11.499	183.978
51	0.024	0.006	0.004	0.048	0.193	0.240	0.077	0.517	0.199	0.089	7.473
52	0.044	0.494	0.024	0.924	1.086	2.643	1.048	2.411	0.473	12.398	4015.081
53	0.056	1.453	1.031	4.824	1.582	629.845	7.789	9.724	0.360	330.008	3435.475
54	0.019	0.003	0.003	0.026	0.048	0.157	0.102	0.442	0.023	0.032	0.189
55	0.017	0.001	0.003	0.016	0.072	0.023	0.041	0.484	0.020	0.017	2.068
56	0.160	4.172	1.033	3.834	4.818	14.912	2.017	14.128	0.948	200.819	9547.905
57	0.156	7.469	1.033	8.093	22.380	162.250	24.964	26.707	8.233	153.907	2498.089
58	0.019	0.015	0.013	0.021	0.058	1.074	0.286	0.923	0.067	0.952	19.051
59	0.048	0.004	0.004	0.026	0.247	0.288	0.016	1.056	0.091	0.159	0.575
60	0.414	4.085	1.114	1.188	12.821	192.929	2.040	29.161	1.300	377.470	4314.663
61	0.029	0.002	0.003	0.026	0.086	0.163	0.056	0.152	0.139	0.088	0.189
62	0.059	0.096	0.047	0.258	2.997	5.806	0.051	1.355	0.127	8.352	108.407
63	0.070	1.947	0.556	1.915	4.774	1.073	37.385	8.884	0.472	110.597	6596.127
64	0.019	0.002	0.004	0.008	0.180	0.034	0.011	0.549	0.054	0.046	0.241
65	0.075	0.078	0.027	0.209	1.405	1.609	0.283	1.464	0.204	3.778	45.165
66	0.024	0.004	0.004	0.037	0.122	0.198	0.011	0.361	0.040	0.052	4.501

Table 24: The Time cost (s) on datasets [1]-[66] (Part-1).

Dataset Index	S^3COMP-C	k-FSC	AutoSC	DEC	IDEC	DSCN	PICA	ConClu	EDESC	DMICC	DIVC	LFSS
1	0.367	0.127	0.000	22.177	6.709	1.942	2.601	3.154	3.755	4.611	2.888	26.842
2	36.022	5.766	59.031	89.233	26.961	99.336	87.344	218.419	32.250	137.717	82.611	92.551
3	1.705	0.485	0.000	41.495	23.769	13.412	17.754	55.481	4.979	24.462	19.133	31.945
4	2.886	0.593	7.640	30.110	40.996	12.272	27.595	72.871	3.362	38.400	34.201	47.565
5	1.056	0.425	0.000	24.931	11.952	3.257	7.890	61.508	3.256	11.328	9.709	41.427
6	20.139	3.327	0.000	102.749	23.769	93.360	64.472	133.714	10.885	85.429	70.231	45.329
7	0.442	0.801	0.000	21.179	9.735	5.961	5.664	64.553	3.680	8.305	6.547	28.484
8	2.749	1.491	6.932	42.129	8.580	14.923	26.042	67.615	6.456	43.076	30.541	55.918
9	5.147	0.691	4.822	41.764	29.081	10.924	20.481	60.115	5.248	32.969	25.205	27.873
10	7.105	1.951	24.944	84.919	19.259	34.877	50.715	117.728	4.706	74.650	60.013	84.665
11	22.985	1.187	0.000	134.521	43.532	192.212	118.124	332.505	25.502	194.839	139.713	38.302
12	314.263	3.658	413.826	337.317	94.745	806.534	258.272	605.154	30.459	385.828	309.376	101.702
13	0.780	0.237	0.000	35.343	15.665	4.280	9.906	43.955	4.378	15.872	12.437	25.574
14	0.660	0.111	1.234	23.900	14.207	4.329	7.535	25.687	4.888	11.643	9.067	46.283
15	0.784	0.586	0.761	7.266	9.517	12.739	4.974	54.773	2.735	11.669	6.140	29.135
16	8.294	1.568	38.162	100.509	94.745	44.916	59.900	155.041	14.982	82.549	74.572	36.754
17	0.610	0.029	0.858	23.720	9.355	4.077	5.882	60.768	2.390	8.119	6.078	30.096
18	0.864	0.800	0.000	21.057	9.980	3.302	5.023	57.742	3.473	8.165	6.772	29.656
19	252.828	34.940	549.459	463.212	24.071	757.877	247.269	515.042	21.284	376.377	296.739	276.373
20	6.466	0.314	0.000	50.620	32.563	9.043	22.610	69.564	5.681	32.532	20.699	23.841
21	0.696	0.280	0.000	6.432	9.513	2.662	5.015	59.240	3.901	8.070	4.620	50.895
22	0.387	0.432	0.000	15.939	6.995	2.581	2.701	2.351	3.327	4.914	2.681	32.057
23	378.348	2.457	415.643	296.164	89.515	382.810	220.766	540.077	13.213	402.254	219.317	115.389
24	2.957	1.041	3.328	17.986	89.515	4.047	14.434	55.397	4.607	22.623	13.303	40.694
25	18.368	3.496	0.000	78.955	19.649	21.672	49.787	224.092	4.478	83.604	45.233	45.520
26	2.525	3.498	6.963	50.358	8.012	8.353	21.388	61.567	4.096	35.031	22.293	83.714
27	0.565	0.782	0.000	6.404	8.800	9.388	5.215	57.857	4.297	8.359	4.816	32.826
28	298.023	2.604	0.000	270.228	94.296	491.816	245.479	635.500	14.070	389.778	234.521	83.165
29	1.034	0.415	0.000	30.202	15.586	2.540	10.100	69.230	4.210	15.393	9.929	33.310
30	2.859	5.318	0.000	47.941	37.609	8.590	26.645	60.323	4.501	41.011	23.950	79.303
31	0.256	0.475	0.763	22.379	6.210	1.331	2.820	2.193	3.366	4.642	2.483	33.572
32	18.540	1.902	83.622	102.193	37.609	77.150	98.984	262.225	15.462	150.039	94.117	59.418
33	3.531	1.329	4.629	46.033	25.168	11.536	18.237	103.280	6.349	28.630	16.239	71.626
34	3.923	1.235	16.729	67.063	49.040	15.287	36.580	67.344	3.900	52.769	35.032	37.689
35	68.764	6.513	0.000	147.177	23.459	130.153	122.127	382.424	58.164	190.428	114.081	111.224
36	29.145	1.680	54.172	117.570	106.458	61.441	75.989	169.893	11.213	110.043	70.680	76.580
37	5.992	0.680	0.000	29.730	36.596	10.077	23.994	70.594	5.635	38.082	24.343	88.350
38	0.821	0.139	0.000	18.561	9.041	2.066	5.177	50.414	3.542	7.104	4.906	42.715
39	3.561	1.081	0.000	21.140	26.752	9.334	17.142	56.475	2.884	24.420	17.841	34.056
40	156.119	8.283	0.000	381.182	94.384	1048.799	250.300	1124.609	13.583	376.773	236.117	185.872
41	5.800	1.049	6.934	47.662	36.254	11.496	24.156	71.313	5.723	42.144	23.097	61.196
42	43.075	13.857	166.433	276.379	45.900	162.018	146.364	296.794	49.686	190.255	140.324	115.899
43	9.093	1.608	14.692	71.720	51.802	13.662	34.494	62.442	8.578	52.410	33.305	37.213
44	48.188	7.073	95.101	184.010	30.489	175.656	97.735	528.705	8.534	150.237	92.428	161.115
45	9.691	5.703	0.000	70.665	53.472	20.003	36.389	71.834	7.975	56.496	34.973	82.507
46	12.953	1.875	0.000	67.109	64.878	21.156	43.289	96.027	11.048	70.985	44.937	64.303
47	246.482	9.542	0.000	333.316	93.768	550.350	241.384	497.397	14.562	414.421	230.219	137.642
48	2.532	0.525	5.584	25.833	33.251	4.528	22.315	55.214	5.472	36.955	21.299	45.701
49	57.488	2.119	110.257	138.928	43.087	100.902	110.162	304.012	31.522	170.259	108.025	69.671
50	46.074	1.454	28.504	89.857	23.426	36.768	52.186	94.776	14.459	81.031	52.458	51.438
51	6.104	0.492	1.637	29.084	15.772	4.936	9.682	60.871	3.520	15.938	9.780	46.302
52	20.475	2.247	0.000	57.585	18.067	16.974	39.055	100.286	4.264	63.467	37.927	31.079
53	250.064	3.888	0.000	319.244	77.042	720.102	237.725	610.427	14.823	346.115	238.762	77.500
54	0.538	0.135	0.000	22.498	11.471	2.757	7.312	60.383	2.954	11.880	8.125	25.588
55	3.547	0.785	0.000	22.228	9.299	2.927	5.006	51.633	2.957	7.203	4.903	28.464
56	244.532	8.117	487.303	315.048	77.042	873.339	239.411	553.498	48.430	387.511	242.214	192.701
57	414.237	8.693	0.000	309.447	86.277	713.473	223.035	1230.547	40.935	387.723	214.466	146.421
58	6.079	0.313	0.000	53.465	43.012	86.733	26.319	71.149	5.123	35.675	24.942	19.034
59	1.943	1.898	2.255	30.853	18.387	9.865	11.953	71.530	3.320	23.783	11.579	36.301
60	245.363	32.146	0.000	315.097	86.277	937.083	239.262	554.598	76.899	399.541	251.076	174.896
61	1.021	1.336	0.000	20.918	10.898	8.410	7.250	59.745	3.684	19.329	7.642	39.308
62	16.771	0.984	28.194	67.857	20.951	16.552	50.003	129.781	12.907	67.051	52.764	75.960
63	96.237	5.350	219.182	227.453	55.614	150.865	139.646	602.670	9.629	190.008	144.206	112.641
64	1.407	0.167	1.252	29.973	15.476	2.431	9.515	65.248	4.363	14.205	9.711	28.591
65	11.367	3.010	0.000	61.824	54.907	13.548	35.190	213.363	10.594	57.471	36.235	81.221
66	1.384	1.904	1.682	25.348	11.797	2.778	7.418	65.315	4.522	10.630	7.353	44.522

Table 25: The Time cost (s) on datasets [1]-[66] (Part-2).

Dataset Index	KMeans	AggClu	DBSCAN	BIRCH	GMM	OPTICS	SpeClu	MeanShift	k-PC	Affinity	SSC
67	0.028	0.004	0.003	0.012	0.055	0.178	0.048	0.604	0.040	0.061	4.168
68	0.031	0.005	0.004	0.042	0.115	0.210	0.087	0.216	0.072	0.054	6.431
69	0.008	0.001	0.002	0.013	0.069	0.013	0.005	0.171	0.051	0.009	0.143
70	0.015	0.006	0.004	0.048	0.077	0.285	0.127	0.276	0.034	0.104	9.370
71	0.023	0.066	0.045	0.058	0.140	6.204	0.462	1.971	0.196	7.016	87.508
72	0.118	9.083	1.543	5.370	1.668	40.818	71.671	25.334	1.250	558.461	8152.290
73	0.181	2.352	0.733	2.065	12.347	272.430	7.530	9.487	0.942	110.751	2486.083
74	0.021	0.014	0.020	0.084	1.065	0.112	0.344	0.704	0.029	2.562	6.611
75	0.041	0.191	0.051	0.238	0.553	8.369	0.058	1.951	0.132	4.011	35.074
76	0.037	0.008	0.004	0.048	0.187	0.292	0.015	0.306	0.122	0.283	13.764
77	0.021	0.002	0.003	0.021	0.158	0.121	0.045	0.130	0.018	0.016	2.652
78	0.032	0.011	0.005	0.066	0.065	0.342	0.084	0.322	1.038	0.109	74.916
79	0.023	0.013	0.011	0.042	0.086	0.162	0.014	0.563	0.116	1.299	12.491
80	0.105	0.150	0.038	0.472	5.379	5.849	0.337	1.522	0.487	8.760	519.821
81	0.161	0.404	0.041	0.972	2.611	5.834	0.341	2.910	5.263	6.941	2651.364
82	0.330	1.120	0.445	0.632	4.942	18.030	0.500	4.069	0.402	60.053	1662.161
83	0.109	1.459	0.300	2.019	2.942	83.585	11.759	4.479	0.204	79.862	485.065
84	0.242	7.517	1.117	2.070	37.574	532.763	14.782	27.039	6.357	310.988	3110.478
85	0.059	0.063	0.040	0.030	0.709	6.092	0.052	2.050	0.143	5.695	31.054
86	0.360	3.487	1.416	2.278	7.283	628.230	5.224	35.146	1.501	139.177	8020.986
87	0.031	0.024	0.014	0.018	0.117	0.420	0.021	1.061	0.096	1.553	10.484
88	0.126	2.078	0.588	0.951	5.378	56.638	9.741	8.353	0.518	158.136	1974.683
89	0.592	3.296	0.139	4.376	25.399	30.065	2.152	18.995	2.540	47.409	185.288
90	0.772	23.649	0.753	23.746	45.163	364.396	40.511	89.081	6.750	176.260	1998.194
91	5.069	81.334	2.067	72.643	106.137	641.858	10.599	51.214	12.349	394.553	2569.169
92	0.032	0.012	0.007	0.109	0.146	0.602	0.014	0.420	0.084	0.295	1.089
93	0.065	0.098	0.033	0.310	0.567	3.528	0.043	1.724	0.156	5.214	60.541
94	0.253	4.509	1.451	0.345	0.792	19.332	17.925	31.434	0.182	138.731	5811.314
95	0.534	1.511	0.011	3.203	1296.898	0.602	0.361	13.580	0.351	4.643	6.240
96	0.029	0.091	0.059	0.359	0.812	0.094	0.046	1.544	0.078	12.257	33.344
97	0.689	3.179	0.046	5.311	87.149	8.339	3.794	24.544	1.339	9.371	82.107
98	0.065	0.192	0.045	0.367	3.058	5.788	0.526	1.445	0.469	11.748	36.287
99	0.040	0.037	0.012	0.079	0.404	0.825	0.156	0.594	0.068	0.603	3.040
100	0.156	0.053	0.005	0.480	13.217	0.372	0.016	0.881	0.308	0.171	1.122
101	1.569	16.059	0.653	21.128	18.467	305.332	13.609	145.011	7.354	64.906	1142.617
102	0.099	1.213	1.151	4.895	0.673	2.751	6.995	25.970	0.395	212.739	2812.276
103	0.264	1.453	1.181	0.167	1.049	630.629	222.240	14.262	2.894	403.997	324.547
104	0.052	0.060	0.014	0.179	1.529	1.446	0.162	0.606	0.150	2.744	5.417
105	1.012	21.396	1.135	24.394	14.672	646.262	8.691	140.585	9.857	208.848	2768.614
106	0.397	2.543	0.112	3.672	6.386	20.028	0.806	41.887	2.496	18.336	169.391
107	0.682	20.226	1.154	23.673	63.514	635.603	3.549	254.321	8.872	108.639	2788.326
108	0.981	3.449	0.143	4.132	9.815	25.075	0.161	44.930	2.386	21.782	171.150
109	0.691	21.329	1.045	21.789	12.803	640.593	18.242	92.121	8.329	151.105	2724.846
110	0.157	0.263	0.023	0.566	4.865	2.096	0.715	3.189	19.503	4.450	14.278
111	0.202	0.312	0.023	0.717	6.508	2.414	0.462	2.523	2.652	1.723	14.680
112	1.308	11.284	0.054	10.713	15.048	9.399	2.412	10.257	1.295	34.247	41.574
113	0.506	0.417	0.013	0.810	39.716	1.024	0.021	4.692	0.727	2.360	4.368
114	0.470	0.203	0.008	0.378	15.078	0.617	0.015	3.810	0.358	1.186	3.257
115	0.965	25.350	0.010	24.479	20.450	0.634	23.234	1.048	0.407	1.010	1.938
116	0.286	8.016	1.256	9.716	29.924	451.806	1.556	39.075	8.301	97.094	1660.810
117	0.219	1.903	0.627	0.735	1.365	178.842	2.263	8.475	0.743	76.081	2286.553
118	0.786	0.200	0.007	0.423	1045.199	0.306	0.025	4.323	0.879	0.153	0.873
119	0.097	0.258	0.013	1.161	11.451	1.217	0.519	2.302	0.801	1.711	12.991
120	0.164	2.051	0.131	2.990	6.983	25.113	0.147	8.872	1.827	33.556	91.778
121	0.034	0.382	0.158	0.939	3.847	6.790	1.695	2.893	0.432	25.949	389.976
122	0.021	0.490	0.076	1.073	0.980	4.017	4.770	2.487	0.523	31.285	136.807
123	0.026	0.115	0.013	0.715	1.182	0.872	0.093	0.999	0.164	2.451	9.655
124	5.078	171.064	1.129	194.480	1024.369	635.580	164.548	46.693	11.838	538.897	2991.328
125	3.320	178.808	2.934	111.498	292.325	646.709	2.232	61.516	6.871	427.106	3716.442
126	1.617	73.614	0.545	84.873	195.329	184.604	16.516	25.666	7.535	179.785	1625.346
127	9.698	172.163	1.175	210.256	1755.463	630.454	2.156	79.402	11.280	670.174	3392.056
128	3.099	176.738	3.325	165.215	763.302	319.293	115.985	108.861	10.660	531.712	1896.369
129	163.057	1190.028	14.069	965.166	2059.787	567.507	2.502	119.592	6.783	2573.199	6479.839
130	6.545	186.351	2.205	198.558	6362.279	46.631	6.490	44.564	2.619	425.023	194.256
131	78.143	600.573	0.988	574.892	18787.872	346.752	68.886	65.962	6.863	111.995	1714.213

Table 26: The Time cost (s) on datasets [67]-[131] (Part-1).

Dataset Index	S^3COMP-C	k-FSC	AutoSC	DEC	IDEC	DSCN	PICA	ConClu	EDESC	DMICC	DIVC	LFSS
67	6.095	2.390	1.713	13.033	16.182	4.704	9.612	65.390	3.236	15.737	9.817	52.855
68	0.899	0.754	1.455	31.460	15.729	2.586	9.578	67.219	4.896	14.164	9.761	69.202
69	0.736	0.135	0.691	21.942	8.547	2.540	4.916	60.014	2.418	7.063	4.992	50.620
70	1.130	0.802	1.598	28.911	13.961	2.354	9.740	62.549	4.583	18.149	9.764	53.517
71	49.596	1.044	28.739	80.754	74.034	48.738	51.575	279.547	9.723	78.473	52.057	62.405
72	224.471	5.314	0.000	351.963	94.820	571.097	238.337	551.744	16.219	377.805	234.808	77.654
73	150.134	17.109	289.949	308.578	70.758	478.766	185.164	366.898	11.930	289.247	178.357	247.280
74	7.625	0.581	0.000	36.537	94.820	9.937	28.712	76.357	3.415	39.375	28.792	41.870
75	8.369	1.963	0.000	87.545	70.758	33.450	56.308	138.544	14.410	92.362	54.193	92.363
76	1.032	1.675	0.000	29.006	11.212	2.690	10.121	65.098	4.648	19.919	9.854	61.823
77	0.502	0.816	0.000	8.813	8.323	1.949	5.321	61.787	3.817	6.713	4.693	30.904
78	5.894	0.892	2.538	13.212	5.030	9.305	10.188	58.736	3.280	17.046	9.375	29.884
79	3.933	0.231	0.000	22.816	30.433	6.517	19.041	67.998	4.828	26.860	18.149	31.899
80	17.391	5.578	0.000	82.856	5.030	30.769	49.501	282.547	5.778	88.101	45.574	156.487
81	19.567	9.606	28.008	62.262	19.161	30.817	49.912	123.368	5.885	86.719	46.486	84.899
82	85.051	5.793	0.000	176.123	51.030	233.320	133.423	510.666	41.041	205.304	125.380	79.874
83	66.167	3.649	130.225	156.066	39.534	112.088	119.628	279.523	22.464	167.113	122.487	108.287
84	268.529	17.316	0.000	314.355	77.356	702.740	247.208	555.431	15.177	372.923	237.461	181.722
85	17.838	4.603	0.000	77.940	15.875	82.301	47.523	279.895	5.934	67.723	46.105	95.161
86	444.890	28.734	482.052	434.524	93.463	497.616	239.080	603.763	15.082	374.421	231.593	295.440
87	3.246	2.297	0.000	50.579	11.630	9.322	26.064	65.514	5.957	42.024	24.612	54.184
88	145.100	12.562	0.000	227.377	46.821	398.489	147.066	636.304	10.888	238.700	131.656	99.241
89	94.929	25.558	84.225	163.467	28.974	57.450	85.803	238.476	8.557	142.289	76.593	93.839
90	747.463	22.577	384.139	366.632	79.425	757.833	201.796	415.066	13.671	283.880	188.653	429.988
91	920.422	23.579	0.000	386.530	101.593	442.883	250.263	499.519	111.128	395.012	229.945	338.776
92	4.160	2.436	3.988	18.847	6.926	4.663	14.544	61.723	3.658	23.104	13.685	79.602
93	17.812	3.311	0.000	75.340	18.289	9.597	43.068	123.335	11.872	66.684	38.473	48.807
94	791.076	1.463	475.280	268.404	89.843	472.955	246.187	541.834	14.380	338.915	220.275	85.856
95	9.191	7.152	5.493	48.622	11.462	5.702	19.809	14.124	5.190	35.372	18.530	114.968
96	7.001	0.882	0.000	52.852	18.620	13.676	47.371	124.314	4.502	76.607	44.228	32.113
97	10.543	16.406	0.000	94.291	24.658	30.290	55.091	139.147	13.386	104.469	51.316	107.498
98	21.763	3.474	0.000	84.626	18.851	58.076	49.193	281.117	5.891	79.624	44.392	233.757
99	2.439	0.767	5.233	23.975	7.954	3.565	21.032	93.231	5.988	39.990	19.771	42.061
100	6.281	8.071	2.853	12.360	5.320	3.184	10.187	63.810	5.476	16.539	9.287	60.190
101	324.162	76.093	0.000	221.483	64.253	1223.510	196.766	364.010	17.696	311.561	174.968	500.888
102	204.229	12.238	470.114	324.943	90.306	285.491	235.982	554.547	72.227	328.798	217.935	93.160
103	274.903	97.995	0.000	442.398	76.917	809.316	236.566	570.124	18.912	331.701	213.124	120.934
104	7.664	1.130	0.000	55.324	13.060	18.371	27.112	23.036	4.573	40.718	23.951	98.018
105	437.735	50.094	0.000	278.293	95.029	464.973	251.182	570.963	96.058	388.483	224.819	195.596
106	17.267	22.845	67.111	132.796	30.504	92.989	75.804	119.075	23.859	117.212	68.058	156.577
107	404.795	40.005	0.000	384.618	79.122	426.696	249.461	573.656	17.409	375.267	221.887	165.412
108	155.180	23.982	0.000	94.491	34.702	106.886	83.962	450.711	8.363	142.143	73.475	228.707
109	410.232	28.684	428.845	276.364	93.984	550.955	251.640	581.243	87.851	382.977	223.125	399.949
110	7.121	13.498	0.000	62.648	12.396	48.339	36.805	195.046	8.146	70.052	33.639	93.492
111	17.958	17.562	20.665	61.757	12.312	56.599	36.874	196.161	7.959	76.063	33.204	94.563
112	0.000	2.075	30.844	81.698	31.664	52.177	59.891	140.613	5.899	89.220	56.010	107.522
113	20.463	9.555	9.422	50.691	11.071	18.815	24.844	66.863	5.033	39.230	23.025	126.061
114	11.600	10.039	0.000	23.461	9.637	6.919	19.841	13.352	4.556	31.808	18.077	121.681
115	7.913	5.586	0.000	42.483	7.626	10.266	20.514	62.559	3.700	30.361	18.116	58.103
116	293.745	16.828	322.713	329.341	69.757	330.215	221.367	815.046	61.027	408.579	198.830	118.480
117	232.412	3.866	176.196	172.417	59.510	200.503	160.510	287.845	10.462	249.816	143.502	64.234
118	0.000	13.714	0.000	34.350	5.238	6.285	10.774	9.233	10.036	19.091	9.822	185.198
119	28.284	6.740	12.767	55.560	11.560	21.940	28.397	22.334	5.070	45.296	25.037	111.847
120	143.237	5.120	61.209	145.417	32.810	29.927	83.469	214.569	24.023	137.591	74.554	51.986
121	15.384	2.301	98.462	90.691	27.023	133.594	78.469	103.791	6.170	115.750	73.288	116.271
122	30.317	2.392	58.426	103.211	23.038	74.481	66.993	315.970	5.845	97.363	61.992	54.248
123	8.995	1.043	0.000	44.565	8.076	8.457	22.995	55.419	5.934	37.490	20.043	43.650
124	722.267	45.054	614.958	505.053	103.687	574.906	269.685	598.663	96.909	406.847	237.910	677.024
125	180.650	10.899	622.722	398.814	99.108	450.410	270.414	1109.282	42.162	389.016	235.541	258.810
126	502.201	15.848	383.468	270.644	65.986	367.189	186.832	1074.034	43.383	346.717	161.079	123.138
127	894.238	55.072	1446.632	346.666	119.516	668.339	266.735	516.649	23.319	368.011	239.869	403.312
128	139.133	31.994	0.000	328.224	397.632	345.830	236.922	431.006	20.772	299.296	218.689	274.354
129	236.394	76.186	1401.179	1247.324	436.283	750.081	413.133	610.585	89.354	560.993	423.782	639.779
130	23.578	5.235	150.481	572.408	121.890	111.331	145.200	314.410	30.899	197.983	137.241	250.686
131	139.198	41.039	1008.241	1052.915	205.081	403.822	319.091	420.152	124.930	494.253	290.539	874.117

Table 27: The Time cost (s) on datasets [67]-[131] (Part-2).