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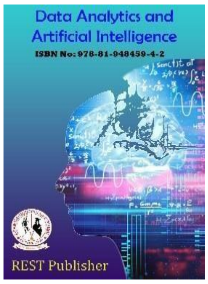

Optimizing Big Data Analytics, a Systematic Assessment of Clustering Techniques Through EDAS Methodology

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Abstract: *This research provides an in-depth evaluation of big data analysis methods using the EDAS (Estimation Based on Distance from Average Solutions) framework. As data volumes continue to rapidly expand, choosing the most appropriate analytics approach has become increasingly important for organizations looking to extract valuable and actionable insights. This research analyzes five widely used clustering algorithms on four key evaluation metrics - Expectation Maximization (EM), Farthest-First (FF), Filtered Clustering (FC), Hierarchical Clustering (HC), and Make Density-Based Clustering (MD). By using the EDAS method, normalized decision ranks and preference scores were generated to evaluate the performance. Among the methods, despite the varying individual metric performance, EM ranked the highest overall (preference score: 0.56843). FC followed with balanced and consistent performance (0.54032), and FF came in third place (0.51761), outperforming RI and Jacquard scores. Interestingly, HC recorded the highest scores in ARI (98.23) and almost perfect Jacquard values (96.34), but ranked the lowest in overall preference (0.46742), emphasizing the need for a complete set of evaluation criteria. The findings suggest that method selection should be aligned with the specific priorities of a use case: EM and FC are best for balanced performance, while HC and MD are best suited for situations requiring high clustering accuracy. This research provides a comparative view of clustering methods in the EDAS context, which assists practitioners and researchers in making data-driven decisions and encourages further exploration into domain-specific or hybrid clustering strategies. Keywords: Big Data Analytics, EDAS Methodology, Clustering Algorithms, Performance Evaluation Metrics, Multi-criteria Decision Analysis*

1. INTRODUCTION

Researchers are increasingly exploring emerging technologies to effectively analyze big data and extract useful information. This paper examines various big data analytics methods, including social media, text, video, and audio analytics. It also highlights key challenges related to data manipulation, processing, and management. In addition, this paper discusses batch and stream processing approaches, the technologies that support each, and the potential benefits of integrating the two.. [1] Essentially, it brings together two key elements – big data and analytics – that together have shaped one of the most important developments in modern business intelligence (BI). To better understand this concept, it is helpful to first define what advanced analytics entails, followed by an exploration of big data and how its integration drives impactful insights. [2] This study focuses only on Twitter as a source of big data and does not aim to cover all the challenges typically associated with big data analysis. However, it emphasizes processing a series of tweets, as opposed to Hardtop, which handles data in a batch manner. [3] Within these frameworks, partitioning and sampling play a key role in scaling and accelerating big data analytics algorithms. This article provides a brief overview of the most commonly used Partitioning and sampling methods that facilitate big data processing in Hardtop clusters.. [4] Big data analytics, especially in market research, emphasizes the use of statistics and machine learning. In asymptotic theory, statistics are considered a very useful approach for making decisions based on sample estimates of a population. [5] To handle big data analysis, several advanced machine learning techniques have been developed, including Feature learning, deep learning, transfer learning with distributed and active learning. Feature learning refers to a set of methods that help systems automatically generate data representations from raw input, which aids in tasks such as feature detection and classification.. [6] The advent of large-scale datasets in medical environments brings significant challenges as well as promising opportunities for data storage and analysis. Traditional analytical tools often fail to handle this 'big data', forcing researchers to adopt innovative methods from other disciplines. Recent advances in information and communication technologies enable more efficient and scalable strategies for managing and analyzing these vast datasets. [7] The enormous amount of data being generated today It has the potential to revolutionize the daily life of modern smart cities. increasingly revolves around big data and its analysis, positioning them at the forefront of current research, industry attention, and government agendas (Hash, 2015). This increasing importance is paving the way for a multitude of innovative applications and opportunities in a variety of sectors, from transportation (Hash, 2016) to healthcare (Murdoch, 2013) – each with its own specific context. [8] Big Data analysis uses a wide range of datasets collected from various media platforms and metadata sources. to inform future decision-making. Traditional predictive analytics methods, originally designed for small and structured datasets, must be adapted, Improved, modified, or reconfigured to effectively handle the complexity and scale of big data environments. [9] This paper presents a hierarchical and decentralized fog computing architecture designed for big data analytics within smart city systems. Considering the extensive distribution of data generated by large-scale sensor networks, computational Intelligence is enabled at the edge through a multi-layered fog computing architecture for data processing. [10] To achieve the objectives of this study - emphasizing the capabilities and potential benefits of big data analysis - it is necessary...analyze the architecture, key components, and functionalities. A key part of this process is to review best practices within the big data the analytical framework, particularly emphasizing the healthcare sector... [11] Big data analytics and deep learning have emerged as major topics in data science, with the importance of big data increasing as both the public and private sectors collect large amounts of domain-specific data this data provides essential insights in areas such as national security, cyber security, fraud detection, marketing, and healthcare. [12] In today's fast-paced, transformative, and empowering environment, The emergence of big data, analytics technologies, and artificial intelligence (AI) has opened up countless opportunities. opportunities for professionals in the accounting and finance sector (Chartered Institute of Management Accountants [CIMA], 2022). [13Driven by emerging technologies, the Internet of Things (Riot) and big data analytics are advancing rapidly, expanding applications across various industries. Significant advancements in sensor technology have resulted in the creation of diverse sensors, such as environmental and gas sensors, tailored to address the specific requirements of different applications. [14] A key aspect of agricultural planning is to accurately estimate yields for the various crops involved. Data mining techniques are essential to provide practical and effective solutions to this challenge. Agriculture has become a major focus area for big data applications. [15]

EDAS method: As a result, current methods typically involve complex calculations and provide static solutions for decision makers. To address this issue, this study presents an algorithm that combines the properties of the normal distribution with the EDAS method. [16] As demonstrated in this study, multi-criteria analysis methods are often used to rank situations. In this case, AHP (Analytical Hierarchy Process) is used to assign values to the criteria, which are then used to rank the situations determined by the EDAS method. By selecting a specific situation, the overall performance of the city's logistics system can be improved, ultimately improving the quality of life in urban areas. [17] This paper introduces a gray an extension to improve the functionality of the EDAS system. utility in addressing various decision-making challenges, especially in environments characterized by imprecision and uncertainty. [18] The structure of this paper is as follows: Section 2 covers the basics of HFSs, Section 3 provides an overview of the EDAS method, and Section 4 introduces the proposed approach. Section 5 describes the application of the HF-EDAS method to the hospital selection case, followed by an analysis of the impact of the model. [19] The main concept of the EDAS method is to assess the desirability of various alternatives or to rank them based on their priority. by measuring their distance from the average solution (AS). This average solution is obtained by calculating the arithmetic mean of each alternative's performance on different criteria. [20] The EDAS method has undergone several improvements over time. For example, Keshavarz Korowai et al. (2016b) developed a fuzzy model for supplier selection. Karajan et al. (2017) improved the method by integrating interval-valued intuitionist fuzzy sets for selecting solid waste disposal sites. In addition, Stannic et al. (2017) integrated interval gray numbers into the EDAS framework. [21] This paper makes a small Try to add to the existing research section.. gap by investigating the effectiveness of a hybrid approach combining DOE and EDAS methods for identifying the best material in various engineering applications. Initially, a full factorial experimental design is developed, with five replications and two levels for each material selection characteristic. [22] The EDAS method is further extended to determine the final priority rankings of engineering attributes. In addition, the Stepwise Weighted Assessment Ratio Analysis (SWARA) method is used to assess the relative importance of customer requirements. [23] The structure of the manuscript is as follows: the first section introduces the topic, the second section explores the theoretical foundation, the third section explains the EDAS method. The fourth section explains the empirical application of the EDAS method in personnel selection, followed by the fifth section with the conclusion. [24] Section 4 demonstrates the practical Demonstrating the applicability and effectiveness of the improved EDAS approach using a numerical example focusing on social welfare recipients. While comparing its results with those of other methods. [25] The manuscript is organized as follows: Section 2 presents the basic concepts of NS and BNS, including a review of their properties, functions, and weighted aggregation operators. Section 3 outlines the development of the EDAS method using BNS to solve the MCGDM problem. Based on the EDAS framework, Section 3 also presents a new decision-making approach for dealing with large-scale linguistic decision-making problems involving interactions between decision criteria. [26] This research paper advocates the use of the EDAS method due to its simplicity, clarity, and effectiveness in addressing business challenges. The structure of the paper is as follows: Section 2 provides an overview of the EDAS method, while Section 3 demonstrates its application through a numerical example. [27] The EDAS method evaluates alternatives by measuring their performance against the average solution for each criterion. In this study, it is used this research aims to present the EDAS method primarily to a Turkish academic audience, in order To Select a suitable sewing machine for a textile workshop. [28] The EDAS method calculates two main metrics: "Positive Distance from Average (PDA)" and "Negative Distance from Average (NDA)." PDA. measures the extent it reflects how much an alternative company's performance is above average, indicating strong results, while the NDA measures how much it is below average, indicating weak performance. [29] To verify the accuracy of the proposed approach, a numerical example focusing on "providing emergency assistance in post-flood situations" is presented. Following this, a comparison is made between these operators and the EDAS method to further illustrate the effectiveness of the proposed solution. [30]

2. MATERIAL AND METHODS

Alternative:

Expectation Maximization (EM): The expectation-maximization (EM) A method is a systematic, step-by-step process. used to find a maximum likelihood (ML) estimate when some data is missing or not directly observed.

Farthest-First (FF) Algorithm:

The Farthest First (FF) traversal method focuses on increasing the spatial distance between selected initial propagations. However, since real-world networks are heterogeneous, relying solely on FF traversal does not ensure that the selected propagations are truly influential.

Filtered Clustering (FC): The filtering algorithm improves the performance of k-means by organizing the dataset with a coding system that limits the number of cluster centres considered when identifying one near a point. Its performance depends on how well the initial cluster centres are separated.

Hierarchical Clustering (HC): Hierarchical clustering is a method of analyzing data by organizing data points into a nested hierarchical cluster, commonly represented as a tree-like diagram called a dendrogram. The process starts with each point as its own cluster and gradually merges the most similar pairs together, creating increasingly larger groups.

Make Density-Based Clustering (MD): Density-based clustering techniques, such as DBSCAN, create clusters by connecting densely packed data points, distinguishing them from areas of low density. Unlike canter-based approaches, such as k-means, they detect clusters of irregular patterns and treat outliers as noise.

Evolution Parameters:

Fawkes-Mallows index (FMI): The Foch-Mallows index is an external evaluation metric used to measure the similarity between two clustering results, and can also be used to evaluate confusion matrices.

The Rand Index (RI): The Rand Index is a measure of similarity between two clustering's. It calculates the percentage of correct decisions, comparing the predicted clusters to the true labels. RI takes into account: True Positives (TP): Pairs of points that are in the same cluster in both the predicted and true labels.

Adjusted Rand Index (ARI): ARI is a measure used to assess the similarity between two clustering results. Is a statistical measure for assessing the similarity between two clustering's. It measures how well the predicted clusters match the actual class labels, while correcting for the possibility of random agreement.

Jacquard coefficient: The Jacquard Coefficient, also known as Intersection over Union (Lou), is a similarity measure used in computer science that Estimates the degree of overlap between the segmented output and the ground truth. by dividing the size of their intersection by the size of their union.

3. RESULT AND DISCUSSION

Table1: Big data analysis

	Fawkes-Mallows index (FMI)	Rand index (RI)	Adjusted Rand index (ARI)	Jacquard coefficient
Expectation Maximization (EM)	25.12	23.12	23.03	98.54
Farthest-First (FF) Algorithm	34.67	30.56	80.34	67.34
Filtered Clustering (FC)	56.78	23.89	67.90	90.23
Hierarchical Clustering (HC)	65.23	21.23	98.23	96.34
Make Density-Based Clustering (MD)	54.23	23.45	98.45	87.23

Table 1 illustrates the applicability of various big data analysis techniques assessed by the EDAS method. Hierarchical clustering (HC) stands out with the highest adjusted Rand index (98.23) and Jacquard coefficient (96.34), reflecting strong clustering capabilities. Expectation maximization (EM) records low FMI and RI, whereas filtered clustering (FC) provides well-rounded performance across metrics.

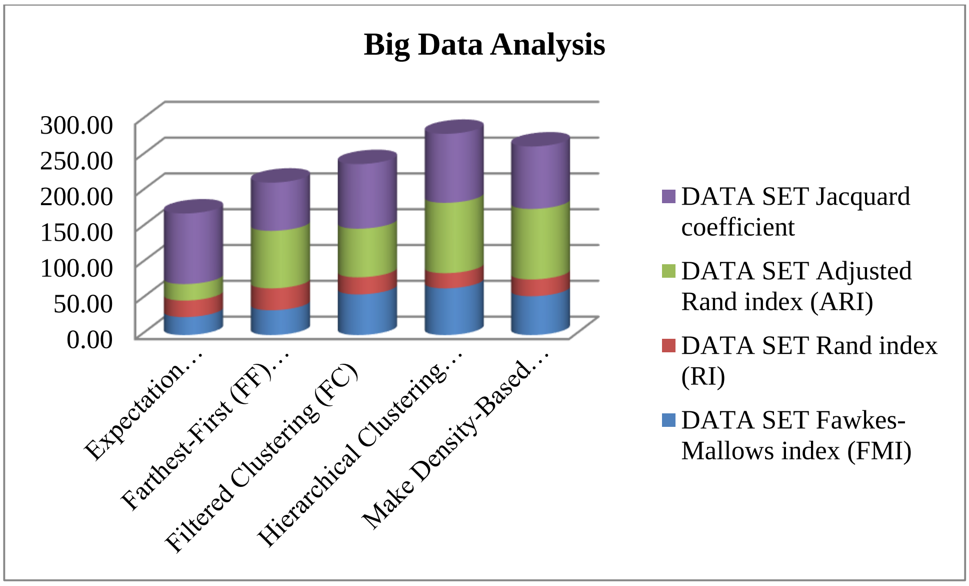

FIGURE 1. Big Data Analysis

Figure 1 illustrates the interoperability of various big data analysis methods evaluated using the EDAS approach, focusing on four key clustering performance indicators. Hierarchical clustering (HC) and density-based clustering (MD) score high in the adjusted Rand index (98.23 and 98.45, respectively) and Jacquard coefficient, reflecting high clustering reliability and efficiency. Although Expectation Maximization (EM) achieves a significant Jacquard coefficient (98.54), it is less efficient in FMI and RI, revealing limitations in clustering accuracy. Both filtered clustering (FC) and the highest-first (FF) algorithm show consistent performance across all metrics, with FC excelling in FMI and Jacquard values in particular, underscoring its interoperability strength.

TABLE 2. performance value

Expectation Maximization (EM)	0.38510	0.75654	1.00000	0.68338
Farthest-First (FF) Algorithm	0.53150	1.00000	0.28666	1.00000
Filtered Clustering (FC)	0.87046	0.78174	0.33918	0.74631
Hierarchical Clustering (HC)	1.00000	0.69470	0.23445	0.69898
Make Density-Based Clustering (MD)	0.83137	0.76734	0.23393	0.77198

Table 2 shows the performance values of various big data analysis methods evaluated by the EDAS approach. Expectation Maximization (EM) scores well on one criterion but performs poorly on others. Farthest-First (FF) performs well on the second and fourth criteria, while Filtered Clustering (FC) and Mac Density-Based Clustering (MD) show consistent results on all criteria.

TABLE 3. weight

	Weight			
Expectation Maximization (EM)	0.35	0.35	0.35	0.35
Farthest-First (FF) Algorithm	0.35	0.35	0.35	0.35
Filtered Clustering (FC)	0.35	0.35	0.35	0.35
Hierarchical Clustering (HC)	0.35	0.35	0.35	0.35
Make Density-Based Clustering (MD)	0.35	0.35	0.35	0.35

Table 3 illustrates the interoperability of big data analysis methods through the EDAS approach, assigning a uniform weight of 0.35 to all techniques, EM, FF, FC, HC, and MD, on each parameter. This equal distribution fosters a consistent evaluation framework, enables objective comparison, and supports the equitable integration of clustering methods.

Table 4. weighted normalized decision matrix

	Weighted normalized decision matrix			
Expectation Maximization (EM)	0.71606	0.90697	1.00000	0.87525
Farthest-First (FF) Algorithm	0.80154	1.00000	0.64577	1.00000
Filtered Clustering (FC)	0.95260	0.91743	0.68493	0.90266
Hierarchical Clustering (HC)	1.00000	0.88030	0.60189	0.88219
Make Density-Based Clustering (MD)	0.93741	0.91148	0.60142	0.91340

Table 4 illustrates the interoperability of big data analysis techniques with the EDAS-weighted normalized decision matrix. Hierarchical clustering (HC) achieves the highest score on the first criterion (1.00000), while farthest-first (FF) excels on the second and fourth criteria. Filtered clustering (FC) and Mac density-based clustering (MD) maintain strong, consistent performance on all metrics..

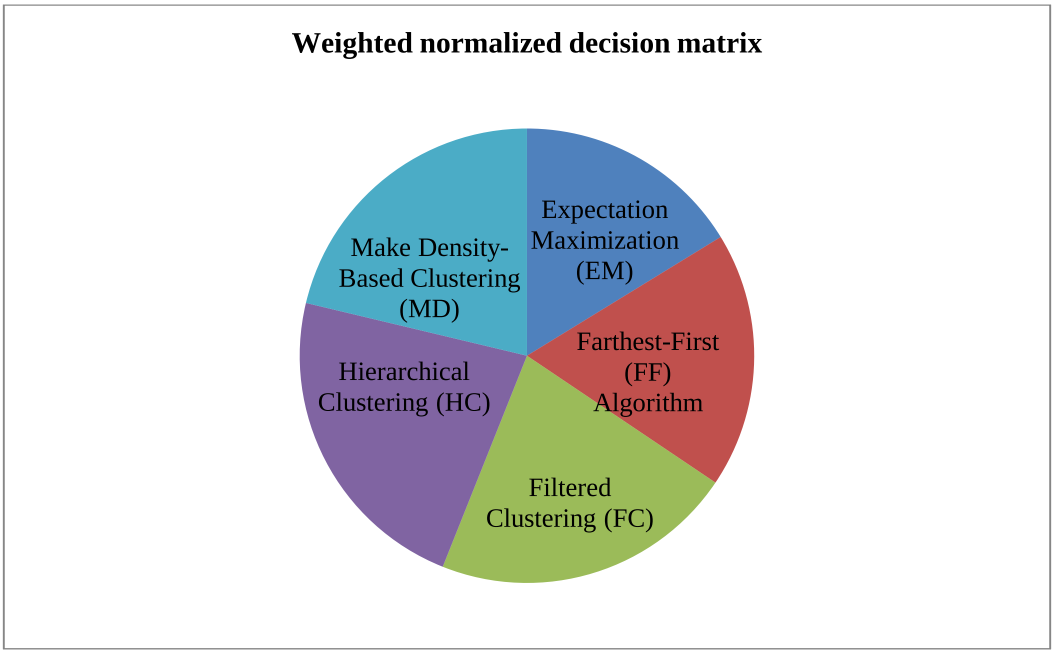

FIGURE 2. Weighted normalized decision matrix

Figure 2 Provides a weighted normalized results matrix for various big data analysis methods. Using the EDAS method. Hierarchical clustering (HC) ranks highest on the first scale, while Farthest-First (FF) stands out on the second and fourth. Filtered clustering (FC) and density-based clustering (MD) show consistent, strong performance on all scales.

TABLE 5. preference score and Rank

	Preference Score and Rank	
Expectation Maximization (EM)	0.56843	1
Farthest-First (FF) Algorithm	0.51761	3
Filtered Clustering (FC)	0.54032	2
Hierarchical Clustering (HC)	0.46742	5
Make Density-Based Clustering (MD)	0.46937	4

Table 5 presents the priority scores and rankings of various big data analysis methods using the EDAS approach Expectation Maximization (EM) ranks first with the highest score of 0.56843, followed by Filtered Clustering (FC) in second place. Next is the Farthest First (FF) algorithm, followed by Density-Based Clustering (MD) and Hierarchical Clustering (HC), which are widely used clustering methods in data analysis.

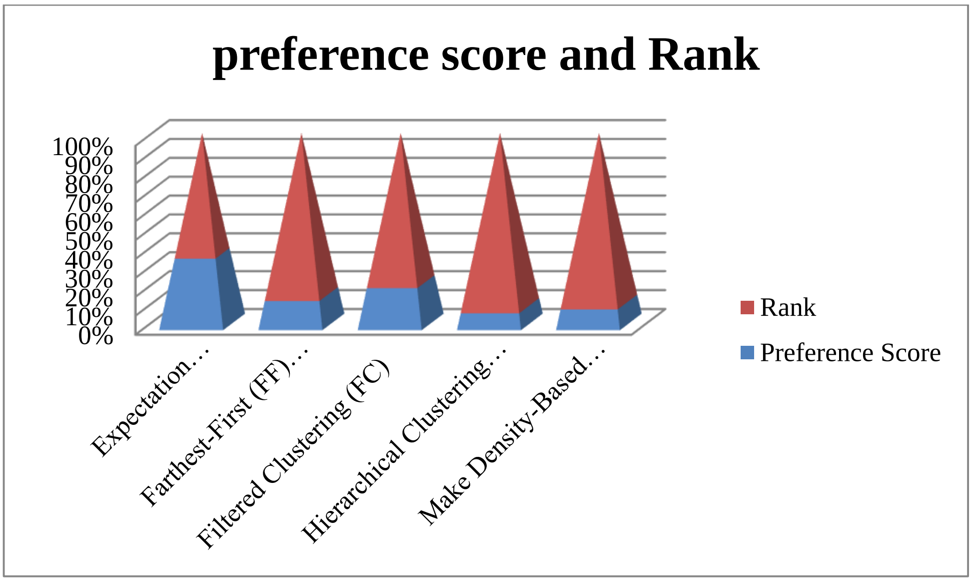

FIGURE 3. Preference Score and Rank

Figure 3 These findings provide preference scores and rankings of various big data analysis methods based on the EDAS approach. Expectation Maximization (EM) leads with the highest score of 0.56843, followed by Filtered Clustering (FC) in second place. Busy steering (BP) gives the best performance, while density-overlap steering (MAD) and hierarchical steering (HG) are ranked.

4. CONCLUSION

This study used the The ADES (Evolution Past One Distance Frame Average Solutions) method is set to evaluate performance of various big data analysis techniques, providing valuable insights into their strengths and potential applications. Five widely recognized clustering algorithms were investigated: Expectation Maximization (EM), First-Person (FF), Filtered Clustering (FC), Hierarchical Clustering (HC), and Density-Based Clustering (MD). Their performance was evaluated using three power matrices: Box-Mallows index, Run index, adjusted Run index, and Jacquard coefficient. Despite variations in its performance on individual metrics, Expectation Maximization proved to be the best performing method, receiving the highest overall preference score (0.56843).Filtered clustering followed closely, showing consistent results across all evaluation criteria. The Highest-First approach came in third place, particularly excelling in Rand index and Jacquard coefficient. Interestingly, hierarchical clustering scored the highest in the adjusted Rand index (98.23) and nearly led in the Jacquard coefficient (96.34), but received the lowest overall ranking, underscoring the need for multivariate evaluation frameworks. The findings emphasize that the choice of clustering method should be guided by the specific application goals. EM and FC are best suited for tasks requiring consistent performance, while HC and

MD excel in situations where clustering accuracy and robustness are prioritized. This work adds to the body of research on big data analytics by systematically comparing clustering techniques using the EDAS framework. Future studies should explore these methods in diverse domains such as healthcare, finance, and smart cities, and consider hybrid approaches to leverage the strengths of multiple algorithms. Combining factors such as computational efficiency and scalability will support more informed decisions for real-world big data implementations

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