An Overview Of Clustering Methods: From Hard Partitioning To Advanced Soft Clustering

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***Abstract*—This research reviews different methods of clustering. The aim is to find a proper method of clustering for classification. For the aim, performance and application of each method have been investigated. It is found that the use of a method depends on its application. Performance of each method as well as advantages and disadvantages of each method has been collected. Some other useful remarks regarding each method have been noted.**

Keywords—* *clustering; supervised; fuzzy; classification

I. Introduction

Clustering is the job of dividing the data points into a number of organizations such that data points in the equal organizations are similar to other data points in the same organization than those in other organizations (Daneshwar 2014,2015). Simply, the aim is to separate organizations with alike traits and cast them into clusters.

To comprehend this with an example, assume, you are the manager of a rental property and wish to know the preferences of your buyers to scale up your marketing. Is it reasonable for you to look at aspects of each customer and create a unique business plan for each one separately? Surely no. But, the thing that you can take is to cluster all of your costumers into for example 10 sets based on their buying practices and use a different plan for costumers in each of these 10 sets. This is what we call it clustering. Thus, we know what clustering is. Let’s take a glance at the kinds or types of clustering.

Clustering, in Data Science, can be utilized for analysis to obtain some precious insights from our data by viewing into what group, data points fall into while clustering algorithm is applied. Nowadays, we look at 5 common clustering algorithms which data scientists want to understand their pros and cons.

Furthermore, fuzzy clustering generalizes partition clustering approaches (medoid as an example) by letting one to be somewhat categorized into more than a single cluster. In normal clustering, each one is a member of only a single cluster. Assume that we have K clusters and we characterise many variables that represent the possibility that something is grouped into cluster k. In distribution clustering algorithms, a single of these states will be a single one, and the rest will be nothing. This describes the case that these algorithms assign an individual into one and only a single cluster. In fuzzy clustering, the association is widespread between all clusters. This now can be between zero and one, with the requirement that the total of their values is one. We call this case a fuzzification of the cluster arrangement. It has the benefit that it does not make everything into a particular cluster. It has the drawback that there is much more data to be translated.

Mostly, clustering methods are unsupervised approaches that can be utilized to classify data into groups-based on relationships among the different data objects. majority of clustering algorithms do not rely on premises simple to conventional statistical techniques, for instance, the underlying demographic division of information, and hence they are useful in spots where little prior experience is available. The potential of clustering algorithms to show the underlying constructions in data can be utilized in a wide range of uses, including categorization, image processing, pattern identification, modelling and identification.

II. Literature Review

Fuzzy clustering has been the heating topic of many recent studies in the field. Scholars have investigated it in various ways and using different methods. It has been the topic of comparative and innovative investigations as well. Fuzzy clustering which is very common in the current days has made it to be seen multidimensionality through different approaches. Studies also show that fuzzy clustering is in high implementation for variety of aspects including medical tools. The following review outlines the most recent studies conducted in this regard:

Saberi H, et al (2017) state that modelling the complicated systems requires large number of FLRs which needs high runtime to train FTS algorithms. In their study they, they introduce (FEFTS) a fast and efficient clustering-based fuzzy time series algorithm in order to handle the deterioration, as well as classification snags. They think that the advantage of FEFTS algorithms over other kinds of FTS algorithms regarding the terms of runtime, training and testing errors is established by putting the algorithm to various benchmark datasets which can be found on the internet. They find that that FEFTS decreases testing RMSE for deterioration data around 40% with the smallest runtime. They also conclude that FEFTS reduces runtime noticeably from 324.33 Sec to 0.0055 Sec. This indicates that there are numerous ways in which fuzzy clustering is taken into consideration and can be studied differently for different purposes. It is also important for researchers to take varieties of fuzzy clustering while doing new experiments.

The iterative BSP chart processing framework is utilized in this study for the execution of off-line batch processing of half-structured chart data. Graph or chart makes iterative calculations on the topmost of the Hadoop cluster. This is achieved by getting away from pricey disk and network actions mandatory in map-reduce framework utilizing outside the core in-memory actions. (Saberi, Rahai, & Hatami, 2017)

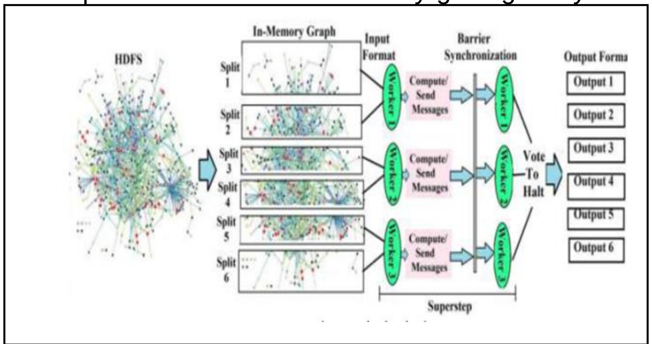

Figure 1: graph processing steps proposed by Saberi, Rahai, & Hatami, 2017.

Regarding the use of fuzzy clusters for the purpose of patterning and graphs, Bhatia and Rani (2017) in their study indicate that clustering is generally used to discover existing parallel patterns in graphs. In this way it is helping to gain valuable insights. They say that in real-world, nodes might be of many clusters, that’s why it is important to study fuzzy cluster membership of nodes. Older central fuzzy clustering algorithms acquire higher cost. They also order a product with lower quality of clusters especially in case of usage for large graphs. That’s why scalable solutions are compulsory for holding vast amounts of data in a fewer computational period. For this purpose, they proposed a parallel fuzzy clustering algorithm which was named ‘PGFC’. It is used for resolving scalable graph data. Having a clustering algorithm is advantageous which can certain the scalability with better quality in clusters for resolving vast graphs. Their proposed algorithm is parallelized through implementing bulk synchronous parallel (BSP). Degree supremacy measure is used for initializing, which the consequences are fewer in iterations. The performance of PGFC is opposed to other cases of art clustering algorithms. Their study conclusions show that the proposed PGFC increases linearly to resolve large graphs through better quality of clustering. In this sense, it can be inferred that fuzzy clustering can process high algorithms and it can resolve graphs having immense data with high quality in the result. (Bhatia & Rani, 2017, Tavoosi,2012).

In another study on fuzzy clustering, Yang and Tian (2015) believe that the fuzzy c-means (FCM) algorithm is the most frequently used clustering method compared to other methods. In their study, they propose a bias-correction term accompanied by an equation to alter the impacts of initialization processes on the fuzzy clustering algorithms. They propose bias-correction fuzzy clustering, this fuzzy clustering is from the mentioned generalized FCM algorithm. Later they construct the algorithms of bias-correction Gustafson and Kessel clustering, bias-correction FCM, and bias-correction inter-cluster separation. Then they compare the proposed algorithms with other algorithms through utilizing numerical instances. They apply bias-correction fuzzy clustering algorithms as well to actual data groups. They conclude that proposed bias-correction fuzzy clustering methods get preeminence and efficiency. In this study it is inferred that bias-correction is in high importance for fuzzy clustering and it can be taken into consideration when for data sets and utilizing numerical instances. It is also important that generalized fuzzy clustering also is implemented in different regards. (Yang & Tian, 2015)

For the general purpose of image segmentation and fuzzy clustering plays a role as well. For this purpose, in their study, Pei, et al (2017) define fuzzy c-means algorithm (FCM) as an influential clustering algorithm and indicate that it is broadly utilized in image segmentation. In the FCM, each of the parameters of the number of clusters and the preliminary membership matrix should be specified in the beginning, their impact on the clustering performance is deadly huge. For their study they propose a new mass of fuzzy c-means algorithm (DFCM)via presenting density for each instance. The density summits are utilized to limit the number of clusters and the preliminary membership matrix mechanically. They come to a result benchmark datasets and medicinal image segmentation data groups quite obviously show proficiency and influence of our D-FCM. (Pei, Zheng, Wang, Li, & Shao, 2017)

We reside prototypes in the feature space, in contrast with MKFC, where prototypes are established in the kernel space. Two different models are shown in Fig. 1 [58]. Jezewski, et al (2018) in a study, propose a fuzzy classifier that its regulation antecedents are found on the basis of the modern approach of Clustering with Pairs of Prototypes (CPP). When the supreme generalization capacity of the classifier on 6 different benchmark datasets, it resulted in a special focus on the program to assist fetal condition evaluation on the basis of classification of cardiotocographic (CTG) signals. The CPP advancement was gained via applying the Fuzzy Clustering with ε-Hyperballs (FCεH) like basal clustering.

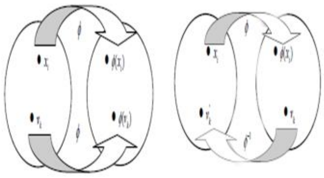

Fig.2: Feature space and kernel space of (a) MAFC and (b) MKFC

They compare the study results were with 3 methods, the consequences indicate high precision of the CPP-based fuzzy classifier during evaluating different sorts of data. Thus, they think that such a resolution has a positive effect on other investigations on intelligent systems. This indicates that fuzzy clustering in some ways is important and it has positive indications for intelligent systems. Thus, it is a good choice to depend on the sorts of fuzzy clustering in this regard as studied in the mentioned research article. (Jezewski, Czabanski, Leski, & Jezewski, 2019). Fuzzy clustering is covered in many recent studies and it is liable for new approaches. Xu (2017) conducted a study about proposing a novel centroids clustering algorithm for categorical data. It is obvious that most of the clustering algorithms are modelled as optimization issues, in which interior clustering functions are used like a mean to detect optimum partitions. Though, majority of approaches consider a sole criterion which can only be functional for finding the specific structure and distribution of information. To surpass such issues, Xu proposed a novel many objective fuzzy centroids clustering algorithms for definite data-consuming orientation point that is based on non-dominated categorization genetic algorithm. He employs operative fuzzy centroids algorithm to project the planned method. This method is different from other k-modes-type methods. In this way, in the study, experiments on numerous data groups validate the dominance of the proposed algorithm over other state-of-the-art approaches regarding the clustering correctness and stability. He sums up by detecting that their method can find clustering numbers if defined in advance with a specified clustering resolution. (Zhu & Xu, 2018)

Fuzzy Clustering has other important implementations in many aspects. There is a medical ray tool called Magnetic Resonance Image (MRI). It processes and analyses, but Kong et al. (2018) think that segmentation methods have been employed for brain Magnetic Resonance Image (MRI) processing and analysis, the performance is unsatisfactory by the system, due to the peculiar features in the brain. These researchers present a new interactive spatial fuzzy clustering (ISFC) algorithm to produce 3D super voxels that are basics of the MRI volume of brain. After certain examinations and they propose spatial fuzzy clustering to accumulate for the overall MRI volume, they found that performance of the proposed algorithm is assessed in two datasets. They come to the result that the proposed algorithm is able to be implemented many brain MRI processing and analysis. the following are the most prominent ones which this approach can be applied; functional parcellation, tissue segmentation, tumour detection and segmentation, and registration. (Kong et al., 2019)

There are studies show that fuzzy clustering procedures are typically data-driven. Tang et al. (2018) conduct a study for modelling novel fuzzy clustering algorithm derived by DVPFCM (stands for Density Viewpoint-induced Possibilistic Fuzzy C-Means). After certain comparisons and considerations, they do some experiments. They come to the conclusion that the DVPFCM algorithm is better in numerous diverse ways regarding the clustering centres and values in the performance indexes. They also conclude that this displays higher presentation in defining the distance between the calculated clustering centres and the orientation centres. (Tang, Hu, Pedrycz, & Song, 2019)

In a study, Das and Sil (2009) present a (DE) algorithm for clustering the pixels of an image in the grey-scale concentration space. Such algorithm entails no former information on the amount of naturally happening clusters in that image. They implement a kernel made resemblance measure as an alternative of the conservative sum-of-squares distance. Thus, a new search-variable depiction scheme is adopted for choosing the ideal amount of clusters from many possible selections. They conclude that the proposed algorithm has an edge over a few state-of-the-art algorithms for automatic multi-class image segmentation. (Das & Sil, 2010)

In a different kind of study, Wang et al. (004) propose that a feature-weight assignment can be observed as a generalization of feature determination. In a way, if all values of feature weights are either 1 or 0, its assignment reprobates to the distinct case of feature selection. Then, in their paper, they show that a suitable assignment of feature-weight can advance the performance of fuzzy c-means clustering. The Experiments made on some UCI databases prove the enhancement of performance by the fuzzy c-means clustering. (X. Wang, Wang, & Wang, 2004)

Although many fuzzy c-means clustering techniques were industrialized to end many problems in amount of areas like pattern recognition, image examination and data mining, Staiano et al. (2005) describe a new approach to fuzzy clustering. They establish the data in clusters on the base of the input data as a summary of the amount of lined local regression models. Their methodology shows to be operative in the training of RBFNNs leading to enhanced performance. (Staiano, Tagliaferri, & Pedrycz, 2006)

Skarmeta et al. (1997) present a substitute approach to produce fuzzy rubrics with a practical resulting associated to the TSK fuzzy model. In their study, in using fuzzy clustering algorithms, they analyse diverse methods to produce the related fuzzy rubrics using in multidimensional orientation fuzzy groups in the product space of the input variables. They find that the rules being produced resemble a TSK fuzzy model. (Gómez-Skarmeta, Delgado, & Vila, 1999)

Setnes (2000) conducts a study that is concerned with the implementation of orthogonal transforms and fuzzy clustering to excerpt fuzzy rules from data. The researcher tends to use the orthogonal least squares approach to oversee the development of the fuzzy clustering algorithm and eliminate clusters of less significance. This method is generally appropriate to the fuzzy -means and connected algorithms. It is concluded that the distance norm fuzzy clustering used to identify Takagi–Sugen type rule, a synthetic sample and a real-world modelling problem are measured to exemplify the working and the applicability of the algorithm. (Setnes, 2000). Researches indicate that many parameters such as routing protocol, average speed of mobile nodes, mobility pattern etc. affect the end-to-end packet postponement in mobile ad hoc network. Nonetheless the nature of connection among end-to-end postponement and such parameters is still not clear. Yang (2019) proposes a new method to forecast the end-to-end postponement; the automatic clustering algorithm is used to produce intervals. later, the difference magnitudes are utilized to produce fuzzy variation datasets. Finally, the predicted difference can be gained by the masses of the fuzzy variation and at last forecasting is made. According to the performance assessment standard, it is concluded that value of the presented approach gives acceptable packed postponement forecast in ad hoc network. (Yang; 2019). Nowadays when the usage of large-scale application of power lithium-ion battery is widespread, (SOF) technology of power lithium-ion batteries became the core of interaction by designers. Wang et al. (2019) select the variables connected to SOF to conduct the fuzzy inference system. They are optimized by the fuzzy c-means clustering procedure, to estimate the SOF of the powerful lithium-ion battery. Later the relations is found by experiment. The conclusions show that results demonstrate the possibility and benefits of the approximation strategy. (D. Wang, Yang, Gan, & Li, 2019). Classification process of the sample set (D. Wang, Yang, Gan, & Li, 2019).

Wen et al. (2018) propose an enhanced K-means algorithm to advance the efficiency and usefulness of ECD. They tend to use principal component analysis (PCA) to decrease the scopes of smart meter time sequence and the original cluster centres were enhanced. After their experiment, they come to a result that the shape-based clustering approach can efficiently detect parallel shapes and classify distinctive electricity consumption designs based on everyday ECPs. (Wen, Zhou, & Yang, 2019). Babuska et al. (2002) conduct research about two techniques for advancing the calculation of the fuzzy covariance matrix in the clustering algorithm of Gustafson Kessel. The researchers found that the advancement is obtained through fixing the ratio between the maximum and minimum values of covariance matrix as the first part of the technique. Secondly, the technique can extract the Takagi–Sugeno models from data. In this way it decreases the harms of overfitting when the number of samples is low compared to the clusters. The proposed techniques are thus, demonstrates the benefits.

Lesot and Kruse (nd) conduct a paper on the typicality degrees as a supervised learning tool for making typical representatives in information or data categories.in their study they propose an extension in the typicality degrees in the unmonitored learning environment for doing clustering. Their proposed algorithm establishes a Gustafson Kessel modification in which it may be possible to recognize ellipsoidal clusters.

Jaina and Shukla (2012) perform a study on the Fuzzy Relational Database and its. Retrieving the data from the fuzzy database, Fuzzy Structured Query Language (FSQL) is used since traditional Structured Query Language (SQL) is not adequate for managing indeterminate queries. Their proposed model is useful for newbies in retrieving relevant results of the non-crisp queries. This stud also uses a fuzzy clustering algorithm which is based on Gustafson-Kessel. The Gustafson-Kessel is required as the results may be unstable. The results of the study show that the algorithms used together are on the basis of cluster validity measurements that show Gustafson-Kessel algorithm performs much better than Fuzzy C-Means fuzzy clustering algorithm.

Son and Hai (2015), in their study, propose a new multiple fuzzy clustering approach which is based on internal clustering validation measures with gradient descent. The algorithms like Fuzzy C-Means, Kernel Fuzzy C-Means and Gustafson–Kessel are implemented as well for building similarity matrixes for each division. Also, those similarity matrixes are combined to a single one through the means of the straight aggregate of weighted vectors. Lastly, the final membership matrix is intended by minimizing the aggregate of square faults by the gradient descent approach.

The proposed method is thus validated in terms of clustering quality in the UCI Machine Learning Repository datasets. The results of their study show that the proposed method is performing much better than any other method lonely.

Table 1: Advantages and disadvantages of a different method of clustering.

NO	References	year	Advantage	Disadvantage
1.	Bhatia, V., & Rani, R. (2017).	2017	In dispersed environments, the PGFC (approach) may gage up very well to hold large charts/graphs by high-speed up.	This cannot make both types of soft and hard clustering. It needs more processors for larger graphs.
2.	Das, S., & Sil, S. (2010).	2010	It can automatically detect the optimal number of clusters. This approach also performs state-of-the-art fuzzy clustering policies like FVGA, KFAC over several image datasets statistically.	The negative side is that the proposed approach is affected by the neighbourhood topologies.

3.	Gómez-Skarmeta, A. F., Delgado, M., & Vila, M. A. (1999).	1999	This study shows new alternatives for fuzzy modelling by utilizing fuzzy clustering algorithms and approaches that are simple and effectual.	Not found
4.	Jezewski, M., Czabanski, R., Leski, J. M., & Jezewski, J. (2019).	2019	This approach obtains a great generalization maintaining the opportunity of understanding the learning consequences. This resolution has an optimistic influence on other investigations on intelligent systems.	A large number of parameters in which their values require to be found through experimental investigations, that may need a lot of time and effort or be a hard process. Also, the number of fuzzy rubrics may be quite high, and this might delay linguistic interpretations.
5.	Kong, Y., Wu, J., Yang, G., Zuo, Y., Chen, Y., Shu, H., & Coatrieux, J. L. (2019).	2018	the proposed algorithm of this study can be applied for the majority of brain MRI processes and examinations such as tissue separation, tumour discovery and separation, practical parcellation and registration.	the approach that is proposed in this study needs a quite lengthy computational time consumption. The new perspectives of this study might lead to new ways to perform the super voxel data.
6.	Pei, H.-X., Zheng, Z.-R., Wang, C., Li, C.-N., & Shao, Y.-H. (2017).	2017	The proposed D-FCM is very efficient and effective. D-FCM not merely improves accuracy but also can cluster effectively and reduce the number of clustering iterations.	The initial membership matrix which is used with this algorithm may affect clustering results.
7.	Saberi, H., Rahai, A., & Hatami, F. (2017).	2017	This method improves the average percentage accuracy by 1.5%. Also, the runtime of FEFTS is negligible as compared to other algorithms.	Other methods to be implemented to handle the problem classification.
8.	Setnes, M.	2000	The implementation of orthogonal transforms and fuzzy clustering for mining fuzzy rules detects and removes less significant clusters. The supervised algorithm proved more efficient than a trial-and-error method	This method needs to be implemented in the real-world example to a more precise result.
9.	Staiano, A., Tagliaferri, R., & Pedrycz, W. (2006).	2006	The methodology used in this study is effective in the training of RBFNNs that cause enhanced performance.	This does not represent an initial model in order to reduce the approximation error. It cant get the best value for the parameter.
10.	Tang, Y., Hu, X., Pedrycz, W., & Song, X. (2019).	2018	This displays a higher presentation in defining the distance between the calculated clustering centres and the orientation centres.	Other areas, such as image segmentation, mechanical fault detection, need a further application of the DVPFCM algorithm. The performance needs enhancement.
11.	Wang, D., Yang, F., Gan, L., & Li, Y. (2019).	2019	It can automatically detect the optimal number of clusters. This approach also performs state-of-the-art fuzzy clustering policies like FVGA, KFAC over several image datasets statistically.	The negative side is that the proposed approach is affected by the neighbourhood topologies.
12.	Wang, X., Wang, Y., & Wang, L. (2004).	2004	UCI databases validate the improvement of the performance of fuzzy c-means clustering.	the proposed WFCM needs to be extended to a sensitivity study of the performance of FCM to the selection of distance metric.
13.	Wen, L., Zhou, K., & Yang, S. (2019).	2019	This study is helpful for researching to analyze and model the delay parameter for MANET in a better way.	Some aspects of this method need improvement such as computational and the forecasting of multi-factor problems. It may fail sometimes when it deals with real-world problems.
14.	Yang, M.-S., & Tian, Y.-C. (2015).	2015	The proposed algorithm is very effective with real data.	It cannot be robust against initializations and become an extremely effective seeking algorithm without using the bias-correction idea to construct a bias-correction PCM
15.	Zhu, S., & Xu, L. (2018).	2018	The implementation of orthogonal transforms and fuzzy clustering for mining fuzzy rules detects and removes less significant clusters. The supervised algorithm proved more efficient than a trial-and-error method.	This method needs to be implemented in the real world example to a more precise result.
16.	Babuska et al.	2002	The reduction of the risks of overfitting with low sample data.	The low sample data may affect the performance.
17.	Lesot and Kruse (nd)		it can establish the Gustafson Kessel variant.	A more comprehensive study of the algorithm is necessary to validate the results. As typicality degrees are based on a crisp partition, this creates limitations.
18.	Jaina and Shukla	2012	handling fuzzy databases.	without using the Gustafson-Kessel algorithm the results are less stable.
19.	Son and Hai	2015	the proposed method is very good in performance. It also enriches the knowledge of deploying clustering algorithms in ensemble environments. Also, it can be applied to various pattern recognition problems.	the new method did not show how many single clustering solutions. The order of single solutions was not taken into account. More numbers of internal clustering validation measures should be used for accuracy.
20.	Wang et al.	2019	Reducing the mean error of estimation, and it is advantageous for easy implementation, fast response and much room for improvement in the future	Non-independent results.
21.	Wen et al	2018	The shape-based clustering way can excellently find similar shapes and identify typical electricity consumption patterns based on daily ECPs. This study is highly significance for residents, electric companies and the government.	Not found

III. CONCLUSION

In this paper, various methods of clustering have been reviewed and investigated. It was found that previous methods were based on some assumptions as well as applications and thus their judgments are not reliable when the assumptions were not satisfied. From this study too, it is seen that numerous methods of clustering are available but no single method is able to handle all issues and requirements. For the future researches, hybrid methods can be considered to cope with different applications.

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