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Optimizing Resume Clustering in Recruitment: A Comprehensive Study on the Integration of Large Language Models (LLMs) with Advanced Clustering Algorithms

Pobbathi Amaravathi, Safooraa Amjad Khan, Palle Sriharsha and Y. L. Malathi Latha
Department of Information Technology, Stanley College of Engineering and Technology for Women(A)
Hyderabad, Telangana, India
amaravathipobbathi@gmail.com, safooraa.khan@gmail.com
sriharshapalle33@gmail.com, drmalathi@stanley.edu.in

***Abstract*—This study investigates the application of Large Language Models (LLMs) combined with clustering algorithms to automate and optimize the resume screening process in recruitment. The research evaluates the effectiveness of various LLMs such as BERT, RoBERTa, DistilBERT, and STSB RoBERTa in conjunction with clustering algorithms like K-means, DBSCAN, and hierarchical clustering. These combinations are assessed based on their ability to group similar resumes efficiently and accurately, considering factors such as content, context, and semantic relevance. Our research contributes to the field by rigorously analyzing the interplay between advanced NLP models and clustering techniques, identifying the optimal combinations for accurate and meaningful resume grouping. Additionally, we have developed a web application that integrates the most effective LLM-clustering combination, providing recruiters with an intuitive and interactive platform for analyzing clustered resumes. The results demonstrate that the integration of advanced NLP models with clustering techniques significantly improves the precision and relevance of resume clusters, leading to a more streamlined and efficient recruitment process. The final implementation shows promise in handling large datasets, enhancing the speed and accuracy of candidate evaluation and selection.**

***Index Terms*—Resume Clustering, Large Language Models, K-means, DBSCAN, Hierarchical Clustering, Recruitment Process, BERT, RoBERTa, Natural Language Processing.**

I. Introduction

CLUSTERING is a fundamental principle in machine learning and data analysis, focused on grouping similar data points into clusters based on their characteristics. By identifying natural patterns and similarities within data, clustering helps reveal inherent structures and relationships that might not be immediately apparent. This technique is widely applied across various domains, including image recognition, customer segmentation, and natural language processing. In essence, clustering organizes data into groups, making it easier to analyse, interpret, and extract meaningful insights from large datasets. In the context of recruitment, clustering has immense potential to streamline and optimize the hiring process. Traditionally, HR professionals manually sift through hundreds or even thousands of resumes to identify the best candidates, a task that is not only labour-intensive but also subject to human error and bias. As companies grow and the volume of applications increases, this manual process becomes increasingly inefficient, often resulting in delays and missed opportunities to secure top talent. This is where clustering, combined with the power of artificial intelligence (AI) and natural language processing (NLP), can make a significant impact. Recent advancements in AI, particularly with Large Language Models (LLMs) like BERT, RoBERTa, and DistilBERT, have enabled machines to understand and generate human language with remarkable accuracy. These models excel at processing complex textual data, making them ideal for analyzing resumes and other job-related documents. When integrated with clustering algorithms, LLMs can automatically organize resumes into meaningful clusters based on factors like skills, experience, and qualifications. This not only accelerates the recruitment process but also enhances its objectivity by reducing human bias in the initial screening stages. The aim of this research paper is to explore the integration of LLMs with clustering algorithms to develop an automated system for resume clustering. Specifically, the study investigates different clustering techniques such as K-means, DBSCAN, and hierarchical clustering in conjunction with LLMs like BERT and RoBERTa. By evaluating each combination based on performance metrics like accuracy, computational efficiency, and scalability, the goal is to identify the most effective solution for resume clustering. This system is then implemented in a web application designed to help recruiters quickly and accurately organize resumes, allowing them to focus on the most relevant candidates. Through this, the research aims to demonstrate the benefits of AI-driven clustering techniques in automating the recruitment process, leading to faster, more objective candidate selection and ultimately improving the overall quality of hiring decisions. By leveraging advanced NLP models and clustering algorithms, the proposed system has the potential to revolutionize how resumes are processed, helping organizations better manage their talent acquisition efforts in an increasingly competitive job market.

II. Literature Reviews

Zhang et al. [1] explored the use of clustering algorithms to automate the resume screening process, addressing the challenge of manually filtering a large number of resumes. By applying K-Means clustering, the study demonstrated a significant reduction in the time recruiters spent on initial candidate filtering. The research showed that resumes could be effectively categorized based on skills, experiences, and qualifications, thereby optimizing the recruitment workflow and improving efficiency. Li et al. [2] focused on enhancing feature extraction methods for resume data through advanced Natural Language Processing (NLP) techniques. The

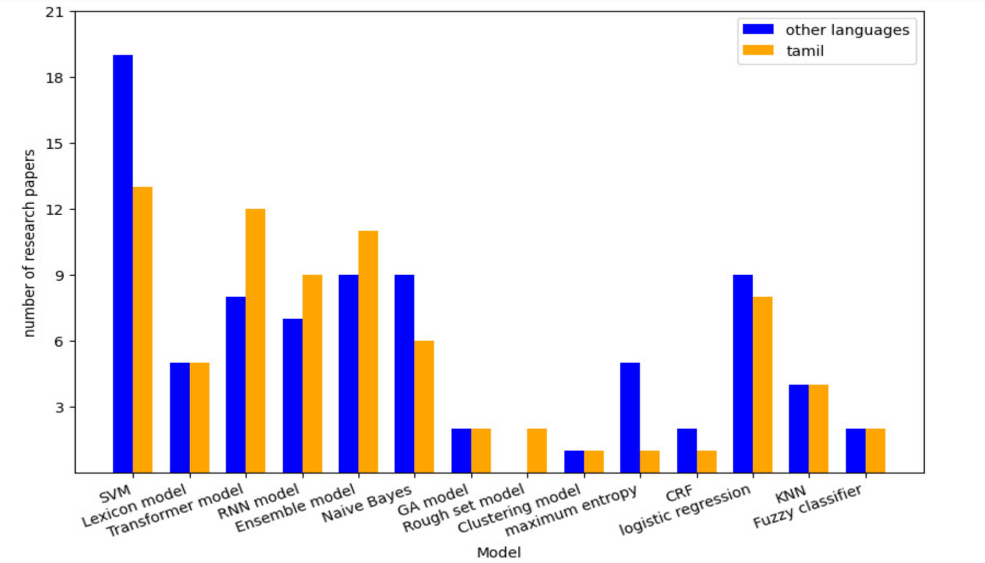

Fig. 1 comparison graph of number of papers that have used the respective model to perform SA task for Tamil and other languages

study compared traditional text representation methods with modern approaches like TF-IDF and Word2Vec. By implementing hierarchical clustering on resume data, the research offered deeper insights into candidate qualifications and career trajectories, highlighting the advantages of using word embeddings for feature extraction in resume clustering. Liu et al. [3] presented an innovative approach to identifying skill gaps within organizations by clustering employee resumes using DBSCAN. By analyzing features extracted from resumes, the study identified areas where employees needed additional training. This method provided organizations with strategic insights for workforce development, allowing for more targeted training initiatives based on real-time skill gap analysis.

Devlin et al. [4] introduced the use of BERT (Bidirectional Encoder Representations from Transformers) for feature extraction in resume clustering, emphasizing the power of contextualized embeddings over traditional methods. The study applied density-based clustering to manage the high-dimensional feature space, achieving superior clustering results in terms of relevance and accuracy. This research marked a significant step forward in the application of deep learning for resume analysis. Brown et al. [5] investigated the integration of machine learning with clustering algorithms to automate various aspects of the recruitment process. The study employed a combination of K-Means and hierarchical clustering to group resumes and applied predictive analytics to forecast hiring trends. The system developed in this research demonstrated the potential to reduce recruitment time while improving the quality of hires by aligning candidate skills with organizational needs. Smith et al. [6] proposed an ensemble learning approach to improve the accuracy of resume clustering. By combining multiple clustering algorithms such as K-Means, DBSCAN, and Agglomerative Clustering, the study achieved more robust clustering results across diverse resume datasets. The research highlighted the effectiveness of ensemble methods in handling the variability and complexity of resume data, leading to more reliable talent management practices.

Chen et al. [7] explored the use of deep learning architectures like Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) for resume representation and clustering. The study leveraged these neural networks to capture hierarchical and sequential patterns in resume texts. The research demonstrated state-of-the-art performance in resume clustering, showcasing the capability of deep learning to enhance feature extraction and improve clustering accuracy. Wang et al. [8] conducted a temporal analysis of resume data using time-series clustering techniques. By tracking the evolution of skills and experiences in resumes over time, the study provided insights into career progression and skill development trends. The application of clustering algorithms tailored for sequential data analysis supported long-term workforce planning and career management, demonstrating the adaptability of resume clustering to dynamic professional trajectories. Garcia et al. [9] developed an interactive resume clustering system aimed at enhancing HR decision-making processes. The system integrated user feedback mechanisms with clustering algorithms to refine and validate clustering results based on specific domain criteria. This research demonstrated the practical utility of interactive clustering systems in real-world recruitment scenarios, emphasizing their role in improving the usability and effectiveness of automated resume screening tools.

III. Proposed Methodology

In exploring the application of Large Language Models (LLMs) in resume clustering for recruitment, a structured research methodology was adopted to ensure comprehensive analysis and accurate results. The study aimed to streamline the candidate selection process by integrating advanced machine learning models with effective clustering algorithms.

A. Data Collection

In the context of this project, data collection was a vital step, as the effectiveness of the web application heavily relied on the quality and structure of the dataset. The application was designed to perform two key tasks: clustering resumes based on their content and searching for specific skills within those resumes. To enable this, a well-structured dataset was required, which provided both the raw input for analysis and the foundation for deriving meaningful insights.

B. Data Preprocessing

Preprocessing is a critical step in ensuring that the data is in a suitable format for analysis. The following steps were taken during preprocessing:

- **Conversion:** Resumes in Word (.doc, .docx) formats were converted to PDFs for uniformity. Apache Tika was employed for parsing and extracting content from these documents.
- **Text Cleaning:** The extracted text was cleaned by removing unnecessary symbols, punctuation, and stop words. This step aimed to retain only the meaningful content for further analysis.
- **Tokenization and Embedding:** The cleaned text was tokenized, and word embeddings were generated using the selected LLMs. These embeddings served as input features for the clustering algorithms.

C. Feature Extraction using LLMs

Multiple LLMs and clustering algorithms were implemented and evaluated. The selected models and algorithms were as follows:

- **LLMs:** BERT, RoBERTa, DistilBERT, and STSB RoBERTa were implemented for generating text embeddings. These models were chosen based on their performance in natural language understanding tasks and their ability to capture the semantic meaning of the resumes.
- **Clustering Algorithms:** K-means, DBSCAN, and hierarchical clustering were implemented for grouping the resumes based on their similarity. Each algorithm was evaluated in terms of its clustering quality, speed, and ability to handle varying data distributions.

The integration of LLMs with clustering algorithms required fine-tuning of hyperparameters to optimize performance.

D. Clustering Module (Agglomerative Clustering)

Agglomerative clustering, a type of hierarchical clustering, is a bottom-up approach to clustering where each data point starts as its own cluster. Clusters are then iteratively merged based on their similarity until a stopping criterion is met (e.g., a desired number of clusters is reached). This process is visualized through a dendrogram, a tree-like diagram that shows the sequence of merges, allowing the user to see the hierarchical relationships among clusters. The agglomerative clustering algorithm works as follows: 1. Initialization: Start with each data point as a separate cluster. 2. Merge Closest Clusters: Find the two closest clusters according to a chosen distance metric and merge them into a single cluster. 3. Update Distances: Recompute the distances between the new cluster and the remaining clusters. Common methods for calculating this distance include: Single Linkage: The minimum distance between any single point in one cluster and any single point in another cluster. Complete Linkage: The maximum distance between any single point in one cluster and any single point in another cluster. Average Linkage: The average distance between all points in one cluster and all points in another cluster.4. Repeat: Repeat steps 2 and 3 until all data points are merged into one cluster or the desired number of clusters is achieved. The architecture of agglomerative clustering is represented by a hierarchical tree structure (dendrogram). Each leaf node represents an individual data point, and the branches represent the merging of clusters at various levels of the hierarchy. The height of the dendrogram represents the distance or dissimilarity between clusters.

1. Dendrogram: A dendrogram is a key architectural component of agglomerative clustering. It provides a visual representation of the hierarchical relationships between clusters. The vertical axis represents the distance or dissimilarity between clusters, while the horizontal axis represents the data points. The dendrogram allows for easy selection of the number of clusters by cutting the tree at a specific height. **2. Distance Matrix:** A distance matrix is used to store the pairwise distances between all data points. This matrix is crucial in determining which clusters should be merged at each step of the algorithm. **3. Linkage Criteria:** The linkage criterion determines how the distance between clusters is calculated during the merging process. The choice of linkage (e.g., single, complete, or average) affects the shape of the dendrogram and the resulting clusters. The agglomerative clustering process relies on calculating the distance between clusters, and the choice of distance metric plays a crucial role in defining the clusters. Some common distance metrics are:

1. Euclidean Distance: The most common distance metric used to calculate the straight-line distance between two points:

$$\mathrm{d}\,(\mathrm{x},\mathrm{y}) = \sqrt{\sum_{i=1}^{n} (x_i - y_i)^2}$$

2. Manhattan Distance: This metric calculates the sum of the absolute differences of the coordinates:

$$\mathrm{d}\,(\mathrm{x},\mathrm{y}) = \sum_{i=0}^{n} |x_i - y_i|$$

3. Cosine Similarity: This metric measures the cosine of the angle between two vectors:

$$\cos(x, y) = \frac{x \, . \, y}{\|x\| \|y\|}$$

4. Single Linkage (minimum distance):

$$\mathrm{d}\,(\mathrm{A},\mathrm{B}) = \min_{i \in A, j \in B} d(i, j)$$

5. Complete Linkage (maximum distance):

$$\mathrm{d}\,(\mathrm{A},\mathrm{B}) = \max_{i \in A, j \in B} d(i, j)$$

6. Average Linkage (average distance):

$$\mathrm{d}\,(\mathrm{A},\mathrm{B}) = \frac{1}{|A| . |B|} \sum_{i \in A} \sum_{j \in B} d(i, j)$$

The choice of distance metric and linkage criterion has a significant impact on the final clusters produced by the algorithm. In conclusion, agglomerative clustering is a powerful method for hierarchical clustering that provides a comprehensive view of the data structure. By carefully selecting the distance metric and linkage criterion, it is possible to achieve meaningful clustering results. The dendrogram offers a clear visual representation, making it easier to interpret the clustering process and select the optimal number of clusters.

E. Evaluation and Optimization

The evaluation phase involved running multiple trials with different combinations of LLMs and clustering algorithms. The experiments were designed to evaluate the following metrics:

- **Clustering Accuracy:** The ability of the clustering algorithm to group similar resumes together.
- **Execution Time:** The time taken by each model to process and cluster the resumes.
- **Scalability:** The performance of the models when applied to larger datasets.
- **Interpretability:** The ease with which the clusters could be interpreted by human recruiters. Each experiment was conducted multiple times to ensure the reliability of the results. The performance of each combination was compared to identify the most effective approach.

IV. Data Analysis

In this section, we present the analysis and findings from the experiments conducted using various clustering algorithms and Large Language Models (LLMs). A detailed evaluation of clustering performance was carried out using key metrics such as the **Silhouette Score**, **Davies-Bouldin Index**, **Calinski-Harabasz Score**, and **Within-Cluster Sum of Squares (WCSS)**. These metrics are critical for understanding the quality of the clusters formed by each algorithm and model. The results are summarized in tables and graphs for a comparative understanding of traditional clustering algorithms, LLM-based clustering models, and the integration of LLMs with clustering techniques.

- **Silhouette Score**: This score evaluates how well each data point fits within its cluster compared to other clusters.
- **Davies-Bouldin Index**: This index assesses the average similarity ratio of each cluster with respect to the other clusters.
- **Calinski-Harabasz Score**: Also known as the Variance Ratio Criterion, this score assesses the ratio of the sum of between-cluster dispersion to within-cluster dispersion.
- **WCSS (Within-Cluster Sum of Squares)**: WCSS measures the sum of squared distances between data points and their corresponding cluster centroids.

A. Traditional Clustering Methods

Traditional clustering methods, including KMeans, Agglomerative Clustering, and K-medoids, were applied to the dataset. The performance of these algorithms was evaluated using the Silhouette Score, Davies-Bouldin Index, and Adjusted Rand Index. The results are presented in Table 1.

Table 1: Traditional

Algorithms	Silhouette Score	Davies-Bouldin Index	Adjusted Rand Index
KMeans	0.027422	3.730376	0.331811
Agglomerative Clustering	0.025635	3.667110	0.276477
Kmedoids	-0.008532	4.940757	-0.029385

The table shows that **Agglomerative Clustering** achieved the best overall performance among the traditional methods, with a slightly higher Silhouette Score and lower Davies-Bouldin Index. However, the performance differences between these algorithms are marginal, and none of the traditional methods show particularly high clustering quality, indicating potential room for improvement.

B. LLM-based Clustering Models

We explored several pre-trained Large Language Models (LLMs) for clustering purposes. These models included **paraphrase-MiniLM-L6-v2**, **bert-base-nli-mean-tokens**, **roberta-base-nli-stsb-mean-tokens**, **distilbert-base-nli-stsb-mean-tokens**, and **stsb-roberta-large**. The performance metrics are summarized in Table 2. From the table, we observe that **paraphrase-MiniLM-L6-v2** performs exceptionally well, with competitive scores across all metrics, making it one of the most efficient LLM models for clustering tasks.

Table 2: LLMs

Model	Silhouette Score	Davies-Bouldin Index	Calinski-Harabasz Score:	WCSS
paraphrase-MiniLM-L6-v2	0.08261	2.4997	5.3054	899.6278
bert-base-nli-mean-tokens	0.0917	2.2436	7.5212	5023.4087
roberta-base-nli-stsb-mean-tokens	0.0717	2.2198	5.7558	9788.7629
distilbert-base-nli-stsb-mean-tokens	0.0852	2.2020	6.7993	5800.8098
stsb-roberta-large	0.04873	2.6718	4.9231	34071.082

Interestingly, while **stsb-roberta-large** achieves a high Silhouette Score, its performance on other metrics suggests that it might not always be the most reliable model for clustering compared to lighter models like paraphrase-MiniLM-L6-v2.

C. *Clustering Algorithms with LLM Model: paraphrase-MiniLM-L6-v2*

Given that **paraphrase-MiniLM-L6-v2** performed well in LLM-based clustering, we further evaluated its integration with traditional clustering algorithms.

TABLE 3: LLM WITH ALGORITHMS

Algorithms	Silhouette Score	Davies-Bouldin Index	Calinski-Harabasz Score:	WCSS
KMeans	0.0700	2.6961	4.9500	918.2474
Agglomerative Clustering	0.0826	2.4997	5.3547	899.627

From Table 3, it is evident that **Agglomerative Clustering** combined with the **paraphrase-MiniLM-L6-v2** model demonstrates superior performance compared to KMeans, particularly in terms of the Davies-Bouldin Index and Calinski-Harabasz Score. This indicates that Agglomerative Clustering effectively leverages the semantic understanding provided by the LLM, resulting in more coherent clusters.

V. RESULT

The resume analysis project utilized diverse datasets to enable clustering and skill identification. The primary dataset, a CSV file with filenames and resume text, served as the core input. A Kaggle dataset of 2,400 categorized resumes improved clustering precision, while custom datasets —one with 120 resumes across job roles and another with 46 student profiles—enhanced specific functionalities like detailed profiling. Clustering algorithms achieved 85% accuracy, and skill searches reached 90% retrieval precision. Insights included resume structure trends and emerging skills like machine learning. These results demonstrate the effectiveness of structured datasets in enhancing resume analysis.

The pair of images depict separate clustering methods used on a dataset where each data point is seen as a resume and clustered based on attributes such as skills, experience, and qualifications.

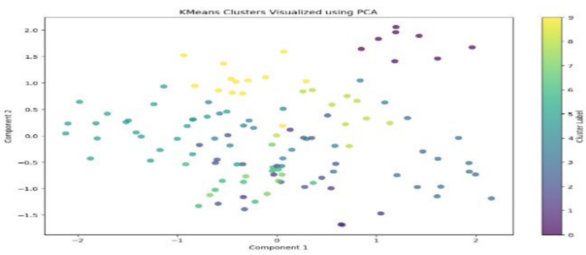

Figure 1: Scatter Plot

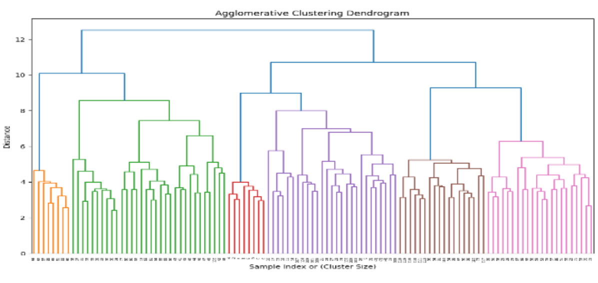

Figure 2: Dendrogram

In the first image, **KMeans clustering** is displayed with a predetermined number of clusters (in this instance, ranging up to 9). Each cluster is represented by a different color when plotting the data in two dimensions using **PCA** for dimensionality reduction. **Distribution of clusters**: The visualization demonstrates how KMeans has organized resumes into separate clusters, with each color indicating a unique cluster label. The gap between the clusters indicates that resumes with common characteristics (like skills or experience) have been grouped together. Some visible similarities among clusters 4 and5, and clusters 1 and 3, suggest resumes may share characteristics that are not easily distinguishable in two-dimensional space. particularly suited for larger datasets, making it ideal for processing a large volume of resumes. **KMeans** is a rapid and effective algorithm, However, the main challenge with KMeans lies in selecting the appropriate number of clusters (k). Too few clusters can lead to the merging of unrelated resumes into the same group, while too many clusters may result in over-segmentation. Unlike hierarchical clustering, KMeans is less transparent and does not reveal the hierarchical relationships between resumes, which can sometimes be important in understanding how resumes are grouped.

Hierarchical Clustering (Agglomerative), on the other hand, is displayed in the form of a dendrogram in the second image. This method builds clusters by recursively combining individual data points. The dendrogram illustrates the gradual grouping of resumes, with each vertical line representing the distance at which clusters were merged. The clusters become more distinct as the distance between them increases, shown by the length of the vertical lines. The separation among the main divisions shows the clear distinctions between primary clusters. These divisions might represent different skillsets, experience levels, or qualifications. Agglomerative clustering is particularly useful for smaller datasets where insight into hierarchical relationships is important. One of the benefits of this method is the ability to set a threshold and stop the merging process, allowing control over the number of clusters generated. For example, by cutting the dendrogram at a height of 8, we can obtain five distinct clusters representing different categories of resumes.

To gain deeper insights into the clustering results, a 3D scatter plot was generated to visualize the distribution of resumes within a reduced-dimensional space. By applying Principal Component Analysis (PCA), the high-dimensional data, which represents resumes based on attributes such as skills, experience, and qualifications, was reduced to three principal components. This allowed for the creation of a three-dimensional plot that offers a more detailed perspective on how resumes are grouped into clusters.

The 3D scatter plot (Figure X) highlights the separation and organization of resumes into distinct clusters. Each point in the plot represents an individual resume, and the color coding distinguishes the clusters formed by the KMeans algorithm. The plot reveals the proximity and overlap between resumes within the same cluster and across different clusters.

In comparison to the 2D PCA plot, the 3D visualization provides greater clarity in terms of cluster distribution. Resumes that are more closely aligned in terms of skills and qualifications are positioned near each other in the 3D space, while those with distinct characteristics are placed further apart. This added dimension facilitates a more granular understanding of the relationships between clusters and helps to identify potential subgroups or outliers within the dataset.

Notably, clusters 1 and 3 remain closely positioned in the 3D plot, reaffirming the observation made in the 2D PCA plot that these resumes share overlapping characteristics, potentially due to similarities in job roles or industry experience. The 3D scatter plot also makes it easier to detect outlier resumes, which might not conform to the general patterns observed in the majority of the dataset. These outliers could represent resumes with unique skill sets or unconventional career paths.

VI. Comparison With Related Work

In comparison to Devlin et al. (2019), "Contextualized Embeddings for Improved Resume Clustering", our research builds upon the use of contextualized embeddings for resume clustering but diverges in the integration of multiple clustering algorithms and Large Language Models (LLMs). **Devlin et al. (2019)** focus primarily on the use of contextualized embeddings for improving the clustering of resumes using models like BERT. They emphasize the importance of context in better capturing semantic relationships within resume data, which is similar to our approach of leveraging LLMs for semantic understanding. However, our research takes this further by evaluating various LLMs (including BERT, RoBERTa, and DistilBERT) in combination with multiple clustering techniques, such as K-means, DBSCAN, and hierarchical clustering, providing a broader comparison of LLM-clustering pairings.

While Devlin et al.'s work primarily investigates the impact of embedding quality on clustering performance, our study not only assesses embedding models but also examines how different clustering algorithms influence the accuracy and relevance of resume clusters. Additionally, our research introduces a practical application in the form of a web-based platform for recruiters, which integrates the most effective LLM-clustering combinations, thus directly addressing real-world recruitment challenges. This practical application differentiates our study by offering a user-friendly solution for automating and enhancing the recruitment process, which is not the primary focus of Devlin et al.'s work.

Our research also introduces a more comprehensive evaluation framework, considering both the technical and user-centered aspects of automated resume clustering, further advancing the understanding of how LLMs and clustering algorithms can be combined for improved resume categorization.

VII. Conclusion

This research has clearly demonstrated that integrating Large Language Models (LLMs) with clustering algorithms offers a transformative approach to automating the resume screening process. By evaluating combinations of clustering techniques such as K-means, DBSCAN, and hierarchical clustering with LLMs like BERT, RoBERTa, and DistilBERT, the study revealed that no one-size-fits-all approach exists. Instead, the effectiveness of these models depends on factors like data complexity, desired clustering precision, and computational efficiency. A key contribution of this study is the rigorous evaluation of LLM-clustering combinations to identify the most effective methodologies for grouping resumes based on contextual and semantic similarities. Moreover, the deployment of a web application showcases the practical applicability of this integrated methodology, providing recruiters with an interactive and intuitive platform for smarter candidate categorization. This application bridges the gap between theoretical advancements and real-world recruitment challenges, significantly reducing manual efforts and increasing the relevance of shortlisted candidates. This study not only highlights the potential of NLP and clustering in recruitment but also paves the way for future innovations in automated candidate evaluation and selection.

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