CONTINUOUS ASSESSMENT TEST 1

BUSINESS INTELLIGENCE LABORATORY

VELORAFLOW : DYNAMIC REVENUE INTELLIGENCE
UNLOCKING REAL-TIME RESERVATION TRENDS
FOR SMARTER PRICING AND PROFITABILITY.

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Hotel Revenue Prediction Dashboard Using Machine Learning and Power BI

Abstract

The hotel reservation industry is highly dynamic, with constant demand fluctuations, seasonal variations, and changing customer behavior. Accurate revenue forecasting is essential for hotels to **optimize pricing, allocate resources efficiently, and maximize profitability**. However, traditional forecasting methods like **time series models and linear regression** often fail to capture the complex factors influencing revenue, including **booking patterns, customer demographics, economic conditions, and competitor pricing**. As a result, hotels relying on outdated techniques may face inaccurate predictions, inefficient resource allocation, and reduced profitability.This project leverages **machine learning** to enhance revenue forecasting accuracy. Using **Random Forest and Gradient Boosting**, the model analyzes historical booking data to identify key revenue patterns. These algorithms handle **large datasets, capture non-linear relationships, and uncover hidden insights** that traditional models miss. A **Voting Regressor** further improves accuracy by combining multiple models. By incorporating machine learning, hotels can make **real-time pricing and resource allocation decisions**, ensuring better financial planning.A key feature of this project is **Power BI**, a business intelligence tool for **interactive data visualization and real-time analytics**. The dashboard provides hotel managers with insights into **key performance indicators (KPIs)** such as **total revenue, average room rate, peak booking periods, and cancellations**. Dynamic filtering allows analysis based on **room types, booking platforms, and customer segments**, helping hotels make informed business decisions.Beyond forecasting, machine learning enables **dynamic pricing strategies** by adjusting rates based on demand, competition, and market trends. **Cancellation prediction models** help hotels develop **overbooking strategies**, minimizing revenue losses. Personalized marketing efforts improve **customer retention and satisfaction**.By updating predictions with **real-time data**, hotels can **respond proactively to market changes**, optimize **staffing and inventory management**, and improve efficiency. This **AI-powered system** ensures **higher profitability, better customer insights, and a competitive edge** in the hospitality industry, driving long-term growth and sustainability.

Objective of the Project

1. Accurate Revenue Prediction
2. Enhanced Machine Learning Techniques
3. Interactive Power BI Dashboard
4. Optimized Revenue Strategies
5. Real-Time Data Integration

Problem Statement:

Revenue forecasting in the hotel industry is challenging due to fluctuating demand, seasonal trends, and evolving customer behavior. Traditional methods fail to capture complex factors like booking trends, demographics, and economic conditions, leading to poor pricing strategies and financial losses. This project uses machine learning (Random Forest, Gradient Boosting, and Voting Regressor) to improve prediction accuracy by analyzing historical booking data. An interactive Power BI dashboard provides real-time insights for better decision-making. By combining AI and business intelligence, this system ensures optimized pricing, improved resource allocation, and increased profitability.

Introduction

Revenue management is a critical function in the hospitality industry, directly influencing profitability and operational efficiency. Hotels must anticipate demand patterns, optimize pricing, and allocate resources effectively to maximize revenue. However, revenue forecasting is a complex task due to the interplay of multiple factors, including seasonality, customer preferences, competitor pricing, and economic conditions. Traditional revenue prediction models, such as time series forecasting, often fail to capture these complexities, leading to suboptimal pricing and resource mismanagement.This project proposes a machine learning-based revenue prediction model that leverages historical booking data to forecast future revenue. By using Random Forest, Gradient Boosting, and a Voting Regressor, the model provides accurate predictions, helping hotels refine their pricing strategies and resource allocation. Machine learning models excel in recognizing patterns within large datasets, making them well-suited for the task of revenue forecasting.In addition to predictive modeling, the project incorporates Power BI to create an interactive Hotel Revenue Prediction Dashboard. This dashboard allows hotel managers and business analysts to visualize revenue trends, compare predictions with actual figures, and filter data based on relevant parameters such as room type, booking date, and length of stay. Key benefits of this approach include:

- Higher accuracy in revenue forecasting compared to traditional methods.
- Enhanced decision-making through interactive data visualization.
- Optimized pricing strategies based on historical booking trends.
- Improved financial forecasting and budget planning for hotel operations.

The integration of machine learning with Power BI creates a powerful decision-support system, enabling hotels to make data-driven business decisions that improve profitability and efficiency. By leveraging advanced analytics and visualization, this project provides a robust framework for next-generation revenue management in the hospitality sector.

Machine Learning Approach

To achieve accurate revenue forecasting, the project employs advanced machine learning techniques that effectively analyze structured datasets and capture complex patterns. The selected models include Random Forest, Gradient Boosting, and a Voting Regressor to enhance predictive accuracy.

- **Random Forest Regressor**: This ensemble learning technique consists of multiple decision trees, making it highly robust in handling non-linear relationships between input features and revenue outcomes. By averaging predictions from multiple trees, Random Forest reduces overfitting, enhances model stability, and improves forecasting accuracy.
- **Gradient Boosting Regressor**: Unlike Random Forest, Gradient Boosting sequentially builds weak learners, with each new tree focusing on minimizing errors from previous iterations. This iterative improvement helps capture intricate relationships within the dataset, leading to precise revenue predictions.
- **Voting Regressor**: To further enhance accuracy, the project integrates a Voting Regressor that combines predictions from the Random Forest and Gradient Boosting models. By leveraging the strengths of both techniques, the ensemble model ensures a more reliable and balanced forecast.

Methodology

The project follows a structured methodology to develop the revenue prediction model and Power BI dashboard. The approach consists of the following steps:

- Data Collection & Preprocessing
- Data Cleaning
- Feature Engineering
- Machine Learning Model Development
- Results and Power BI Dashboard

Data Source: The dataset includes hotel booking details such as booking dates, stay durations, room rates, and revenue figures.

Booking ID	Booking Date	Booking Channel	Loyalty Level	Status	Stay Date	Number of nights	Room Rate
RES009721	22-Sep-24	Phone	5.Preferred	Modified	24-Sep-24	2	34.25
RES009722	17-Jul-24	Velora.com	5.Preferred	Modified	08-Oct-24	2	218.43
RES009723	10-Oct-24	At the hotel	4.Essential	Modified	14-Oct-24	2	189.15
RES009724	19-Sep-24	Velora.com	4.Essential	Modified	27-Sep-24	2	122.89
RES009725	26-Sep-24	At the hotel	0.Non-member	Modified	27-Sep-24	1	122.13
RES009726	21-Sep-24	GDS	1.Iconic	Cancelled	17-Oct-24	1	132.65
RES009727	02-Aug-24	GDS	0.Non-member	Modified	13-Sep-24	2	186.74
RES009728	25-Sep-24	Connected Whole	4.Essential	Modified	27-Sep-24	2	89.45
RES009729	04-Sep-24	At the hotel	0.Non-member	Modified	06-Sep-24	2	196.3
RES009730	10-Oct-24	Velora.com	3.Premier	Modified	10-Oct-24	1	147.71
RES009731	22-Sep-24	GDS	0.Non-member	Cancelled	14-Oct-24	2	132.53
RES009732	10-Sep-24	At the hotel	0.Non-member	Modified	13-Sep-24	1	130.48
RES009733	28-Sep-24	Phone	0.Non-member	Modified	03-Oct-24	1	140.96
RES009734	09-Aug-24	Velora.com	4.Essential	Modified	20-Sep-24	2	200.28
RES009735	02-Sep-24	At the hotel	4.Essential	Modified	05-Sep-24	1	157.57
RES009736	21-Sep-24	App	0.Non-member	Modified	21-Sep-24	5	134.34
RES009737	12-Aug-24	Velora.com	0.Non-member	Modified	23-Sep-24	3	145.33
RES009738	26-Sep-24	Phone	4.Essential	Modified	13-Oct-24	1	119.88
RES009739	03-Sep-24	Phone	4.Essential	Modified	08-Sep-24	2	156.75
RES009740	03-Oct-24	At the hotel	0.Non-member	Modified	04-Oct-24	1	179.39
RES009741	04-Oct-24	GDS	4.Essential	Modified	22-Oct-24	1	112.04
RES009742	16-Sep-24	Phone	4.Essential	Modified	17-Oct-24	1	114.8
RES009743	22-Jun-24	GDS	3.Premier	Modified	16-Oct-24	1	134.34
RES009744	22-Sep-24	At the hotel	3.Premier	Modified	08-Oct-24	1	161

1. Data Cleaning

Data cleaning is a crucial step in ensuring that the dataset is accurate, complete, and ready for analysis. The following steps are undertaken:

- Handling Missing Values: Missing values can significantly impact model performance. These are addressed using appropriate imputation techniques, such as mean/median imputation for numerical fields and mode imputation for categorical variables.

- Standardizing Date Formats: Since booking and stay dates are critical features, all date-related fields are converted into a consistent format (e.g., YYYY-MM-DD) to ensure uniformity across the dataset.

- Identifying and Managing Outliers: Extreme values in room rates or booking durations can distort predictions. Statistical techniques like the interquartile range (IQR) method or log transformation are applied to detect and handle anomalies.

2. Feature Engineering

Feature engineering enhances predictive power by transforming raw data into meaningful input features.

- Revenue Calculation: The total revenue is computed as:

  Revenue=Number of nights × Room Rate

This derived feature becomes the target variable for the model.

- Date-Based Features:
  - Booking Lead Time: The difference between the stay date and booking date helps capture customer booking behavior.
  - Day of the Week: The booking day is extracted to analyze demand trends (e.g., higher demand on weekends).
- Encoding Categorical Variables: Categorical features such as room type and booking channel are converted into numerical values using one-hot encoding, ensuring compatibility with machine learning algorithms.
- Feature Scaling: Numerical features like room rates and booking durations are normalized using StandardScaler, which standardizes data to improve model performance and prevent bias towards larger values

Machine Learning Model Development

- Train-Test Split**:** The dataset is divided into **80% training and 20% testing sets**.
- Model Selection:
  - **Random Forest Regressor:** Effective for handling non-linear relationships in revenue data.
  - **Gradient Boosting Regressor:** Improves accuracy by iteratively refining predictions.
  - **Voting Regressor:** Combines the outputs of both models for enhanced prediction accuracy.
- Model Evaluation: Performance is measured using Mean Squared Error (MSE).

ML CODE:

```
import pandas as pd

import numpy as np
```

```
from sklearn.model_selection import train_test_split

from sklearn.ensemble import RandomForestRegressor, GradientBoostingRegressor, VotingRegressor

from sklearn.preprocessing import StandardScaler

df = pd.read_csv("biproj_dataset.csv") # Step 1: Load the dataset

df['Revenue'] = df['Number of nights'] * df['Room Rate']# Step 2: Add revenue and calculate derived columns

df['Booking Date'] = pd.to_datetime(df['Booking Date'], format='%d-%b-%y')# Ensure correct parsing of the dates

df['Stay Date'] = pd.to_datetime(df['Stay Date'], format='%d-%b-%y')

df['How far away?'] = (df['Stay Date'] - df['Booking Date']).dt.days # Calculate the derived columns

df['Day name'] = df['Stay Date'].dt.day_name()

df['Day of week'] = df['Stay Date'].dt.weekday

df = pd.get_dummies(df, columns=['Day name'], drop_first=True)# Step 3: Convert categorical features ('Day name') to dummy variables (one-hot encoding)

X = df[['Number of nights', 'Room Rate', 'How far away?', 'Day of week'] + [col for col in df.columns if 'Day name_' in col]]# Step 4: Select features and target

y = df['Revenue']

scaler = StandardScaler()# Step 5: Standardize numerical features

X_scaled = scaler.fit_transform(X)

X_train, X_test, y_train, y_test = train_test_split(X_scaled, y, test_size=0.2, random_state=42)# Step 6: Split the data into train and test sets

rf_model = RandomForestRegressor(n_estimators=100, max_depth=20, random_state=42) # Step 7: Train the models

gb_model = GradientBoostingRegressor(n_estimators=100, random_state=42)

rf_model.fit(X_train, y_train)

gb_model.fit(X_train, y_train)

voting_regressor = VotingRegressor(estimators=[('rf', rf_model), ('gb', gb_model)]) # Step 8: Combine models using Voting Regressor

voting_regressor.fit(X_train, y_train)

def predict_revenue(): # Function to take user input and predict revenue

  try:

    nights = int(input("Enter number of nights: "))

    rate = float(input("Enter room rate: "))
```

```
        distance = int(input("Enter days between booking and stay: "))
        day_of_week = int(input("Enter day of the week (0=Monday, 6=Sunday): "))
        day_name_features = [0] * (len([col for col in df.columns if 'Day name_' in col])) # One-hot encoding for day name
        user_input = np.array([[nights, rate, distance, day_of_week] + day_name_features])
        user_input_scaled = scaler.transform(user_input) # Scale input
        predicted_revenue = voting_regressor.predict(user_input_scaled)[0] # Predict revenue
        print(f"Predicted Revenue: ${predicted_revenue:.2f}")
    except ValueError:
        print("Invalid input. Please enter numbers correctly.")
predict_revenue() # Run the prediction function
```

OUTPUT:

```
Enter number of nights: 3
Enter room rate: 120
Enter days between booking and stay: 5
Enter day of the week (0=Monday, 6=Sunday): 2
Predicted Revenue: $364.28
```

Results and Power BI Dashboard

Overview of the Dashboard

This Power BI dashboard is designed to analyze hotel booking trends and revenue insights. It visualizes various metrics, such as total bookings, revenue, cancellation trends, loyalty levels, and booking channels. The interactive elements enable hotel managers to make data-driven decisions for revenue optimization.

Key Performance Indicators (KPIs)

The top section of the dashboard highlights critical KPIs:

- Booking Count: 5000 – Total number of bookings in the selected period.
- Sum of Revenue: 1.33M – Total revenue generated from bookings.
- Cancellation Count: 1436 – Total number of canceled bookings.
- Average Room Rate: 147.75 – The average price per room.

These KPIs provide an instant overview of the hotel's performance and financial status.

Table : "Who is Booking?"

This table categorizes bookings based on Loyalty Levels and Booking Channels:

- Columns: Loyalty Levels (Non-member, Iconic, Elite, Premier, Essential, Preferred, Select)
- Rows: Booking channels (App, At the hotel, Connected Wholesaler, GDS, Phone, Velora.com)

Who is booking?

Loyalty Level	App	At the hotel	Connected Wholesaler	GDS	Other	Phone	Velora.com	**Total**
0.Non-member	412	877	180	274	3	180	112	**2038**
1.Iconic		76		43		7	74	**200**
2.Elite		29		144		11	180	**364**
3.Premier		24		151		29	235	**439**
4.Essential	198	157	51	217	3	134	276	**1036**
5.Preferred	11	34	3	186	1	41	259	**535**
6.Select	15	34	6	147		37	149	**388**

- **Insights:**
  - Non-members (2038 bookings) dominate the bookings, mainly through "At the Hotel" and "Velora.com".
  - Elite and Premier customers have higher engagement in "GDS" and "Connected Wholesaler" channels.
  - Direct bookings from the app are relatively low.

Chart : Booking Count by Day of the Week

- Shows distribution of bookings from Monday to Sunday.
- Bookings are higher during weekdays, indicating business travel trends.
- Lower weekend bookings may suggest an opportunity for targeted marketing.

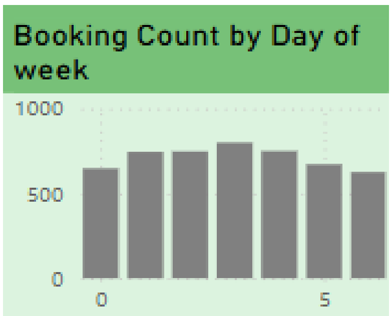


Chart : Sum of Room Rate by Loyalty Level

- Non-members pay the highest room rates, while loyal customers get discounted rates.
- This emphasizes the effectiveness of loyalty programs in providing discounted stays.

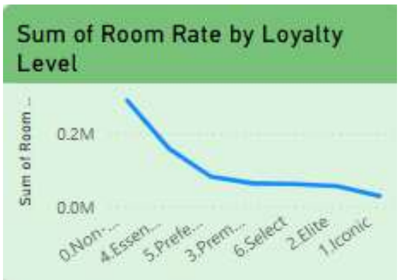


Chart : Cancellation Count and Booking Channel

- Most cancellations come from GDS and Online Channels (Velora.com, Apps).
- Hotels may need better cancellation policies or incentives to retain

  these bookings.

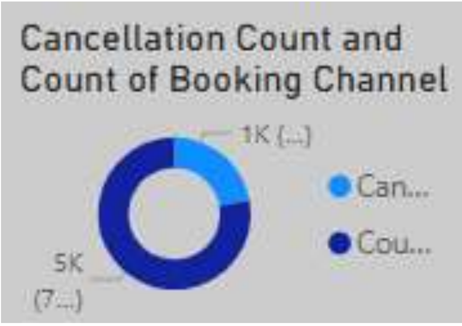


Chart : Booking Lead Time (How far ahead customers book)

- Most bookings happen within one week of stay, while long-term bookings are rare.
- The hotel could implement early-bird discounts to encourage advance bookings.

Chart : Total Revenue by Booking Channel

- The hotel website (Velora.com) and direct hotel bookings generate the highest revenue.
- Third-party channels (GDS, App, Wholesalers) contribute but take a commission, impacting overall profitability.

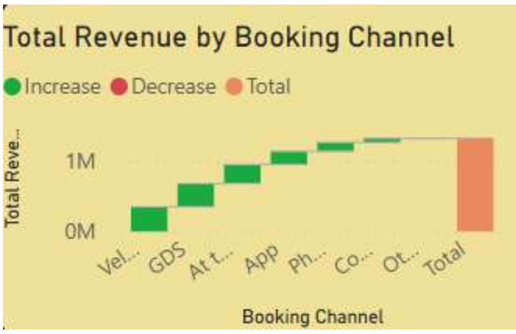


Table: Sum of Revenue and Sum of Room Rate by Month

Description:
This table presents the total revenue and room rate for each month, providing insights into the financial performance across different months.

Columns:

- Month – The month of the year (e.g., September, October, November).
- Sum of Revenue – Total revenue generated in that month.
- Sum of Room Rate – Total room rate charges in that month.

Insights:

- October had the highest revenue compared to other months.
- Revenue significantly dropped in November.
- Room rate trends closely follow revenue trends.

Table: Revenue by Year and Category

Description:
This table breaks down revenue across multiple categories for each year.

Columns:

- Year – The financial year under consideration.
- Category 0-5 – Different revenue streams or classifications.

Insights:

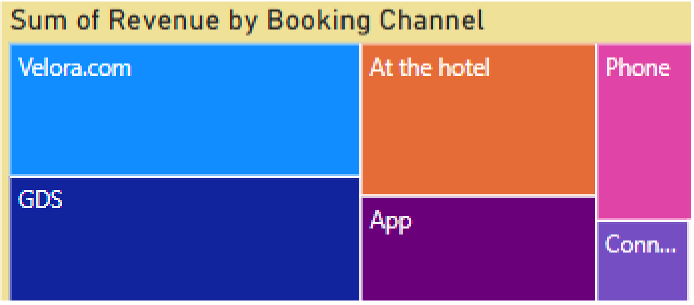
- Categories 1 and 2 contribute the most to the overall revenue.
- Category 5 has the lowest revenue generation.

Table: Revenue by Booking Channel

Description:
This table displays the total revenue generated from different booking channels.

Columns:

- Booking Channel – Various channels like App, GDS, Velora, etc.
- Total Revenue – The total amount of revenue generated from each channel.



Insights:

- The "At the hotel" channel generates the highest revenue.
- Other channels like "Connected Wholesaler" and "Velora.com" contribute less.

Table: Revenue by Loyalty Level and Booking Channel

Description:
This table categorizes revenue based on customer loyalty levels and booking channels.

Columns:

- Loyalty Level – Different levels such as Non-member, Essential, Preferred, etc.
- App, At the Hotel, Connected Wholesaler, etc**.** – Revenue generated from each channel.

Insights:

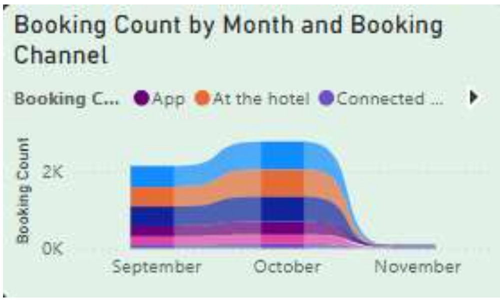
- "At the hotel" is the dominant revenue contributor.
- Elite and Premier loyalty members have higher spending.

Table: Booking Count by Month and Booking Channel

Description:
Displays the number of bookings per month, grouped by booking channels.

Columns:

- Month – The month under consideration.
- Booking Channel – Different booking channels.



Insights:

- A peak in bookings is observed in October.
- Different booking channels show varying seasonal trends.

Table: Sum of Revenue by Booking Channel

Description:
This visualization shows the total revenue distribution across different booking channels, helping to understand which channels are the most profitable.

Columns:

- **Booking Channel** – Categories such as Velora.com, At the hotel, GDS, App, etc.
- **Sum of Revenue** – The total revenue contributed by each channel.

Insights:

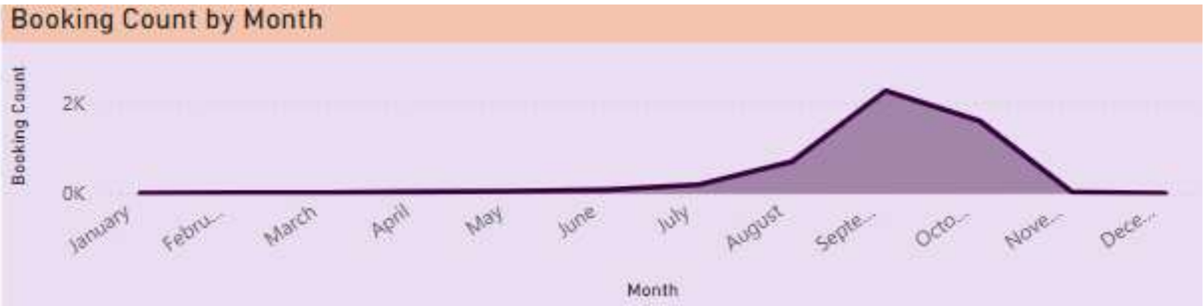
- "At the hotel" and "Velora.com" contribute significantly to revenue.
- GDS has a notable revenue share of **₹3,30,687.10**.
- Other channels like Phone and App also contribute a significant portion.

Chart: Booking Count by Month

Description:
This line chart shows the number of bookings over time, aggregated by month.

Columns:

- Month – Different months from January to November.
- Booking Count – Total number of bookings recorded in each month.



Insights:

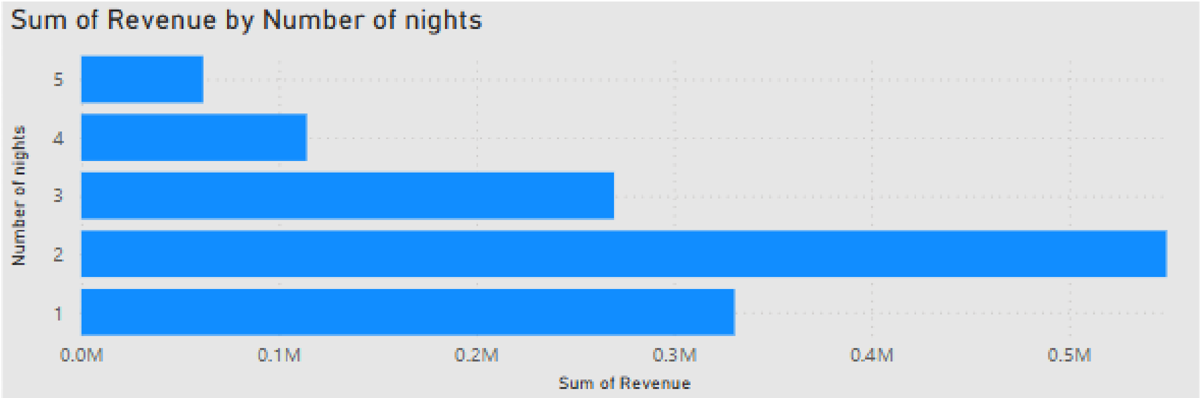
- A sharp increase in bookings is seen from July to October.
- Booking count peaks around October and then declines in November.

Table: Sum of Revenue by Number of Nights

Description:
This horizontal bar chart displays the revenue generated based on the number of nights booked.

Columns:

- Number of Nights – The duration of stay (1, 2, 3, etc.).
- Sum of Revenue – Revenue corresponding to each stay duration.



Insights:

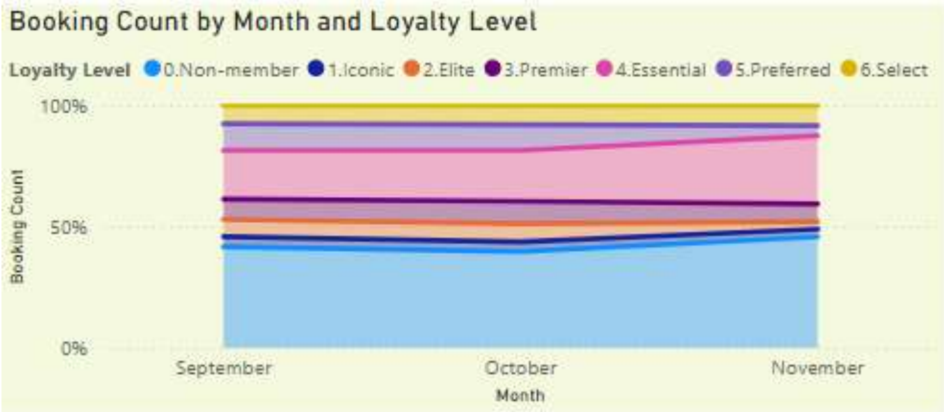
- Bookings for 2 nights generate the highest revenue.
- Longer stays beyond 4 nights contribute less revenue.

Stacked Bar Chart: Booking Count by Month and Loyalty Level

Description:
This visualization presents the booking count distribution across different loyalty levels.

Columns:

- Month – The month under consideration (September, October, November).
- Loyalty Level – Categories such as Non-member, Iconic, Elite, Premier, etc.
- Booking Count – The number of bookings from each loyalty level.



Insights:

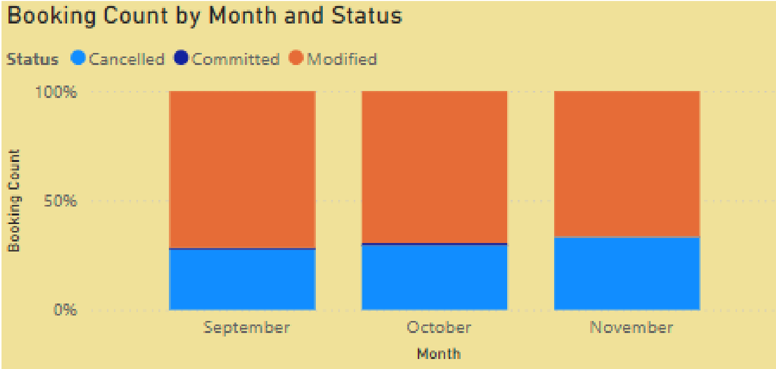
- Non-members have the highest booking count.
- Loyalty members contribute significantly but in smaller proportions.
- The distribution remains fairly stable across months.

Stacked Bar Chart: Booking Count by Month and Status

Description:
This chart represents bookings categorized by their status—whether they were committed, modified, or canceled.

Columns:

- Month – The month under review (September, October, November).
- Status – Canceled, Committed, or Modified.
- Booking Count – Total bookings under each status.



Insights:

- A significant portion of bookings are modified, indicating frequent changes in reservations.
- Cancellations form a substantial part of total bookings.
- The trend remains consistent across the three months.

Total Revenue by Booking ID – Ad Hoc Query Report

Overview:

This ad hoc query report provides a real-time visualization of total revenue per Booking ID, helping hotel managers track high-value reservations and analyze revenue patterns.

Key Details:

- Chart Type: Horizontal bar chart
- X-Axis: Total Revenue
- Y-Axis: Booking ID
- Sorting: Descending order (highest revenue first)

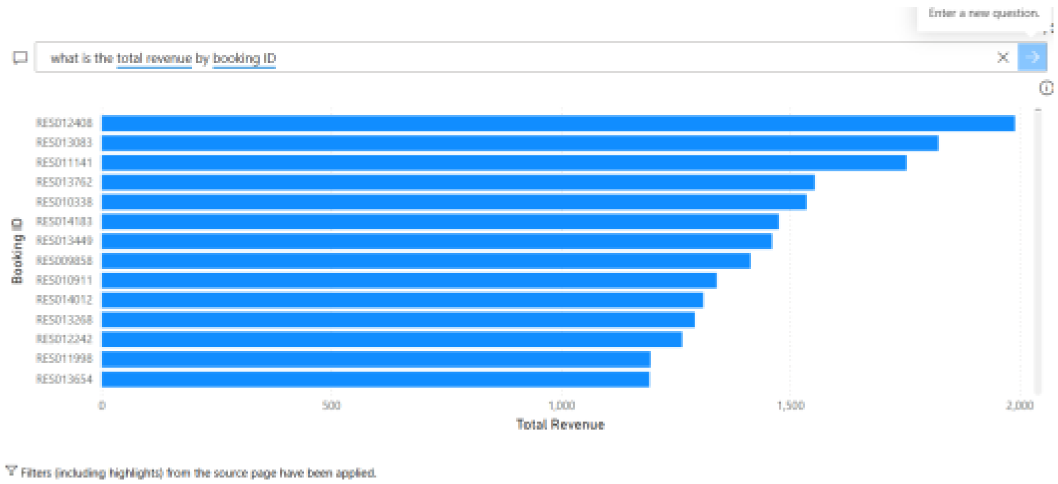
Insights & Benefits:

- Identify top revenue-generating bookings.
- Analyze customer spending patterns and peak bookings.
- Adjust pricing strategies and marketing efforts based on trends.

Filters Applied:

Data is refined with applied filters to ensure relevant insights for decision-making.

This ad hoc query enables quick analysis and strategic planning for revenue optimization.



Data-Driven Decision Making (DDDM) in Hotel Revenue Management

In the hospitality industry, making informed decisions based on data is essential for optimizing revenue, improving customer experience, and enhancing operational efficiency. Traditional decision-making approaches often rely on intuition or historical trends without real-time insights. However, Data-Driven Decision Making (DDDM) transforms this process by leveraging real-time analytics, predictive modeling, and interactive dashboards to drive strategic actions.

This project integrates machine learning models (Random Forest, Gradient Boosting, and Voting Regressor) with Power BI dashboards to facilitate intelligent revenue management. By analyzing historical booking data, customer behavior, and pricing trends, hotel managers can make precise, evidence-based decisions to maximize profitability.

Key Aspects of DDDM in the Project

1. Revenue Forecasting and Pricing Strategies

- The model predicts future revenue trends by analyzing seasonal variations, room demand, and customer segmentation.
- Hotels can implement dynamic pricing strategies based on demand fluctuations, optimizing room rates for peak and off-peak seasons.
- The Voting Regressor model enhances prediction accuracy by combining multiple algorithms, reducing errors in revenue forecasting.

2. Customer Segmentation and Loyalty Analysis

- The Loyalty Level analysis helps hotels understand customer spending behavior across different segments (Non-members, Iconic, Elite, Premier, etc.).
- The Power BI dashboard reveals which loyalty groups contribute the most revenue, enabling targeted promotions and personalized offers.

- Insights from segmentation allow the hotel to adjust loyalty benefits and enhance guest retention strategies.

3. Cancellation Trends and Risk Management

- High cancellation rates (1436 bookings in the dataset) indicate potential revenue leakage.
- The dashboard highlights which booking channels (GDS, Apps, Website) have the highest cancellation rates.
- By analyzing past trends, the hotel can adjust cancellation policies, introduce non-refundable rates, or offer incentives for confirmed bookings.

4. Booking Channel Performance Optimization

- The dashboard evaluates the performance of various booking channels (Website, App, GDS, Wholesalers, Direct Hotel Bookings, Phone Calls).
- Direct bookings via Velora.com and at the hotel generate the highest revenue, reducing commission fees paid to third-party platforms.
- This insight enables data-driven marketing strategies to shift customers toward more profitable booking channels.

5. Advanced Visualization for Real-Time Insights

- Interactive Power BI filters allow managers to explore booking trends by stay dates, number of nights, and booking sources.
- The "Booking Count by Day of the Week" chart helps in demand forecasting, enabling optimized staffing and resource allocation.
- Real-time visualization of average room rates and customer booking behavior ensures timely and well-informed business decisions

Benefits of DDDM in Hotel Revenue Management :

✓ Increased Profitability: Data-driven pricing adjustments and targeted marketing strategies improve revenue generation.
✓ Better Resource Allocation: Insights on peak booking days and cancellation patterns help optimize workforce management.
✓ Improved Customer Satisfaction: Personalized offers based on loyalty levels enhance guest experience.
✓ Reduced Revenue Leakage: Cancellation trend analysis allows preventive actions, reducing financial losses.
✓ Competitive Advantage: Predictive analytics provides an edge over competitors by identifying market trends in advance.

Conclusion

This project successfully develops a machine learning-based revenue prediction model integrated with an interactive Power BI dashboard. By leveraging Random Forest, Gradient Boosting, and Voting Regressor models, the system enhances forecasting accuracy compared to traditional methods. The

Power BI dashboard provides a comprehensive visualization of revenue trends, enabling hotel managers to make data-driven decisions .By merging machine learning with business intelligence, this project delivers a powerful tool for revenue management, helping hotels optimize pricing strategies, improve resource allocation, and enhance profitability.

References:

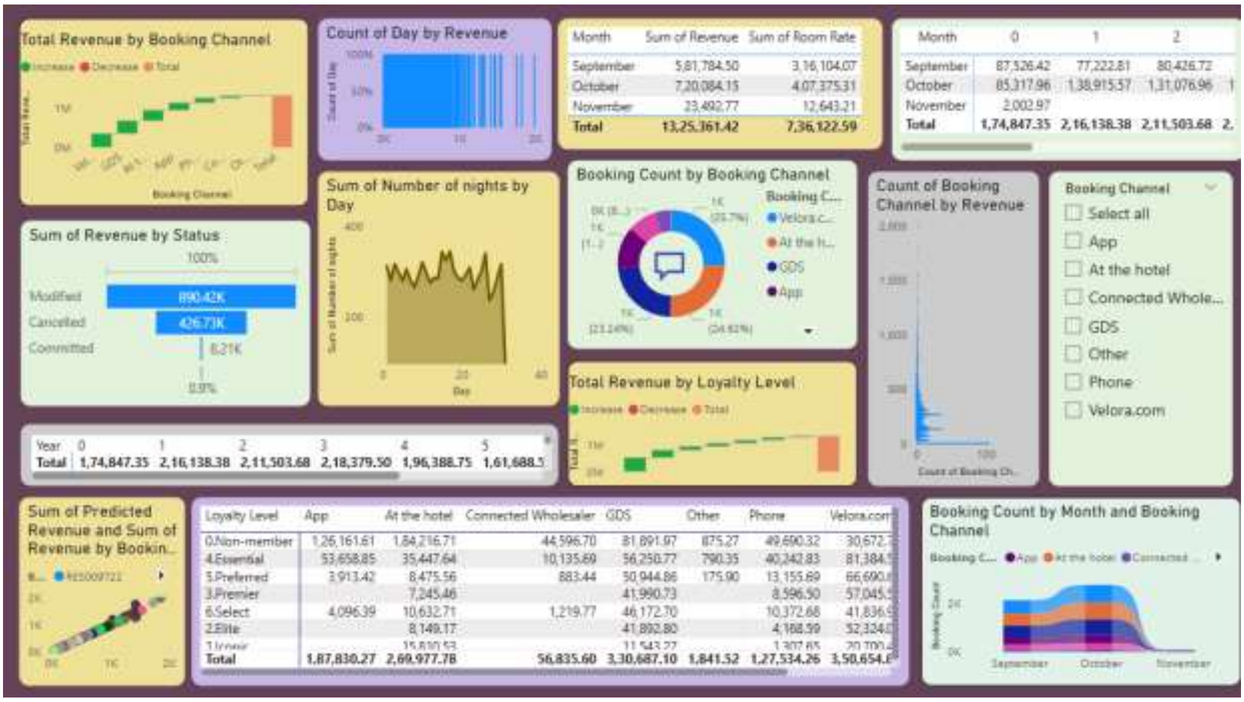
https://www.youtube.com/live/qjzjYurmb5s?si=LTaB74wpYmSIGPYD

https://www.kaggle.com/code/xiaotingb/hotel-reservation-analysis-power-bi?utm_source.com

https://www.kaggle.com/code/xiaotingb/hotel-reservation-analysis-power-bi?utm_source.com

Anshika10022001/Hotel-Analysis: Aimed to analyze the Hotel Booking data and created Power BI Dashboard showing useful insights.

Dashboard:


Total Revenue by Booking Channel
Count of Day by Revenue
Month
Sum of Revenue
Sum of Room Rate
September
5,81,784.50
3,16,104.07
October
7,20,084.15
4,07,375.31
November
23,492.77
12,643.21
Total
13,25,361.42
7,36,122.59
Sum of Revenue by Status
Modified
Cancelled
Committed
890.42K
426.73K
8.21K
Sum of Number of nights by Day
Booking Count by Booking Channel
Count of Booking Channel by Revenue
Booking Channel
Select all
App
At the hotel
Connected Whole...
GDS
Other
Phone
Velora.com
Total Revenue by Loyalty Level
Sum of Predicted Revenue and Sum of Revenue by Bookin...
Loyalty Level
App
At the hotel
Connected Wholesaler
GDS
Other
Phone
Velora.com
0.Non-member
4.Essential
5.Preferred
3.Premier
6.Select
2.Elite
1.Iconic
Total
1,87,830.27
2,69,977.78
56,835.60
3,30,687.10
1,841.52
1,27,534.26
Booking Count by Month and Booking Channel
September
October
November


VELORA
Website
Room Rpt
Occupancy
F&B Rpt
Sum of Revenue by Booking Channel
Velora.com
At the hotel
Phone
GDS
App
Conn...
Booking Count by Month
Sum of Revenue by Number of nights
Sum of Revenue
Number of nights
Date aggregati...
Year
Quarter
Month
Day
Booking Count by Month and Loyalty Level
Loyalty Level
0.Non-member
1.Iconic
2.Elite
3.Premier
4.Essential
5.Preferred
6.Select
Booking Count by Month and Status
Status
Cancelled
Committed
Modified
September
October
November
Month