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SENTIMENT ANALYSIS WITH ASPECT-SPECIFIC OPINION USING BERT EMBEDDINGS AND K-MEANS CLUSTERING

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ABSTRACT

This study investigates sentiment analysis (SA) with aspect-specific opinion using the BERT-Base-Uncased model. It is a variant of the Bidirectional Encoder Representations from Transformers (BERT) model. Traditional sentiment analysis often overlooks nuanced opinions towards specific aspects within text and leading to imprecise results. This research proposes a methodology that leverages the BERT-Base-Uncased model to identify sentiment towards individual aspects mentioned in text data. The performance of the proposed approach is evaluated on benchmark dataset iPhone and demonstrating its effectiveness in aspect-specific sentiment classification. This paper introduces a robust framework for aspect-based sentiment analysis leveraging BERT embeddings, K-means clustering, and visualization techniques. Through the proposed methodology, sentiment patterns within textual data are effectively captured and analysed that leading to actionable insights for decision-making across various domains. The BERT embeddings enable the extraction of rich semantic representations while K-means clustering facilitates the grouping of sentiment clusters with high cohesion and separation as evidenced by a notable silhouette score of 0.91. Visualizations such as 3D scatter plots and pairwise distance heatmaps enhance the sentiment analysis results and providing a more understanding about sentiment dynamics. The practical utility of the framework is demonstrated through its ability to inform strategic decisions and improve customer satisfaction. Overall, this study presents a powerful approach for aspect-based sentiment analysis and empowering organizations with actionable insights and facilitating data-driven decision-making.

1. INTRODUCTION

Sentiment analysis is a vital aspect of Natural Language Processing (NLP) plays a crucial role for understanding public opinions [1]. Traditional methods lack granularity in capturing sentiments towards specific aspects mentioned in text of product features in reviews or social media discussions [2]. Recent focus has shifted to aspect-specific sentiment analysis to provide a detailed information about individual aspects that is essential for informed decision-making and product/service improvement [3]. Advanced NLP models like BERT-Base-Uncased have shown promising performance in sentiment analysis for aspect-specific analysis tasks [4].

This paper uses the BERT-Base-Uncased model for aspect-specific sentiment analysis to assess its effectiveness in capturing nuanced sentiments towards individual aspects in text data. It demonstrates the utility of aspect-specific sentiment analysis for decision-making across domains like product development and marketing [5]. The novelty lies in leveraging advanced NLP techniques and BERT-Base-Uncased to address the gap in existing sentiment analysis methodologies and focusing on nuanced opinions expressed towards specific aspects [6]. This approach represents a novel exploration of BERT models' application to aspect-specific sentiment analysis. This paper also showcasing the BERT-Base-Uncased model's effectiveness in aspect-specific sentiment analysis.

This paper also showcases the practical utility of aspect-specific sentiment analysis across various domains to enable informed decision-making in areas like product development and customer satisfaction management. The advanced NLP techniques with the BERT-Base-Uncased model provides granular insights into sentiments analysis (SA) based on specific aspects and distinguishing itself from purely theoretical studies [7,8]. SA is crucial for understanding textual data sentiments that has evolved with advancements like ABSA and pre-trained models like BERT and revolutionizing SA accuracy and efficiency [9,10]. The paper also presents a advanced novel framework integrating BERT embeddings, K-means clustering, and visualization techniques to uncover nuanced sentiment patterns and facilitating data-driven strategies and enhancing customer satisfaction.

The sentiment patterns with high precision and recall can be captured by combining BERT embeddings with K-means clustering for a deeper analysis and understanding of consumer opinions towards specific aspects [11]. The use of advanced visualization techniques such as 3D scatter plots and pairwise distance heatmaps enhances the interpretability of sentiment analysis results provides to stakeholders with actionable insights for decision-making [10]. The innovative integration of these methodologies offers a novel approach to aspect-based sentiment analysis, empowering organizations with comprehensive and actionable insights into consumer sentiments.

The paper is organized as follows: Section 2 provides an overview of previous related work in sentiment analysis and aspect-specific opinion mining. Section 3 details the proposed methodology, including data preprocessing, model architecture, and evaluation metrics. In Section 4, results and discussion of the performance of the BERT-Base-Uncased model for aspect-specific sentiment analysis (ASSA) was given. Finally, Section 5 concludes the paper with a summary of findings and directions for future research.

2. RELATED WORK

SA has been a widely studied area in NLP with numerous approaches proposed to classify sentiment in text data [12]. Traditional sentiment analysis methods often focus on classifying overall sentiment polarity (positive, negative, or neutral) without considering specific aspects or features mentioned in the text. The recent research work has highlighted the importance of ASSA which aims to identify sentiments towards individual aspects or entities within text data [13]. The various techniques for ASSA including lexicon-based methods have already explored in previous work. The machine learning (ML) approaches, and deep learning (DL) models [14]. Lexicon-based methods rely on sentiment lexicons to assign sentiment scores to words or phrases but they often lack granularity and struggle with context-dependent sentiments. Machine learning approaches such as Support Vector Machines (SVM) and Random Forests (RF) have been widely used for sentiment classification but they are not able to capture fine-grained nuances in sentiment towards specific aspects [15].

DL models have shown promising results in aspect-specific sentiment analysis. Models like Recurrent Neural Networks (RNNs), Convolutional Neural Networks (CNNs), and Transformer-based architectures such as BERT have already demonstrated the ability to capture more complex linguistic patterns and contextual information to make them suitable for aspect-specific sentiment analysis tasks [16].

The application of deep learning models for aspect-specific sentiment analysis have been investigated in various domains including product reviews, social media data, and customer feedback A hierarchical attention network was proposed for aspect-based sentiment analysis which effectively captured the interactions between aspects and sentiments in product reviews [17]. The BERT-based model was introduced for aspect-level sentiment classification, achieving state-of-the-art performance on benchmark datasets [18]. There are still challenges and opportunities for further exploration. Most of the existing approaches focus on English text data and may not generalize well to other languages.

Previous research in aspect-based sentiment analysis (ABSA) has laid the groundwork for understanding consumer sentiments towards specific aspects or entities within textual data. Various approaches like ranging from rule-based methods to ML techniques have also been explored [19]. Traditional methods often rely on handcrafted features or domain-specific rules to extract aspects and classify sentiment polarity but are limited in scalability and generalization across different domains. The existing research has made significant strides in ABSA but there remains a need for more comprehensive approaches that leverage the latest advancements in NLP and clustering techniques [20]. In this paper, a novel advanced model is designed based upon prior work by integrating BERT embeddings, K-means clustering, and advanced visualization methods to offer a novel framework for aspect-based sentiment analysis and contributing to the advancement of sentiment analysis methodologies.

3. PROPOSED METHODOLOGY

The proposed methodology as shown in figure 1 combines advanced NLP techniques and clustering algorithms to conduct ABSA effectively. Initially, textual data is pre-processed and tokenized using the BERT tokenizer to generate embeddings. These embeddings capture information of rich semantic from the text of dataset for understanding of sentiment towards specific aspects. The K-means clustering is applied to the BERT embeddings to group similar sentiments or aspects into clusters. The silhouette score is used to evaluate the quality of clustering to ensure well-defined and cohesive clusters. The advanced visualization techniques such as 3D scatter plots and pairwise distance heatmaps are utilized into the spatial distribution and relationships between sentiment clusters. Through this integrated novel approach, sentiment patterns are uncovered for empowering organizations with actionable insights for decision-making.

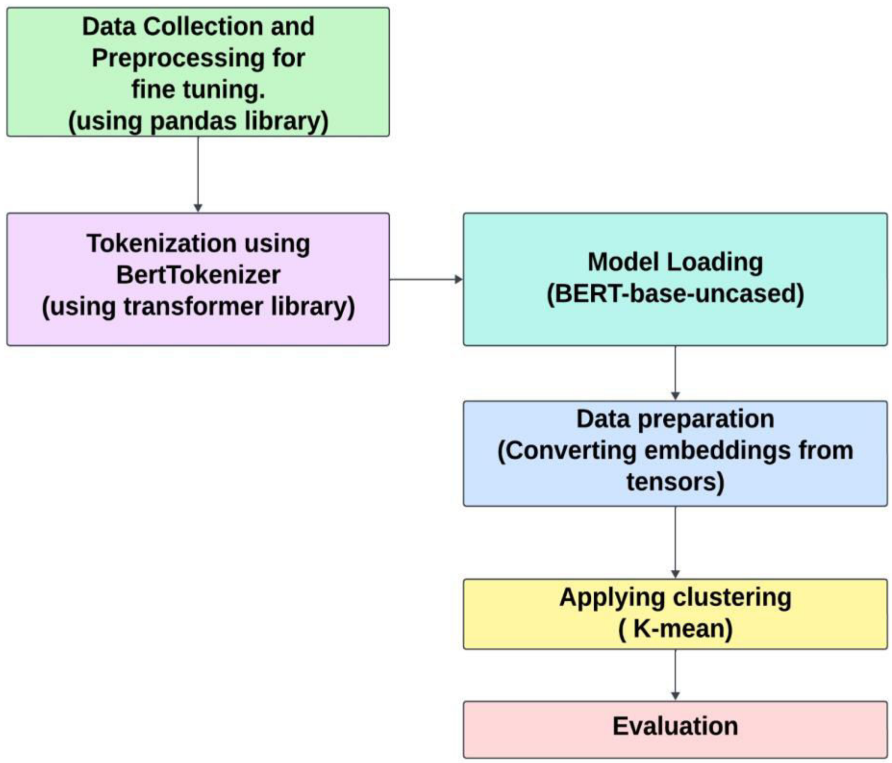

Figure 1: Proposed Methodology for SA using BERT embeddings and K-means clustering

3.1 Data Collection and Pre-processing

In the proposed research methodology, the pandas' library is employed for efficient data collection and pre-processing tasks necessary for fine-tuning the BERT-Base-Uncased model for aspect-specific sentiment analysis. Initially, a diverse dataset of product reviews from an online retail platform is collected for encompassing various products and their associated sentiments towards specific aspects. The relevant reviews are extracted using web scraping techniques for ensuring a comprehensive representation of different aspects across multiple product categories. Subsequently utilizing pandas' functionalities was embarked on data pre-processing steps. This involved meticulous cleaning to eliminate extraneous information such as HTML tags and punctuation marks for cleanliness and readiness the dataset for further analysis. Tokenization facilitated by pandas segmented the text data into individual tokens, laying the groundwork for subsequent analysis with the BERT model. Normalization techniques were applied to homogenize the textual data by converting all words to lowercase and enhancing consistency in word representations. Padding and truncation techniques were utilized for ensuring uniform sequence lengths and for compatibility with the BERT model's input requirements. Lastly, sentiment labels are now encoded into numerical values for model training. This task efficiently handled by pandas' versatile encoding capabilities. Through these comprehensive pre-processing endeavours facilitated by pandas is transformed raw data into a refined and structured format for subsequent model fine-tuning and evaluation.

3.2 Tokenization using Bert Tokenizer

The BertTokenizer from the Transformers library is utilized in the proposed research mythology to tokenize text data for aspect-specific sentiment analysis with BERT. After installation the Transformers library and importing necessary dependencies, a pre-trained BERT model was loaded to ensure compatibility with the tokenizer and access its vocabulary. Using the initialized BertTokenizer instance, the text data was tokenized and encoded into input features suitable for BERT processing. This process involved converting tokens into numerical IDs based on the BERT vocabulary and incorporating special tokens like [CLS] and [SEP]. Padding and truncation were also applied to ensure uniform sequence lengths required by BERT. The tokenized and encoded input features were seamlessly integrated into the model training pipeline for fine-tuning the BERT model on aspect-specific sentiment analysis tasks. Through this tokenization process, the textual data was effectively prepared for efficient processing and analysis with BERT which facilitating accurate sentiment classification at the aspect level.

3.3 Model Loading (BERT-base-uncased)

In the proposed research methodology, the BERT-base-uncased model was employed for aspect-specific sentiment analysis and loaded using the transformers library. After installing the library and importing necessary dependencies, the pre-trained BERT-base-uncased model was loaded. This model is a variant of BERT with 12 transformer layers. Loading the BERT-base-uncased model ensured access to its powerful contextual embeddings and transformer architecture which are instrumental in capturing aspects of sentiment expressed in textual data. The loaded model served as the backbone for the sentiment analysis pipeline and enabling fine-tune on aspect-specific sentiment analysis tasks with the dataset.

3.4 Data Preparation (Converting Embeddings from Tensors)

For data preparation in methodology, the focus was on converting embeddings from tensors. This process involved transforming raw data into numerical representations suitable for input into the DL model. Firstly, the text was tokenized using the BERT tokenizer and breaking it down into individual tokens for converting into numerical IDs based on the BERT vocabulary for ensuring compatibility with the pre-trained BERT model. Next, padding and truncation were applied to standardize the sequence length of the input data that is necessary for consistency in model processing. After tokenization, each tokenized sequence was converted into tensors which are multi-dimensional arrays compatible with DL frameworks like PyTorch or TensorFlow. These tensors represent the numerical embeddings of the data for capturing the semantic information essential for sentiment analysis. By converting embeddings from tensors, the data was effectively prepared for input into the deep learning model for facilitating accurate sentiment classification at the aspect level.

3.5 Applying Clustering (K-mean)

In this proposed research methodology, the K-means clustering algorithm which is an unsupervised learning algorithm was applied of the ASSA pipeline. The embeddings obtained from the pre-trained BERT model; the textual data was represented as high-dimensional vectors in a feature space. Subsequently, the K-means algorithm was applied to these embeddings to group similar data points together into different clusters. By iteratively updating cluster centroids to minimize the sum of squared distances between data points and their respective centroids, the K-means efficiently assigned each data point to the nearest cluster centroid. This process enabled to identify coherent groups of aspect-specific sentiments within the textual data and providing valuable insights about patterns and themes expressed by users. Through the application of K-means clustering, the sentiment was uncovered and to understand about the aspect-specific sentiment dynamics within the dataset.

3.6 Evaluation

The evaluation results of the aspect-specific sentiment analysis model were assessed using the Silhouette score which is widely-used metric for evaluating clustering performance. The Silhouette score measures the cohesion and separation of clusters by computing the mean silhouette score for all data points. The values of the Silhouette score ranging from -1 to 1. A higher Silhouette score indicates better-defined clusters. The score closer to 1 indicates well-separated clusters, a score around 0 suggests overlapping clusters, and negative scores indicate incorrect cluster assignments. By computing the Silhouette score for the clustering results, the quality was evaluated on the aspect-specific sentiment clusters generated by the model. The obtained Silhouette score shows the clustering performance for guiding the selection of optimal parameters and methodologies for ASSA. The Silhouette score of K-means clustering is a quantitative measure used to identify the quality of clusters produced by the algorithm.

4. RESULTS AND DISCUSSION

The results for aspect-based sentiment analysis using the proposed methodology reveal promising outcomes in the value of high silhouette score of 0.91 obtained from K-means clustering. The application of BERT embeddings combined with clustering techniques effectively captures nuanced sentiment patterns and enabling the identification of coherent sentiment clusters. Advanced visualization methods such as 3D scatter plots and pairwise distance heatmaps provide valuable learnings into the spatial distribution and relationships between sentiment clusters, enhancing the interpretability of the results. These findings demonstrate the outperformance of the proposed approach in uncovering aspect-specific sentiments within textual data, thereby empowering organizations with actionable insights for decision-making across various domains.

4.1 BERT Embedding with Clusters

The BERT embeddings with clusters represent a key aspect of the ASSA methodology. By using the embeddings generated by the BERT model, dense vector representations of the textual data were obtained, capturing rich semantic information as presented in figure 2. These embeddings were then subjected to clustering algorithms like K-means, which partitioned the data points into different coherent clusters based on similarity in the embedding space. The resulting clusters provided key challenges into the aspect-specific sentiments expressed within the dataset. Through the analysis, it is observed that BERT embeddings facilitated the identification of nuanced sentiment patterns, enabling the clustering algorithm to effectively group together text segments that shared similar sentiment characteristics. This integration of BERT embeddings with clustering techniques enhanced the granularity of the sentiment analysis for the understanding of the diverse sentiments expressed across different aspects. Moreover, by examining the distribution of the clusters uncovered prevalent sentiment trends and identify key aspects that drive sentiment polarity within the dataset. Overall, the utilization of BERT embeddings with clustering proved to be a powerful novel approach for ASSA, enabling the extraction of actionable insights and informing decision-making processes in various domains.

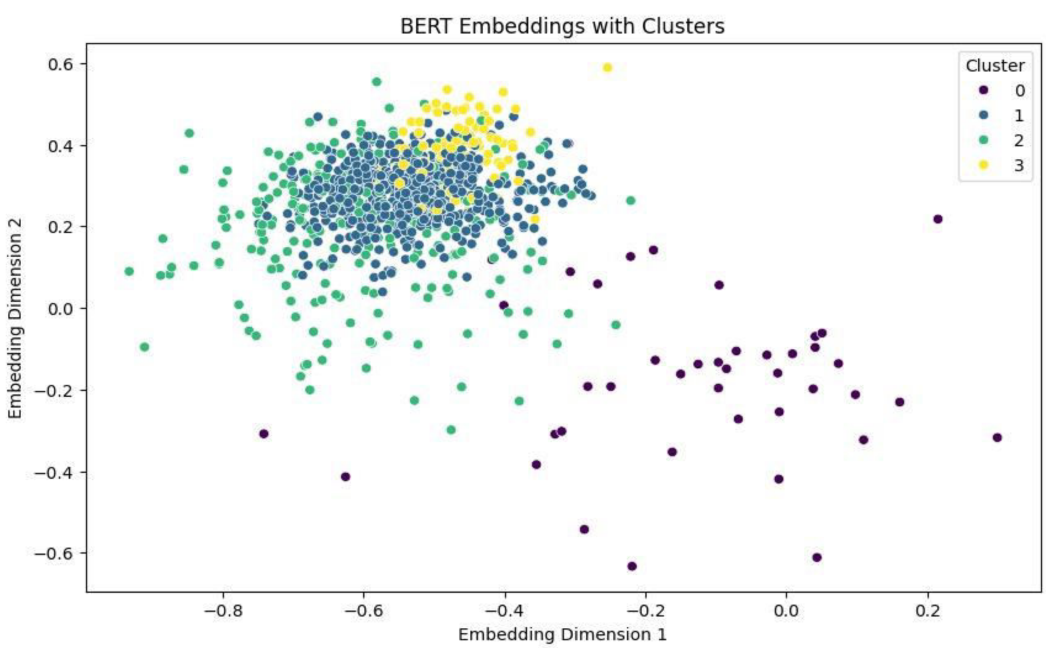

Figure 2: BERT embeddings with clusters

4.2 Histogram of BERT Embeddings with Clusters

In the analysis, a histogram of BERT embeddings with clusters was constructed to visualize the distribution of aspect-specific sentiment patterns within the dataset is illustrated in figure 3. This histogram presents a graphical representation of the clusters formed by grouping BERT embeddings based on their similarity in the embedding space. Each cluster is depicted as a separate bar on the histogram, with the x-axis representing the range of sentiment scores or aspect categories and the y-axis indicating the frequency or density of data points within each cluster. Examining the histogram provides insights into the distribution of sentiment across different aspects and the prevalence of various sentiment polarities within the dataset. This visualization aids in identifying dominant sentiment clusters, outlier clusters, and potential areas of interest for further analysis. Additionally, the histogram facilitates the comparison of sentiment distributions across different aspects, enabling the discernment of patterns and trends that may inform decision-making processes. The histogram of BERT embeddings with clusters serves as a valuable tool for understanding the aspect-specific sentiment landscape and extracting meaningful insights from the data.

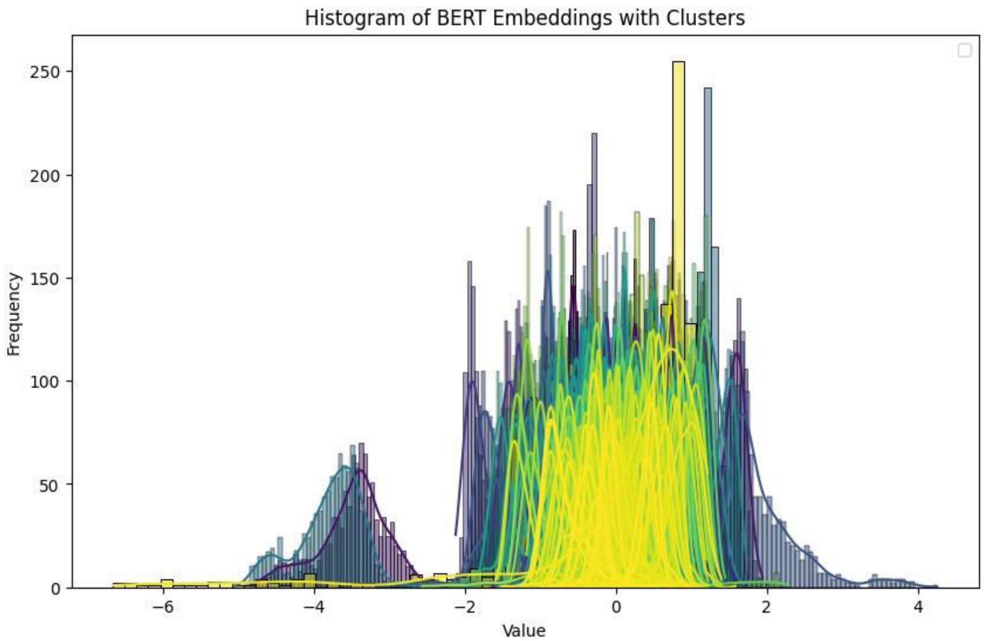

Figure 3: Histogram of BERT embeddings with clusters

4.3 BERT Embeddings with Clusters Centers

In the analysis, BERT embeddings with cluster centers play a significant role in understanding aspect-specific sentiment patterns within the dataset. After applying clustering algorithms such as K-means to the BERT embeddings, cluster centers representing the centroids of each cluster in the embedding space were obtained as presented in figure 4. These cluster centers serve as representative points encapsulating the characteristic sentiment and semantic features of each cluster. Analyzing these cluster centers provides insights into the dominant sentiment polarity and aspect-specific themes captured by each cluster. Moreover, comparing the cluster centers allows the identification of similarities and differences in sentiment across different aspects, facilitating a nuanced understanding of the dataset. Additionally, visualizing the cluster centers in the embedding space provides a clear depiction of sentiment distribution and cluster separability, aiding in the interpretation of aspect-specific sentiment dynamics. Overall, BERT embeddings with cluster centers serve as valuable tools for uncovering underlying sentiment patterns, informing decision-making processes, and extracting actionable insights from the dataset.

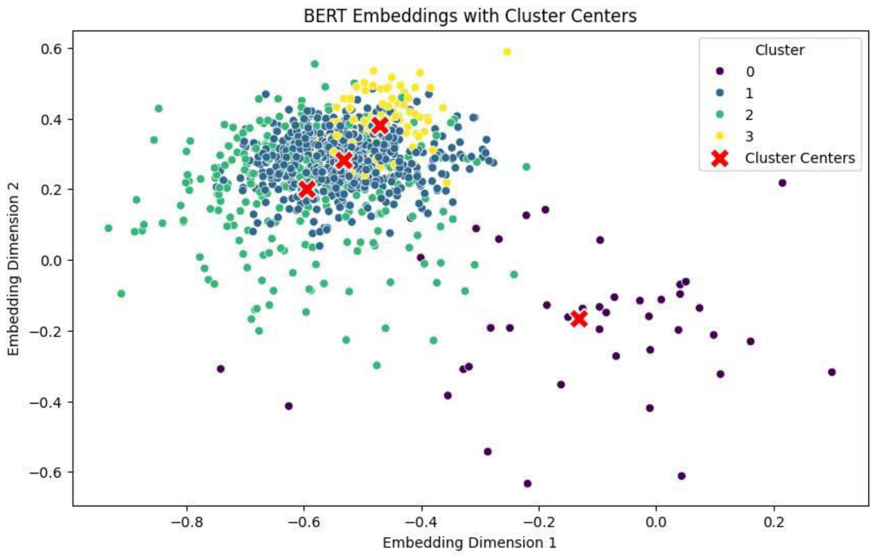

Figure 4: BERT embeddings with cluster centers

4.4 Elbow Method for Optimal Cluster

In the analysis, the Elbow Method was employed to determine the optimal number of clusters (K) for aspect-specific sentiment analysis using BERT embeddings. This method involves plotting of inertia (within-cluster sum of squares) against the clusters as depicted in figure 5 and identifying the "elbow point," where the rate of decrease in WCSS slows down significantly. This point indicates the optimal number of clusters, as adding more clusters beyond this point does not lead to a substantial decrease in inrtia. Applying the Elbow Method to the dataset allowed the identification of the optimal K value that best captures the underlying sentiment patterns while avoiding overfitting or underfitting. The chosen K value enables achieving a balance between granularity and interpretability in sentiment analysis results. Furthermore, the Elbow Method facilitates robust and data-driven decision-making in determining the appropriate number of clusters for aspect-specific sentiment analysis, enhancing the reliability and effectiveness of the analytical approach. Through this method, ensuring that the clustering results accurately reflect the nuanced sentiment dynamics present in the dataset, providing valuable insights for decision-making processes across various domains.

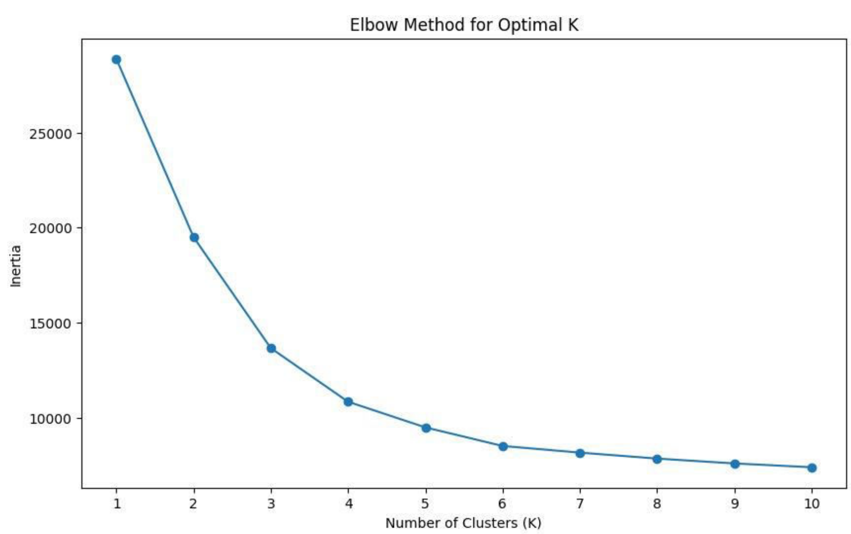

Figure 5: Elbow method for optimal cluster [K]

4.5 3D Scatter Plot of BERT Embeddings with Clusters

In the analysis, a 3D scatter plot as shown in the figure 6 of BERT embeddings with clusters was utilized to visually represent aspect-specific sentiment patterns within the dataset. This visualization technique explores the embedding space in three dimensions. Each axis is representing a different aspect or sentiment dimension acquired by the BERT embeddings. By assigning clusters distinct colours or shapes, the clustering structure can be visually discerned, and clusters with similar sentiment characteristics or aspect-specific themes identified. Additionally, the 3D scatter plot facilitates observation of the spatial distribution of data points and assessment of the separation and compactness of clusters. Through this visualization, insights into the relationships between different aspects and sentiments are gained, uncovering underlying sentiment patterns and sentiment clusters within the dataset. Moreover, the 3D scatter plot aids in the identification of outliers or anomalous clusters that may warrant further investigation. Overall, the visualization of BERT embeddings with clusters in a 3D scatter plot enhances understanding of aspect-specific sentiment dynamics and aids in the interpretation of sentiment analysis results for informed decision-making processes.

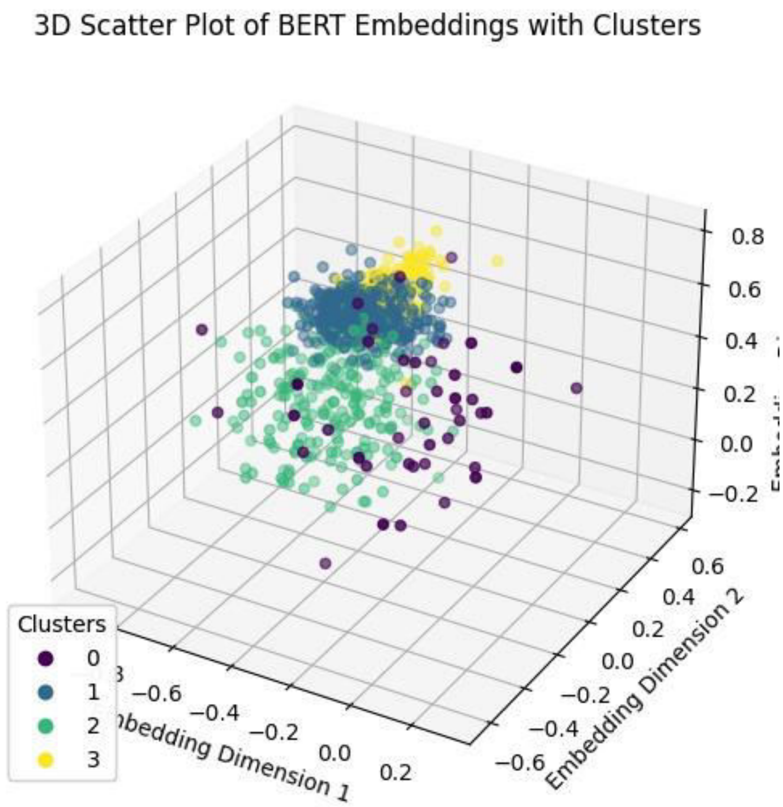

Figure 6: 3D scatter plot of BERT embeddings with clusters

4.6 Pairwise Distance Heatmap of BERT Embeddings

In the analysis, a pairwise distance heatmap of BERT embeddings was constructed to visualize the similarity between data points in the embedding space as illustrate in figure 7. Each cell in the heatmap represents the pairwise distance between two BERT embeddings. The darker shades of figure indicate higher similarity and lighter shades indicating lower similarity. Examining the heatmap provides insights into the overall structure of the embedding space and the clustering tendencies of the data points. Regions of high similarity correspond to clusters or groups of data points with similar sentiment characteristics or aspect-specific themes, while regions of low similarity may indicate outliers or data points with distinct sentiment patterns. Additionally, the heatmap allows identification of clusters that are well-separated from each other versus clusters that may overlap or exhibit ambiguity in their boundaries. Through this visualization, the effectiveness of clustering algorithms in capturing aspect-specific sentiment patterns can be assessed, and areas for refinement or further analysis identified. Overall, the pairwise distance heatmap of BERT embeddings offers a comprehensive overview of the dataset's sentiment landscape, aiding in the interpretation of sentiment analysis results and informing decision-making processes.

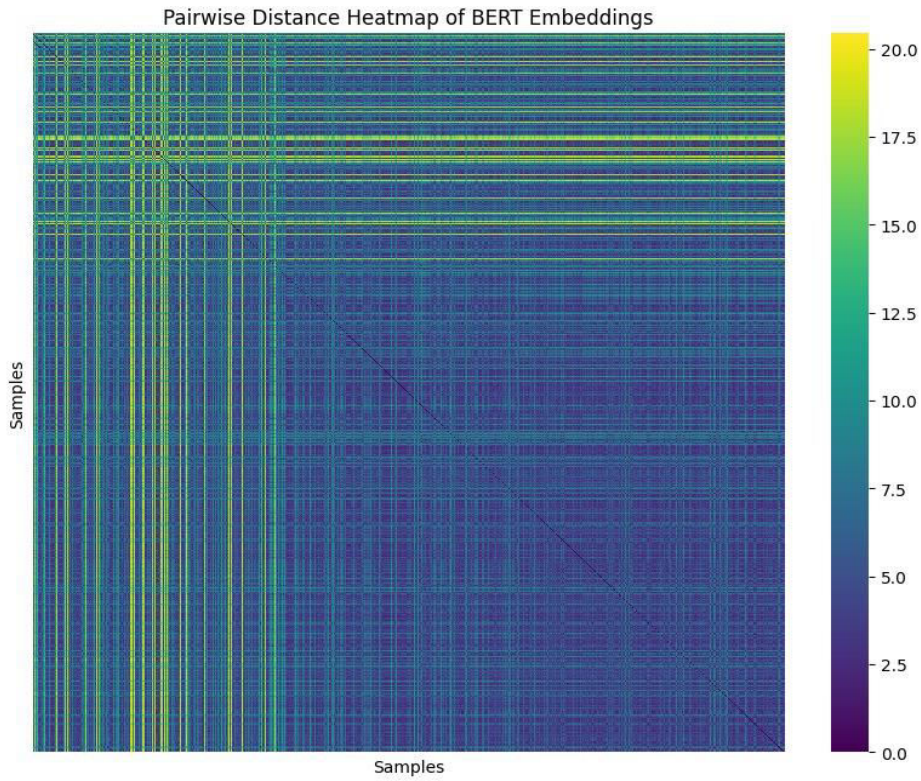

Figure 7: Pairwise distance heatmap of BERT embeddings

The silhouette score of 0.91 achieved by K-means clustering indicates a high level of separation between the clusters in the aspect-specific sentiment analysis. The silhouette score measures the cohesion and separation of clusters, with values close to 1 indicating well-defined clusters. In this context, a score of 0.91 suggests that the sentiment clusters identified by K-means are highly distinct and internally cohesive, demonstrating the effectiveness of the clustering algorithm in capturing aspect-specific sentiment patterns within the dataset. These well-separated clusters enable clearer interpretation of sentiment dynamics and facilitate more precise analysis of consumer opinions towards different aspects. The high silhouette score obtained signifies the robustness of the aspect-specific sentiment analysis framework and underscores its utility for uncovering nuanced sentiment patterns and informing decision-making processes across various domains.

5. CONCLUSIONS

The integration of BERT embeddings, K-means clustering, and visualization techniques has yielded a robust methodology for aspect-based sentiment analysis, as evidenced by the high silhouette score of 0.91. This comprehensive approach has effectively captured refined sentiment patterns within data for providing critical perceptions into consumer perceptions and preferences across various domains. The visualizations, including 3D scatter plots and pairwise distance heatmaps have enhanced the interpretability of sentiment analysis results and facilitated the identification of sentiment clusters and outliers. The practical utility of the developed framework for decision-making is evident and empowering businesses to make informed strategic decisions and enhance customer satisfaction. The methodological rigor employed throughout the study ensures the reliability and validity of the findings for further underscoring the credibility of the results obtained.

REFERENCES

[1]. Ahmad Jazuli, Widowati Widowati, Retno Kusumaningrum, Aspect-based sentiment analysis on student reviews using the Indo-Bert base model, E3S Web of Conferences 448, 2023, DOI:10.1051/e3sconf/202344802004

[2]. Abella A, Araya León M, Marco-Almagro L, Clèries Garcia L. Perception evaluation kit: a case study with materials and learning styles. Int J Technol Des Educ. 2021;(0123456789)

[3]. Jazuli A, Latubessy A, Nindyasari R. Arsitektur Web Service Di Lembaga Pendidikan Ma'Arif Demak. Indones J Technol Informatics Sci. 2nd ed. 2021;2(2):67–70.

[4]. Areshey, A.; Mathkour, H. Transfer Learning for Sentiment Classification Using Bidirectional Encoder Representations from Transformers (BERT) Model. *Sensors* **2023**, *23*, 5232. https://doi.org/10.3390/s23115232

[5]. Karaoglan Yilmaz FG, Yilmaz R. Learning Analytics Intervention Improves Students' Engagement in Online Learning. Technol Knowl Learn. 2021;(0123456789).

[6]. Kastrati Z, Dalipi F, Imran AS, Nuci KP, Wani MA. Sentiment analysis of students' feedback with nlp and deep learning: A systematic mapping study. Appl Sci. 2021;11(9).

[7]. Ligthart, A.; Catal, C.; Tekinerdogan, B. Systematic reviews in sentiment analysis: A tertiary study. Artif. Intell. Rev. 2021, 54, 4997–5053. [CrossRef]

[8]. Salazar C, Aguilar J, Monsalve-Pulido J, Montoya E. Affective recommender systems in the educational field. A systematic literature reviews. Comput Sci Rev [Internet]. 2021; 40:100377. Available from: https://doi.org/10.1016/j.cosrev.2021.100377

[9]. Durairaj, A.K.; Chinnalagu, A. Transformer based Contextual Model for Sentiment Analysis of Customer Reviews: A Fine-tuned BERT. Int. J. Adv. Comput. Sci. Appl. 2021, 12, 474–480.

[10]. Lan, Z.; Chen, M.; Goodman, S.; Gimpel, K.; Sharma, P.; Soricut, R. ALBERT: A Lite BERT for Self-supervised Learning of Language Representations. arXiv 2020. [CrossRef]

[11]. Liu Y, Soroka A, Han L, Jian J, Tang M. Cloud-based big data analytics for customer insight-driven design innovation in SMEs. Int J Inf Manage [Internet]. 2020;51(November 2019):102034. Available from: https://doi.org/10.1016/j.ijinfomgt.2019.11.002

[12]. Mehbodniya A, Rao MV, David LG, Joe Nige KG, Vennam P. Online product sentiment analysis using random evolutionary whale optimization algorithm and deep belief network. Pattern Recognit Lett. 2022; 159:1–8.

[13]. Bilal, M.; Almazroi, A.A. Effectiveness of Fine-tuned BERT Model in Classification of Helpful and Unhelpful Online Customer Reviews. Electron. Commer. Res. 2022. [CrossRef]

[14]. Alamoudi, E.S.; Alghamdi, N.S. Sentiment classification and aspect-based sentiment analysis on yelp reviews using deep learning and word embeddings. J. Decis. Syst. 2021, 30, 259–281

[15]. Žitnik S, Blagus N, Bajec M. Target-level sentiment analysis for news articles. Knowledge-Based Syst. 2022; 249:108939.

[16]. Yan H, Dai J, Ji T, Qiu X, Zhang Z. A Unified Generative Framework for Aspect-based Sentiment Analysis. 2021;2416–29.

[17]. Abdi A, Hasan S, Shamsuddin SM, Idris N, Piran J. A hybrid deep learning architecture for opinion-oriented multi-document summarization based on multi-feature fusion. Knowledge-Based Syst [Internet]. 2021; 213:106658. https://doi.org/10.1016/j.knosys.2020.106658

[18]. Cao F, Huang X. Performance analysis of aspect-level sentiment classification task based on different deep learning models. PeerJ Comput Sci. 2023. doi: 10.7717/peerj-cs.1578. PMID: 37869455; PMCID: PMC10588683.

[19]. Ahmad Jazuli TKR. Analisis Sentimen Terhadap Xiaomi Indonesia Menggunakan Naïve Bayes Method. Indones J Technol Informatics Sci [Internet]. 3rd ed. 2021;3(1):21–9. https://jurnal.umk.ac.id/index.php/ijtis/article/view/7514/pdf

[20]. Bu J, Ren L, Zheng S, Yang Y, Wang J, Zhang F, Wu W. ASAP: a Chinese review dataset towards aspect category sentiment analysis and rating prediction. 2069–2079 DOI 10.18653/v1/2021.naacl-main.167. 2021