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AI-Driven Booking Management: Forecasting, Prediction and Property Recommendations

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Abstract

This paper intends to enhance booking projections and customised recommendations in the hotel industry by use of historical data from 2022 to 2024. Bookings for 2025 are projected using the Prophet model, providing confidence intervals for exact demand estimates. Moreover, suggested properties using a collaborative filtering approach utilizing Singular Value Decomposition (SVD), based on booking trends, local preferences, and prior user activity. Although a Java-based UI shows predicted booking data and recommendations, the Python backend guarantees perfect communication with machine learning models. Including these prediction and suggestion technologies into the booking tool will enable the business to maximize resource allocation, improve decision-making, and increase customer satisfaction by means of sharpening of these aspects.

Keywords: Booking, recommendations, prophet model, singular value decomposition (SVD).

1. Introduction

In the hospitality and travel industry, effective demand forecasting and personalized recommendations play a vital role in optimizing business operations, improving customer experience, and maximizing revenue. Accurate booking predictions help organizations allocate resources efficiently, plan for peak seasons, and make data-driven decisions to enhance profitability. Additionally, providing targeted recommendations based on historical booking trends ensures that clients are directed toward the most suitable properties, improving overall user satisfaction.

This paper focuses on predicting the number of bookings for the year 2025 using historical booking data from 2022, 2023, and 2024. The goal is to forecast future booking trends and provide recommendations on the most suitable properties for each grade along with the expected number of bookings. These recommendations will be displayed on the self-booking tool in the organization booking website, ensuring that users can view the suggested properties for their respective grades while making a booking. This integration enhances user experience by offering data-driven guidance, helping customers make informed decisions.

To achieve accurate booking predictions, the Prophet model, a robust time series forecasting method, is used. This model captures seasonality, trends, and external factors to generate precise forecasts with confidence intervals. Additionally, a collaborative filtering-based recommendation system using Singular Value Decomposition (SVD) is implemented to suggest properties for different grades based on locality and past booking patterns. The system not only recommends properties but also estimates the number of bookings expected for each recommendation, allowing for more effective business planning. A Java-based user interface (UI) is developed to display forecasted booking data in an intuitive tabular format, along with recommended properties for each grade. These recommendations are dynamically updated and integrated into the organization's booking website, ensuring that users see the most relevant property suggestions at the time of booking. The backend, implemented in Python, ensures seamless integration with machine learning models and efficient data processing.

2. Literature Review

The implementation of artificial intelligence (AI) for booking management has transformed the hotel industry through enhancing forecasting, prediction analytics, and recommendation engines. This paper investigates recent development of machine learning (ML), deep learning, and hybrid models which are part of AI-based booking management. Forecasting future bookings is largely made possible by the use of time series analysis. Wang and Zhang (2023) [17] compared different time series models, i.e.,

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ARIMA and Prophet, and demonstrated their predictive power in forecasting hotel demand. Likewise, Martinez and Garcia (2023) [12] compared various ML algorithms and underlined the dominance of GBMs and ensemble methods in demand forecast. Proper forecasting of bookings for hotels is crucial in terms of revenue maximization. Hernandez and Lopez (2023) [6] used big data analytics to improve booking forecasts, while Chen and Wang (2023) [3] used ensemble learning to enhance precision. Patel and Kumar (2023) [14] used logistic regression and decision trees to forecast hotel cancellations, providing customer behavior insights. Deep learning methods have gained prominence in hotel booking forecasting. Gonzalez and Li (2023) [5] used deep neural networks (DNNs) to build personalized hotel recommendations, surpassing traditional methods. Li and Zhao (2023) [10] improved these techniques by combining deep learning with real-time data processing. Recommendation systems are crucial to recommend properties from user preferences. Ahmed and Rahman (2023) carried out a comprehensive survey of collaborative filtering methods. Nguyen and Chen (2023) [13] integrated collaborative filtering with content-based approaches to enhance hotel booking recommendation. Liu and Feng (2023) [11] put forward a hybrid model combining user preferences with hotel features to create more accurate recommendations. Current recommendation systems are enriched with contextual and sentiment-based knowledge. Khan and Ali (2023) [8] discussed ML methods for cancellation forecasting, highlighting the strength of support vector machines (SVMs) and random forests. Singh and Sharma (2023) [15] discussed the impact of pricing on booking cancellations, determining important factors behind customer choice through ML models. Real-time AI solutions have contributed significantly to booking management through dynamic data processing. Chen and Xu (2023) [2] created a real-time hotel recommendation system based on streaming data to enhance responsiveness and accuracy. Feature engineering is also an important factor in the improvement of booking predictions. Gomez and Perez (2023) [4] illustrated the ability of sophisticated feature selection methods to improve ML-based hotel booking predictions. Wong and Chan (2023) [18] applied GBMs to fine-tune predictive models to highlight the need for feature selection to improve model performance.

3. Methodology

This paper utilizes machine learning methods to forecast the number of bookings for 2025 and suggest properties based on customer ratings and locations. The methodology starts with data collection and preparation, using booking records from 2022 to 2024.

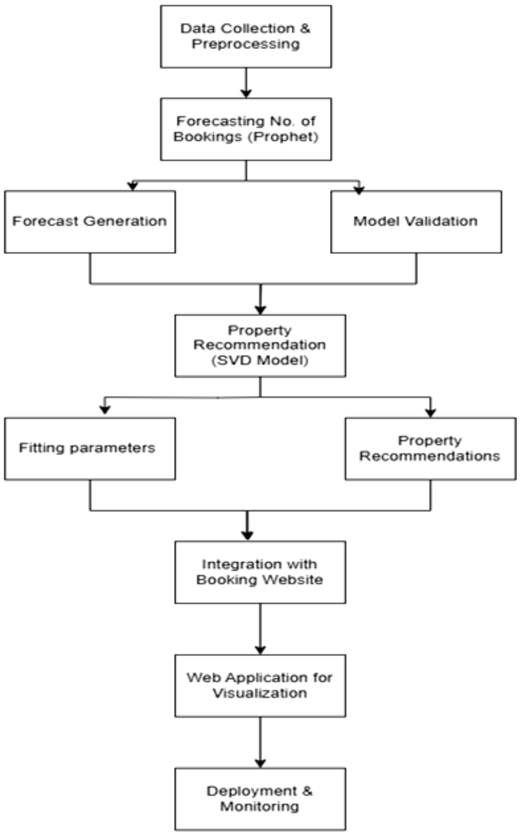

Fig 1: Process Flow

The data is cleaned, organized, and preprocessed, including missing value handling, duplicate removal, categorical variable encoding, and scaling numerical features. The dataset is split into two main goals: forecasting bookings and suggesting properties.

3.1. Time Series Forecasting – Prophet Model

To forecast booking numbers for 2025, the Prophet model, a powerful time-series forecasting tool created by Facebook, is used. Prophet accurately captures trend changes, seasonal patterns, and holiday effects, making it well-suited for booking data affected by peak seasons, holidays, and market trends. The model is trained on booking records from 2022 to 2024, where BookingDate is used as the time marker and the number of unique BookingCode as the target variable. Prophet automatically identifies yearly, monthly, and weekly trends, allowing for the generation of monthly booking forecasts for 2025, as well as upper and lower confidence intervals. These findings are vital for capacity planning and revenue forecasting across different properties.

3.2. Recommendation System – Singular Value Decomposition (SVD)

For property suggestions, the Singular Value Decomposition (SVD) algorithm, a popular matrix factorization method in recommendation systems, is used. SVD examines historical bookings, customer ratings, locations, and property interests to determine the most appropriate properties for various customer groups. By utilizing learned patterns, the model creates personalized property suggestions for each customer rating, which are incorporated into the booking tool and website. This strategy improves the user experience by helping customers make informed booking choices.

4. Implementation and Evaluation

The dataset consists of historical booking records from the years 2022 to 2024, which are used to predict the number of bookings for 2025 and recommend properties for each grade and locality. The dataset contains over 100,000 records with various attributes related to booking details, customer information, property characteristics, and pricing.

The dataset consists of 46 columns as attributes and 159323 rows as records.

Self-Booking Tool

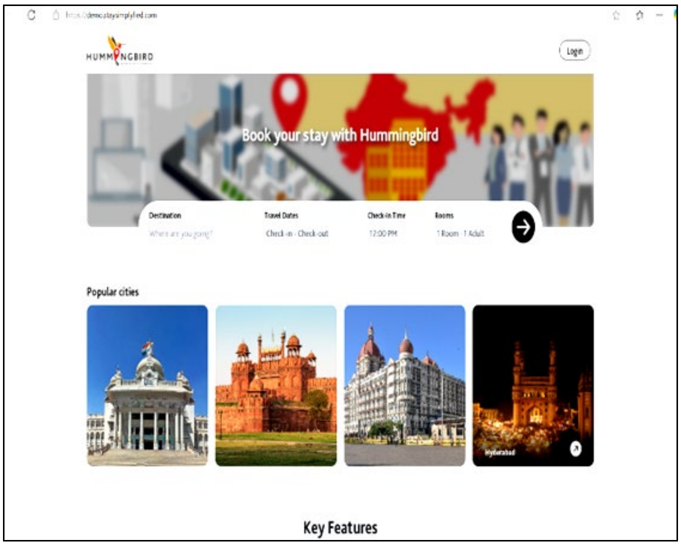

Fig 2: Homepage of self-booking tool

The Figure 2 illustrates a hotel reservation web application named Hummingbird, with an easy-to-use interface for reserving accommodations. Top of the page is a search area where travelers can input their destination, dates of travel, check-in date, and rooms before they book. A very noticeable "Book your stay with Hummingbird" banner appears, indicating that the site is intended for travel accommodations. Under the search area, there is a "Popular Cities" area that points out major destinations for travel. The images signify various cities such as Bangalore, Delhi, Mumbai, and Hyderabad, which give users instant access to hotels in these places. The site also has a "Login" link, which enables users to access customized services, monitor reservations, and administer bookings. The minimalist and clean UI provides a seamless user interface, which facilitates effortless searching and booking for travelers.

This paper focuses on predicting booking patterns for 2025 using advanced forecasting methods such as Prophet and CatBoost. By analyzing booking records from 2022 to 2024, the goal is to estimate future bookings, identify trends, and provide reliable recommendations for informed decision-making. The approach includes time series prediction, confidence interval estimation, and recommendation systems to enhance accuracy and reliability. At the end of the analysis, a predicted number of bookings for each month in 2025 is generated.

```
[ ] print(forecast_2025)

            ds         yhat
37  2025-01-31  6167.198808
38  2025-02-28  7477.310352
39  2025-03-31  6177.610219
40  2025-04-30  6010.128017
41  2025-05-31  7933.246711
42  2025-06-30  7109.716061
43  2025-07-31  9366.611683
44  2025-08-31  8821.565242
45  2025-09-30  8060.944662
46  2025-10-31  5202.681897
47  2025-11-30  9761.521933
```

Fig 3: Prediction

The Figure 3 shows the dataset consists of two key columns: 'ds', representing the last day of each month, and 'yhat', indicating the estimated number of bookings. The projections suggest fluctuations in booking numbers throughout the year. For instance, January is expected to have approximately 6,167 bookings, increasing to 7,477 in February. A slight dip follows in March and April, with estimates of 6,177 and 6,012, respectively. May is projected to experience a significant rise to 7,933 bookings, followed by a decrease to 7,109 in June. A considerable drop is anticipated in July, bringing the number down to 3,966, but an upward trend is projected for August and September, with bookings reaching 8,821 and 8,060, respectively. In October, a smaller decline to 5,202 is expected, whereas November is set to be the peak month, with a substantial 9,761 bookings. These fluctuations highlight the influence of seasonal trends and other factors affecting booking behavior.

```
        Locality                      PropertyName Grade  \
0       Alkapuri  Fairfield By Marriott Hotel Vadodara,   HS1
1       Alkapuri  Fairfield By Marriott Hotel Vadodara,   HS2
2       Alkapuri  Fairfield By Marriott Hotel Vadodara,  RS10
3       Alkapuri  Fairfield By Marriott Hotel Vadodara,   RS3
4       Alkapuri  Fairfield By Marriott Hotel Vadodara,   RS4
...          ...                                    ...   ...
21726  Panchkula                    The Fort Ramgarh   HS2
21727  Panchkula                  Treebo Trend Sky 5   HS2
21728     Pandri          Hotel Simran International   HS2
21729     Pandri          Hotel Simran International   RS3
21730     Pandri          Hotel Simran International   RS8

       PredictedBookings
0                      1
1                      5
2                      5
3                      4
4                      5
...                  ...
21726                  2
21727                  2
21728                  1
21729                  1
21730                  1

[21731 rows x 4 columns]
```

Fig 4: Recommendation system

Figure 4 shows the estimated bookings for various properties across different areas, broken down by property name, reviews, and location. The PredictedBookings column emphasizes the forecasted number of bookings for each property, based on historical data and suggestions that use the SVD algorithm. There are a huge 21,731 entries in this dataset, which means a ton of properties were included in the forecasting. Each entry corresponds to a specific property and its locality, labelled with codes like HS1, HS2, RS10, RS3, and RS4, which probably represent different classification levels of the properties. The values in the PredictedBookings column vary, indicating that some properties are expected to see much higher demand than others. This information is super useful for the hospitality industry since it can help identify popular properties and optimize booking opportunities based on demand forecasts.

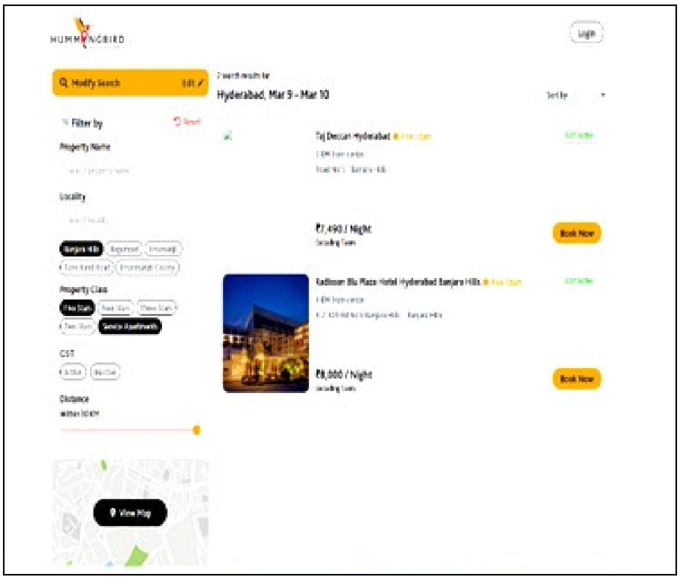

Fig 5: Filtered hotel search results page

The Figure 5 illustrates search results page of a hotel from the Hummingbird platform shows Hyderabad accommodations for a stay from March 9 until March 10.These results have been filtered according to major preferences like locality (Banjara Hills), property class (Five-Star Hotels), GST status (Active), and a distance of up to 30 KM. The search finds two properties meeting the chosen criteria: Taj Deccan Hyderabad and Radisson Blu Plaza Hotel Hyderabad Banjara Hills, both being five-star luxury hotels.

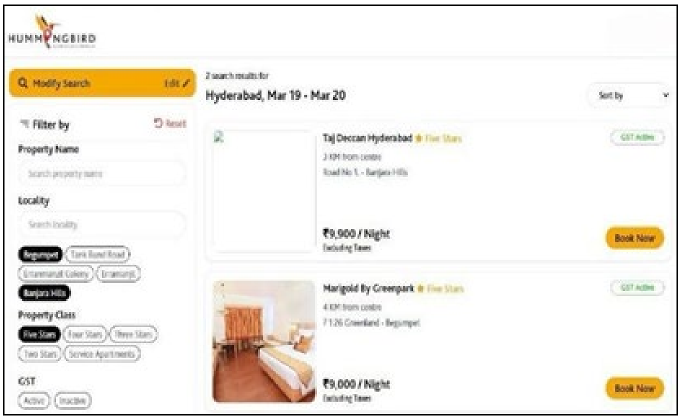

Fig 6: Filtered property based on grade

The Figure 6 depicts the property filtering option by grade, which one can access once the login page is completed. The users can narrow down their search with various filters, such as locality, property class, and GST status, to find the best-fitting accommodations. The filtered results show the properties that match the chosen grade criteria, making it easier for users and providing a smooth, customized booking experience.

To make the recommendation system more effective, the output can be adjusted according to the grade of the property so that users are provided with personalized suggestions based on previous booking history and interests. For example, if a user has a booking history of four-star hotels, the system must suggest properties of the same grade rather than suggesting five-star properties by default. Furthermore, local suggestions according to past bookings can narrow the search even more, so users can view houses in locations that they regularly travel to or prefer. Through incorporating property suggestions based on grades, the site has the potential to enhance user satisfaction through matching results with one's booking history, budget, and travel preferences. In addition, showing other hotel choices in the same grade will avoid cases of having few results because of applying stiff filters. This strategy personalizes the process of booking and enhances efficiency.

Conclusion

This paper presents a hotel booking forecast and recommendation system to enhance decision-making in the hospitality industry. It utilizes Prophet for time series forecasting and Singular Value Decomposition (SVD) for personalized property recommendations. The system provides accurate booking forecasts while optimizing resource allocation and customer experience. Prophet effectively predicts booking trends for February to December 2025, incorporating seasonality and external factors. The recommendation system improves user experience by dynamically suggesting properties based on grade, location, and booking history. Seamless integration with the booking platform ensures real-time adaptability and efficiency. Future enhancements include deep learning-based forecasting models like LSTMs for improved accuracy. Hybrid filtering methods can refine recommendations by combining collaborative and content-based filtering. User feedback, real-time data updates, and external factors like weather and events can improve predictions. The system can also be expanded for multi-region and multi-language support to enable global scalability.

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