Advancements in AI-Driven Real Estate Recommendations: Hybrid Filtering Techniques for Personalized Property Suggestions

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ABSTRACT-Real estate search experiences have experienced significant improvement through artificial intelligence (AI) applications in recommendation systems. The discussion provides detailed technical details about a hybrid recommendation system which incorporates content-based filtering with collaborative filtering and location-based filtering. The system develops customized property suggestions after analysing what users like and studying property details alongside their locations. This section examines the system architecture together with data pre-processing functions as well as the process of system integration with user-friendly interfaces. The outcomes from the study prove that combining different recommendation strategies leads to more precise recommendations and satisfied users. The document presents future development plans and research proposals toward system enhancement.

AI Recommendation System applied to real estate engages three filtering methods which are Content-Based Filtering and Collaborative Filtering and Location-Based Filtering to provide personalized recommendations.

I. INTRODUCTION

Real estate professionals now conduct business through artificial intelligence-based solutions during a transformational period in their operations. The AI recommendation system makes property recommendations based on user preferences thus minimizing search duration and facilitating better decision making. A recommendation approach used individually produces restricted output results. An AI recommendation system which combines various approaches serves as a solution to deliver the best outcomes.

A comprehensive evaluation of hybrid recommendation systems exists in this paper to explore the operational components of content-based filtering with collaborative filtering and location-based filtering.

II. LITERATURE REVIEW

Recommendation systems have demonstrated substantial development within the real estate market. RE-RecSys represents an end-to-end recommendation system that Venkatesh et al. (2024) developed to enhance property recommendations through collaborative and content-based hybrid methods [1]. The research by Nguyen et al. (2021) integrated content-based and collaborative filtering into one system to enhance real estate applications by processing user preferences together with behavioral patterns [2].

A thorough assessment of recommendation system evolution occurs in Li et al. (2023) where hybrid solutions combining multiple filtering frameworks help achieve better prediction models [3]. Wu et al. (2021) examined various deep learning model-based approaches which boost property recommendation accuracy in personalized recommendations systems according to their paper [4].

The academic utilization of recommendation systems has gained prominence according to Bai et al. (2020) who detailed their universal applicability across various domains [5]. Traditional collaborative filtering methods pioneered by Linden et al. (2003) about Amazon's recommendation engine continue to influence real estate applications that handle large volumes of user interaction data [6].

Jannach and Adomavicius (2016) examined recommendation system challenges while proposing future research directions about existing method shortcomings that support real estate recommendation system enhancements [7].

III. CORE COMPONENTS OF THE RECOMMENDATION ENGINE

A. Content-Based Filtering

The recommendation system suggests properties by analysing these features alongside the properties the user has interacted with previously. Property recommendation relies on fundamental features that include pricing along with house measurements and bedroom counts as well as property types. The categorical feature known as property type gets transformed into numerical vectors using one-hot encoding Additionally, cosine similarity is used to measure the similarity between properties based on these feature vectors, ensuring accurate and relevant recommendations.

The main strength of content-based filtering derives from its capability to produce suitable recommendations through single-user preference analysis. The system faces a drawback since it cannot recommend properties that fall beyond what the user has interacted with previously.

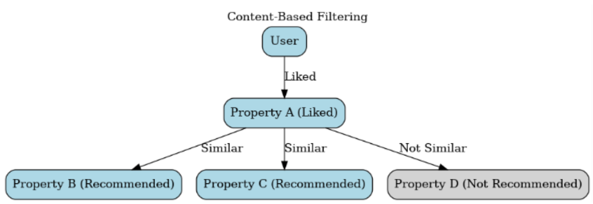

*Fig **1.** Content-based filtering figure*

B. Collaborative Filtering

Recommendations are determined through analysing data which multiple users provide. The system develops a user-property interaction matrix which divides users into rows and properties into columns. The system identifies properties that might interest a user through analysing how other users behave similarly in this process.

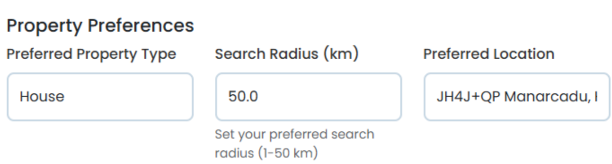

Fig 2. Applying preferences on project

The two fundamental approaches under collaborative filtering consist of user-based and item-based filtering models. The user-based collaborative filtering method links users who share common taste preferences and the item-based collaborative filtering system checks if properties share matching characteristics.

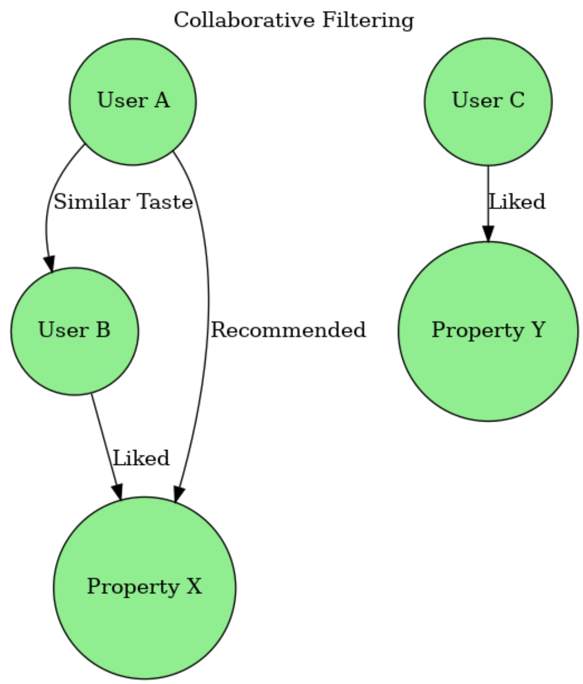

Fig 3. Collaborative Filtering Figure

C. Location-Based Filtering

The system proposes properties which are situated nearest to a user's set location through location-based filtering functions. The system conducts distance computations by using position coordinates from preferred locations to accessible properties. Users who orient themselves towards properties situated in particular geographical areas obtain optimum value from this recommendation technique.

The recommendation system performs better when users specify their desires including property type together with their preferred prices, desired amenities, and locations.

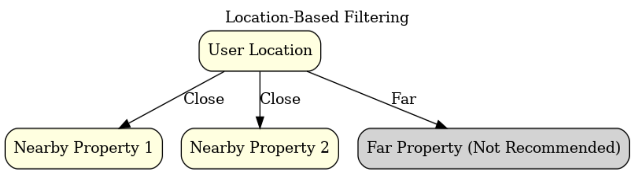

Fig 4. Location-Based Filtering Figure

IV. HYBRID RECOMMENDATION SYSTEM

An improved property recommendation solution results from merging all three recommendation filters within a single hybrid system. A weighted scoring model within this hybrid system enables users to receive relevant property recommendations that also ensure variety in suggestions.

The system enables adjustable weights that determine factor importance according to how users interact with the system. User activity with specific locations receives elevated weight in location-based filtering routines from the recommendation system. Collaborative filtering becomes the dominant recommendation system for new users as they have no established data history.

The system uses a weighted adjustment method that provides precise accurate recommendations which meet users as their preferences shift.

Method	**Strength**	**Weakness**	**Best For**
Content-Based	Personalized suggestions	Needs user history	Returning users
Collaborative	Learns from similar users	Requires lots of data	Popular properties
Location-Based	Focuses on location	Limited to location data	Local property searches
Hybrid	Best overall accuracy	More complex to compute	General recommendations

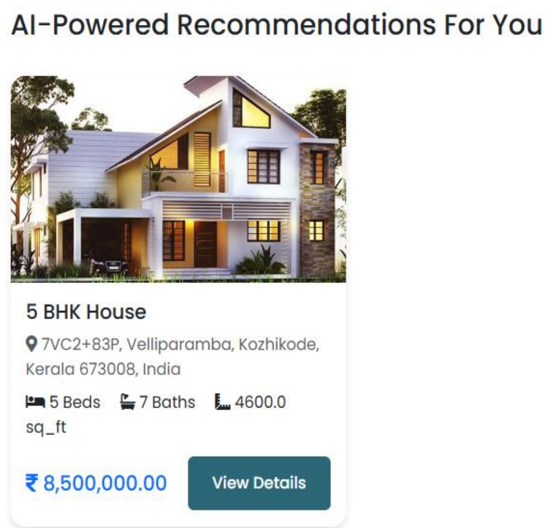

Fig 5. Recommendation from project

V. USER INTERFACE INTEGRATION

Users can access the recommendation system through a seamless interface section for improved navigation inside the platform. The system presents customized properties to users after they log in through the main homepage interface. The platform generates property suggestions dynamically through user preferences combined with their search records and their system interaction patterns. Through this system all users can locate their suitable properties rapidly without conducting prolonged searches.

About a page for customized property suggestions exists within the user dashboard section. User interaction with the platform causes the section to deliver real-time refinements of recommendations. Transparency is achieved through the dashboard design because it shows clear explanations for property recommendations which builds trust between users and the AI system.

Users can find an extensive list of recommended properties through an isolated recommendations page. Users may filter results on this page through property type selection and price range specification and location choosing. Users can provide ratings to recommendations through an interface feedback system which enables the reinforcement learning capability of the algorithm to enhance its accuracy.

VI. TECHNICAL IMPLEMENTATION

The hybrid recommendation system possesses a designed structure which supports both high performance and growth potential. The initial phase for data preparation consists of two key steps which include value imputation and numerical feature normalization beside categorical data transformation through one-hot encoding. Reliable recommendations stem from clean data processing.

Model training processes three different models which support content-based filtering, collaborative filtering and location-based filtering. The models continuously receive current data updates to achieve better relevance. User preferences undergo constant analysis to detect behavioural modifications so the system keeps providing responsive services.

The recommendation accuracy gets evaluated using precision, recall and F1-score metrics together. User feedback plays an essential role in the evaluation process because it helps build ongoing improvements. The system deploys caching systems and cloud infrastructure to optimize performance which enables handling large amounts of data effectively.

VII. CONCLUSION

The proposed hybrid AI recommendation system enhances property searches because it provides users with suitable recommendations tailored to their preferences. A recommendation process achieves thorough accuracy through the integration of content-based and collaborative and location-based filtering methods.

Future work focuses on combining real-time user activity data while improving algorithm performance and bringing in new external information sources to generate better predictions.

VIII. REFERENCES

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