



Optimizing Tourism Recommendations with a Hybrid Model: Bridging User Preferences and Behavioral Patterns

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Abstract

Recommender systems play a crucial role in personalized decision-making, particularly in the tourism industry, where users seek destinations that align with their preferences. However, traditional recommendation methods often struggle to provide accurate recommendations. This research introduces a hybrid recommendation framework that combines Content-Based Filtering (CBF) with Apriori-based association rule mining to improve the accuracy and relevance of recommendations. First, CBF was implemented using TF-IDF, Word2Vec, and BERT embeddings to compute the similarity between user preferences and tourism destinations. The Top-N recommended destinations from each method were then used as antecedents in Apriori to identify associative patterns and co-occurrence relationships among tourism destinations. By leveraging both semantic preference matching and association rule mining, the proposed system refines the recommendation process, ensuring not only personalized suggestions but also uncovering implicit travel patterns. The experimental results demonstrate that the hybrid model improves recommendation relevance and accuracy compared to standalone CBF methods. The accuracy of the CBF model was 53.96%, whereas that of the hybrid model was 94.31%. The integration of CBF and Apriori offers a more comprehensive and data-driven recommendation framework, which is valuable for personalized tourism applications.

Keywords: apriori; content-based filtering; cosine similarity; hybrid model; tourism

How to Cite: R. Hammad, M. Azwar, and M. A. Syarif, "Optimizing Tourism Recommendations with a Hybrid Model: Bridging User Preferences and Behavioral Patterns", *J. RESTI (Rekayasa Sist. Teknol. Inf.)*, vol. 9, no. 4, pp. 894 - 904, Aug. 2025.

Permalink/DOI: <https://doi.org/10.29207/resti.v9i4.6510>

Received: March 27, 2025

Accepted: August 12, 2025

Available Online: August 22, 2025

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Published by Ikatan Ahli Informatika Indonesia

1. Introduction

Lombok Island holds a prominent position as one of the islands with high tourism potential in West Nusa Tenggara Province [1], [2]. This potential is in the form of natural beauty and culture[3]. Based on data provided by the West Nusa Tenggara Province Tourism Office, the number of tourism destinations on the island of Lombok has reached 38 tourist destinations [4] and 56 tourist village [5]. The wide variety of tourism destinations introduces complexity in tourists' decision-making processes when selecting destinations aligned with their personal preferences and requirements. Until now, there is an application available that people can use to obtain information related to tourism on the island of Lombok, namely the "Come on to Lombok" application. This application provides users with the information they need regarding tourism on the island of Lombok [6]. However, it does not yet provide information related to tourism recommendations that

are in accordance with tourist preferences, so tourists need to search for information one by one at this time, where currently providing personalized tourism recommendations is important to improve the experience and satisfaction of tourists [7], [8]. So the problem currently faced is that there is no system that can provide information related to tourism destinations that suits the preferences and needs of each tourist. Therefore, we need a system that can present information and provide recommendations related to tourist destinations that suit tourists' preferences and needs.

There are several methods that can be used to present tourist information according to tourists' preferences and needs, such as the content-based filtering method[9], [10]. Content-Based Filtering is a filtering technique that can be used to provide recommendations regarding an item based on the content, features or attributes of the item[11]. Content-based filtering has

several algorithms [12]. However, the algorithm used in this research is Cosine Similarity[13]. Cosine Similarity is an algorithm *used to find similarities between entities based on desired preferences*[14]. Apart from content-based filtering, there are also algorithms that can be used to recommend tours, namely apriori [15] - [18]. Apriori is an algorithm used to find association patterns from the data provided [19] - [21].

Numerous prior studies have been conducted that are relevant to this research such as research: Muneer et al. explored the development of a tourism recommendation system based on content-based filtering techniques [22]. Chalkiadakis et al. [23] discussed the application of content-based filtering in the development of a tourism recommendation system. Virutamasen et al [24] explored the application of content-based filtering in tourism recommendation systems, highlighting its potential to enhance the overall tourism experience. Henni et al. explored the design and implementation of a tourism recommendation system based on content-based filtering techniques [25]. And there are many other studies that discuss the development of recommendation systems [26] - [31].

Although the Apriori algorithm is extensively applied in data-mining for detecting frequent itemsets and revealing concealed patterns within massive datasets, [32] - [35]. Its capability to reveal underlying relationships in user interactions has made it valuable for e-commerce [36], healthcare [37], and music recommender systems [38]. However, its application in tourism recommender systems remains limited. Additionally, many tourism recommendation models fail to capture multi-criteria preferences, such as the category of attractions, facilities, and budget considerations. To overcome these limitations, this research introduces a novel hybrid recommendation framework that combines Content-Based Filtering (CBF) with Apriori-driven association rule mining to enhance recommendation accuracy and personalization. This approach first applies CBF to generate a personalized top-N list of recommendations, which is then refined using association rules derived from Apriori to enhance the accuracy and relevance of suggestions. The proposed system analyzes user preferences based on category, available facilities, and budget, utilizing TF-IDF, Word2Vec, and BERT embeddings for similarity computation. The choice of the Cosine Similarity algorithm in this study is based on its effectiveness in measuring similarity between item and user preferences[39]. While the Triangle Multiple Jaccard algorithm achieved an accuracy of 70% [40]. The final recommendations are adjusted based on association rules, ensuring that suggested destinations align with frequent travel patterns and user behavior trends. This study aims to design and assess an integrated tourism recommendation system that enhances recommendation accuracy. By bridging this research gap, the study aims to advance the field of tourism recommender systems, providing valuable

insights for both industry practitioners and academic researchers.

2. Methods

This research introduces a hybrid tourism recommender that combines Content-Based Filtering (CBF) with the Apriori algorithm to deliver personalized destination suggestions. The goal is to combine the advantages of both techniques to enhance the accuracy and relevance of recommendations for users. The methodology is structured into distinct phases: data collection, data preprocessing, feature extraction and engineering, model development (incorporating Content-Based Filtering and Apriori algorithm), and systematic evaluation. The research methodology is illustrated in Figure 1.

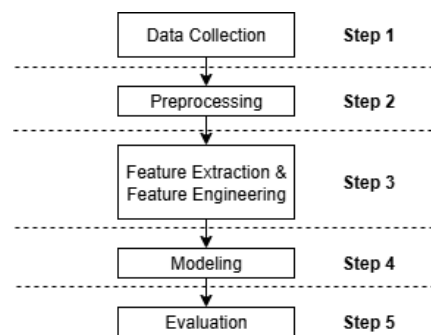


Figure 1. Research methodology

2.1 Data Collection

The data collection phase involves acquiring two primary datasets tailored to support the hybrid recommendation system: one specifically designed for Content-Based Filtering (CBF), and another formulated to enable Apriori-based association rule mining. The CBF dataset consists of detailed information about tourism destinations and user preferences. It comprises two main components: the destinations dataset, which includes attributes such as destination names, categories, available facilities, and budget requirements, and the preferences dataset, which records user preferences regarding destination categories, preferred facilities, and budget constraints. These datasets enable the system to analyze user interests and recommend destinations based on content similarity. Meanwhile, the Apriori dataset focuses on user visit patterns by recording past visits to various tourism destinations. This dataset is essential for identifying associations between destinations and uncovering frequently visited location combinations. By applying association rule mining, the Apriori algorithm enhances the recommendation process by suggesting destinations based on users' historical visit behaviors. All datasets were collected through SQL-based data aggregation from the lomboktripfinder.com database, which has been specifically developed to provide comprehensive tourism data for this study. The data collection process adheres to ethical and legal considerations, as user consent and developer approval

were obtained during the initial user registration process and outlined in the platform's terms and conditions. This ensures that the collected data is used responsibly for further system development, including enhancing recommendation features. To ensure data quality, a validation procedure was implemented. This includes: duplicate removal and missing value handling.

2.2 Preprocessing

Data preprocessing is a crucial process to guarantee that the gathered data is clean, consistent, and ready for subsequent analysis. [41]. This process involves transforming raw data into a structured format that can be effectively utilized in the recommendation model.

The preprocessing techniques applied in this study include text preprocessing (Case Folding and Tokenization) [42] and noise removal (punctuation). These steps help standardize the data, remove unnecessary variations. The cleaned and processed data is then used as input for the feature extraction and feature engineering phase, ensuring optimal performance of the recommendation system.

2.3 Feature Extraction & Feature Engineering

Feature extraction and feature engineering play a crucial role in transforming raw data into structured representations that can be effectively utilized in the recommendation model. Feature extraction converts textual attributes into numerical or vectorized representations, enabling the model to measure similarity between destinations and user preferences. This work employs TF-IDF, Word2Vec, and BERT to encode attributes such as categories and facilities into high-dimensional vectors [43]. Meanwhile, feature engineering involves restructuring the transactional visit data into grouped records based on user visits. This transformation ensures that the Apriori algorithm can effectively analyze patterns of user behavior and identify frequent itemset [44].

TF-IDF integrates Term Frequency (TF) and Inverse Document Frequency (IDF) to assess the significance of a term within a specific document, reflecting its relevance in distinguishing that document from a larger corpus. TF is determined using the formula presented in Equation 1, while IDF is computed as shown in Equation 2. By combining Equations 1 and 2, the TF-IDF formula is derived, as presented in Equation 3 [45].

$$tf(t, d) = \frac{\text{The number of times the term } t \text{ appears in document } d}{\text{The total number of terms present in document } d} \quad (1)$$

$$idf(t) = \log\left(\frac{1+n}{1+df(t)}\right) + 1 \quad (2)$$

$$tf - idf(t, d) = tf(t, d) \times idf(t) \quad (3)$$

With $tf(t, d)$ representing the frequency of term t within document d , it quantifies how often a specific term appears in a given document. $idf(t)$ representing IDF of the term t . Here, n denotes the total number of

documents in the corpus, while $df(t)$ represents the count of documents that contain the term t .

In addition to TF-IDF, Word2Vec is the second feature extraction method used in this study. Word2Vec is a language modeling technique developed by Mikolov et al. to represent words as numerical vectors based on their context in text. It employs two main approaches: The Continuous Bag of Words (CBOW) model predicts a target word from its surrounding contextual words, while the Skip-Gram model works in reverse by predicting the context around a given word [46]. BERT advances feature extraction through bidirectional context modeling, offering a significant improvement over Word2Vec's left-to-right or right-to-left approach. Its training on Masked Language Model and Next Sentence Prediction enables deep understanding of word meanings in context, revealing nuanced relationships between tourism-related terms. This enables BERT to perform exceptionally well in natural language processing tasks demanding a deep and holistic grasp of language structure and semantic meaning [47]. In this study, IndoBERT is utilized as the third feature extraction method, specifically designed for the Indonesian language[48].

2.4 Modeling

The modeling phase involves implementing two recommendation techniques: Content-Based Filtering (CBF) and the Apriori algorithm. Content-Based Filtering is used to generate personalized recommendations by calculating item similarity [9], which in this study refers to the similarity between tourism destinations and user preferences based on extracted features. This similarity is computed using cosine similarity, which measures the closeness between the vectorized representations of destinations and user preferences derived from TF-IDF, Word2Vec, and BERT. The higher the similarity score, the more relevant the destination is to the user's preferences. Cosine similarity measures the cosine of the angle between two non-zero vectors, producing a value between -1 and 1, where 1 indicates perfect similarity and -1 indicates complete dissimilarity[49]. Equation 4 provides the formula for calculating the cosine similarity between vectors A and B , which quantifies how similar they are in terms of orientation in vector space.

$$\text{cosine similarity } (A, B) = \frac{A \cdot B}{\|A\| \|B\|} \quad (4)$$

Where: $A \cdot B$ is the dot product of vectors A and B
 $\|A\| \|B\|$ are the magnitudes (norms) of vectors A and B , respectively.

This similarity score helps identify how closely a user's preferences align with a particular destination, based on the extracted features. In contrast, the Apriori algorithm is applied to analyze user visit patterns and discover frequent itemsets among tourism destinations. The transactional dataset, which consists of records of user

visits, is grouped based on unique users, allowing the algorithm to identify associations between frequently visited destinations. These association rules help refine recommendations by incorporating insights from previous user behaviors.

Figure 2 illustrates the architecture of the hybrid model, where feature extraction is performed using TF-IDF, Word2Vec, and BERT to transform textual attributes

into numerical representations. The cosine similarity metric is then applied to compute the closeness between tourism destinations and user preferences, producing a ranked recommendation list. Simultaneously, the Apriori algorithm processes user visitation data to extract association rules, which identify relationships between frequently visited destinations. These rules are used to filter and refine the recommendations generated by CBF, ensuring they align with past user behaviors.

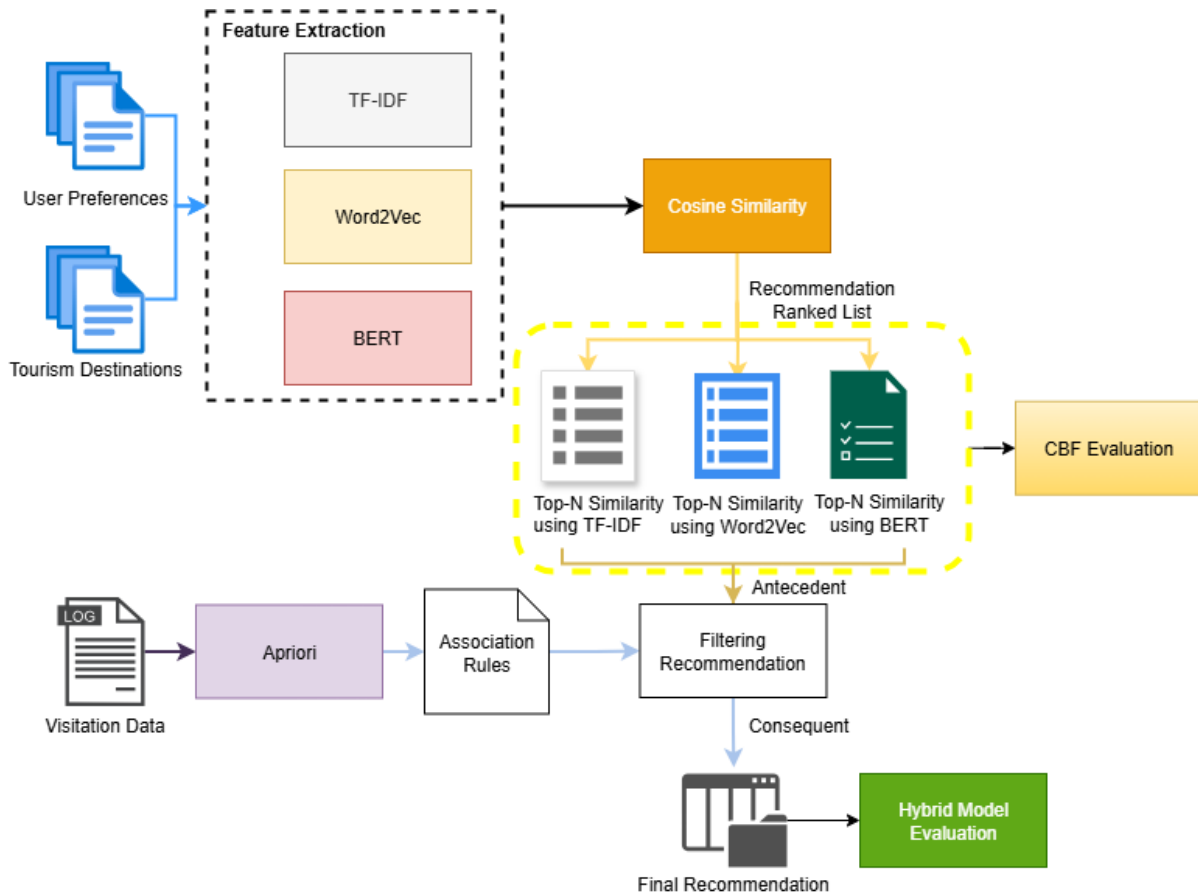


Figure 2. Architecture of the Proposed Hybrid Recommendation System

The CBF-based recommendation generates a ranked list of top-N destinations based on similarity scores obtained from TF-IDF, Word2Vec, and BERT. This list is evaluated using a testing dataset, ensuring that the model's performance is assessed on testing data. The accuracy of each feature extraction technique is measured to determine the most effective method for computing user-tourism destination similarities. The Apriori algorithm was applied to identify frequent patterns in user visit data, aiming to generate association rules that enhance the recommendation system.

The Apriori algorithm follows a bottom-up approach to discover frequent itemsets and generate association rules from transactional data [50]. It begins by setting minimum support and minimum confidence thresholds to filter significant patterns. The process starts with identifying frequent 1-itemsets, followed by generating larger candidate itemsets while ensuring that all their

subsets are also frequent (Apriori Property). In the Apriori algorithm, two key metrics are used to determine relationships between items: Support and Confidence[51]. Support measures how frequently an itemset appears in the dataset, as calculated in Equation 5. Confidence indicates how often item Y appears in transactions that already contain item X, as calculated in Equation 6. The algorithm then calculates the support for each candidate and removes those that do not meet the threshold. Once frequent itemsets are obtained, association rules are derived in the form of $X \Rightarrow Y$, where confidence is calculated to determine the strength of the relationship. Only rules that satisfy the minimum confidence are retained for analysis.

$$\text{Support}(X) = \frac{\text{Number of transactions containing } X}{\text{Total number of transactions}} \times 100\% \quad (5)$$

X is the item or itemset being analyzed.

$$\text{Confidence } (X \Rightarrow Y) = \frac{\text{Support } (X \cap Y)}{\text{Support } (X)} \quad (6)$$

Where, X is the antecedent. Y is the consequent. $(X \cap Y)$ represents the number of transactions containing both items. By integrating CBF with Apriori, the hybrid recommendation model leverages both content-based similarities and behavioral patterns to enhance the accuracy and relevance of tourism recommendations.

2.5 Evaluation

The evaluation phase aims to measure the effectiveness of both the Content-Based Filtering (CBF) model and the hybrid recommendation model that integrates CBF with Apriori. The evaluation process consists of two key components. First, the CBF evaluation assesses the accuracy of recommendations by comparing the suggested destinations with actual user visits from the testing dataset. Second, the hybrid model evaluation is conducted by applying association rules from Apriori to refine the recommendations generated by CBF. The model's performance is evaluated using precision as a measure of accuracy. The precision calculation follows Equation 7. Precision is a performance metric used in top-N recommendation systems to measure the proportion of relevant items among the total recommended items, indicating how accurately a recommendation system suggests relevant content to users [52]. The same performance metric is used to assess the hybrid approach, ensuring a direct comparison with standalone CBF. Through this evaluation, the study aims to determine whether integrating content similarity and user visitation patterns results in more relevant and personalized recommendations.

$$\text{Precision @}k(u) = \frac{|rel(u) \cap rec_k(u)|}{k} \quad (7)$$

u is a user identificatory, $rel(u)$ is a list of relevant items for user u from the test set, $rec_k(u)$ is a recommendation list for user u containing top- k recommended items. k is the number of items in test set for each user. After calculating the precision for each user in the test set, the average precision is then determined.

3. Results and Discussions

This section evaluates the proposed hybrid recommendation system by examining the results from each phase: data collection, data preprocessing, feature extraction and feature engineering, modeling, and final evaluation.

3.1 Data Collection

The data-collection stage compiled 70 tourism destinations, each annotated with its category, available facilities, and budget bracket. A representative excerpt of this dataset is shown in Table 1. Additionally, 958 user preference records were obtained, detailing individual interests in destination categories, facilities, and budget constraints. Table 2 presents a sample of data from the preferences dataset. For the Apriori dataset, user visit records were compiled, resulting in 3961 transactions that represent past visits to different destinations. These visit records were analyzed to extract frequent patterns and associations between locations. Table 3 presents a sample of data from the visit dataset. The collected data serves as the foundation for the hybrid recommendation system, ensuring that both user preferences and historical visit behaviors contribute to more accurate and personalized recommendations.

Table 1. Sample Data of Tourism Destinations

ID	Tourist Attraction	Category	Budget	Facilities	Activities	Rating
29	Ende Tourism Village	Culture	Rp15.000	Tourist Information Center, Public Toilets, Place of Worship	Photography, Cultural Tourism	4,6
17	Semeti Beach	Beach	Rp150.000	Security or Guard, Public Toilets, Parking Lot	Photography	4,5
21	Tebing Beach	Beach	Rp10.000	Parking Lot	Nature Trekking, Photography	3,3

Table 2. Sample Data of User Preferences

User_id	Name	Category_preference	Facility_preference	Budget_preference
18	Joko Melati	Waterfall	Tourist Information Center, Public Toilets	125000
108	Mario Lestari	Beach	Public Toilets, Parking Lots	310000
243	Ahmad Purnama	Waterfall	Security or Guard, Tourist Information Center, Parking Lots	500000

Table 3. Sample Data of User Visits

Id	Transaction	User_id	Destination_id
4	1	1	4
5	1	1	66
6	2	2	4

3.2 Preprocessing

The preprocessing stage for Content-Based Filtering (CBF), several techniques were applied to textual data. First, lowercasing was performed to standardize all text data and prevent mismatches caused by capitalization differences. Next, punctuation removal was conducted to eliminate unnecessary symbols, reducing noise in the dataset. After that, tokenization was applied to break down textual attributes into individual words,

facilitating better feature extraction. These preprocessing steps ensured that the dataset was clean and structured, making it suitable for similarity computation. The features used here are category, budget, and facilities. The processed text is presented in Tables 4 and 5. The processed text data was then converted into numerical representations using feature extraction technique, allowing the system to accurately measure the relevance between tourism destinations and user preferences. As a result, the recommendation model was able to generate more precise and personalized destination suggestions.

Table 4. Preprocessed Tourism Destination Data

ID	Tourist Attraction	Category	Budget	Facility
29	['village', 'tourism', 'ende']	['culture']	15000	['center', 'information', 'tourism', 'toilet', 'public', 'place', 'worship']
17	['beach', 'semeti']	['beach']	150000	['security', 'or', 'guard', 'toilet', 'public', 'place', 'parking']
21	['beach', 'cliff']	['beach']	10000	['place', 'parking']

Table 5. Preprocessed User Preferences Data

User_id	Category_p reference	Facility_preference	Budget_p reference
18	['waterfall']	['center', 'information', 'tourism', 'toilet', 'public']	125000
108	['beach']	['toilet', 'public', 'place', 'parking']	310000
243	['waterfall']	['security', 'or', 'guard', 'center', 'information']	500000

Table 6. Feature extraction results

Feature Extraction	Category	Budget	Facility
Input Text	['Culture']	15000	['center', 'information', 'tourism', 'toilet', 'public', 'place', 'worship']
TF-IDF	array([[0., 1., 0., 0., 0., 0., 0., 0., 0.]])	15000	array([[0., 0., 0., 0., 0., 0., 0., 0., 0.38997206, 0.32977242, 0., 0., 0., 0., 0., 0., 0.28137686, 0., 0., 0., 0., 0., 0.32977242, 0., 0., 0., 0.50974047, 0.30221182, 0.30221182, 0., 0., 0.32977242]]) Vector Shape (1, 37)
Word2Vec	Vector Shape (1, 9) array([-8.7274825e-03, 2.1301615e-03, -8.7354420e-04, ..., 6.6758976e-03], dtype=float32)	15000	array([-1.21967890e-03, 4.07561241e-03, 2.71094800e-03, ..., 5.50269010e-03], dtype=float32)
BERT	Vector Shape (1, 100) array([[-4.91606027e-01, 1.85083106e-01, 7.09157363e-02, ..., 6.34397984e-01]], dtype=float32) Vector Shape (1, 768)	15000	Vector Shape (1, 100) array([[7.03498900e-01, -4.98377830e-01, -6.55717850e-01, ..., 3.84545594e-01]], dtype=float32) Vector Shape (1, 768)

These structured numerical representations enabled precise similarity calculations, allowing the recommendation model to generate personalized and relevant tourism destination suggestions. For feature engineering, the transactional dataset, which contains

3.3 Feature Extraction & Feature Engineering

In the feature extraction process, textual data from the category and facilities attributes were first preprocessed using lowercasing, punctuation removal, and tokenization to standardize the text. These preprocessed features were then converted into numerical representations using TF-IDF, Word2Vec, and BERT, enabling the system to measure the similarity between tourism destinations and user preferences. The budget feature, being a numerical value, was directly incorporated into the model without transformation. The feature extraction process resulted in different dimensional representations for each technique used. TF-IDF produced vectors with dimensions corresponding to the number of unique words in the dataset, as each term in the category and facilities attributes was assigned a numerical weight based on its importance across all records. Meanwhile, Word2Vec transformed words in these attributes into 100-dimensional vectors, capturing semantic relationships between terms based on their contextual usage. Additionally, BERT provided a more complex representation by encoding the text into 768-dimensional vectors, preserving deep contextual meanings and relationships between words. Table 6 presents the feature extraction results of vectors derived from the input text.

user visit records to various destinations, was reformatted into grouped transactions based on user visit history. This transformation allowed the Apriori algorithm to identify frequently visited destination patterns, improving the recommendation process. By

applying these techniques, the model successfully structured the data into a format suitable for both Content-Based Filtering (CBF) and the Apriori algorithm, enhancing the accuracy and relevance of the recommendations. Table 7 presents the feature engineering results for the Apriori algorithm.

Table 7. The result of features engineering

Transaction	User_id	Destination_id
1	1	4, 66
2	2	4

3.4 Modelling

The modeling phase integrates Content-Based Filtering (CBF) with the Apriori algorithm to develop a hybrid tourism recommendation system. CBF analyzes user preferences and tourism destination features to generate personalized recommendations, while Apriori identifies frequent destination visit patterns from user visitation data. Various parameters were tested to optimize rule generation. The hyperparameters evaluated in this study include minimum support, minimum confidence, and itemset size. The values tested for each hyperparameter are as follows: supports = [0.01, 0.05, 0.1, 0.15, 0.2, 0.25, 0.3], confidences = [0.5, 0.6, 0.7, 0.80, 0.90, 1], and itemset_sizes = [1, 2, 3, 4]. The experimentation was carried out by performing an exhaustive search through all possible combinations (i.e., the Cartesian product) of these hyperparameters. With 7 support thresholds, 6 confidence levels, and 4 itemset sizes, a total of 168 parameter configurations were evaluated. Lower support values allowed for more extensive rule discovery, capturing less frequent patterns, while higher confidence thresholds ensured that only strong relationships between visited destinations were retained. The itemset size parameter controlled the number of destinations in a single rule, balancing specificity and generalizability. Through this process, the Apriori model extracted 16,969 rules, highlighting significant patterns in user visit data.

The performance of each configuration was evaluated based on two key criteria: the total number of rules generated (as a measure of coverage) and the average confidence of the rules (as an indicator of rule strength). The configuration with the highest number of rules was found at support = 0.01, confidence = 0.5, and itemset size = 4, resulting in 2,232 rules with an average confidence of 81,22%. On the other hand, the configuration with the highest average confidence was obtained at support = 0.3, confidence = 1.0, and itemset size = 4, producing 3 highly confident rules with 100% confidence. These findings illustrate the trade-off between rule quantity and rule strength. Lower support and confidence thresholds produce more rules, capturing a broader range of user behaviors, whereas higher thresholds yield fewer but more reliable rules.

These rules provided insights into user preferences and behavioral trends, forming the basis for improved

recommendations. The generated rules were further refined by integrating the antecedents from the Combined Feature Extraction model, ensuring that only unique top-N recommendations from Content-Based Filtering (CBF) were considered. This filtering process enhanced recommendation relevance by merging content-based similarity with behavioral patterns from user visits. The integration of CBF and Apriori proved highly effective in improving recommendation accuracy. By leveraging both content-based preferences and frequent visitation patterns, the system was able to offer more personalized and precise recommendations. The high number of extracted rules confirmed the existence of distinct patterns in user tourism behavior, demonstrating that frequent itemset mining is a valuable enhancement for content-based recommendation systems.

3.5 Evaluation

The evaluation of the recommendation models was conducted by analyzing the accuracy of different feature extraction techniques and the hybrid approach. Table 8 presents the average accuracy (%) achieved by each model, providing insights into their effectiveness in generating personalized tourism recommendations.

Table 8. CBF and Hybrid results evaluation

No	Model	Average Accuracy (%)
1	TF-IDF	53,96
2	Word2Vec	22,84
3	BERT	38,90
4	Hybrid Model	94,31

Table 9. Recommendation Results from TF-IDF

User_id	Destination list	Recommendation list	Accuracy
176	Kuta Lombok Beach, Senggigi Beach, Gili Trawangan, Gili Air	Gili Kondo, Gili Trawangan, Gili Air, Gili Kedis	0,5
177	Kuta Lombok Beach, Senggigi Beach, Gili Trawangan	Gili Trawangan, Gili Air, Gili Kedis	0,333333
178	Kuta Lombok Beach, Senggigi Beach, Gili Trawangan, Gili Air, Gili Meno	Gili Kondo, Gili Trawangan, Gili Air, Gili Kedis, Gili Meno	0,6
179	Gili Meno, Gili Air, Gili Trawangan, Kuta Lombok Beach, Tanjung Aan Beach, Senggigi Beach	Gili Kondo, Gili Trawangan, Gili Air, Gili Kedis, Gili Meno, Gili Nanggu	0,5

User_id	Destination list	Recommendation list	Accuracy
180	Kuta Lombok Beach, Tanjung Aan Beach, Senggigi Beach, Gili Trawangan, Gili Air, Gili Meno	Gili Kondo, Gili Trawangan, Gili Air, Gili Kedis, Gili Meno, Gili Nanggu	0,5

The TF-IDF-based CBF model achieved the highest accuracy among individual feature extraction methods, scoring 53.96%. This strong performance is due to the dataset's characteristics, where the number of unique words and variations in features is relatively small. Since TF-IDF directly compares words using cosine similarity, exact matches—such as comparing "apple" with "apple"—result in high similarity scores, making it highly effective for this specific dataset.

Table 10. Recommendation Results from Word2Vec

User_id	Destination list	Recommendation list	Accuracy
176	Kuta Lombok Beach, Senggigi Beach, Gili Trawangan, Gili Air	Gili Kondo, Gili Kedis, Gili Lampu, Gili Nanggu	0
177	Kuta Lombok Beach, Senggigi Beach, Gili Trawangan	Gili Kedis, Gili Lampu, Gili Nanggu	0
178	Kuta Lombok Beach, Senggigi Beach, Gili Trawangan, Gili Air, Gili Meno	Gili Kondo, Gili Kedis, Gili Lampu, Gili Nanggu, Gili Sudak	0
179	Gili Meno, Gili Air, Gili Trawangan, Kuta Lombok Beach, Tanjung Aan Beach, Senggigi Beach	Gili Kondo, Gili Kedis, Gili Lampu, Gili Nanggu, Gili Sudak, Gili Trawangan	0,166667
180	Kuta Lombok Beach, Tanjung Aan Beach, Senggigi Beach, Gili Trawangan, Gili Air, Gili Meno	Gili Kondo, Gili Kedis, Gili Lampu, Gili Nanggu, Gili Sudak, Gili Trawangan	0,166667

In contrast, Word2Vec-based CBF performed significantly lower, with an accuracy of 22.84%. Although Word2Vec captures semantic relationships

between words, its effectiveness depends on extensive training data. Given the limited vocabulary and variations in this dataset, Word2Vec struggled to generate meaningful numerical representations for recommendations. The BERT-based CBF model, which also incorporates contextual meaning, performed better than Word2Vec, achieving 38.90% accuracy. This confirms that BERT is more effective in understanding contextual relationships compared to Word2Vec. However, due to the dataset's small size and limited feature variations, BERT's advantage over TF-IDF was not as significant. This suggests that for datasets with limited unique words and feature variations, TF-IDF remains the most effective standalone feature extraction method.

Table 11. Recommendation Results from BERT

User_id	Destination list	Recommendation list	Accuracy
176	Kuta Lombok Beach, Senggigi Beach, Gili Trawangan, Gili Air	Gili Kondo, Gili Kedis, Gili Trawangan, Gili Nanggu	0,25
177	Lombok Beach, Senggigi Beach, Gili Trawangan	Gili Kedis, Gili Trawangan, Gili Nanggu	0,333333
178	Kuta Lombok Beach, Senggigi Beach, Gili Trawangan, Gili Air, Gili Meno, Gili Air, Gili	Gili Kondo, Gili Kedis, Gili Trawangan, Gili Nanggu, Gili Lampu	0,2
179	Trawangan, Kuta Lombok Beach, Tanjung Aan Beach, Senggigi Beach Kuta Lombok Beach, Tanjung Aan Beach, Senggigi Beach, Gili	Gili Kondo, Gili Kedis, Gili Trawangan, Gili Nanggu, Gili Lampu, Gili Meno	0,333333
180	Trawangan, Gili Air, Gili Meno	Gili Kondo, Gili Kedis, Gili Trawangan, Gili Nanggu, Gili Lampu, Gili Meno	0,333333

To improve recommendation accuracy, a combined feature extraction approach was implemented, integrating TF-IDF, Word2Vec, and BERT. However, only the recommendation outputs from these three models were selected and utilized, ensuring that the final recommendations leverage the strengths of each feature extraction method for better accuracy and

relevance. This combined feature extraction output was then utilized as a filtering rule for the Apriori-based recommendation model, where only unique combinations from all feature extraction models were used as antecedents in the Apriori association rules. When evaluated with testing data, the hybrid model incorporating CBF and Apriori achieved a significantly higher accuracy of 94.31%. This result confirms that integrating content-based recommendations with frequent pattern mining from user visitation data leads to a more accurate, relevant, and personalized recommendation system. To compare the differences in recommendations, Tables 9, 10, and 11 present the recommendation results generated by the three models. Each table displays the user ID, the actual destination list, and the recommended destinations, allowing for a clear comparison of how each feature extraction method influences the recommendation outcomes. Table 12 presents the recommendation results generated by the hybrid model.

Table 12. Recommendation Results from Hybrid Model

User_id	Destination list	Recommendation list	Accuracy
176	Kuta Lombok Beach, Senggigi Beach, Gili Trawangan, Gili Air	Kuta Lombok Beach, Gili Trawangan, Gili Air, Senggigi Beach	1
177	Kuta Lombok Beach, Senggigi Beach, Gili Trawangan	Kuta Lombok Beach, Gili Trawangan, Senggigi Beach	1
178	Kuta Lombok Beach, Senggigi Beach, Gili Trawangan, Gili Air, Gili Meno	Gili Trawangan, Gili Meno, Kuta Beach Lombok, Gili Air, Senggigi Beach,	1
179	Gili Meno, Gili Air, Gili Trawangan, Kuta Lombok Beach, Tanjung Aan Beach, Senggigi Beach	Gili Trawangan, Gili Meno, Kuta Beach Lombok, Gili Air, Tanjung Aan Beach, Senggigi Beach	1
180	Kuta Lombok Beach, Tanjung Aan Beach, Senggigi Beach, Gili Trawangan, Gili Air, Gili Meno	Gili Trawangan, Gili Meno, Kuta Beach Lombok, Gili Air, Tanjung Aan Beach, Senggigi Beach	1

Based on the results, the findings indicate that TF-IDF is the best option when dealing with small datasets with

limited unique words and feature variations. However, for more robust recommendations, combining contextual and non-contextual models improves accuracy. The hybrid approach, which leverages both feature extraction and user behavioral patterns, significantly enhances recommendation quality, making it the most effective method for tourism recommendations in this study. The experimental results indicate that the hybrid recommendation system, which combines CBF with Apriori, significantly improves the quality of recommendations for users compared to traditional standalone methods. Although the hybrid system provides promising results, there are some limitations. The Apriori algorithm requires sufficient data to generate meaningful association rules, and its performance may degrade with smaller datasets. That's why the use of different hyperparameters results in many rules that capture the hidden patterns within the data.

4. Conclusions

In conclusion, this research presents a hybrid recommendation system that integrates Content-Based Filtering (CBF) with the Apriori algorithm for personalized tourism recommendations. By leveraging multiple techniques such as TF-IDF, Word2Vec, and BERT for feature extraction and similarity computation, the system effectively addresses the challenge of providing relevant recommendations tailored to user preferences. The integration of association rule mining with the Apriori algorithm further enhances the system by uncovering frequent patterns and relationships between destination attributes. The experimental results demonstrate the effectiveness of the proposed system in providing accurate recommendations, achieving an impressive 94.31% accuracy. This highlights the strength of the hybrid approach, which significantly outperforms traditional standalone methods. The combination allows the system to capture both individual user preferences and broader behavioral patterns, resulting in more personalized and relevant recommendations. Future work can focus on expanding the dataset to include a more diverse range of user preferences and tourism destinations, ensuring greater generalizability. Additionally, incorporating user feedback mechanisms could further refine recommendations based on real-time interactions, enhancing system adaptability.

Acknowledgements

We thank the Ministry of Education, Culture, Research and Technology (via the Directorate of Research, Technology and Community Service) for supporting this study through the Beginner Lecturer Research grant (FY 2024). We appreciate the support and facilitation provided by LPPM Bumigora University in the course of this research.

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