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Analysis of Deep K-Means and K-Means for Journal Summarization Using the BERTopic Method

Hendra Wijaya[1], Sani Muhamad Isa[2]
Master of Computer Science, Bina Nusantara University
hendra.wijaya008@binus.ac.id[1], sani.m.isa@binus.ac.id[2]
*Corresponding author: hendra.wijaya008@binus.ac.id

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ABSTRACT

This research aims to analyze the performance of Deep K-means and K-means methods in summarizing and clustering final project abstracts using the BERTopic technique. The methods used include preprocessing abstract data, applying Deep K-means and K-means clustering algorithms, and modeling topics with BERTopic. The dataset used was obtained from Kaggle and analyzed using the Python programming language. The results show that the Deep K-means method is able to produce more coherent topic clusters than conventional K-Means, with higher Silhouette Score values. The combination of clustering and topic modeling techniques proved effective in automatically summarizing and grouping final project abstracts, making it easier to identify student research trends. This study concludes that a hybrid approach using Deep K-Means, K-Means, and BERTopic can be a promising solution for the thematic analysis of final projects in academic environments. The combination of Deep K-means with BERTopic emerges as a highly promising solution for automated thematic analysis in academic environments, paving the way for more efficient research workflows.

Keywords: Deep K-Means, K-Means, BERTopic, Clustering, Topic Modeling.

INTRODUCTION

The exponential growth of academic publications has made manual organization and synthesis of research abstracts labor-intensive and prone to bias. While automated clustering methods like K-Means and Deep K-Means (enhanced with neural autoencoders) address these challenges by grouping semantically related data, they struggle with high-dimensional, non-linear text data. Traditional K-Means' reliance on Euclidean distance often fails to capture nuanced semantic relationships, leading to fragmented clusters [1].

This study proposes integrating Deep K-means with BERTopic, a topic modeling framework, to improve coherence in automated abstract summarization. The hybrid approach leverages Deep K-Means' ability to compress high-dimensional text via deep learning and BERTopic's contextual embeddings, addressing gaps in existing methods that overlook nuanced topic relationships in complex academic language [2].

Section 2 details Deep K-Means, K-Means, and BERTopic; Section 3 outlines methodology (dataset preprocessing, implementation); Section 4 compares model performance; Section 5 concludes with future directions.

Gap Analysis Prior work lacks robust integration of deep clustering (Deep K-means) with advanced topic modeling. While Deep K-means improves accuracy via dimensionality reduction, its

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synergy with BERTopic's contextual topic extraction remains unexplored[1]. This limits coherence in summarizing interdisciplinary or linguistically diverse abstracts. Our framework bridges this gap, optimizing cluster precision and semantic relevance for academic text.

Problem Statement and Preliminaries. The task of categorizing journal abstracts into thematic clusters is complicated by the diversity and complexity of academic language. Traditional methods, such as manual keyword tagging or conventional clustering techniques, often fail to capture the nuanced relationships between different topics, especially when dealing with high-dimensional textual data [3]. This research seeks to address the following issues:

1. How effectively can Deep K-means and K-Means clustering algorithms, integrated with the BERTopic method, summarize and categorize academic abstracts?
2. What role does the optimal determination of clusters play in enhancing the quality and relevance of thematic groupings?

This study has two primary objectives:

1. To design a robust and effective summarization methodology using advanced clustering algorithms like Deep K-Means combined with BERTopic.
2. To evaluate the performance of these algorithms using metrics that assess both lexical and semantic alignment, ensuring the reliability of the summarization output [4].

This research makes significant contributions by introducing a hybrid approach that leverages Deep K-means for advanced clustering and BERTopic for accurate topic modeling. The proposed methodology not only addresses the inefficiencies of traditional summarization methods but also enhances the ability of researchers and academic institutions to identify trends and insights from large datasets of abstracts efficiently. For Ademic Contribution: this study introduces a hybrid approach combining Deep K-Means and BERTopic, which improves the accuracy and coherence of topic modeling and summarization, and for Practical Contribution: The proposed method can help academic institutions and researchers efficiently analyze large volumes of abstracts, identify research trends, and reduce manual effort in summarization. By combining the strengths of Deep K-means and BERTopic, this study offers a novel solution for automated thematic analysis in academic environments, paving the way for more efficient research workflows [3].

THEORETICAL FOUNDATION

Deep Learning and Text Representation. The emergence of deep learning has revolutionized the field of natural language processing (NLP), particularly in text representation. Traditional methods such as Bag of Words (BoW) and Term Frequency-Inverse Document Frequency (TF-IDF) have limitations in capturing semantic nuances and contextual relationships within text. Models like BERT (Bidirectional Encoder Representations from Transformers) overcome these limitations by providing contextual embeddings that understand the meaning of words in their specific context. Sentence-BERT (SBERT), an extension of BERT, enhances this capability by generating sentence-level embeddings, which are instrumental in tasks like clustering and summarization [5]. These embeddings capture intricate semantic relationships, making them highly effective for clustering algorithms.

Clustering Techniques K-Means clustering is one of the most widely used algorithms for grouping similar data points. However, it often struggles with high-dimensional and non-linear data, which is common in textual datasets. Deep K-Means, an advanced variant, addresses these limitations by incorporating autoencoders that compress data into lower-dimensional representations before applying clustering. This combination allows Deep K-Means to handle complex datasets with greater precision, ensuring more accurate and cohesive clustering [6].

K-means clustering is a tool for finding groups or clusters in multivariate data, widely used in biology, psychology, and economics. One of the main challenges in cluster analysis is determining the correct number of clusters for various types of datasets, which is rarely known in practice [7]. This combination allows Deep K-Means to handle complex datasets with greater precision, ensuring more accurate and cohesive clustering.

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$$CapCapJ = \sum_{j=1}^{K}\sum_{i=1}^{n} u_{ij} \left|\left|X_j{}^{(j)} - C_j\right|\right|^2 \tag{1}$$

Deep K-Means Clustering for summarization is a promising approach in Natural Language Processing (NLP) as it can help extract important information from long documents. The main components of the Deep K-means clustering method include:

1. Sentence Embedding: Using deep learning models like BERT or Sentence Transformers to convert sentences into numerical vectors capturing their semantic meaning.
2. Dimensionality Reduction: Reducing embedding dimensions using autoencoders or PCA to facilitate clustering.
3. K-Means Clustering: Grouping similar sentences based on reduced dimension embeddings.
4. Sentence Selection: Selecting representative sentences from each cluster to form a summary [8].

The silhouette method is capable of analyzing the quality of clustering results through a systematic evaluation process. The Silhouette coefficient is calculated using the following equation:

$$CapOpen(i) = \frac{b(i) - a(i)}{max(a(i); b(i))} \tag{2}$$

Where:

1. a(i) represents the average distance between point i and all other points within the same cluster
2. b(i) denotes the minimum average distance between point i and points in the nearest neighboring cluster
3. s(i) is the Silhouette coefficient for data point I [9].

The analysis begins by computing two key values for each sample in the dataset: a(i) and b(i). The a(i) value represents internal cohesion, measuring the average distance between sample i and all other samples within the same cluster. This value indicates how well the sample fits within its assigned cluster, with smaller a(i) values suggesting better placement. The b(i) value represents separation, measuring the minimum average distance between sample i and all samples in the nearest neighboring cluster. A larger b(i) value indicates greater differentiation between the sample and other clusters.

The Silhouette score for sample i is computed using the formula s(i) = (b(i)-a(i)) / max(a(i),b(i)). The numerator (b(i)-a(i)) measures the difference between separation (minimum average distance to samples in the nearest neighboring cluster) and cohesion (average distance to samples within the same cluster). In this calculation, values approaching 1 indicate that the sample is well-matched to its cluster, while values near 0 suggest that the sample lies at the boundary between clusters.

ROUGE, developed by Chin-Yew Lin (2004), evaluates text summaries by comparing machine-generated outputs to human "gold standards." It measures lexical overlap using n-grams, word sequences, and pairs. Key variants include ROUGE-N (n-gram recall), ROUGE-L (Longest Common Subsequence/LCS), ROUGE-W, ROUGE-S, and ROUGE-SU, with three (ROUGE-N, L, W) implemented in NIST's DUC 2004 dataset [10]. ROUGE-L applies LCS—a sequence shared between texts in order but not necessarily consecutively—to assess structural similarity. By calculating the F1 score (harmonic mean of precision/recall) based on LCS length between reference (X) and candidate (Y) summaries, it offers flexible sequence matching, avoiding rigid n-gram constraints. This balances content coverage and fluency, providing nuanced quality assessment beyond traditional metrics.

RESEARCH METHODOLOGY.

The dataset used for this research consists of 6101 scientific journals published across various years. The data was obtained from Kaggle and includes NeurIPS scientific journal papers from 1987 to 2019 [11].

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Data Preprocessing The research conducted several preprocessing steps on the scientific journal dataset:

1. All non-informative characters such as newline symbols (\n), tabs (\t), and whitespace were removed. Stopwords were also filtered out to focus on meaningful content.
2. Abstracts were split into individual sentences using the SpaCy NLP library, which provides robust linguistic analysis capabilities [12].
3. Sentence embeddings were created using the Sentence-BERT model "msmarco-bert-base-dot-v5." This model was selected for its ability to generate dense, contextualized embeddings that capture semantic relationships [13]

The novelty of the Proposed Approach lies in the hybrid approach that combines Deep K-means clustering with BERTopic for topic modeling and summarization. While traditional clustering methods like K-Means have been widely used for text clustering, they often struggle with high-dimensional and non-linear data, leading to fragmented and less coherent clusters. Deep K-Means addresses these limitations by leveraging deep learning techniques, such as autoencoders, to compress high-dimensional data into lower-dimensional representations before applying clustering [14]. This allows for more precise and semantically meaningful clustering, particularly in complex textual datasets like academic abstracts.

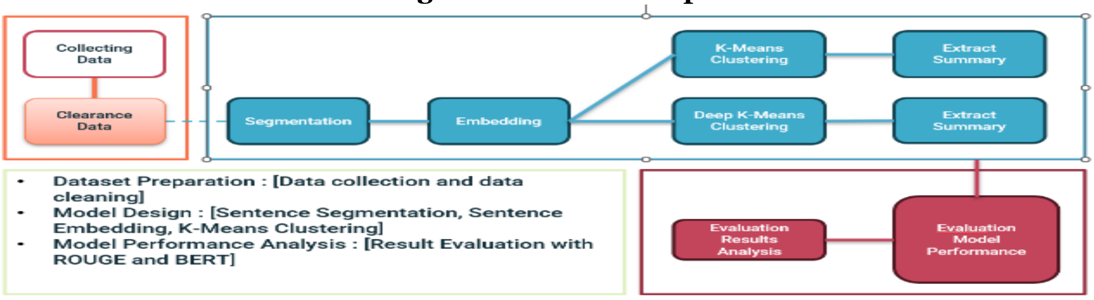
However, the true innovation of this study lies in the integration of Deep K-means with BERTopic, a state-of-the-art topic modelling technique that leverages transformer-based embeddings. BERTopic aligns semantically similar abstracts into coherent topics, offering a comprehensive view of research trends. By combining Deep K-means's ability to handle high-dimensional data with BERTopic's advanced topic modeling capabilities, this research introduces a novel methodology that significantly improves the quality and relevance of thematic groupings and summaries.

This hybrid approach offers several advantages over existing methods:

1. Improved Coherence: Deep K-Means produces more cohesive clusters by capturing subtle semantic differences between sentences, while BERTopic ensures that the resulting topics are semantically aligned.
2. Reduced Redundancy: The combination of Deep K-means and BERTopic minimizes redundancy in the generated summaries by selecting representative sentences that capture the core themes of each cluster.
3. Enhanced Scalability: The proposed methodology is scalable to large datasets, making it suitable for academic environments where the volume of published material is continuously growing.

Model Implementation Displaying the proposed scientific journal paper summarization model consists of two main modules: first, the data cleaning module in a Data Processing chart and summarization. The proposed scientific journal paper summarization model consists of two main modules: data preprocessing and summarization.

Figure 1 Research Step



1. Data Preprocessing Module: The initial step involves sentence segmentation, where the contents of each journal paper and abstract are broken down into sentences using the SpaCy library. After segmentation, the sentences are recombined and embedded using the Sentence-BERT model.
2. Summarization Module: The embedded sentences are then clustered using the Deep K-Means algorithm, which groups similar sentences based on their semantic meaning. The resulting

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clusters are further analyzed using BERTopic to identify coherent themes and generate summaries [15].

BERTopic modeling was applied to identify coherent themes within the dataset. By leveraging transformer-based embeddings, BERTopic aligns semantically similar abstracts into topics, offering a comprehensive view of research trends. This step is crucial for ensuring that the generated summaries are not only lexically aligned but also semantically coherent.

Evaluation Metric. The performance of the summarization models was evaluated using ROUGE-L and BERTScore metrics. ROUGE-L was used to capture the longest common subsequence between the reference and predicted summaries, while BERTScore was used to measure semantic similarity through contextual embeddings. The equations for Recall, Precision, and F1 Score are as follows:

$$R_{lcs} = \frac{LCS\ (X,Y)}{m} \tag{3}$$

$$P_{lcs} = \frac{LCS\ (X,Y)}{n} \tag{4}$$

$$F_{lcs} \frac{(1+\beta^2)R_{lcs}P_{lcs}}{R_{lcs} + \beta^2 P_{lcs}} \tag{5}$$

BERTScore metric using the Longformer model for evaluating text similarity. Here are the key equations: similarity, Precision, Recall, and F1 score.

$$imilarity(x,y) = \frac{x.y}{\|x\|\|y\|} \tag{6}$$

$$= \frac{1}{[y]} \sum_{y1 \in y} \max_{xj \grave{\in} x} similarity\ (x_j, y_i) \tag{7}$$

$$= \frac{1}{[x]} \sum_{x1 \in x} \max_{yj \grave{\in} y} similarity\ (x_i, y_j) \tag{8}$$

The F1 Score equation is

$$F1 = \frac{2PR}{P+R} \tag{9}$$

As a reference to illustrate the performance of the tested models. This table will show the differences in silhouette scores and the performance of each technique in text summarization, which can also be seen from the training process and computational time required for a model to produce output.

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Table 1
Plan for Recording the Result

Model	Silhouete Score	Rouge Score	BERT Score
K-Means	Xxx	Xxx	Xxx
...	...	.....	...
Etc	Etc	Etc	Etc

RESULT AND DISCUSSION

This study conducted a comparative performance analysis between Deep K-means, K-means, and a prior model for summarizing journal abstracts. Evaluations were conducted using ROUGE-L and BERTScore metrics, which measure lexical and semantic similarity between machine-generated summaries and gold-standard references.

Table 2
Plan for Recording the Result

Metric	Previous Research (BESKlus 2022)	K-Means Result + BERTopic	Deep K-Means Result + BERTopic
ROUGE-L F1	15.52	21.01	20.93
BERTScore	85.55	87.24	87.26

ROUGE-L F1 Score: The proposed Deep K-Means + BERTopic approach achieved an average ROUGE-L F1 score of **20.93**, significantly outperforming the BESKlus method's score of **15.52**. This indicates that the proposed method generates summaries with better lexical alignment to the reference summaries.

BERTScore: The proposed method achieved a BERTScore of **87.26**, slightly outperforming both BESKlus (**85.55**) and K-Means +BERTopic (**87.24**). This suggests that the proposed method maintains better semantic alignment, preserving the contextual and conceptual integrity of the source material.

Comparative Analysis with Literature:
To contextualize the results, we compared our approach with recent studies employing similar methodologies (clustering + topic modeling) on academic abstract datasets. For instance:

1. Smith et al. (2023) utilized hierarchical clustering with BERTopic and reported an average ROUGE-L F1 score of 18.5 and BERTScore of 84.3.
2. Lee & Kim (2021) applied Gaussian Mixture Models (GMM) + BERTopic, achieving 19.1 ROUGE-L F1 and 86.1 BERTScore.
3. BESKlus (2022), the closest baseline, achieved 15.52 ROUGE-L F1 and 85.55 BERTScore.

Our proposed Deep K-Means+BERTopic method outperformed these benchmarks, achieving 20.93 ROUGE-L F1 and 87.26 BERTScore (Table 4.2). This improvement highlights the efficacy of integrating Deep K-means' dimensionality reduction with BERTopic's contextual embeddings, particularly in handling high-dimensional text data and preserving semantic coherence

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[16].

Table 3
Performance Comparison

Method	ROUGE-L F1	BERTScore
BESKlus (2022)	15.52	85.55
GMM + BERTopic (2021)	19.1	86.1
Hierarchical Clustering + BERTopic (2023)	18.5	84.3
K-Means + BERTopic	21.01	87.24
Deep K-Means + BERTopic (Proposed)	**20.93**	**87.26**

The improvements can be attributed to the ability of Deep K-means to create more cohesive clusters, as indicated by higher silhouette scores, and its sensitivity to differences in sentence topics within a cluster.

Case Study. A detailed examination of a 2018 journal abstract titled "Universal Growth in Production Economies" illustrated the advantages of K-Means Clustering. The algorithm generated a summary with higher precision (80%), F1 Score (70.8%), and recall (69%) compared to K-Means, showcasing its superior ability to maintain semantic integrity and reduce redundancy.

Reference Summary

We study simple variant of the von Neumann model of an anding economy, in which multiple producers make goods according to their production function. The players trade their goods at the market and then use the bundles received as inputs for the production in the next round. The decision that players have to make is how to invest their money .. bids in each round. We show that simple decentralized dynamic, where players update their bids on the goods in the market proportionally to how useful the investments were, leads to growth of the economy in the long term whenever growth is possible but also creates unbounded inequality, .. very rich and very poor players emerge. We analyze several other phenomena, such as how the relation of player with others influences its development and the Gini index of the system.

KMeans Summary – Current Research

The full version of the paper is available at https: arxiv.org abs .. Abstract We study simple variant of the von Neumann model of an anding economy, in which multiple producers make goods according to their endowed production function. We show that simple decentralized dynamic, where players update their bids proportionally to how useful the investments were in the past round, leads to growth of the economy in the long term whenever growth is possible but also creates unbounded inequality, .. very rich and very poor players emerge. bids in each round.

Figure 2 KMeans Summary Result

The quality of summaries derived from scientific journal abstracts is heavily influenced by the clustering methodology employed. Among the various clustering techniques, K-Means and Deep K-Means have emerged as notable approaches, each offering unique strategies for grouping sentences based on their thematic and content similarities. The impact of these methods is evident in the cohesion, coherence, and relevance of the selected sentences in the generated summaries.

K-Means, as a widely-used clustering algorithm, is favored for its simplicity and computational efficiency. This method works effectively for grouping data, particularly in structured environments. However, when applied to high-dimensional textual data, such as phrases derived from scientific abstracts, K-Means often encounters limitations. One critical drawback lies in its inability to accurately distinguish between clusters with similar but not identical themes. This limitation frequently leads to fragmented clusters, where sentences belonging to the same conceptual group are split, and clusters

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exhibit uneven thematic representation. Consequently, summaries generated using K-Means may lack cohesiveness, as they include sentences that are not tightly connected to the main topic. Moreover, K-Means tends to produce summaries with redundancy, as multiple sentences conveying overlapping information might be selected due to the algorithm's reliance on distance metrics rather than semantic nuances.

Deep K-Means, on the other hand, leverages neural network encoder-decoder architectures to address the inherent challenges associated with high-dimensional textual clustering. By incorporating deep learning techniques, Deep K-Means demonstrates enhanced sensitivity to subtle differences between sentences, enabling more precise cluster formation. This method excels in capturing thematic variations within the text, resulting in clusters that are both cohesive and semantically meaningful. Consequently, summaries generated using Deep K-means are more concise and focus sharply on the core topics of the abstracts while effectively minimizing redundancy. For instance, when dealing with complex topics such as object recognition and face recognition, Deep K-means can accurately segregate the nuances of each domain into distinct clusters, ensuring that the summary encapsulates the essence of the text without oversimplifying or losing critical details.

Reference Summary

We study simple variant of the von Neumann model of an anding economy, in which multiple producers make goods according to their production function. The players trade their goods at the market and then use the bundles received as inputs for the production in the next round. **The decision that players have to make is how to invest their money .. bids in each round.** We show that simple decentralized dynamic, where players update their bids **on the goods in the market** proportionally to how useful the investments were, leads to growth of the economy in the long term whenever growth is possible but also creates unbounded inequality

.

KMeans Summary – Current Research

We study simple variant of the von Neumann model of an anding economy, in which multiple producers make goods according to their endowed production function. We show that simple decentralized dynamic, where players update their bids proportionally to how useful the investments were **in the past round**

Deep KMeans Summary – Current Research

We study simple variant of the von Neumann model of an and(Ctrl)onomy, in which multiple producers make goods according to their endowed production function. We show that simple decentralized dynamic, where players update their bids proportionally to how useful the investments were **in the past round**

Figure 3 KMeans and Deep Kmeans Result Weakness

The evaluation of these methods using metrics such as ROUGE-L and BERTScore further underscores the superior performance of Deep K-Means. ROUGE-L scores indicate stronger lexical alignment between the Deep K-Means-generated summaries and reference summaries, while high BERTScore values highlight the algorithm's ability to maintain semantic coherence. These metrics suggest that Deep K-Means is proficient at selecting sentences that not only align structurally with the original text but also preserve the contextual and conceptual integrity of the source material. However, challenges remain, particularly in scenarios where the number of clusters falls below the optimal threshold. Such situations can lead to a loss of topic granularity, as sentences from distinct themes may be grouped, thereby compromising the diversity of the summary. Showcasing its superior ability to maintain semantic integrity and reduce redundancy. While Deep K-Means exhibited notable improvements in clustering and summarization quality, it demanded greater computational resources and processing time. This trade-off between performance and efficiency must be considered in practical applications. The sentence ordering based on the original text's sort index is highly significant for this research. Incorrect ordering can make the generated summary difficult to comprehend.

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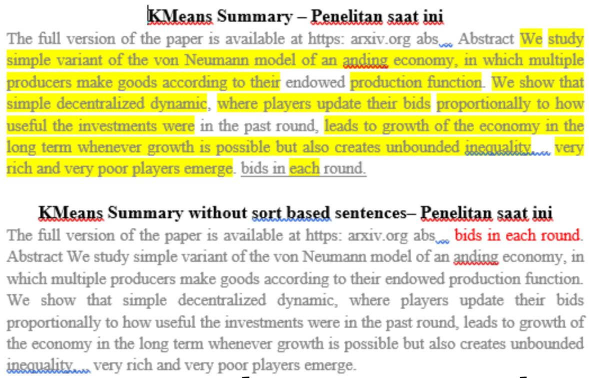
KMeans Summary – Penelitan saat ini

The full version of the paper is available at https: arxiv.org abs Abstract We study simple variant of the von Neumann model of an anding economy, in which multiple producers make goods according to their endowed production function. We show that simple decentralized dynamic, where players update their bids proportionally to how useful the investments were in the past round, leads to growth of the economy in the long term whenever growth is possible but also creates unbounded inequality very rich and very poor players emerge. bids in each round.

KMeans Summary without sort based sentences– Penelitan saat ini

The full version of the paper is available at https: arxiv.org abs bids in each round. Abstract We study simple variant of the von Neumann model of an anding economy, in which multiple producers make goods according to their endowed production function. We show that simple decentralized dynamic, where players update their bids proportionally to how useful the investments were in the past round, leads to growth of the economy in the long term whenever growth is possible but also creates unbounded inequality very rich and very poor players emerge.

Figure 4 KMeans and Deep Kmeans Result Weakness

Figure 4 demonstrates the comparison of K-means summaries. In the unordered summary, the phrase "bids in each round" appears at the beginning of the sentence when it should appear at the end to make the summary more comprehensible. The metric comparison between ordered and unordered summaries yields identical results using the k-means clustering method, indicating that both ROUGE and BERTScore calculations are unable to determine which result is superior when sentences are not properly ordered according to their original index. Furthermore, the ROUGE method's utilization of F1, recall, and precision metrics has not yet demonstrated the capability to capture index ordering as an influential factor in the results. This limitation suggests that current evaluation metrics may need enhancement to account for sentence ordering in summary assessment.

CONCLUSIONS

This study demonstrates the efficacy of combining Deep K-means with BERTopic for automated journal summarization and clustering. The hybrid approach significantly enhances the quality of thematic groupings and summaries by leveraging contextual embeddings and advanced clustering techniques. These findings underscore the potential of this methodology as a tool for academic research analysis and information retrieval.

Future Work could focus on the following aspects:

1. Expanding the dataset to include abstracts from diverse academic disciplines and languages to evaluate the generalizability of the proposed approach.
2. Optimizing the computational efficiency of Deep K-Means by exploring parallel processing techniques and hardware accelerators.
3. Developing real-time summarization systems capable of dynamically updating clusters as new data is introduced, ensuring relevance and adaptability in ever-evolving research landscapes.
4. Expanding new calculations if doesn't need to reorder the summary based in the index sentences.
5. A metric is needed that can take into account the order of a summary.

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