Investigate Business Hotel using Data Visualization

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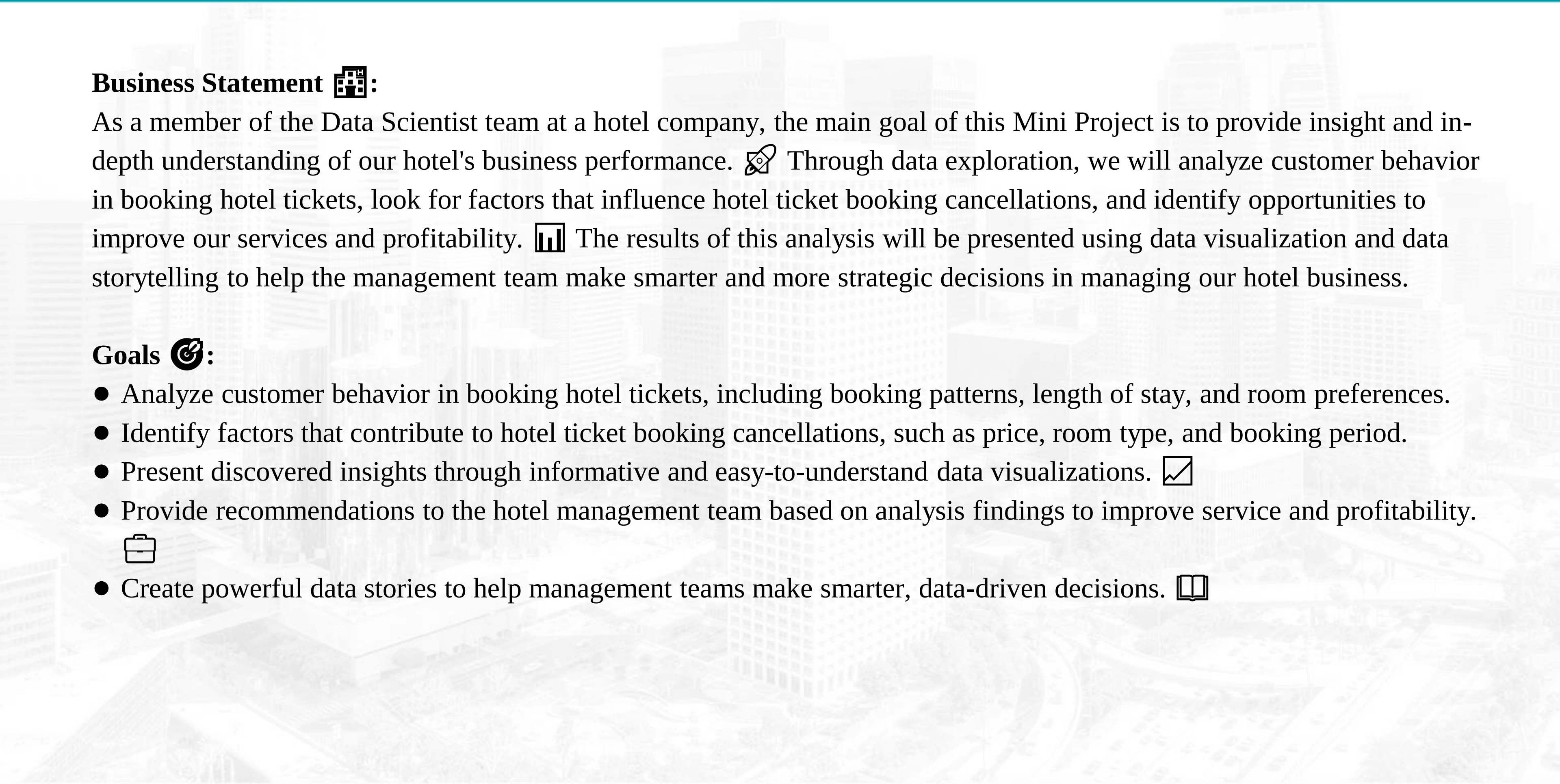
“A data enthusiast who has completed a course in this field and is ready to start his career. Have a excellent understanding in statistics, programming, and data processing. Proficient in using tools such as Python, R, and SQL. Able to collect, clean and analyze data with the necessary techniques. Have skills in data visualization and simple statistical modeling. Creative problem solver and has a passion for learning. Ready to contribute to data-driven projects and collaborate in teams. Committed to further developing data science skills and achieving significant results in data analysis.”

Data Overview



Business Statement 🏨:

As a member of the Data Scientist team at a hotel company, the main goal of this Mini Project is to provide insight and in-depth understanding of our hotel's business performance. 🚀 Through data exploration, we will analyze customer behavior in booking hotel tickets, look for factors that influence hotel ticket booking cancellations, and identify opportunities to improve our services and profitability. 📊 The results of this analysis will be presented using data visualization and data storytelling to help the management team make smarter and more strategic decisions in managing our hotel business.

Goals 🎯:

- Analyze customer behavior in booking hotel tickets, including booking patterns, length of stay, and room preferences.
- Identify factors that contribute to hotel ticket booking cancellations, such as price, room type, and booking period.
- Present discovered insights through informative and easy-to-understand data visualizations. 📈
- Provide recommendations to the hotel management team based on analysis findings to improve service and profitability. 💼
- Create powerful data stories to help management teams make smarter, data-driven decisions. 📖

Data Preparation

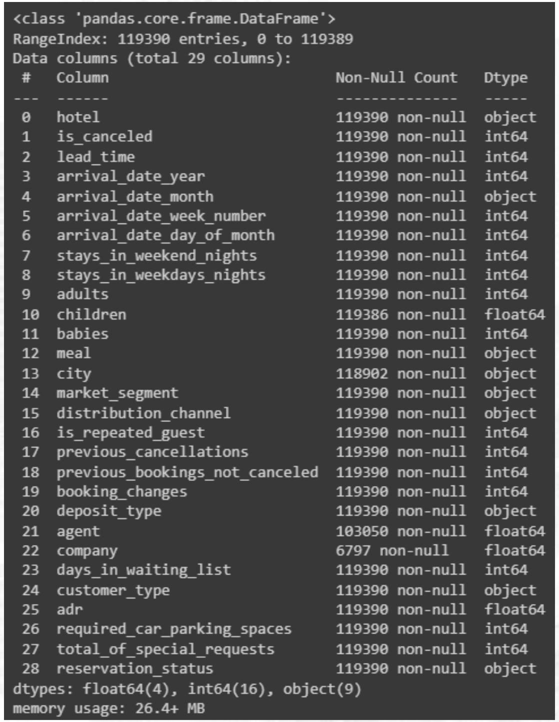
Project Data Column Information:

- **Hotel type**: (Resort Hotel or City Hotel).
- **is_canceled**: Indicates if the order was canceled (1 = Yes, 0 = No).
- **lead_time**: Number of days between booking date and arrival date.
- **arrival_date_year**: The year the customer arrived.
- **arrival_date_month**: The month the customer arrived.
- **arrival_date_week_number**: Week number in the year of arrival.
- **arrival_date_day_of_month**: Arrival day in month.
- **stays_in_weekend_nights**: Number of weekend nights spent by the customer.
- **stays_in_weekdays_nights**: Number of weeknights spent by the customer.
- **adults**: The number of adults in the booking.
- **children**: Number of children in the booking.
- **babies**: Number of babies in the order.
- **meal:** The type of meal ordered.
- **city:** Destination city code.

Data Preparation

- **market_segment**: Customer market segment.
- **distribution_channel**: Order distribution channel.
- **is_repeated_guest**: Signs if the customer is a repeat guest (1 = Yes, 0 = No).
- **previous_cancellations**: Number of orders previously canceled by the customer.
- **previous_bookings_not_canceled**: Number of previous bookings that were not canceled by the customer.
- **booking_changes**: Number of changes made to the booking.
- **deposit_type**: Type of deposit paid (No Deposit, Non Refund, or Refundable).
- **agent**: ID of the agent who placed the order.
- **company**: Company ID if the order was made by a company.
- **days_in_waiting_list**: The number of days in the waiting list before the booking is confirmed.
- **customer_type**: Customer type (Transient, Contract, or Group).
- **adr**: Average Daily Rate, average daily rate.
- **required_car_parking_spaces**: Number of parking spaces required by the customer.
- **total_of_special_requests**: Number of special requests submitted by customers.
- **reservation_status**: Reservation status (Canceled, Check-Out, or No-Show).

Data Preprocessing



```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 119390 entries, 0 to 119389
Data columns (total 29 columns):
 #   Column                          Non-Null Count   Dtype
---  ------                          --------------   -----
 0   hotel                           119390 non-null  object
 1   is_canceled                     119390 non-null  int64
 2   lead_time                       119390 non-null  int64
 3   arrival_date_year               119390 non-null  int64
 4   arrival_date_month              119390 non-null  object
 5   arrival_date_week_number        119390 non-null  int64
 6   arrival_date_day_of_month       119390 non-null  int64
 7   stays_in_weekend_nights         119390 non-null  int64
 8   stays_in_weekdays_nights        119390 non-null  int64
 9   adults                          119390 non-null  int64
 10  children                        119386 non-null  float64
 11  babies                          119390 non-null  int64
 12  meal                            119390 non-null  object
 13  city                            118902 non-null  object
 14  market_segment                  119390 non-null  object
 15  distribution_channel            119390 non-null  object
 16  is_repeated_guest               119390 non-null  int64
 17  previous_cancellations          119390 non-null  int64
 18  previous_bookings_not_canceled  119390 non-null  int64
 19  booking_changes                 119390 non-null  int64
 20  deposit_type                    119390 non-null  object
 21  agent                           103050 non-null  float64
 22  company                         6797 non-null    float64
 23  days_in_waiting_list            119390 non-null  int64
 24  customer_type                   119390 non-null  object
 25  adr                             119390 non-null  float64
 26  required_car_parking_spaces     119390 non-null  int64
 27  total_of_special_requests       119390 non-null  int64
 28  reservation_status              119390 non-null  object
dtypes: float64(4), int64(16), object(9)
memory usage: 26.4+ MB
```

During the data preprocessing phase, several crucial steps were taken to ensure the data's quality and usability:

- **Removing Duplicate Data**: Duplicate records were identified and eliminated from the dataset. This step guarantees that each entry in the dataset is unique, preventing any redundancy in the analysis.
- **Correcting Data Types**: Some columns required adjustments in their data types to accurately represent the information they contain. This ensures that calculations and operations on the data are performed correctly.
- **Handling Invalid Data**: Invalid or missing data values were addressed by appropriate employing strategies. For example, zero values were filled in for missing values in certain columns, and 'unknown' values were assigned to others where data was unavailable.
- **Dropping Unnecessary Data**: Columns that did not contribute significantly to the analysis or were irrelevant to the project's objectives were removed. This streamlines the dataset, making it more focused and efficient for further analysis.

These meticulous data preprocessing steps were executed to prepare the data for in-depth analysis and to ensure the accuracy and integrity of the insights derived from it.

Data Preprocessing

1. Removing the duplicate data

The dataset originally had 119,210 rows and 29 columns. After removing duplicate rows, the dataset size is reduced to 85,953 rows while retaining the same number of columns. This reduction in dataset size indicates the presence of duplicate records in the original dataset. Removing duplicates improves data integrity and quality, ensuring that the data used for analysis is free from redundancy and data entry errors.

2. Handling a Missing Values

In the dataset, there are missing values present in several columns. Here is a brief summary of the columns with missing data:

- **company (Float64):** This column has the highest number of missing values, with 81,019 entries (approximately 94.07% of the total) being null. It likely indicates that most entries in this column do not involve a company.

- **agent (Float64):** There are 11,941 missing values (approximately 13.86% of the total) in this column. These missing values suggest that a substantial number of entries do not have an associated agent.

Data Preprocessing

- **city (Object**): Around 450 entries (approximately 0.52% of the total) have missing values in the 'city' column. These entries likely represent cases where city information was not available.children (Float64): A small number of entries (4 in total) have missing values (approximately 0.0046% of the total) in the 'children' column. This might indicate that these customers did not specify the number of children when booking.It's important to address these missing values appropriately during data preprocessing to ensure accurate and meaningful analysis.

3. Handling Incorrect Data Types

In this data preprocessing step, the data types of three columns in the DataFrame were converted to 'int64' as follows:

- children Column: The 'children' column was converted to 'int64' data type, ensuring that it contains integer values.
- agent Column: Similarly, the 'agent' column was also converted to 'int64' data type, ensuring it contains integer values.
- company Column: Lastly, the 'company' column was converted to 'int64' data type, making sure it consists of integer values.By performing these data type conversions, the DataFrame now contains these columns as integers, which may be more suitable for certain types of analysis and computations.

4. Handling Incorrect Missing Values

After preprocessing the 'meal' column, the data values have been cleaned and reduced to the following refined categories:

- **'Breakfast’**
- **'Full Board’**
- **'Dinner’**
- **'No Meal’**

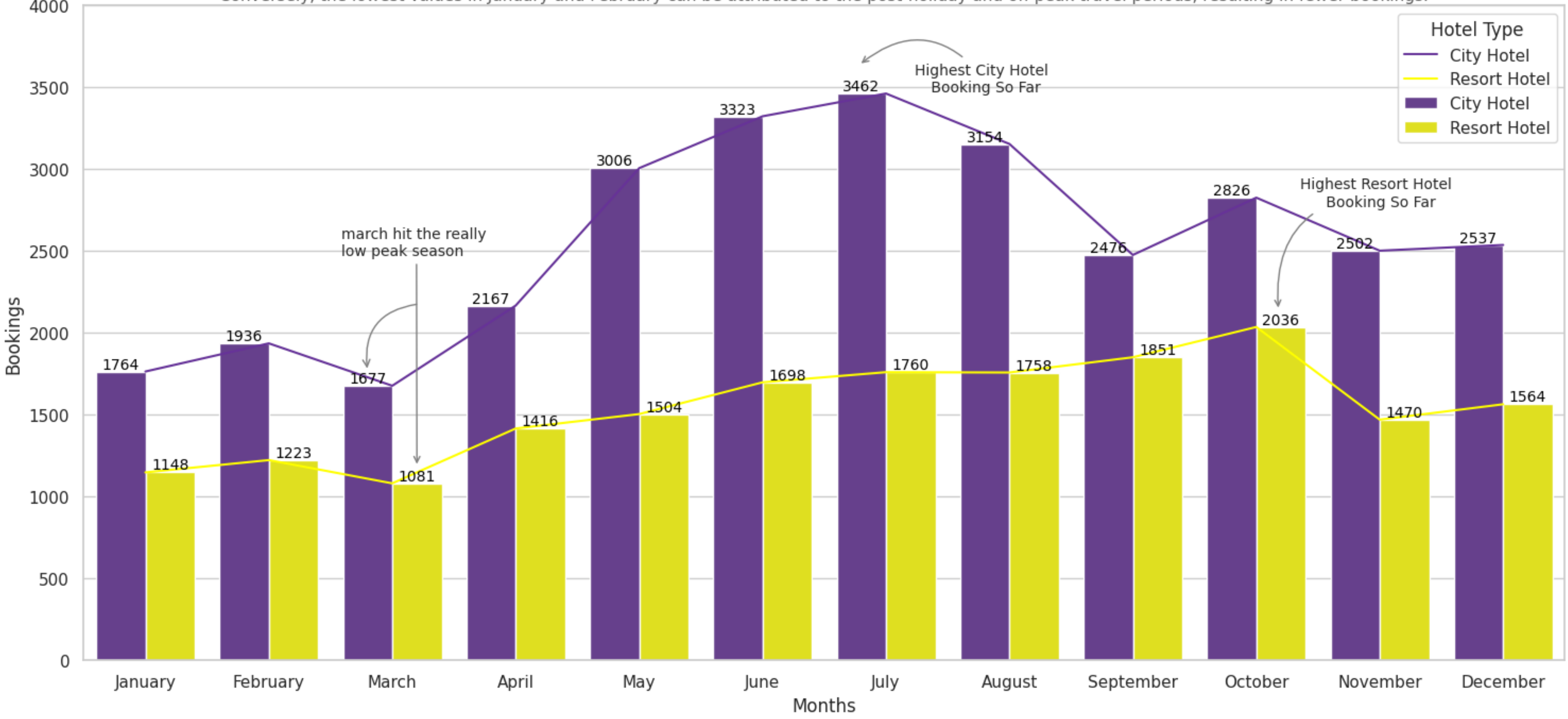
The 'Undefined' category has been gracefully omitted from the dataset.

For more information about the project, click here

Monthly Hotel Booking Analysis Based on Hotel Type

Monthly Average Hotel Bookings Based on Hotel Type

The highest values for reservations and bookings in the summer months, particularly in July and August, are likely a result of increased hotel bookings during the peak vacation season. Conversely, the lowest values in January and February can be attributed to the post-holiday and off-peak travel periods, resulting in fewer bookings.



Monthly Hotel Booking Analysis Based on Hotel Type

Summary from the plot

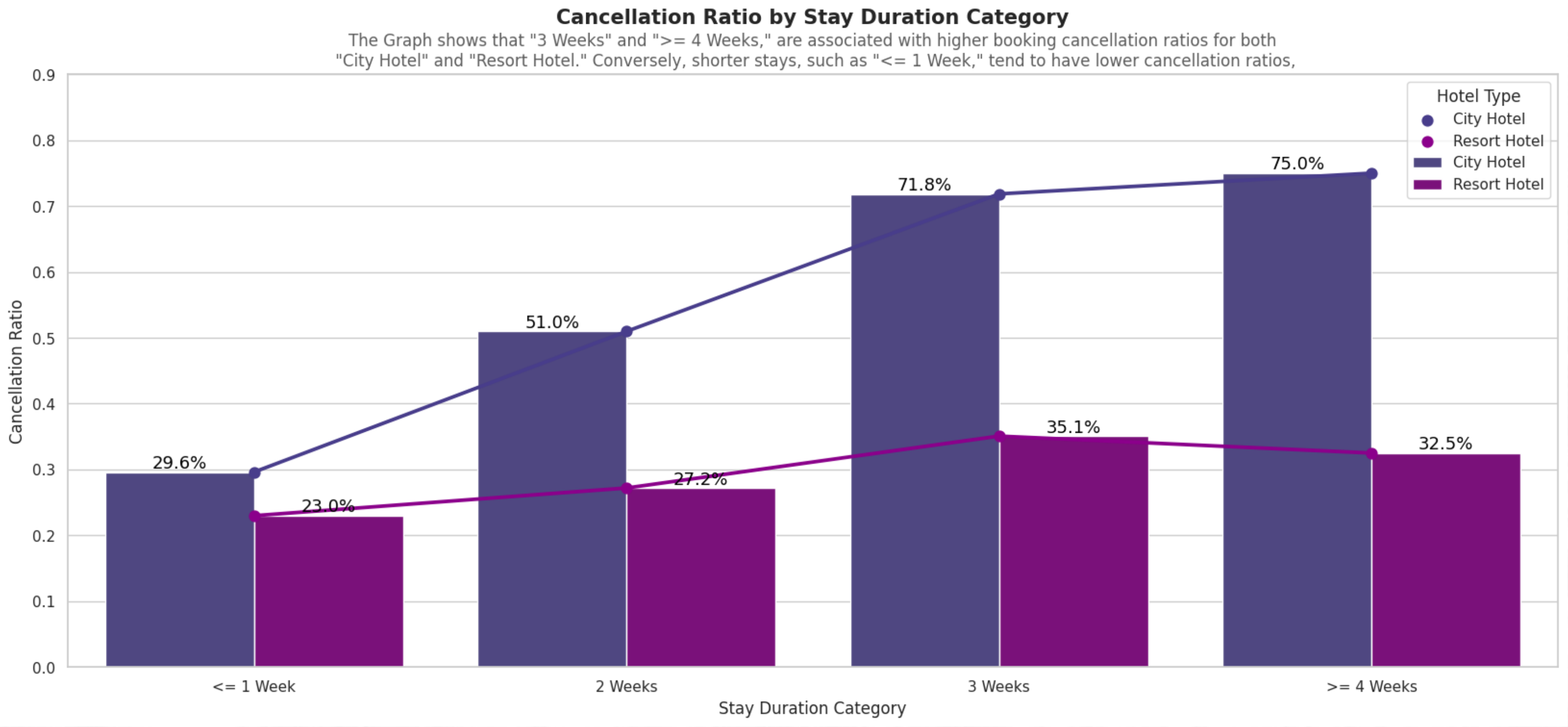
- 🌞 The highest values for reservations, cancellations, and bookings shine during the summer months of **July** and **August**. This peak is attributed to the bustling vacation season when sunseekers flock to book hotels. 🌴🏖️

- ❄️ The lowest values, akin to a winter lull, emerge in **January** and **February**. This quiet period follows the holiday season and ushers in off-peak travel, leading to fewer bookings. ☃️

- □ **September** and **October** bring an intriguing twist. These months boast three "Total Years" of data. A puzzle yet to be unraveled – could unique events or uncharted factors influence hotel bookings during these months? Further investigation is required to decode this data anomaly. 🕵♂🔍

Impact Analysis of Stay Duration on Hotel Bookings Cancellation Rates

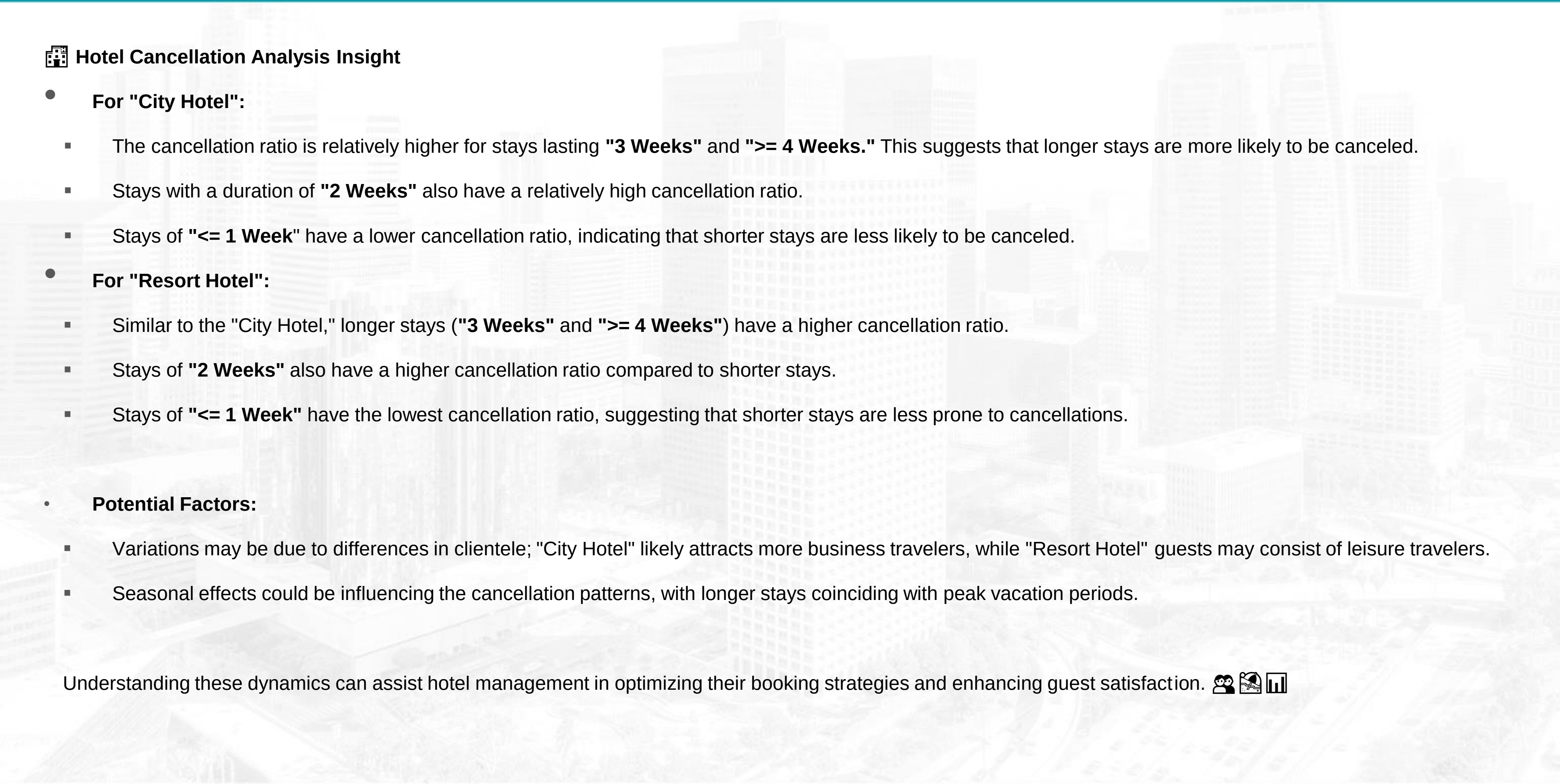
From perspective on my plot:



Cancellation Ratio by Stay Duration Category

The Graph shows that "3 Weeks" and ">= 4 Weeks," are associated with higher booking cancellation ratios for both "City Hotel" and "Resort Hotel." Conversely, shorter stays, such as "<= 1 Week," tend to have lower cancellation ratios,

Impact Analysis of Stay Duration on Hotel Bookings Cancellation Rates



🏨 Hotel Cancellation Analysis Insight

- **For "City Hotel":**
  - The cancellation ratio is relatively higher for stays lasting **"3 Weeks"** and **">= 4 Weeks."** This suggests that longer stays are more likely to be canceled.
  - Stays with a duration of **"2 Weeks"** also have a relatively high cancellation ratio.
  - Stays of **"<= 1 Week**" have a lower cancellation ratio, indicating that shorter stays are less likely to be canceled.
- **For "Resort Hotel":**
  - Similar to the "City Hotel," longer stays (**"3 Weeks"** and **">= 4 Weeks"**) have a higher cancellation ratio.
  - Stays of **"2 Weeks"** also have a higher cancellation ratio compared to shorter stays.
  - Stays of **"<= 1 Week"** have the lowest cancellation ratio, suggesting that shorter stays are less prone to cancellations.

- **Potential Factors:**
  - Variations may be due to differences in clientele; "City Hotel" likely attracts more business travelers, while "Resort Hotel" guests may consist of leisure travelers.
  - Seasonal effects could be influencing the cancellation patterns, with longer stays coinciding with peak vacation periods.

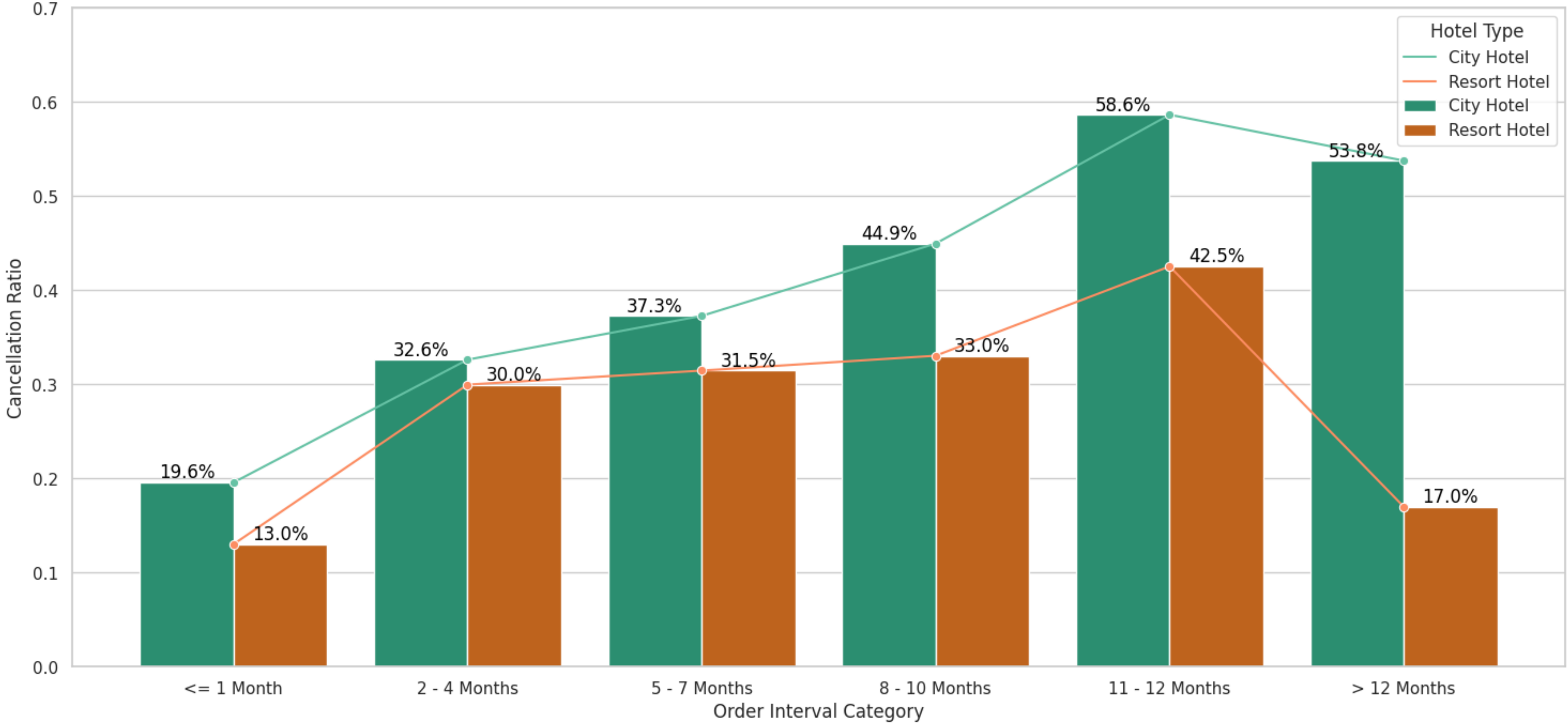
Understanding these dynamics can assist hotel management in optimizing their booking strategies and enhancing guest satisfaction. 👥🏖📊

Impact Analysis of Lead Time on Hotel Bookings Cancellation Rate

Rakamin Academy

Cancellation Ratio Based on Lead Time for Each Hotel Type

"City Hotel" exhibits its highest cancellation ratio at an 11-12 month lead time (58.6%), decreasing substantially for bookings made within a month (19.6%). In contrast, it generally has a higher cancellation ratio compared to "Resort Hotel." "Resort Hotel" has a lower cancellation ratio for bookings made over 12 months in advance (17.0%) but sees increased cancellations as the lead time shortens.



Impact Analysis of Lead Time on Hotel Bookings Cancellation Rate

Insight and Assumptions from the Plot

The data reveals a compelling relationship between lead time (booking interval) and cancellation ratios for "City Hotel" and "Resort Hotel." 📊

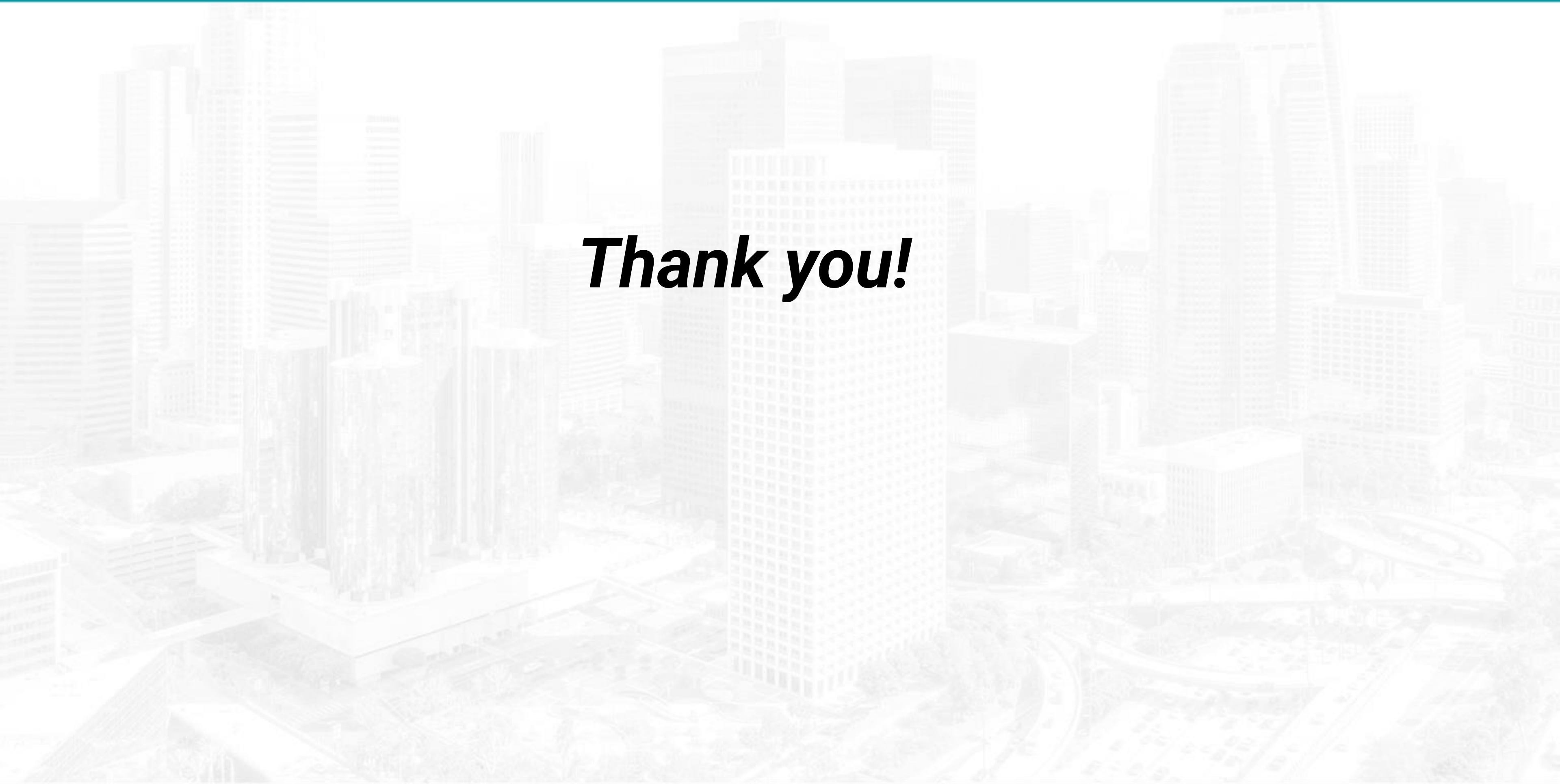
Insight:

- Shorter Lead Time, Lower Cancellation Ratio: Both hotel types exhibit a consistent pattern where decreasing lead time corresponds to lower cancellation ratios. For instance, "City Hotel" experiences its highest cancellation ratio when bookings are made 11-12 months in advance (58.6%), decreasing for lead times within one month (19.6%).

- Variations between Hotel Types: "City Hotel" generally maintains a higher cancellation ratio compared to "Resort Hotel," regardless of lead time. "Resort Hotel" enjoys a lower cancellation ratio for bookings more than 12 months ahead (17.0%), but this ratio increases as lead time shortens.

Assumptions and Implications:

- **Booking Confidence and Planning**: It is likely that guests booking well in advance may harbor some uncertainty about their travel plans, leading to higher cancellation rates. Conversely, guests with lead times of one month or less may have more concrete plans and thus exhibit lower cancellation ratios
- **Business and Leisure Travel**: "City Hotel" may cater more to business travelers who tend to plan trips closer to the travel date, resulting in a higher cancellation ratio. On the other hand, "Resort Hotel" attracts leisure travelers who plan ahead, showing a lower cancellation ratio.
- **Pricing and Policies**: Differences in cancellation policies, pricing strategies, or the types of market segments targeted by the hotels could contribute to the variations in cancellation ratios. Further analysis of these factors is required to gain a more comprehensive understanding of the observed trends. 💼🏖️💰



Thank you!