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Optimizing Adaptive Learning: Insights from K-Means Clustering in Intelligent Tutoring Systems

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Abstract: In the realm of intelligent tutoring systems, the concept of clustering groups holds immense potential for enhancing the adaptability and efficacy of educational platforms. Clustering techniques play a pivotal role in organizing learners into meaningful groups based on various criteria, such as learning preferences, proficiency levels, and engagement patterns. In this groundbreaking research paper, we meticulously evaluate the performance of clustering algorithms within the context of intelligent tutoring systems. Our study employs three key metrics—Caliński-Harabasz (CH) Index, Silhouette Score, and Diversity Index—to assess the outcomes of clustering processes across diverse datasets. The investigation is specifically tailored to inform the clustering of learners into groups within intelligent tutoring systems. Our analysis spans datasets such as R15, Aggregation, D31, Pathbased, Jain, and Spiral, offering profound insights into the strengths and limitations of clustering methodologies in the context of educational adaptability. By elucidating optimal clustering scenarios, our findings aim to guide the creation of tailored learning groups, fostering personalized and efficient educational experiences for learners within intelligent tutoring systems. This research significantly advances the discourse on clustering strategies, providing valuable insights for the enhancement of intelligent tutoring systems.

Keywords: *Adaptive Learning, Intelligent Tutoring Systems, Clustering Algorithms, Evaluation Metrics.*

1. Introduction

In the rapidly evolving landscape of educational technology, Intelligent Tutoring Systems (ITS) have become instrumental in shaping personalized and adaptive learning experiences. A crucial facet of this transformative paradigm is the intricate process of clustering learners into groups based on shared characteristics, allowing for nuanced and responsive instructional strategies. This research embarks on a multifaceted journey into the realm of clustering algorithms within ITS, aiming to unveil their potential for optimizing group formation and, consequently, enhancing educational adaptability.

The primary impetus behind intelligent tutoring is to transcend traditional one-size-fits-all models, acknowledging the diverse and evolving needs of learners. Clustering algorithms, by organizing learners into groups with similar attributes, offer a promising avenue to tailor instructional content, pacing, and methodologies. These attributes may span a spectrum, encompassing learning preferences, proficiency levels, and engagement dynamics. Through a meticulous exploration of clustering methodologies, our research seeks not only to enhance the adaptability of tutoring systems but also to contribute to the creation of dynamic, responsive, and learner-centric educational environments.

Our investigation hinges on the utilization of three key evaluation metrics—Caliński-Harabasz (CH) Index, Silhouette Score, and Diversity Index. These metrics serve as critical yardsticks for gauging the quality and effectiveness of group formation within the tutoring system. The datasets selected for analysis, including R15, Aggregation, D31, Pathbased, Jain, and Spiral, represent diverse educational scenarios, mirroring the intricate nature of real-world learning datasets.

As we navigate the labyrinth of clustering intricacies, pivotal questions come to the fore. How does one determine the optimal cluster size that aligns with the ground truth of the educational context? What are the trade-offs and implications associated with different clustering metrics? What insights can be gleaned from the analysis of varied datasets, each posing unique challenges and opportunities?

The forthcoming sections of this research delve into a granular analysis of results, unraveling the nuanced interplay between clustering methodologies and educational datasets. We dissect each dataset, exploring the subtleties of metric interactions, optimal cluster configurations, and deviations from ground truth. Our aim is not only to contribute to the academic discourse on educational adaptability but also to provide actionable insights for educators, instructional designers, and system developers striving to optimize the efficacy of intelligent tutoring platforms.

By the culmination of this research endeavor, we envision

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not only a deeper understanding of clustering methodologies within ITS but also a tangible impact on the design and implementation of future educational technologies. The insights derived from this exploration promise to propel the evolution of intelligent tutoring systems toward a future where learning is not just adaptive but truly individualized and responsive to the unique needs of each learner.

2. Theoretical Background

2.1. Social constructivism

The emergence of social constructivism as a learning theory has been greatly influenced by the works of various researchers, namely Lev Vygotsky in 1934. Social constructivist learning theory emphasizes learners' autonomy, problem-solving, collaborative learning, and scaffolding [1], Vygotsky aimed to transcend behaviorism, introducing additional elements that could enhance the process of knowledge assimilation. This evolution brought forth fresh insights into how individuals engage with their surroundings. Extending Vygotsky 's ideas, Doise, Mugny, and Perret-Clermont (cited in Joshua and Dupin) [2] build upon this foundation, asserting that within sociocultural contexts, the interaction between two learners sparks sociocognitive conflicts, thereby fostering a potent avenue for effective knowledge acquisition.

Social constructivism underscores the significance of the social aspect in learning, pointing out that knowledge is formed through interactions in problem-solving contexts. In this framework, teaching is aimed at steering students towards collaborative activities, providing them with chances to mold their understanding through the experiences of their peers and the resources present in their learning surroundings.

Within the platform of social constructivism, learning unfolds through the collective efforts of a community of learners. This approach encourages learners to engage with the diverse human resources within the learning environment, including teachers, tutors, and fellow learners. Such interactions lead to sociocognitive conflicts that contribute to the development of the learner's psychological functions and the expansion of their zone of proximal development [3]. Consequently, knowledge acquisition becomes more efficient.

At the core of the principles advocated by social constructivist scholars lies the acknowledgment of the inherently social essence of learning. Certain scholars have taken this notion a step further by emphasizing the dispersion of intelligence across individuals and their surroundings. However, recognizing that learning unfolds within a social framework is no longer adequate for guaranteeing profound learning achievements. The potential of group work to elevate the quality of learning could be compromised without a thorough evaluation of pivotal factors, which encompass:

- Diverse learning styles
- Methodology for forming groups.
- Modes of interaction
- Task characteristics

Furthermore, effecting change in individuals' habits and conceptions presents a formidable challenge, thereby exacerbating the complexity of problem situations. Ultimately, the dominance of subjectivity during collaborative tasks over individual learning remains a persistent risk.

2.2. Unsupervised machine learning for online education customization

It is commonly understood that people learn in various methods. Authors in [4] (Khopiya) suggest that certain individuals prefer teaching, while others prefer self-directed learning. Therefore, Creating and adapting information to meet the requirements of diverse learners is crucial for optimizing and accelerating the procedure of learning. This is known as "personalizing" e-learning [5]. Personalization is a popular issue in e-learning. Adapting information to students' various electronic devices is crucial for maximizing and accelerating learning. E-learning customization involves two key tasks: categorization and suggestion. Classification attempts to divide the dataset into distinct classes based on certain parameters. Recommendation aims to optimize or enhance a performance measure by recommending a course of study based on the previously indicated categorization.

Classification is an important stage in the e-learning customization process. The approach relies on grouping related points in a collection under one umbrella. This allows the system to produce better recommendations. There are several aspects.

categorization is necessary for several purposes, including question/task categorization and the status of students classification [6]. E-learning customization includes recommendation as the second stage. This stage suggests the right course of action in accordance with the categorization findings. According to authors in [7], the recommended action aims to optimize customer pleasure and utility. These systems are utilized in several industries, including e-commerce and public transit route planning. In e-learning, recommender systems play a key role in modifying course material by suggesting content suitable to interests of learners, stage of learning, and so forth, in [8] authors suggest categorizing material based on its prior categorization and users.

Uncertainty about students' learning styles and participation prevents the implementation of supervised classification methods. Hence, unsupervised machine learning methods must be used to group the students are divided into distinct groups. According to the author in [9], unsupervised machine learning involves inferring a function or pattern from unlabeled training data. The training data consists of inputs (x1, x2, …, xM) with no known outcomes. Unsupervised learning algorithms analyze training data to identify patterns and relationships. Grouping and clustering data points is an effective technique to make sense of them. Creating a limited collection of groups instead of randomized data points improves data understanding and organization.

The word "clustering" is used instead of "classification" when points of data lack labels for specific classes. Unsupervised machine learning methods have recently been suggested in the literature for online education [10].

2.3. Clustering

Clustering[11] is an unsupervised method [12], involving activities of segmenting data sets into similar clusters such that components in the same set are as similar and items in a separate cluster are as different as possible. It Clustering has a long and distinguished history in a diversity of systematic disciplines such as biology, medicine, anthropology, psychology, mathematics, computer science, psychology, and engineering. Clustering's major goal is to partition a dataset into several clusters so that data in one cluster have similar features while data in other clusters have distinct features from data in another cluster. Various types of similarity metrics could be used to identify classes, based on the data and the function, with the similarity measure controlling how the clusters are generated. The K-means method [13] is the most popular and simple partitioning algorithm. The K-Means Algorithm[14] has numerous variations depending on centroid initiation, distance metrics, k mean reliability variants, and so on.

2.4. K-means clustering algorithm

The K-means clustering technique is a basic unsupervised learning system that solves the well-known clustering issue. The process uses a basic and straightforward approach to classify a given data set using a predetermined number of clusters (k clusters). The primary concept is to specify k centroids, one per every cluster. These centroids ought to be set in a strategic manner since various locations provide varied results. The ideal option is to arrange them as far apart as possible. The following step is to link each point in the data set at hand with its closest centroid. When no points are outstanding, the initial step is accomplished, and an early "grouping" occurs. At this point, we must recalculate K new centroids that serve as the barycenters for the clusters created in the preceding phase. Once there are those K new centroids, a fresh connection must be performed across the previous data set points and a nearby new centroid. A continuous sequence has been created. As the outcome of this loop, we can see the way the K centroids alter their position at each step until no further changes occur. In other words, centroids have no movement anymore. Algorithm 1 demonstrates that.

Algorithm 1: K-Means Grouping

1. Initialize initial approximations for the averages (m_1, m_2,..., m_k).

2. Continue the subsequent steps until there are no modifications in any average:

2.1 Utilize the approximated averages to categorize the samples into clusters.

2.2 For (i) from 1 to (k), execute the following:

2.5. K-means methods

On the other hand, its main drawback is that it asks for the number of clusters as a parameter to enter which breaks the problem of the most optimal number of clusters and in this its several metrics have been developed over time as the elbow method, The Cali´nski-Harabasz method, The silhouette method and the diversity method.

2.5.1. The elbow method

The elbow technique [15] looks at how much variance is described by clustering as a function of the amount of clusters k. If we plot the per cent of variation described versus k, first clusters will be able to clarify a large number of variances, however, the margin gain will decrease at some point, resulting in a graph with an "elbow." At this stage, the optimal k is chosen since adding more clusters would not improve the dataset's description of variance, albeit such an "elbow" cannot always be detected unambiguously [16]. We utilize a an altered modification of this method in this study, which plots the intra-cluster variation curve [17]:

$$E(K) = \sum_{r=1}^{k} W(C_r) \quad (1)$$

where W(Cr) is the variance within the r-th cluster Cr

2.5.2. The Cali´nski-Harabasz method

Milligan et al [18] assessed 30 unlike methods to estimate the number of clusters in a set, and found that the best performing method is given by Cali´nski and Harabasz [19].

$$CH(K) = \frac{B(K)/(K-1)}{W(K)(n-K)} \quad (2)$$

where B(k) is the inter-cluster alteration (i.e. the sum of squared distances for the k clusters), and W(k) is the intracluster variance. The predicted number of clusters is obtained by maximizing CH(k) versus various values of K.

2.5.3. The silhouette method

The silhouette approach was suggested by Rousseeuw et al [20], and its major goal is to determine whether an item (i) is well categorized in the cluster or not. The silhouette of each item or point (i) is measured in terms:

$$S(i) = \frac{b(i) - a(i)}{\max(a(i), b(i))} \quad (3)$$

While a (i) is the average distance of item i to all the items in the same cluster and b(i) is its average distance to all the items in the near cluster. The i-th item is well-clustered if the value of S(i) approaches the maximum which is 1, while an S(i) value of 0 indicates that item (i) belongs to the other cluster. Subsequently plotting the silhouette score averaged over all the items in contradiction of dissimilar values of k, the right number of clusters is predictable to be the k yielding the maximum average silhouette score.

2.5.4. The diversity method

We use the output of the given clustering method (such as k-means) to identify the optimal number of clusters in a set of data within items, and then determine the difference between all the diversity of clusters and the sum of each cluster's local diversity of their members, defined by Q(k) and provided by

$$Q(k) = Div^G - \sum_{r=1}^{k} Div_r^L \quad (4)$$

where DivG is the global variety of k clusters (each cluster being a species), and DivL r is the localized diversity of the r-th cluster (each member item of the cluster being a species), as evaluated by Rao's quadratic probability (Equation) (4). For different values of k, i.e., for k from 1 to n, we compute the diversity-based statistic Q(k), and the highest amount of Q(k) should be able to determine us the ideal clusters in the dataset, i.e.,

$$k = arg \max_{1 \le k \le n} Q(k) \quad (5)$$

This diversity method's basic concept is that efficient clustering, the items inside each cluster should be as homogenous as feasible (i.e., less local diversity), whereas the clusters themselves should be as varied as possible (i.e., more global diversity). A high degree of diversity across clusters implies a balancing of cluster sizes.

It is worth noting that the 'elbow' method relies primarily on a graphical representation, leveraging human visual perception to detect the optimal number of data clusters by observing the transition point in the curve, resembling an elbow shape. Therefore, this method will not be addressed in this study.

3. Proposed Approach

In the given context, user models are repositories of individualized data, encompassing information such as the user's knowledge level, progress, age, occupation, and emotional state. While these details aren't directly utilized for system adaptation, they serve the purpose of categorizing users into stereotypes. These stereotypes, indicative of common user behaviors, enable the system to foresee and understand user actions more effectively. The organization of users into meaningful groups is facilitated through these stereotypes, proving particularly advantageous in the domain of learning multiple languages. To implement this organizational process, an unsupervised clustering algorithm, specifically the K-means algorithm, is integrated into the system's workflow.

Figure 1 shows the proposed workflow of our method. The workflow begins by determining the number of clusters (k) to be formed. Following this, (k) entities are randomly chosen to act as initial cluster centers. The system then iteratively recomputes the clusters and adjusts the cluster centers. The distance between the remaining entities and the central cluster points is calculated, leading to the assignment of entities to the cluster represented by the nearest center. Clustering outcomes are generated based on this process.

Subsequently, the system verifies the results. If the verification is successful, a decision is made. If not, the system checks whether the cluster centers have altered since the last iteration. If there is a change, the process returns to recomputing clusters. If there is no change, the system concludes. This iterative cycle ensures that the system continuously refines its understanding of user behaviors and adapts to any evolving patterns within the user data.

In order to achieve better performance in our system, especially in the group creation phase, it is essential to select the optimal number of clusters for K-means. To accomplish this, we must utilize the most effective metric that yields the best results. In this article, we will take data for which we already know the number of clusters and analyze it using various metrics, namely diversity, CH (Caliński-Harabasz), and silhouette. The goal is to determine the metric that produces the best results.

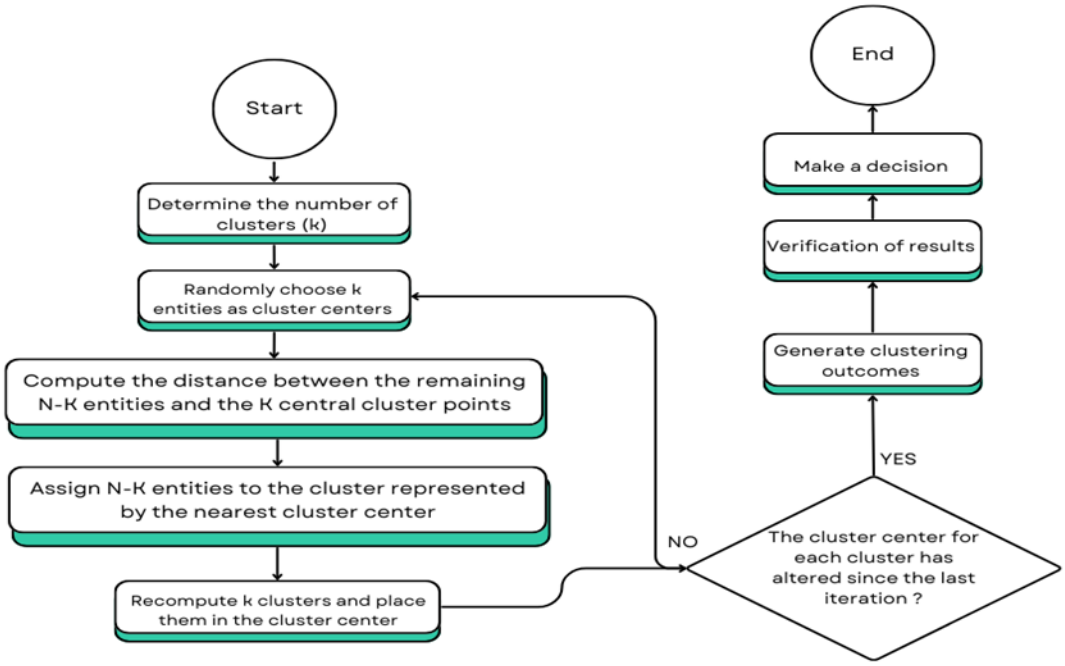

Fig 1. The proposed approach workflow.

4. Datasets used

In this comprehensive research endeavor focused on clustering algorithms within Intelligent Tutoring Systems (ITS), a diverse selection of datasets has been meticulously curated to capture the complexity and variability inherent in educational contexts. The datasets selected for analysis encompass a range of characteristics and a predefined number of clusters (K), providing nuanced scenarios for evaluating the performance of clustering methodologies. The datasets presented in figure 2 under scrutiny are as follows:

4.1. R15 Dataset

The R15 dataset [11] encapsulates a rich spectrum of learning characteristics, simulating an environment with fifteen distinct clusters. Learners within each cluster exhibit diverse preferences, proficiency levels, and engagement patterns, providing a robust benchmark for evaluating the adaptability of clustering algorithms. This dataset serves as a foundational benchmark, offering a clear ground truth for optimal clustering scenarios. Its multifaceted nature enables the exploration of how clustering methodologies respond to varied learning attributes.

4.2. Aggregation Dataset

The Aggregation dataset [21] poses a unique challenge for clustering algorithms due to its intricate and non-uniform structure. Learners are grouped in a way that demands algorithms to discern subtle relationships and patterns within the data, mirroring the complex nature of real-world educational datasets. This dataset aims to assess the adaptability of clustering methodologies to scenarios where the underlying structure is not immediately apparent, providing insights into the algorithms' capability to uncover intricate learning patterns.

4.3. D31 Dataset

The D31 dataset [22] is characterized by thirty-one clusters, presenting a diverse range of proficiency levels and learning attributes. This dataset emulates scenarios where learners exhibit a wide spectrum of skills and knowledge, enabling a nuanced exploration of optimal cluster configurations. With a multitude of clusters, this dataset facilitates an examination of clustering performance in scenarios where learners vary significantly in their learning attributes, contributing to the understanding of diverse educational settings.

4.4. Pathbased Dataset

The Pathbased dataset [11] is designed to challenge clustering algorithms by featuring intricate learning paths. Learners within this dataset follow non-linear trajectories, introducing complexities that test the adaptability of clustering methodologies to unconventional learning structures. This dataset offers insights into how clustering algorithms respond to learners with diverse and non-linear learning trajectories, reflecting real-world scenarios where students may follow unique educational paths.

4.5. Jain Dataset

The Jain dataset [11] presents specific challenges to clustering algorithms due to its distinctive characteristics. It requires algorithms to adapt to scenarios where traditional approaches may face limitations, emphasizing the need for adaptability to unique learning contexts. This dataset contributes to understanding the nuanced interplay between algorithmic adaptability and specific learning attributes, shedding light on scenarios where conventional methods may encounter challenges.

4.6. Spiral Dataset:

The Spiral dataset [22] introduces a unique structure, where learners exhibit interconnected and non-linear learning patterns resembling a spiral. This dataset aims to explore how clustering methodologies

respond to scenarios with unconventional learning structures. By challenging algorithms with a spiral structure, this dataset provides insights into the adaptability of clustering methodologies to complex and interconnected learning scenarios, contributing to a more holistic understanding of educational contexts.

Each dataset has been meticulously chosen to encapsulate diverse educational scenarios, ensuring a comprehensive evaluation of clustering methodologies within the context of Intelligent Tutoring Systems. The subsequent sections will delve into a detailed analysis of each dataset, unraveling the intricacies and insights gained from the application of clustering algorithms in these rich learning environments.

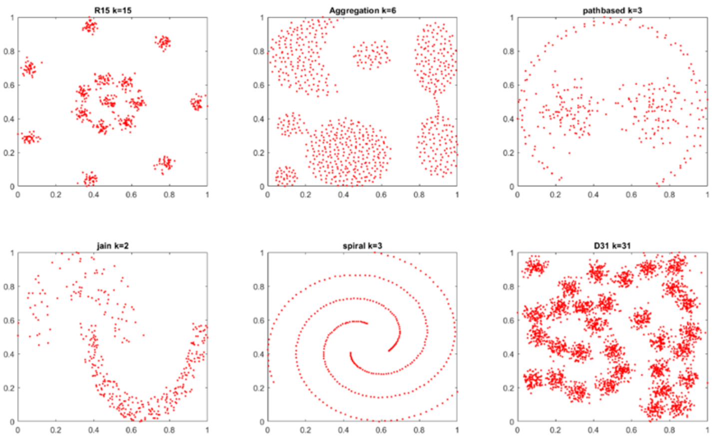

Fig 2 Datasets used

5. Results and discussion

The extensive analysis of clustering results across diverse datasets provides valuable insights into the performance and behavior of clustering algorithms under different conditions. The evaluation metrics employed, including the Caliński-Harabasz (CH) Index, Silhouette Score, and Diversity Index, offer a comprehensive understanding of the effectiveness and limitations of the clustering processes; assess the optimal number of clusters using various methods. Ultimately, we color the obtained results, labeling them as correct in green, false in red, and close estimations in orange, in the following results (Table 1).

Table 2. Comparative Analysis of Clustering Performance Metrics Across Diverse Datasets

		CH		*Silhouette*		*Diversity*	
DataSet	***k****	***k***	***Error=(k-k*)/k****	***k***	***Error=(k-k*)/k****	***k***	***Error=(k-k*)/k****
R15	15	15	0%	14	-7%	14	-7%
Aggregation	6	29	383%	4	-33%	7	17%
D31	31	34	10%	33	6%	31	0%
Pathbased	3	30	900%	3	0%	2	-33%
Jain	2	17	750%	7	250%	2	0%
Spiral	3	30	900%	30	900%	3	0%
AVERAGE of the Error			491%		199%		9%

The error term, expressed as Error = (k - k^*)/k*, serves as a metric for evaluating the performance of clustering algorithms. Here, k represents the number of clusters determined by the algorithm, and (k*) denotes the pre-defined or ground truth number of clusters in the dataset. The error calculation involves subtracting the actual number of clusters (k) from the pre-defined number (k*), dividing this difference by the pre-defined number (k*), and finally expressing this as a fraction.

The resulting error metric provides valuable insights into the alignment between the algorithm's output and the actual structure of the dataset. A lower error indicates a closer match between the algorithmic clustering and the pre-defined clusters, signifying higher accuracy. Conversely, a higher error suggests a divergence from the ground truth, indicating potential challenges or limitations in the algorithm's performance in accurately determining the optimal number of clusters. This error term serves as a quantitative measure to assess the effectiveness of clustering algorithms in capturing the inherent structure of the data, guiding the quest for optimal cluster configurations.

Beginning with the R15 dataset, both the CH Index and Silhouette Score align optimally with the ground truth (k) of 15, demonstrating a remarkable consistency and accuracy in capturing the underlying patterns within the data. This dataset serves as a benchmark for an ideal clustering scenario.

Contrastingly, the Aggregation dataset poses challenges, especially evident in the substantial errors reflected by both the CH Index and Silhouette Score. The large error percentages suggest a considerable divergence from the ground truth, emphasizing the sensitivity of the algorithm to the intrinsic complexity and structure of the data. The Diversity Index, however, provides a contrasting perspective, indicating a moderate discrepancy. This discrepancy may indicate a nuanced aspect of diversity that the other metrics might not fully capture.

Moving to the D31 dataset, the clustering performance is notably stable, with relatively low errors in both the CH Index and Silhouette Score. The minimal error percentages suggest a commendable alignment with the ground truth, emphasizing the algorithm's ability to discern underlying patterns in datasets of varying complexity.

In the case of the Pathbased dataset, the CH Index reflects a substantial error, indicating challenges in capturing the inherent structure. However, the Silhouette Score, which is optimal at (k= 3), highlights a robust performance in terms of individual cluster quality. This discrepancy underscores the importance of considering multiple metrics to gain a holistic understanding of clustering outcomes.

The Jain dataset presents a scenario where both the CH Index and Silhouette Score exhibit considerable errors, suggesting challenges in accurately representing the underlying structure. The Diversity Index, on the other hand, shows no error, indicating a perfect match with the optimal clustering. This raises questions about the interpretation of diversity and the trade-offs between different metrics.

The Spiral dataset introduces an interesting dynamic where the CH Index indicates a substantial error, while the Silhouette Score suggests optimal clustering at a value significantly different from (k). This scenario highlights the importance of careful metric selection, as different metrics may capture distinct aspects of clustering quality.

The averaged errors across datasets serve as a crucial summary, emphasizing the variability in performance metrics across different datasets. The high average error for the CH Index underlines the challenges in achieving consistent performance. The Silhouette Score, with a lower but still significant average error, reflects the algorithm's sensitivity to variations in the optimal number of clusters. In contrast, the Diversity Index maintains a relatively low average error, signifying a more consistent performance in capturing the diversity of clusters.

The diversity, silhouette, and Calinski-Harabasz methods were employed to evaluate the clustering performance, as illustrated in Figures 2, 3, and 4, respectively, as depicted in the appended index. Figure 2 showcases the outcomes of the Diversity method, providing insights into the variability of learning attributes within the formed clusters. Meanwhile, Figure 3 delineates the results of the Silhouette method, offering a visual representation of the quality and cohesion of individual clusters. Lastly, Figure 4 illustrates the outputs of the Calinski-Harabasz method, presenting a comparative analysis of the separation and compactness of clusters across diverse datasets. These figures collectively contribute to a comprehensive understanding of the effectiveness and adaptability of clustering algorithms within the context of Intelligent Tutoring Systems.

6. Conclusion

In conclusion, this research offers a thorough exploration and analysis of clustering algorithms within the realm of Intelligent Tutoring Systems (ITS). The study delves into the adaptability and efficacy of these algorithms across diverse educational datasets, shedding light on their ability to form meaningful learner groups. Utilizing three key metrics—Caliński-Harabasz Index, Silhouette Score, and Diversity Index—the research meticulously evaluates the clustering outcomes across various datasets with pre-defined and varying cluster structures.

The findings from this study highlight the nuanced interplay between algorithmic performance and dataset characteristics. Datasets with pre-defined cluster structures, such as R15 and D31, provide a benchmark for assessing the accuracy of clustering algorithms. The presented metrics, visualized in Figures 3, 4, and 5, offer a comprehensive understanding of the quality, cohesion, and diversity within the formed clusters.

Through this exploration, the research not only contributes valuable insights into the optimal configurations of clustering algorithms for educational adaptability but also addresses the broader implications for the design and implementation of ITS. The outcomes serve as a guide for educators, instructional designers, and system developers seeking to enhance the efficacy of adaptive learning platforms. By understanding the strengths and limitations of clustering methodologies, we pave the way for the continued evolution of intelligent tutoring systems, fostering personalized and responsive learning environments for diverse learners.

6.1. Appendix

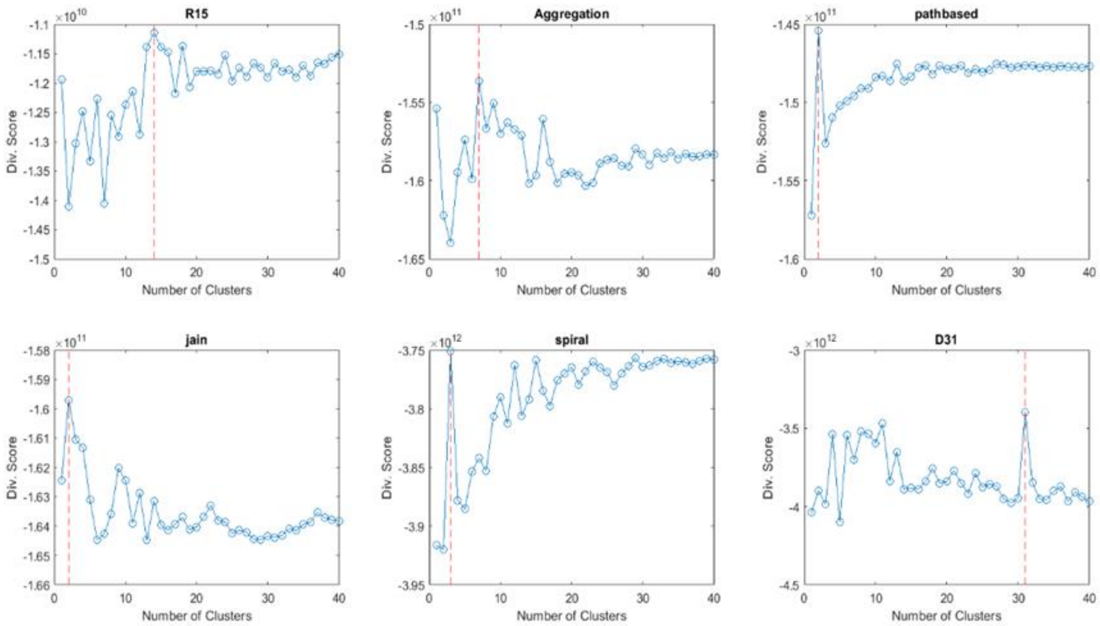

Fig 3. Result of the Diversity method

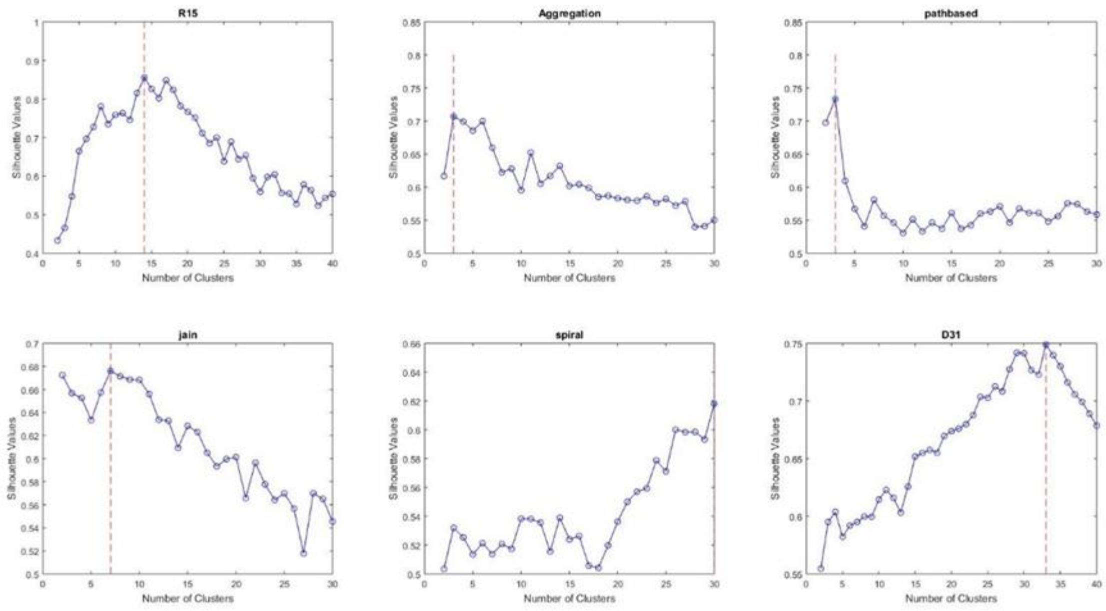

Fig 4. Results of the sillouhette method

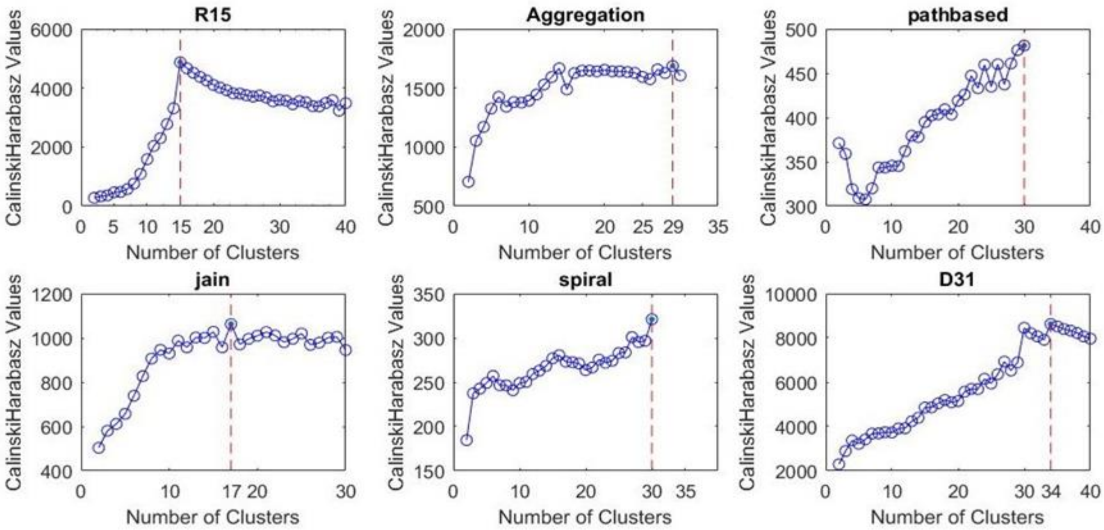

Fig 5. Result of the calinski harabaz method

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