Enhanced Feature-Based Mobile Recommendations Through Hybrid Model

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Abstract. In today's world, smart devices have become an integral part of our daily routine, from the moment we wake up to the time we go to bed. Among these devices, smartphones stand out as a beneficial aid in making our lives easier. The project focuses on developing a recommendation system that can assist users in selecting a phone that best suits their specific requirements. To achieve this, a survey was conducted among students of a university to gain insights into their preferences. Which are analyzed using collaborative, content, and hybrid models. A Hybrid Recommendation System (HRS) is crucial in creating personalized content suggestions. It integrates user preferences and item attributes and uses collaborative and content-based models to generate accurate recommendations. HRS combines diverse data sources to improve the preciseness and relevance of the recommendations, making it a robust approach for personalized content suggestion systems.

Keywords: Recommender system, User-Item, Collaborative Filtering, Content-based filtering,hybrid model

1 Introduction

Mobile phones have come a long way from being just communication devices in today's fast-moving digital world. They now offer a plethora of features and specifications that cater to the needs of various users. With an extensive range of options available in the market, it can be overwhelming for consumers to pick the perfect mobile phone that aligns with their preferences. To solve this problem, recommendation systems that leverage selecting technical specifications like storage capacity, processing power, and battery life have emerged as a significant solution. Mobile phone recommendation systems are intelligent algorithms designed to assist users in making informed decisions by analyzing diverse technical specifications associated with mobile devices. These specifications encompass critical elements, including battery capacity, storage availability, RAM, processor performance, camera quality, and display characteristics. The fusion of these metrics into a recommendation algorithm allows for a comprehensive evaluation of each

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mobile phone model, ultimately aiding users in a device that best suits their specific requirements. The paper delves into the development and implementation of a sophisticated mobile phone recommendation system, emphasizing the utilization of technical specifications as primary evaluative criteria. The key components of this recommendation system include data collection, data processing, feature selection, algorithm design, user preference modeling, scoring mechanism, recommendation generation, and continuous testing and optimization. To begin, an extensive collection of mobile phone data, encompassing specifications of various models, is curated. The raw data consists of 400 rows of various phone models and about 100 user inputs. The data is meticulously processed to ensure consistency and accuracy, establishing a solid foundation for subsequent analyses. Following this, a robust algorithm is designed, integrating selected features and user preferences to compute a comprehensive score for each mobile phone model. The scoring mechanism is paramount, allowing for weighted evaluation based on user-defined priorities, reflecting individualpreferences. The primary objective of the paper is to build a framework that simplifies the decision-making process for consumers seeking to purchase a mobile phone. By incorporating their preferences into the scoring algorithm, users are presented with personalized recommendations that align with their specific needs, be it an emphasis on ample storage capacity, superior camera quality, or other pertinent aspects.

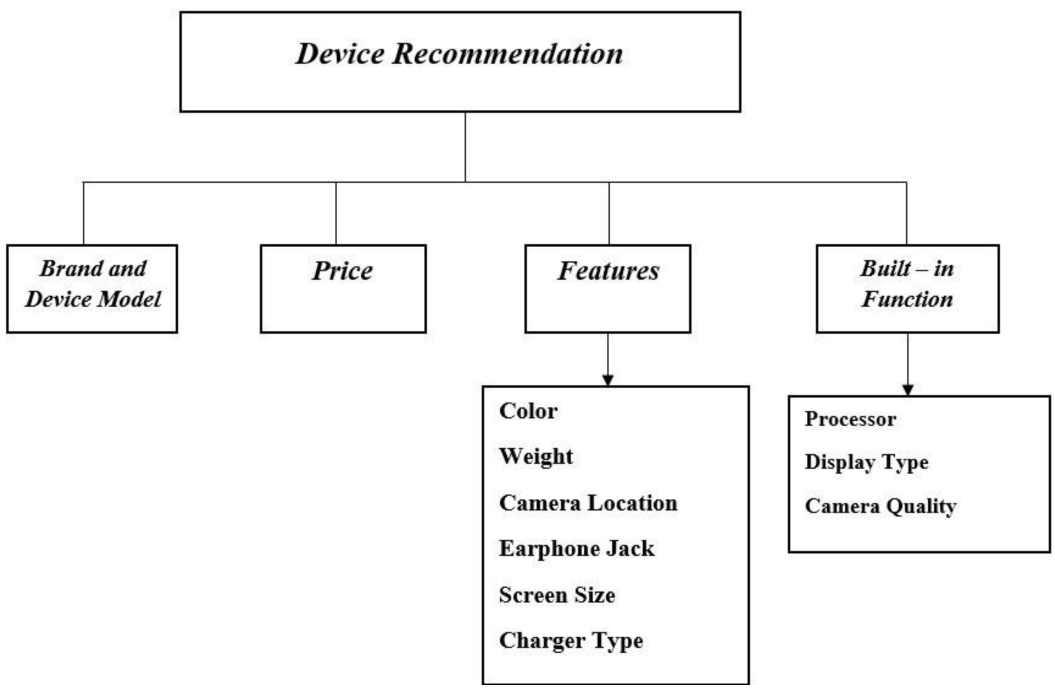

Figure.1. Mobile Features

2 Related work

In their study, Ting-Peng Liang et al [1] found that an AHP-based recommendation system for mobile phone selection is effective and feasible. The AHP-based system provided better recommendations and higher user satisfaction than the benchmark rank-based system. The study also confirmed the dependability and validity of the measurement instrument.

ChoseAmobile is a web-based recommendation system created by Sheeraz Akram et al [2]. It collects and analyzes user reviews using advanced techniques such as web scraping and sentiment analysis. By providing real-time data and sentiment analytics on mobile phone specifications and features, ChoseAmobile helps users make informed decisions. The system is highly effective and delivers precise recommendations. The platform aims to explore analyzing reviews over time and incorporating user location and interests into its recommendations.

W Chen et al. [3] developed a user recommendation model for mobile services that takes into account user psychology. They discovered that overall happiness drove referral willingness after analysing data from 480 3G mobile consumers. Customer happiness affected flow experience, which increased the possibility of referrals. Overall satisfaction was determined by perceived quality and perceived engagement. This research helps businesses develop referral behaviour among mobile service users.

Safiek Mokhlis et al. [4] investigated variables impacting mobile phone selections among Malaysian undergraduate students. Participants assessed preferences on a 7-point scale using a self-administered questionnaire comprising 29 items. Functionality emerged as the primary priority, with "customer excitement" and fundamental necessities having less influence.Innovative features, personal recommendations, pricing, and durability/portability were all notable impacts. The study reveals that usability may not be as important as popularly believed, emphasising the importance of features, aesthetics, and price in mobile phone purchases.

Felix von Reischach et al. [5] introduced APriori, a mobile product recommendation system that uses auto-ID activated phones to collect and submit ratings. It features dynamic rating criteria that adapts to mobile users' attention spans. The article covers APriori's design, application, and assessment, as well as unresolved issues. Challenges include user and rating acquisition, user motivation, and quality management. Further research includes examining the social effects of mobile ratingand combining data from reputable sources.

Deng-Neng Chen et al. [6] developed a personalized recommendation system for selecting mobile phones using the Analytic Hierarchy Process. The AHP-based solution outperformed rank-based and equal weight-based systems in terms of user satisfaction in a study involving 244 users. However, the study suggests lowering input requirements and enhancing interface designs to further improve user satisfaction.

3 Existing work

Within the field of recommender systems, and more specifically in the niche of mobile phone recommendations, a noteworthy study called "Chose A mobile" offers a methodical approach intended to improve the efficacy of suggestions for mobile phone products. The study begins with the compilation of a heterogeneous dataset containing essential mobile phone specs, user reviews, and ratings. This creates a strong basis for the analysis processes that follow. By utilizing machine

learning techniques, such as collaborative and content-based filtering, the study identifies complex patterns and correlations between mobile phone parameters and user preferences. Moreover, the writers utilize sentiment analysis to glean subtle insights from user feedback, improving the system's ability to take into account the arbitrary preferences of users. By incorporating web scraping methods, real-time data is acquired and the system is better able to adjust to the ever-changing mobile phone market. Besides these technical features, the study includes user feedback loops that allow iterative interactions and user input to continuously refine the system. Standard metrics like accuracy, precision, and recall are used in the subsequent assessment, which is supplemented by user-centric evaluations obtained from studies or surveys. The study's methodological framework, which combines cutting-edge technologies with data-driven insights to advance the field of mobile phone recommendations, essentially reflects a sophisticated and holistic approach.
Distinguishing itself from the aforementioned study, our framework HRS introduces a distinctive feature by adopting a hybrid recommendation approach. Unlike previous work, which relied solely on collaborative and content-based filtering, our methodology incorporates both techniques. This hybrid model combines collaborative filtering for personalized recommendations based on user similarities with content-based filtering for mobile phone attributes. This novel approach yields a more comprehensive and adaptive recommendation system capable of making nuanced and accurate recommendations. The hybrid methodology in HRS framework addresses the limitations of single approaches, making our contribution more visible and advanced in adapting to dynamic user preferences and the evolving mobile phone market.

4 Proposed work

This section gives a thorough explanation of the suggested approach. Figure 2 depicts the general flow of the proposed work.

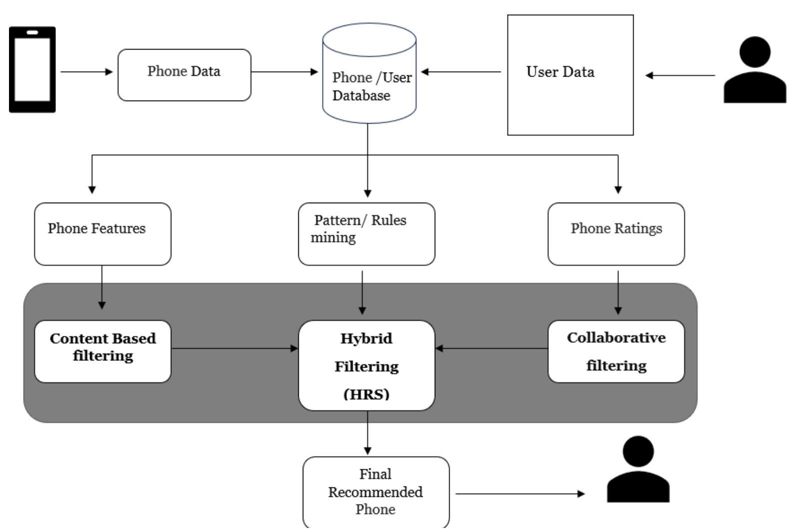

Figure.2. HRS framework

a. Data collection:

A campus-wide poll collected data on current phone models, ideal characteristics, and personal reviews to better understand student mobile phone usage. This data informs improvement decisions, provides individualized product suggestions, and improves campus mobile services. The dataset, which spans 2021 to 2023 and focuses on five major brands—Vivo, Samsung, Oppo, Mi, and One Plus—allows for research and comparison of performance, features, and customer happiness across time.

b. Pre-processing:

The pre-processing stage involved a methodical handling of null and missing values. Data from survey replies was combined with knowledge on different mobile models, and survey questions were converted into crucial keywords for recommendation models. The outcome of this smooth integration is an advanced dataset optimized for content, collaborative, and hybrid modeling techniques. This data is carefully prepared, laying the foundation for the creation of a strong recommendation system. This system will provide an extensive array of features and guarantee top-notch performance in many settings, hence augmenting professionalism.

c. Sentimental analysis:

The survey's gathered user comment on current devices was preprocessed, which included stop word removal, space and emoji removal, and stemming for dataset refining. Subjectivity and polarity analysis gave complex sentiment insights. This thorough approach produces a succinct, sentiment-analyzed dataset that is useful for identifying user experience patterns. Cosine similarity compares textual data to help consumers choose a phone model that matches their preferences, recommending those with the highest similarity. The calculated using the formula:

$$cosine\ similarity(A, B) = \frac{AB}{|A| \cdot |B|}$$

A and B represent the combined feature vectors of various phone models.

d. Content-based:

Content-based filtering, creates user and item profiles based on past choices, actions, or attributes. The system then suggests items by matching user profiles with item profiles, often using mathematical methods like cosine similarity or TF-IDF. This system for phone models is implemented through a series of steps that leverage cosine similarity to generate recommendations. The process begins by selecting relevant columns and cleaning missing data within the phone model dataset. Textual information is transformed into a numerical format using CountVectorizer. A dictionary is then created to map phone models to indices, allowing for efficient retrieval and comparison of the phone models. This method provides an effective approach for generating personalized recommendations for users based on their preferences and past interactions with phone models.

e. Collaborative:

Collaborative filtering recommends things based on user preferences and behaviors. It employs a user-item matrix, in which rows represent users, columns represent items (e.g., phone models), and values are user ratings. The algorithm recognizes similar user profiles and proposes items that are most similar to the user's tastes by calculating cosine similarity between itemvectors. This method uses user interactions to give personalized suggestions, making it useful for suggesting phone models depending on a user's history and interests.

f. Hybrid:

The Hybrid Recommendation System (HRS) optimizes personalized suggestions by integrating content-based and collaborative filtering. HRS smoothly mixes collaborative filtering, leveraging user ratings (Rui) to construct a user-item matrix, and measuring user vector similarity via cosine similarity within recommendation systems. Concurrently, content-based filtering uses phone model features such as RAM, storage, pricing, color, camera quality, CPU, and rating to generate feature vectors. Count Vectorizer creates a sparse vectorization matrix. The hybrid technique uses a weighted average formula to integrate various similarity matrices, resulting in greater accuracy and efficacy in tailored recommendations.

Hybrid Similarity = $\alpha * Collaborative\ similarity + (1 - \alpha) * Content\ similarity$

The alpha parameter governs the influence of collaborative filtering on recommendations. An alpha value of 0.5 was considered. Scores from a hybrid method guide recommendations, with top phones sorted accordingly, ignoring the input model. This practical application highlights the synergy between collaborative and content-based filtering, resulting in accurate and diversified suggestions.

5 Evaluation metrics

Table.1. Performance Metrics of all models

Model	Precision	Recall	F1-score	Accuracy	Specificity
Collaborative	0.60	0.22	0.32	0.70	0.75
Content	0.66	0.29	0.40	0.75	0.80
Hybrid	0.80	0.45	0.50	0.85	0.90

Table.1 summarizes a detailed review of three popular recommendation models, namely Collaborative, Content, and Hybrid, using a variety of performance indicators. These measures are critical in characterizing the models' capabilities across important dimensions of suggestion quality.

The Collaborative model, which is defined by its focus on user-item interactions, has a precision of 0.60. This precision indicator highlights the model's accuracy in accurately recognizing relevant items recommended to consumers. Concurrently, the model's recall, which measures its capacity to detect all relevant events, is stated to be 0.22. The specificity, which measures the model's ability to prevent false positives, is set at 0.75. The accuracy measure, which represents the overall correctness of the model's predictions, is 0.70. The F1 Score, a harmonic mean of accuracy and recall, combines both measurements and is calculated at 0.32, offering a fair assessment of the performance of the Collaborative model. Conversely, the precision of the Content-based recommendation model, which is based on item properties, is 0.66. This represents the model's ability to propose things based on their intrinsic features. The recall is 0.29, indicating that the model was successful in collecting a wide range of relevant elements. The specificity, which reflects the model's ability to minimize false positives, is represented as 0.80. The total accuracy is 0.75, indicating that the model correctly predicted user preferences. The F1 Score, which combines accuracy and recall, is 0.40, emphasising the Content model's equilibrium in suggestion quality.

The Hybrid Model emerges as the forerunner in this study as an amalgamation of Collaborative and Content methods. Its precision of 0.80 indicates a high level of accuracy in optimistic predictions. The model's recall of 0.45 demonstrates its ability to capture a wide range of relevant circumstances. The model's specificity, which is an impressive 0.90, demonstrates its ability to reduce false positives. The model's general robustness is confirmed by the accuracy statistic, which achieves a commendable 0.85. Notably, the F1 Score approaches 0.50, demonstrating an appropriate ratio of precision and recall. These cumulative indicators place the HRS framework as the most efficient recommendation paradigm.

The comprehensive evaluation of the Collaborative, Content, and Hybrid recommendation models demonstrates that the Hybrid model outperforms the others, displaying an ideal combination of precision and recall. The Hybrid model emerges as the best choice for recommendation systems, delivering a solid and well-rounded solution for personalized content distribution. It has high accuracy, specificity, and F1 Score of 0.50. The F1 score in the model might be caused by an imbalance in precision and recall, possibly due to inadequate data representation or algorithmic constraints. In contrast, the proposed model's increased precision could be attributed to effective feature selection, robust model training, and meticulous data preprocessing, all of which contribute to more relevant recommendations and fewer false positives.

6 Conclusion

The paper presents a comprehensive exploration of recommendation systems, covering collaborative filtering, content-based filtering, and a hybrid approach. A HRS framework which follows a hybrid approach, combination of collaborative and content-based filtering was introduced. The study extensively delves into the underlying methodologies, including cosine similarity for collaborative and content-based filtering, as well as a hybrid recommendation strategy. The results highlight the potential of HRS to leverage the strengths of both collaborative and content-based techniques, achieving a balance between user preferences and item attributes to improve recommendation quality. When compared to other approaches HRS provided a system with an accuracy of 85%, recall of 45%.

7 Future work

To further improve the precision and customization of recommendations, the article recommends investigating cutting-edge recommendation strategies in the future, such as reinforcement learning and deep learning-based models. In order to respond to evolving user needs and solve privacy issues in recommendation systems, real-time user interactions, context awareness, and privacy-preserving techniques must be included.

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