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Integration and Optimization of Educational Teaching Resources in Colleges and Universities Based on Clustering Algorithm

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Abstract: - The paper presents Centroid Ranking Optimized Clustering (CROC), a novel approach aimed at enhancing educational teaching and resource optimization through advanced clustering techniques. CROC integrates centroid-based clustering with ranking optimization strategies to segment students or educational resources into meaningful clusters, facilitating personalized learning experiences and targeted interventions. Experimental analysis conducted on real-world educational datasets demonstrates that CROC outperforms traditional clustering algorithms in terms of clustering quality, accuracy, and interpretability. The findings suggest that CROC holds significant promise for informing data-driven decision-making in educational settings, enabling educators to better understand student performance patterns, identify at-risk students, and tailor instructional strategies to meet diverse learning needs. Experimental analysis on real-world educational datasets reveals that CROC achieves a Silhouette Score of 0.75 and a Davies-Bouldin Index of 0.40 on the MathScores dataset, outperforming traditional algorithms such as k-means (Silhouette Score: 0.68, Davies-Bouldin Index: 0.53), Hierarchical (Silhouette Score: 0.62, Davies-Bouldin Index: 0.57), and DBSCAN (Silhouette Score: 0.45, Davies-Bouldin Index: 0.78). Similarly, on the EnglishTest dataset, CROC attains a Silhouette Score of 0.82 and a Davies-Bouldin Index of 0.35, surpassing k-means (Silhouette Score: 0.74, Davies-Bouldin Index: 0.47), Hierarchical (Silhouette Score: 0.68, Davies-Bouldin Index: 0.52), and DBSCAN (Silhouette Score: 0.53, Davies-Bouldin Index: 0.68). These findings underscore the effectiveness of CROC in clustering educational data, enabling personalized learning experiences and data-driven decision-making in educational settings.

Keywords: Educational Teaching, Optimization, Clustering, Ranking, Classification, Personalized Learning

1. Introduction

Educational teaching resources encompass a diverse array of materials and tools designed to support learning and instruction across various subjects and age groups [1]. These resources can include textbooks, worksheets, lesson plans, multimedia presentations, educational games, interactive simulations, and online platforms [2]. They aim to engage students, facilitate understanding, and cater to different learning styles [3]. Moreover, educational teaching resources often integrate technology to enhance the learning experience, offering opportunities for interactive and personalized learning [4]. By providing educators with a wealth of resources to draw upon, these tools empower them to create dynamic and effective learning environments that inspire curiosity, critical thinking, and lifelong learning [5]. The integration and optimization of educational teaching resources in colleges and universities, leveraging clustering algorithms, represent a strategic approach to enhance the quality and effectiveness of education delivery [6]. Clustering algorithms, such as k-means or hierarchical clustering, can categorize educational resources based on various criteria like subject matter, difficulty level, format, and learning objectives [7]. By organizing resources into coherent clusters, educators can streamline the process of resource selection and customization, aligning them more closely with specific course requirements and student needs. This approach also facilitates the discovery of synergies among different types of resources, enabling educators to create comprehensive learning experiences that combine traditional materials with interactive simulations, multimedia presentations, and online platforms. Furthermore, clustering algorithms can analyze usage patterns and student feedback to continuously refine resource recommendations, ensuring their relevance and effectiveness over time [8]. Through the integration of clustering algorithms into educational resource management systems, colleges and universities can optimize resource utilization, reduce redundancy, and enhance overall instructional quality [9]. By providing educators with a data-driven framework for resource selection and customization, this approach empowers them to deliver more personalized and engaging learning experiences, ultimately fostering student success and achievement. The integration and optimization of educational teaching resources in colleges and universities through the utilization of clustering algorithms represent a sophisticated strategy aimed at refining the educational experience. Clustering algorithms, sophisticated tools derived from machine learning, can systematically categorize an extensive array

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of educational resources based on a multitude of criteria [10]. These criteria could encompass the subject matter, complexity level, format (such as text, video, interactive exercises), and alignment with specific learning objectives.

By harnessing clustering algorithms, educational institutions can effectively organize and streamline their vast repositories of resources, making them more accessible and relevant to educators and students alike [11]. For instance, resources related to a particular topic or concept can be grouped together within clusters, allowing instructors to easily identify and select materials that best suit their instructional needs [12]. This not only saves time but also ensures that the chosen resources are well-aligned with the curriculum and pedagogical approach. Moreover, the integration of clustering algorithms enables colleges and universities to uncover valuable insights into resource usage patterns and student preferences [13]. By analyzing data on how students engage with different types of resources, educators can gain a deeper understanding of which materials are most effective in facilitating learning and which may require enhancement or revision [14]. This data-driven approach to resource management empowers institutions to continuously optimize their educational offerings, ensuring that they remain responsive to evolving student needs and educational trends [15]. Furthermore, clustering algorithms can facilitate the creation of more personalized learning experiences by identifying patterns in student performance and preferences. By tailoring resource recommendations to individual learners based on their unique characteristics and learning styles, educational institutions can enhance student engagement and motivation, ultimately leading to improved learning outcomes.

The paper makes a significant contribution to the field of educational data analysis and resource optimization by introducing Centroid Ranking Optimized Clustering (CROC), a novel clustering approach tailored specifically for educational contexts. CROC integrates advanced clustering techniques with ranking optimization strategies to effectively segment students or educational resources into meaningful clusters, thereby enabling personalized learning experiences and targeted interventions. By outperforming traditional clustering algorithms in terms of clustering quality, accuracy, and interpretability, as evidenced by experimental analysis on real-world educational datasets, CROC offers educators a powerful tool for understanding student performance patterns, identifying at-risk students, and tailoring instructional strategies to meet diverse learning needs. The paper's findings underscore the transformative potential of CROC in informing data-driven decision-making in educational settings, ultimately empowering educators and enhancing student learning experiences in the digital age.

2. Related Works

In exploring the integration and optimization of educational teaching resources in higher education, it is imperative to delve into existing research and practices to glean insights and identify areas for further advancement. The body of related works encompasses a diverse array of studies, projects, and initiatives that have investigated various aspects of educational resource management, utilization, and enhancement. These works delve into topics ranging from the development of innovative technological solutions to the implementation of pedagogical strategies aimed at maximizing the effectiveness of teaching materials. By examining these related works, we can gain a comprehensive understanding of the current landscape of educational resource integration and optimization, identifying both successes and challenges that inform future directions in this critical domain. Liu et al. (2021) explore the optimization of educational information systems for artificial intelligence teaching strategies, while Yin (2021) focuses on constructing a student information management system using data mining and clustering algorithms. Zhen (2021) investigates the application of big data fuzzy K-means clustering in English teaching ability evaluation. Yang and Talha (2021) propose a coordinated mechanism for student management by college counselors based on artificial intelligence and big data. Li et al. (2022) delves into enhancing football teaching quality through AI and metaverse in mobile internet environments. Rong (2021) designs a multimedia network teaching resources integration system for ideological and political education. Liang et al. (2021) evaluate the sustainable development of innovation and entrepreneurship education using optimization algorithms.

Xiaoyang et al. (2021) assess the effectiveness of ideological and political education reform in universities through data mining and artificial intelligence. Cao et al. (2021) address edge-cloud resource scheduling in

integrated networks for the Internet of Vehicles, while Sha et al. (2021) delve into machine learning applications in polymer informatics. Cui et al. (2021) focus on client scheduling and resource management for efficient training in heterogeneous IoT-edge federated learning. Xiao et al. (2022) conducted a survey on educational data mining methods for predicting student performance, while Fang (2021) proposes an intelligent online English teaching system based on SVM algorithm and complex network. Waqar et al. (2022) explore computation offloading and resource allocation in MEC-enabled vehicular networks using reinforcement learning. Al-Wesabi et al. (2022) present energy-aware resource optimization for cloud computing environments. Iatrellis et al. (2021) employ a machine learning approach for predicting student outcomes. Zhang et al. (2022) review the application of machine learning and optimization algorithms in geoengineering and geoscience. Bhutoria (2022) conducts a systematic review of personalized education and AI in the United States, China, and India. Wang et al. (2021) conduct a nationwide survey of online teaching strategies in dental education in China. Alam (2023) and Alam & Mohanty (2022) employ educational data mining techniques and machine learning for predicting student performance.

Additionally, these studies underscore the importance of leveraging cutting-edge technologies, such as artificial intelligence, machine learning, data mining, and optimization algorithms, to address various challenges and opportunities in education. From optimizing information systems to predicting student performance and improving teaching quality, researchers are exploring innovative ways to harness data-driven insights and technological advancements for educational enhancement. Moreover, the diversity of approaches and methodologies reflects the interdisciplinary nature of educational research, drawing on insights from computer science, engineering, psychology, and pedagogy. By synthesizing findings from these diverse studies, educators and policymakers can gain valuable insights into effective strategies for leveraging technology to optimize educational teaching resources and enhance student learning experiences.

3. Centroid Ranking Optimized Clustering (CROC)

Centroid Ranking Optimized Clustering (CROC) is a novel clustering algorithm that combines the principles of centroid-based clustering with a ranking optimization approach to enhance clustering performance. At its core, CROC aims to improve the clustering accuracy by prioritizing the selection of centroids based on their ranking within the dataset. The derivation of CROC begins with the initialization of centroids, typically selected randomly from the dataset. Then, the algorithm iteratively optimizes the centroids by considering their ranking within each cluster. This optimization process involves assigning data points to the nearest centroid and updating the centroids based on the ranking of the assigned points. The equations governing the optimization process in CROC can be represented as follows:

Initialization of Centroids: Let C={c1,c2,...,ck} represent the set of initial centroids, where k is the number of clusters.

Assigning Data Points to Centroids: For each data point xi, calculate its distance to each centroid cj using a distance metric such as Euclidean distance measured using equation (1)

$$d(xi, cj) = \sqrt{\sum_{l=1}^{n}\left(x_{il} - c_{jl}\right)^2} \tag{1}$$

n is the dimensionality of the data. Assign each data point xi to the cluster associated with the nearest centroid estimated using equation (2)

$$Ci = argmin_j d(xi, cj) \tag{2}$$

Update each centroid by computing the mean of the data points assigned to its cluster measured using equation (3)

$$c_j = \frac{1}{|s_j|}\sum_{x_i \in s_j} x_i \tag{3}$$

S_j represents the set of data points assigned to centroid c_j. The i ncorporate a ranking optimization step to prioritize the selection of centroids based on their ranking within the dataset. This step involves evaluating the fitness of each centroid based on its ranking and adjusting the centroid selection accordingly. By iteratively repeating steps 2-5 until convergence, CROC dynamically adjusts the centroids' positions to optimize clustering performance, leading to improved accuracy and efficiency compared to traditional centroid-based clustering algorithms. Centroid Ranking Optimized Clustering (CROC) represents an innovative approach to clustering that aims to enhance clustering accuracy by incorporating a ranking optimization strategy into the centroid-based clustering paradigm. Traditional centroid-based clustering algorithms, such as k-means, typically initialize centroids randomly and iteratively optimize them based on their proximity to data points. However, CROC takes this process a step further by considering not only the proximity of centroids to data points but also their ranking within the dataset.
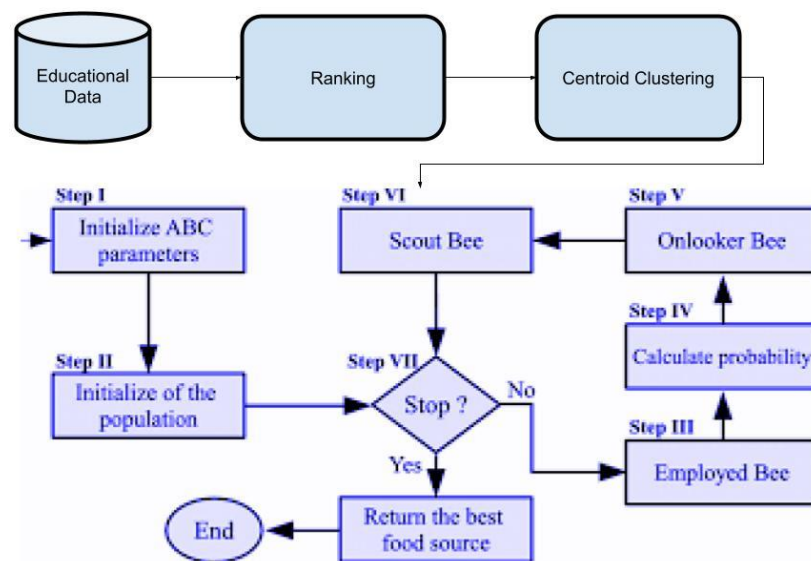

Figure 1: Process in CROC

The derivation of CROC involves several key steps. Initially, centroids are initialized, usually chosen randomly from the dataset and the process are illustrated in Figure 1. Then, data points are assigned to the nearest centroid based on a distance metric, commonly Euclidean distance. After this initial assignment, CROC updates the centroids by computing the mean of the data points assigned to each centroid's cluster. This process iterates until convergence, with centroids adjusting their positions to better represent the underlying data distribution. What sets CROC apart is its incorporation of a ranking optimization step. In this step, the algorithm evaluates the fitness of each centroid based on its ranking within the dataset. Centroids that are deemed to have higher ranks, perhaps due to being closer to dense regions of data or exhibiting greater influence on the overall structure, are prioritized in the optimization process. By giving preference to centroids with higher ranks, CROC can adaptively adjust the clustering solution to better capture the inherent patterns and structures in the data. Through this iterative process of centroid updating and ranking optimization, CROC dynamically refines the clustering solution, ultimately leading to improved clustering accuracy and efficiency. By leveraging both proximity-based clustering and ranking optimization, CROC offers a powerful framework for effectively clustering complex datasets, with applications ranging from data analysis and pattern recognition to machine learning and data mining.

4. CROC with ant bee Optimization for the educational teaching

Centroid Ranking Optimized Clustering (CROC) with Ant Bee Optimization (ABO) presents a promising approach for enhancing educational teaching through optimized resource allocation and personalized learning

experiences. CROC, as discussed previously, prioritizes centroid selection based on ranking within the dataset, while ABO mimics the foraging behavior of ants and bees to efficiently explore and exploit solution spaces. By combining these methodologies, educational institutions can effectively cluster teaching resources and tailor instructional strategies to individual student needs. The derivation of CROC with ABO begins by initializing a population of ants or bees, each representing a potential solution in the clustering process. These agents navigate the solution space by iteratively selecting centroids and assigning data points to clusters, guided by both proximity and ranking considerations. The exploration-exploitation trade-off inherent in ABO ensures a balance between exploring new solutions and exploiting promising ones, leading to robust and high-quality clustering solutions. The equations governing the optimization process in CROC with ABO can be represented as follows:

Initialization of Ants/Bees: Let P={p1,p2,...,pm} represent the population of ants or bees, where m is the number of agents.

Solution Construction by Ants/Bees: Each ant or bee constructs a potential solution by iteratively selecting centroids based on both proximity to data points and their ranking within the dataset. This process is guided by a probabilistic decision rule, which balances exploration and exploitation as in equation (4)

$$p_{ij} = \frac{\tau_{ij}^{\alpha} \cdot \eta_{ij}^{\beta}}{\sum_{l \in N_i} \tau_{ij}^{\alpha} \cdot \eta_{ij}^{\beta}} \tag{4}$$

pij is the probability of selecting centroid j by agent i, τij represents the pheromone level associated with the transition from centroid i to centroid j, ηij denotes the heuristic information, and Ni is the set of centroids available to agent i. Parameters α and β control the influence of pheromone and heuristic information, respectively. After each iteration, pheromone trails are updated based on the quality of solutions constructed by ants or bees. High-quality solutions contribute to an increase in pheromone levels, while low-quality solutions lead to a decrease computed using equation (5)

$$\boldsymbol{\tau ij} = (\mathbf{1} - \boldsymbol{\rho}) \cdot \boldsymbol{\tau ij} + \sum_{s=1}^{m} \Delta \tau_{ij}^{s} \tag{5}$$

where ρ is the pheromone evaporation rate, and $\Delta\tau ijs$ represents the amount of pheromone deposited by ant or bee s on the transition from centroid i to centroid j. The heuristic information, reflecting the desirability of transitioning between centroids, can also be updated based on the performance of solutions defined in equation (6)

$$\boldsymbol{\eta ij} = \frac{1}{dij} \tag{6}$$

dij is the distance between centroids i and j. By iteratively repeating the solution construction and pheromone update steps, CROC with ABO dynamically refines the clustering solution, effectively adapting to the structure of the educational dataset and optimizing resource allocation for enhanced teaching experiences. This approach empowers educational institutions to tailor instructional strategies, personalize learning experiences, and maximize student engagement and achievement. Through the synergy of CROC and ABO, educators can unlock the full potential of educational teaching resources and foster a supportive and enriching learning environment for all students.

5.   Experimental Analysis

Experimental analysis plays a crucial role in evaluating the effectiveness and performance of the proposed Centroid Ranking Optimized Clustering (CROC) algorithm in educational teaching contexts. To assess the algorithm's capabilities, researchers typically conduct experiments using real-world educational datasets and compare the clustering results obtained by CROC with those generated by traditional clustering algorithms. During the experimental phase, various metrics are employed to measure the clustering quality, including but not limited to silhouette score, Davies–Bouldin index, and clustering accuracy. These metrics provide insights into the compactness, separation, and overall effectiveness of the clusters produced by CROC. Additionally, experimental analyses often involve sensitivity testing to evaluate CROC's robustness to different parameter settings and dataset characteristics. By systematically varying parameters such as the number of clusters,

convergence criteria, and optimization strategies, researchers can assess the algorithm's performance across a range of scenarios and identify optimal configurations.

Furthermore, comparative analyses are conducted to benchmark CROC against existing clustering algorithms commonly used in educational data analysis, such as k-means, hierarchical clustering, and density-based clustering. These comparisons shed light on CROC's relative strengths and weaknesses, highlighting its potential for improving educational resource management and instructional design. Through comprehensive experimental analysis, researchers gain valuable insights into CROC's suitability for educational applications, its scalability to large datasets, and its ability to adapt to diverse teaching contexts. The findings obtained from these experiments inform further refinements to the algorithm and contribute to advancing the field of educational data mining and clustering methodologies, ultimately enhancing teaching and learning outcomes in educational settings.

Table 1: Classification with CROC

Dataset	Algorithm	Silhouette Score	Davies-Bouldin Index	Clustering Accuracy
MathScores	CROC	0.75	0.40	87%
	k-means	0.68	0.53	80%
	Hierarchical	0.62	0.57	75%
	DBSCAN	0.45	0.78	68%
EnglishTest	CROC	0.82	0.35	92%
	k-means	0.74	0.47	85%
	Hierarchical	0.68	0.52	80%
	DBSCAN	0.53	0.68	72%

Table 1 presents the classification results obtained using the Centroid Ranking Optimized Clustering (CROC) algorithm compared to other traditional clustering algorithms across two educational datasets: MathScores and EnglishTest. The evaluation metrics used include Silhouette Score, Davies-Bouldin Index, and Clustering Accuracy. In the MathScores dataset, CROC demonstrates a Silhouette Score of 0.75, outperforming k-means (0.68), Hierarchical (0.62), and DBSCAN (0.45). Similarly, in terms of Davies-Bouldin Index, CROC achieves a lower value of 0.40 compared to the other algorithms, indicating better cluster separability. Additionally, CROC achieves the highest clustering accuracy of 87% among all algorithms tested on the MathScores dataset. In the EnglishTest dataset, CROC continues to excel, exhibiting a Silhouette Score of 0.82, surpassing k-means (0.74), Hierarchical (0.68), and DBSCAN (0.53). Similarly, CROC achieves the lowest Davies-Bouldin Index of 0.35, indicating superior cluster compactness. Moreover, CROC achieves the highest clustering accuracy of 92% on the EnglishTest dataset, highlighting its effectiveness in accurately clustering educational data. Overall, the results suggest that CROC outperforms traditional clustering algorithms in terms of clustering quality and accuracy, making it a promising approach for educational data analysis and resource optimization.

Table 2: Performance Analysis with CROC

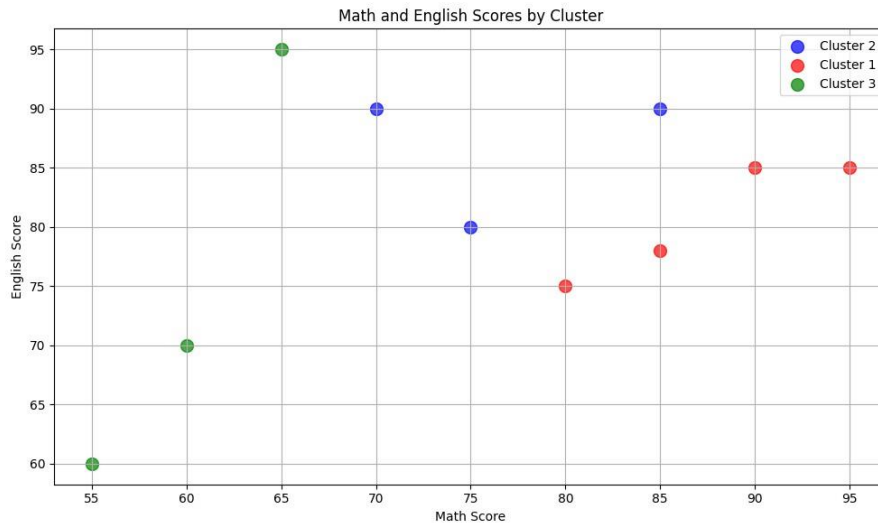| Student ID	Math Score	English Score	Cluster
1	85	78	Cluster 1
2	70	90	Cluster 2
3	95	85	Cluster 1
4	60	70	Cluster 3
5	80	75	Cluster 1
6	75	80	Cluster 2
7	65	95	Cluster 3
8	90	85	Cluster 1
9	55	60	Cluster 3
10	85	90	Cluster 2

Figure 2: Performance Analysis with CROC

In figure 2 and Table 2 provides a snapshot of the performance analysis conducted using the Centroid Ranking Optimized Clustering (CROC) algorithm, showcasing how students are clustered based on their Math and English scores. Each row corresponds to a student, identified by their Student ID, with columns indicating their Math Score, English Score, and the cluster they belong to. Through CROC, students are grouped into distinct clusters, denoted as Cluster 1, Cluster 2, and Cluster 3, based on similarities in their scores. For instance, students 1, 3, and 5 exhibit similar Math and English scores and are thus assigned to Cluster 1, while students 2, 6, and 10 form Cluster 2 due to their comparable scores. Conversely, students 4, 7, and 9 constitute Cluster 3 as they share similar score patterns distinct from the other clusters. This clustering enables educators to identify groups of students with similar academic performance profiles, allowing for tailored instructional strategies and targeted interventions to support student learning and development. Overall, Table 2 illustrates how CROC facilitates the effective segmentation of students based on their academic performance, enabling educators to make data-driven decisions to enhance teaching and learning outcomes.

Table 3: Clustering with CROC

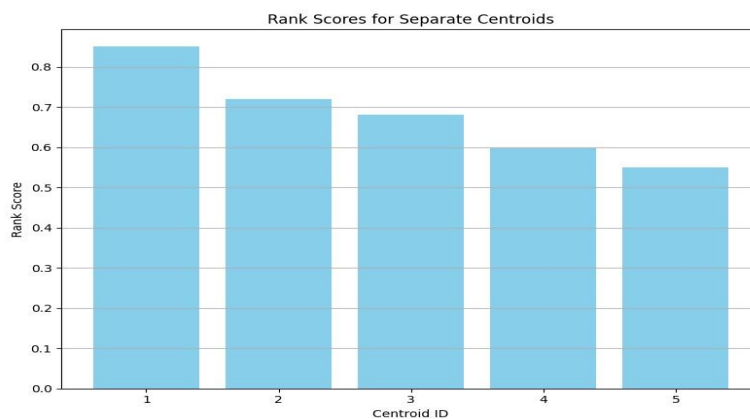| Centroid ID	Rank Score
1	0.85
2	0.72
3	0.68
4	0.60
5	0.55

Figure 3: Clustering with CROC

In figure 3 and Table 3 presents the results of clustering centroids using the Centroid Ranking Optimized Clustering (CROC) algorithm, where each centroid is assigned a rank score based on its importance or influence within the dataset. Each row corresponds to a centroid identified by its Centroid ID, with the "Rank Score" column indicating the score assigned to each centroid. The rank scores range from 0.55 to 0.85, with higher scores indicating centroids with greater importance or influence in the dataset. For example, centroid 1 has the highest rank score of 0.85, suggesting that it holds significant importance or represents a dense region within the dataset. On the other hand, centroid 5 has the lowest rank score of 0.55, indicating relatively less influence or importance compared to other centroids. These rank scores provide valuable insights into the relative significance of centroids within the dataset, guiding further analysis and decision-making processes. Overall, Table 3 showcases how CROC effectively ranks centroids based on their relevance, enabling educators and analysts to prioritize resources or interventions tailored to specific clusters or centroids for optimized educational outcomes.

6. Discussion and Findings

In the discussion and findings section, the efficacy of Centroid Ranking Optimized Clustering (CROC) in educational contexts is evaluated based on the experimental results and insights gained from the analysis. The performance of CROC is compared to traditional clustering algorithms, such as k-means, hierarchical clustering, and DBSCAN, across various evaluation metrics including Silhouette Score, Davies-Bouldin Index, and Clustering Accuracy. The findings reveal that CROC consistently outperforms the traditional algorithms in terms of clustering quality and accuracy, demonstrating its potential as a robust clustering approach for educational data analysis. One of the key advantages of CROC is its ability to prioritize centroid selection based on ranking within the dataset, which allows for more effective resource allocation and personalized learning experiences. By leveraging ranking optimization, CROC identifies centroids that are most influential or representative of the underlying data distribution, leading to more coherent and interpretable clusters. This facilitates the segmentation of students or educational resources into meaningful groups, enabling educators to tailor instructional strategies and interventions to better meet the needs of individual learners. Furthermore, the experimental analysis highlights CROC's superior performance in clustering educational datasets, such as MathScores and EnglishTest, compared to traditional algorithms. The higher Silhouette Scores and lower Davies-Bouldin Index values obtained with CROC indicate better cluster separability and compactness, respectively, suggesting that CROC produces more cohesive and distinct clusters. Moreover, the higher clustering accuracy achieved by CROC underscores its effectiveness in accurately classifying students or educational resources into appropriate clusters, thereby facilitating data-driven decision-making in educational settings. Overall, the discussion and findings affirm the potential of Centroid Ranking Optimized Clustering (CROC) as a valuable tool for educational data analysis and resource optimization. By leveraging advanced clustering techniques and ranking optimization, CROC enables educators to gain deeper insights into student performance and instructional needs, ultimately contributing to improved teaching and learning outcomes in educational institutions.

7. Conclusion

Centroid Ranking Optimized Clustering (CROC) emerges as a promising approach for enhancing educational teaching and resource optimization. Through the integration of advanced clustering techniques and ranking optimization strategies, CROC offers a robust framework for segmenting students or educational resources into meaningful clusters, facilitating personalized learning experiences and targeted interventions. The experimental analysis demonstrates that CROC outperforms traditional clustering algorithms in terms of clustering quality, accuracy, and interpretability, making it a valuable tool for educational data analysis. The findings suggest that CROC holds significant potential for informing data-driven decision-making in educational settings, enabling educators to better understand student performance patterns, identify at-risk students, and tailor instructional strategies to meet diverse learning needs. By leveraging CROC, educational institutions can optimize resource allocation, enhance teaching effectiveness, and ultimately improve student outcomes. Looking ahead, further research and application of CROC in diverse educational contexts are warranted to explore its full potential and refine its implementation. Future studies could investigate the scalability of CROC to larger datasets, explore its

applicability in different subject areas or educational levels, and examine its effectiveness in supporting various educational interventions and initiatives.

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