

Comprehensive Report on Hotel Booking Cancellations

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Introduction

In today’s highly competitive hospitality industry, understanding and predicting hotel booking behavior is a critical component of revenue management, operational planning, and customer satisfaction strategies. Online travel agents, direct booking platforms, and corporate reservation channels have created a complex landscape where guest preferences can change quickly—and so can their likelihood of canceling a reservation.

This report analyzes a **large hotel booking dataset** consisting of over 115,000 entries. The goal is to uncover factors that contribute to booking cancellations and to recommend strategies for predictive modeling. By identifying key indicators—such as the length of time between booking and arrival (lead time), previous cancellation patterns, and seasonal trends—hotels can more effectively manage their inventory, anticipate demand fluctuations, and tailor marketing efforts to reduce lost revenue from last-minute cancellations.

Motivation

- 1. **Revenue Optimization:** Hotel rooms are a perishable asset. Once the night has passed, any unbooked room represents lost revenue. Predicting cancellation patterns enables hotels to adopt strategies like overbooking certain days or adjusting prices to maximize occupancy without risking too many no-shows.
- 2. **Operational Efficiency:** Staffing, housekeeping schedules, food and beverage orders, and other operational factors depend on accurate forecasts of room occupancy. High cancellation rates can lead to inefficient resource allocation if not properly accounted for.
- 3. **Customer Satisfaction & Loyalty:** By understanding guest behaviors—such as whether loyal guests are less likely to cancel or if certain market segments cancel more often—hotels can design targeted

loyalty programs and personalized offers to improve guest retention.

- 4. **Fraudulent or Abusive Bookings:** Some bookings might repeatedly cancel or make spurious reservations. Understanding these patterns helps hotels implement better verification systems or deposit policies to reduce abuse.

Context

- **Hotel Booking Dynamics:**
The dataset contains a mix of **City Hotel** and **Resort Hotel** bookings. City hotels often serve business travelers with shorter stays and more last-minute bookings. Resort hotels may have longer stays, often booked farther in advance.
- **Distribution Channels:**
Reservations come from diverse channels such as **Online Travel Agents (OTAs)**, **Travel Agents/Tour Operators (TA/TO)**, and **direct** channels. Different channels cater to different customer segments with varying cancellation behaviors.
- **Industry Benchmarks:**
Cancellation rates can vary from 15% to over 40% depending on the region, hotel type, and booking policies. This dataset shows a cancellation rate of ~37.7%, which aligns with industry observations for hotels that rely heavily on OTAs.
- **Seasonality:**
Seasonality strongly affects the hospitality industry. High demand months—like summer or major holiday periods—often see higher booking volumes, but also possible spikes in cancellations when guests find better deals or change their travel plans.

Data Overview

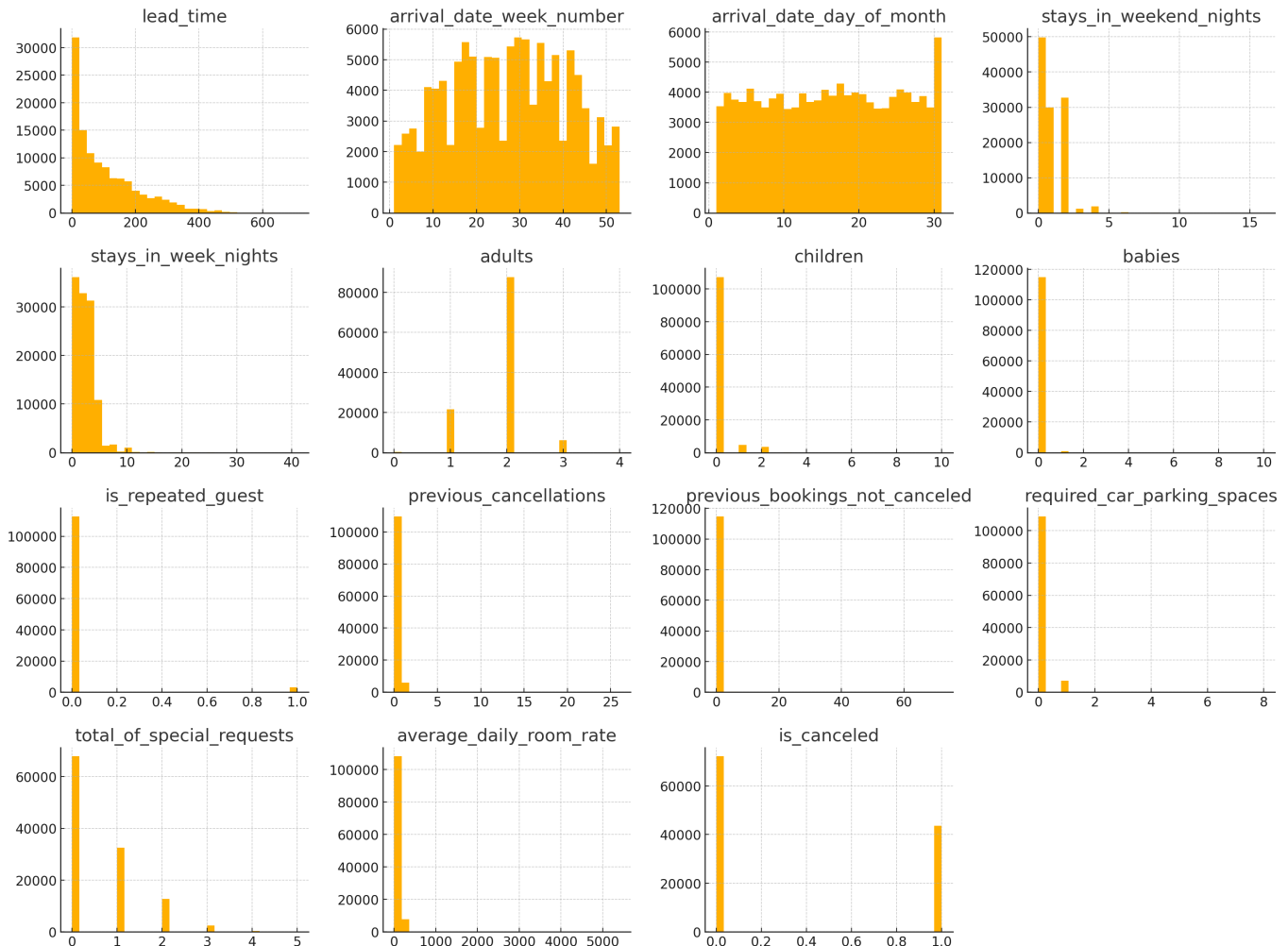
- **Dataset Size:** 115,833 entries, 23 columns.
- **Data Types:**
 - 13 integer columns
 - 2 float columns
 - 8 categorical columns
- **Missing Values:** None (the dataset is complete).
- **Target Variable:** `is_canceled` — a binary classification (0 = Not Canceled, 1 = Canceled).
- **Key Statistics:**
 - **Cancellation Rate:** ~37.7% of bookings were canceled.
 - **Lead Time:** Mean of ~106 days; maximum up to 709 days.
 - **Room Rates:** Prices vary widely (some extreme values reach up to \$5,400 per night).
 - **Market Segment:** Majority of bookings come from **Online TA (Travel Agents)**.
 - **Hotel Type:** ~67.4% of records are for **City Hotels**, with the remainder for **Resort Hotels**.

Understanding the data composition is the first step toward developing robust predictive models. A large sample size with diverse categorical and numerical features provides ample opportunity to detect complex patterns—both linear and non-linear—associated with cancellations.

Numerical Feature Distributions Insights

To better understand the distribution and potential skewness of continuous features, we examine histograms and density plots:

Numerical Feature Distributions



1. Lead Time

- **Right-skewed** with a mean of ~106 days and a maximum of 709 days.
- Many bookings are made within 30 days of arrival, but some guests book far in advance (over 500 days).

2. Stay Duration (often derived from arrival date and departure date)

- Most stays range from **1 to 3 nights**.
- A few outliers extend up to 41 nights—more common for resort vacations or long-term business stays.

3. Adults & Children

- The majority of bookings are for **2 adults** without children or babies.
- Some outliers with unusually high numbers of children or no adults at all (which may indicate data entry errors or unusual group bookings).

4. Previous Cancellations

- Most guests have **0** previous cancellations, but some have up to **26**—which can be indicative of potentially fraudulent or at least erratic booking behavior.

5. Special Requests

- Many customers make **0** or **1** special request (e.g., high floor, king bed, non-smoking room).
- Some bookings have up to 5 special requests, indicating a higher level of guest involvement and potentially lower likelihood of cancellation.

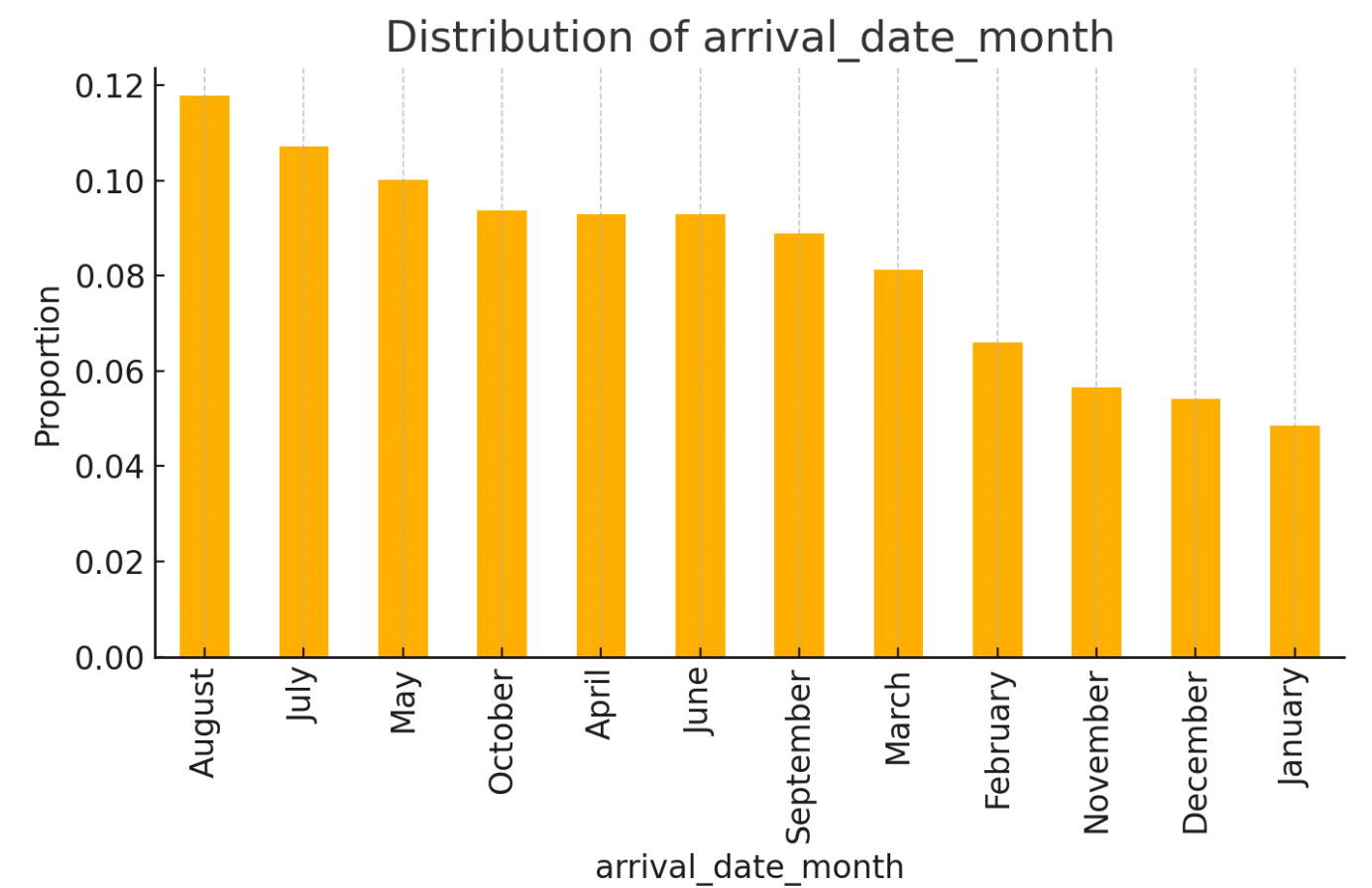
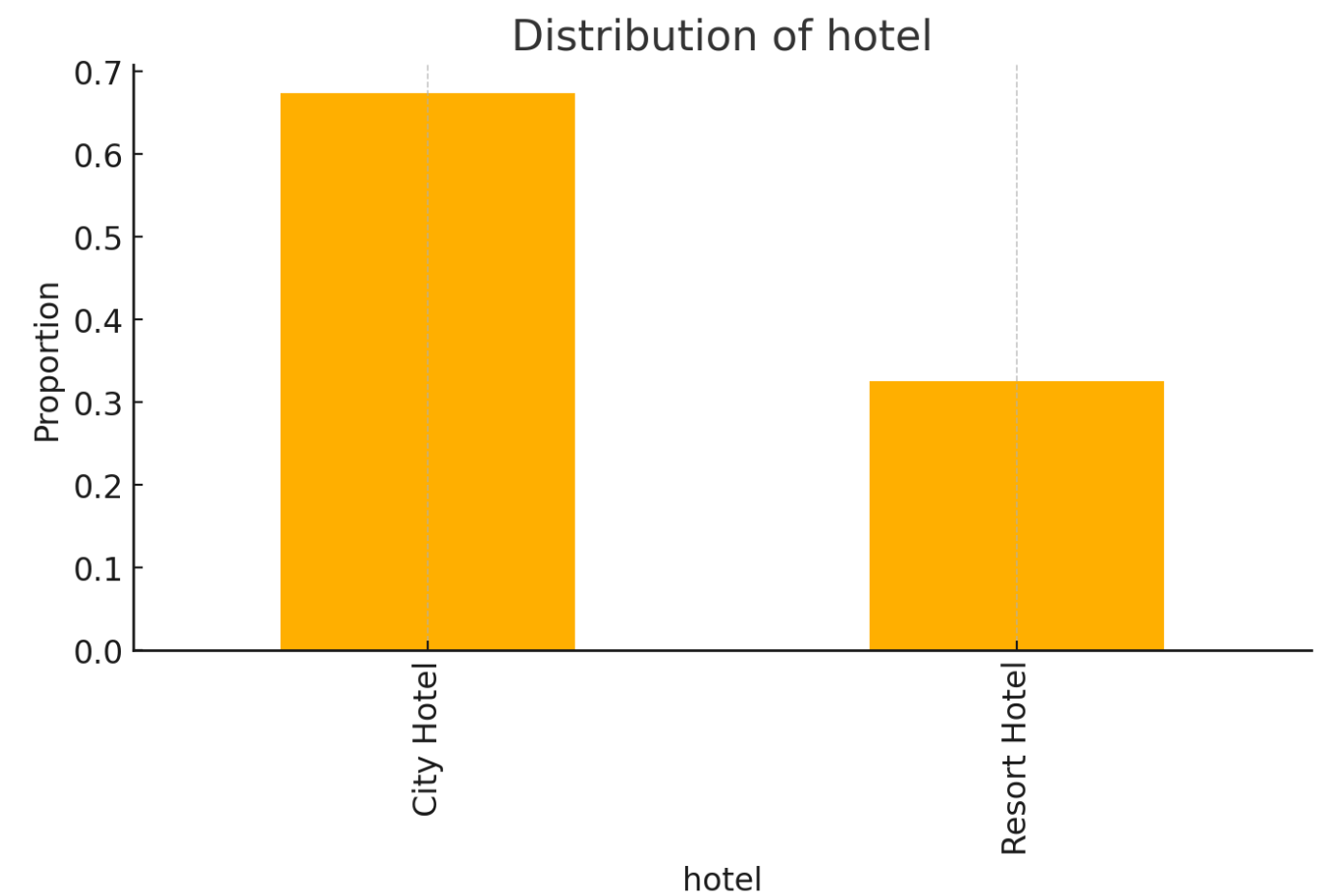
6. Room Rates

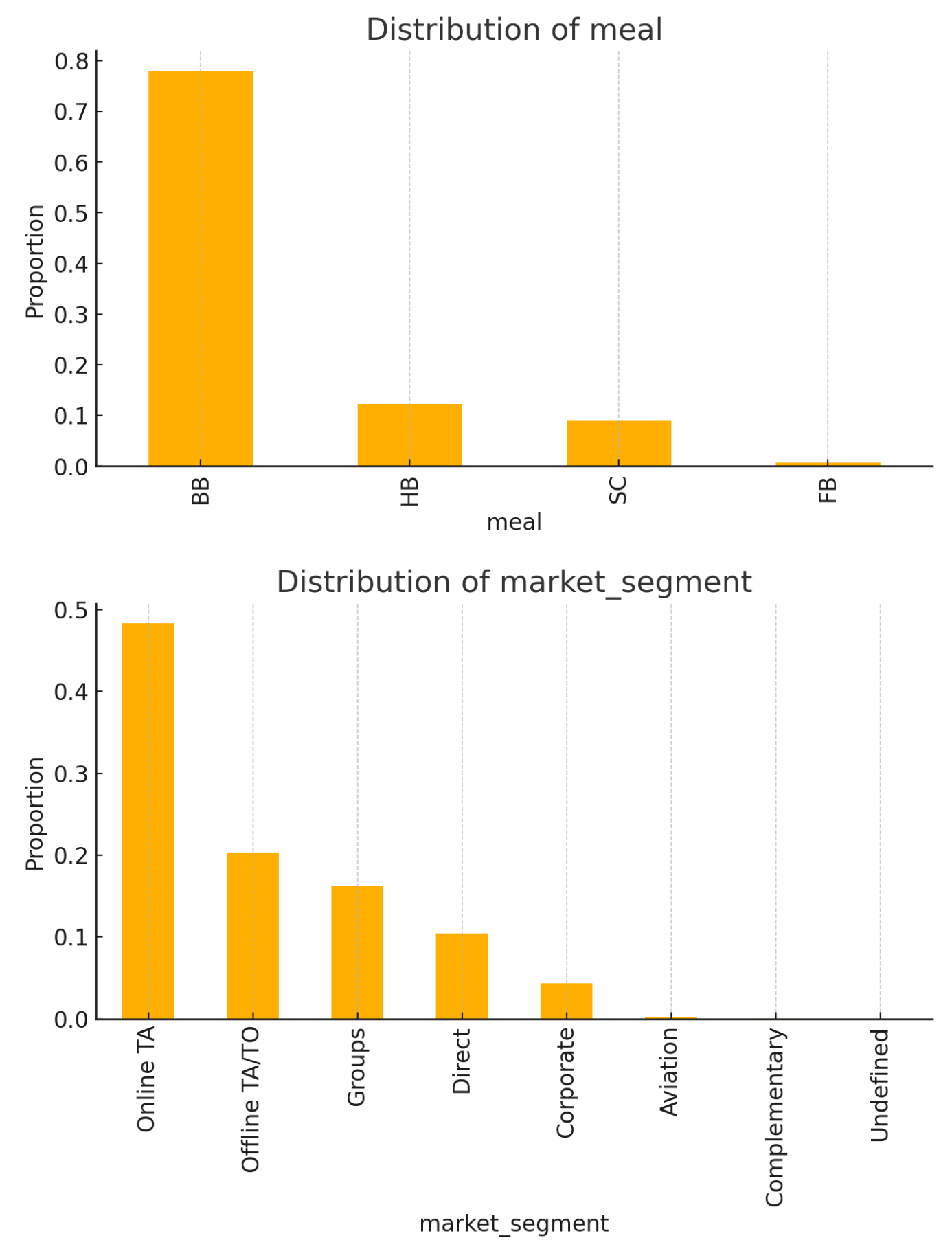
- Typically under **\$200/night**, with a **median** in the \$100-\$150 range.
- Extreme outliers can reach over \$1,000, and the dataset mentions up to \$5,400/night for ultra-luxury or premium suites.

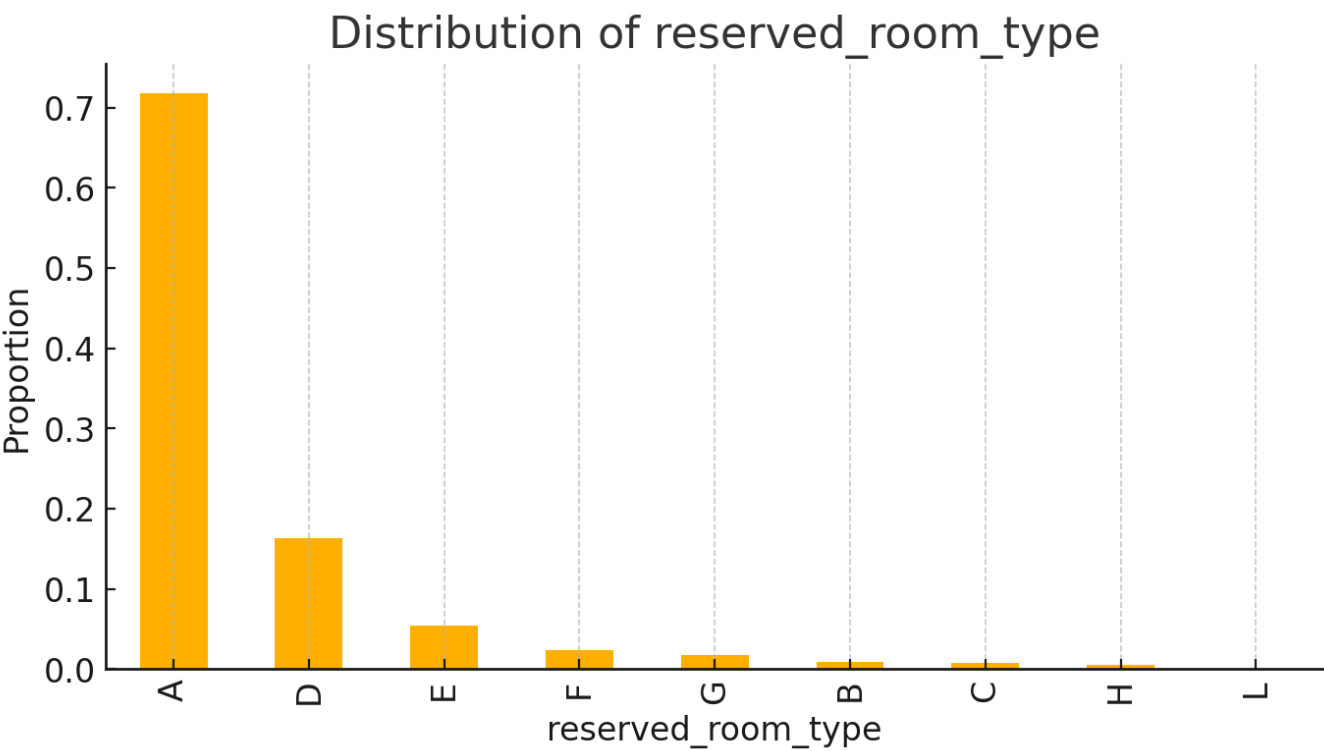
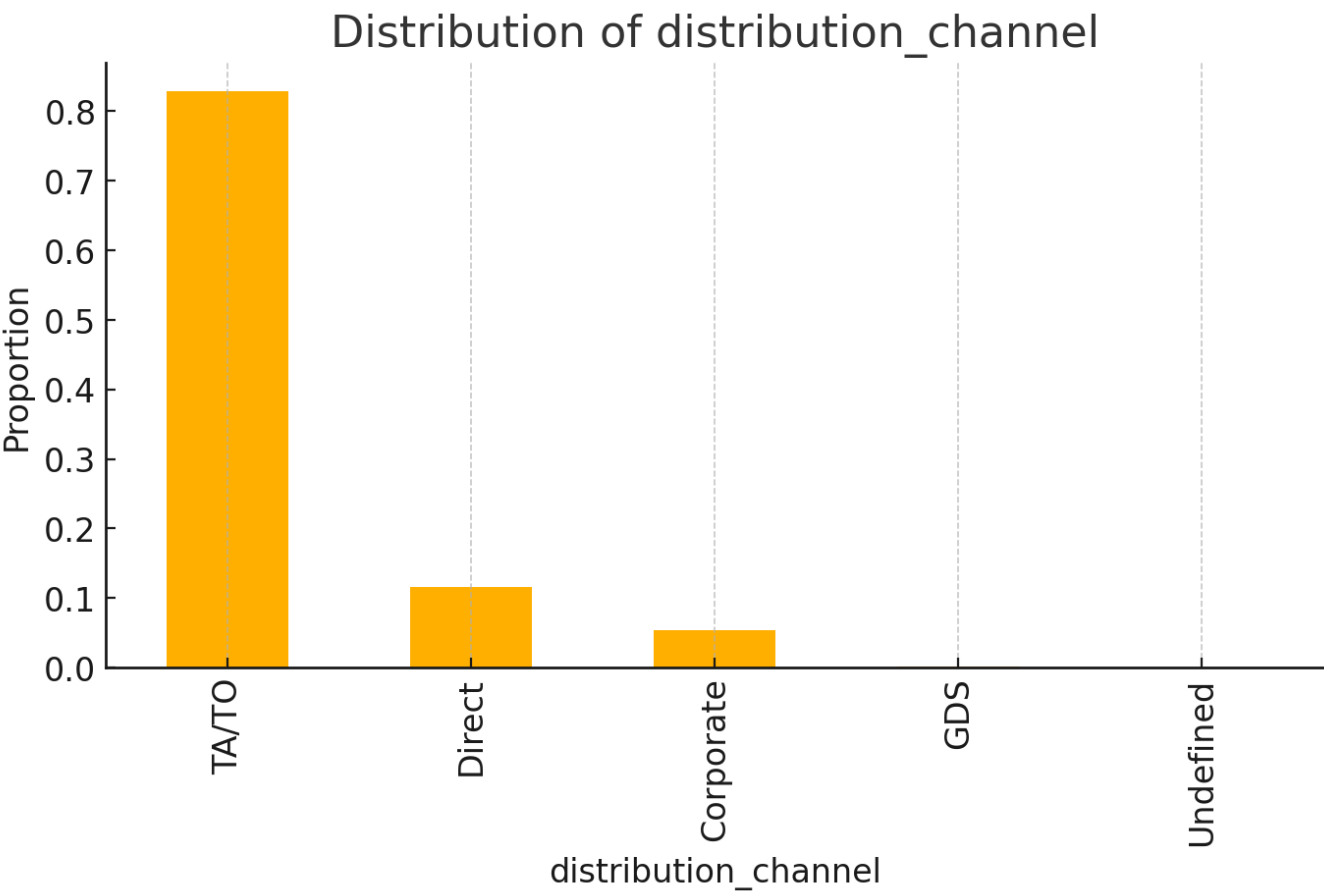
The skewness in features like **lead time** and **room rate** suggests that transformations (e.g., log transform) or specialized outlier handling might be necessary for building effective models.

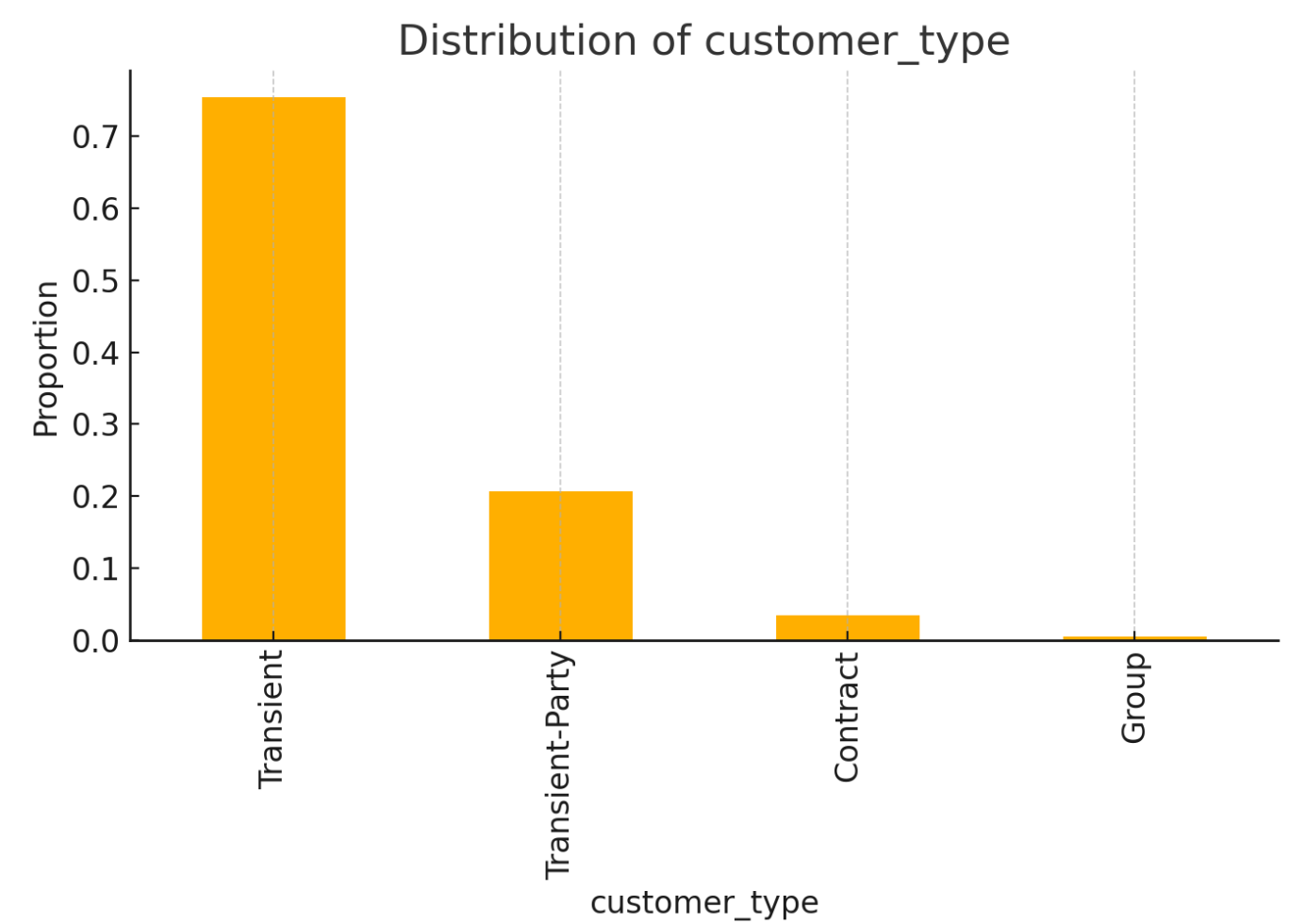
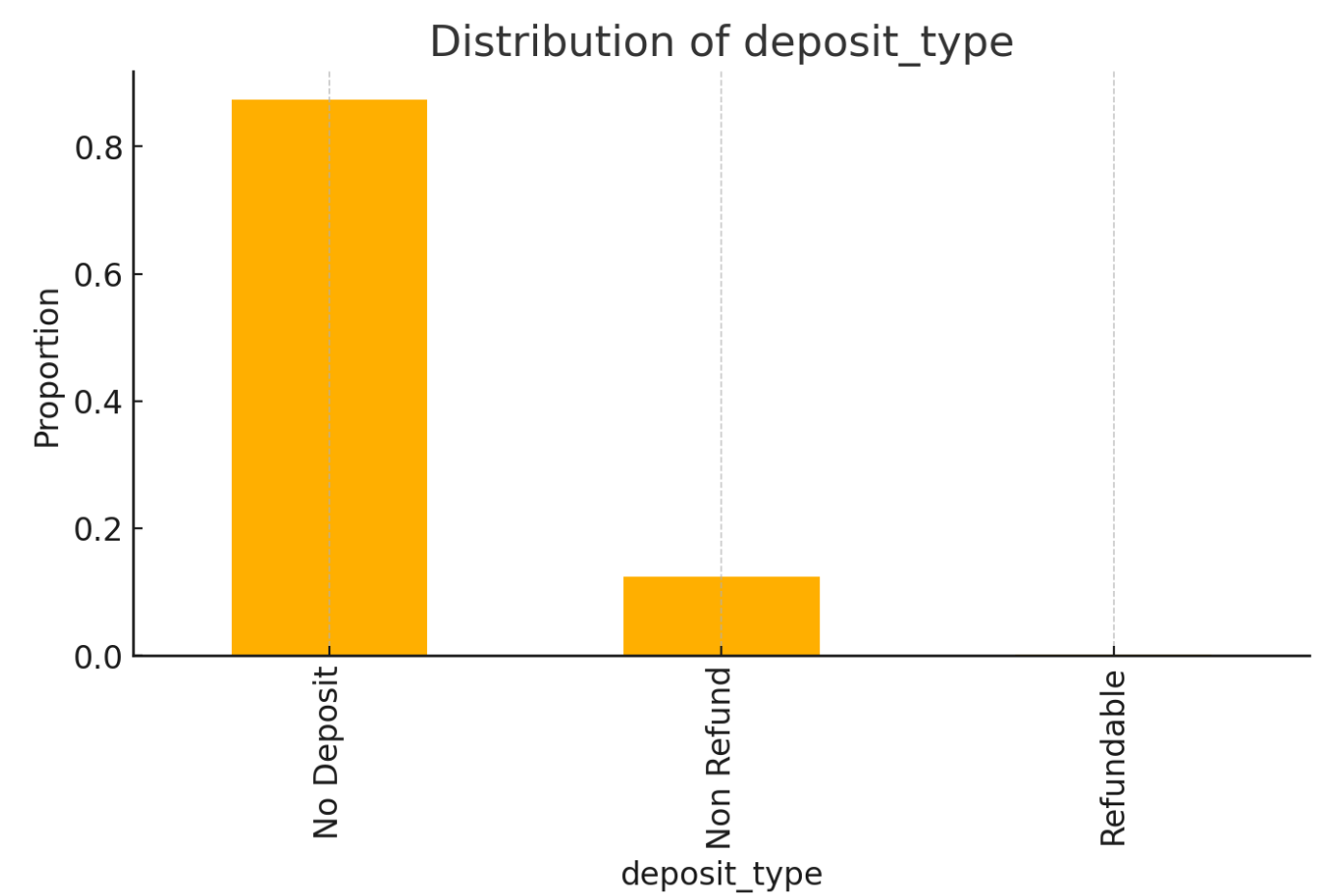
Categorical Feature Distributions Insights

Next, we explore the categorical features to see common booking patterns:









- **67%** of bookings are for **City Hotels**, while the rest are for **Resort Hotels**.
- City Hotel bookings often have shorter lead times and shorter stays compared to resort bookings.

2. Arrival Month

- Shows pronounced **seasonality**. August is the busiest month, followed by July. Off-peak months (like November or January) see fewer bookings.

3. Meal Plans

- The majority choose **BB (Bed & Breakfast)**. Other options like HB (Half Board) and FB (Full Board) exist but are less common.

4. Market Segment

- **Online TA** dominates, reflecting the industry trend toward online travel agencies (Booking.com, Expedia, etc.).
- **Direct** bookings (phone calls, hotel website) are the second most frequent.

5. Distribution Channel

- **TA/TO (Travel Agent/Tour Operator)** is the most common channel, aligning closely with the Online TA segment.
- Some smaller channels may have specialized clientele or corporate partnerships.

6. Room Type

- **Room Type A** is the most frequently booked, followed by a few others (B, C, D, etc.).
- Overbooking of a particular room type sometimes leads to "Room Type Assigned" changes upon arrival.

7. Deposit Type

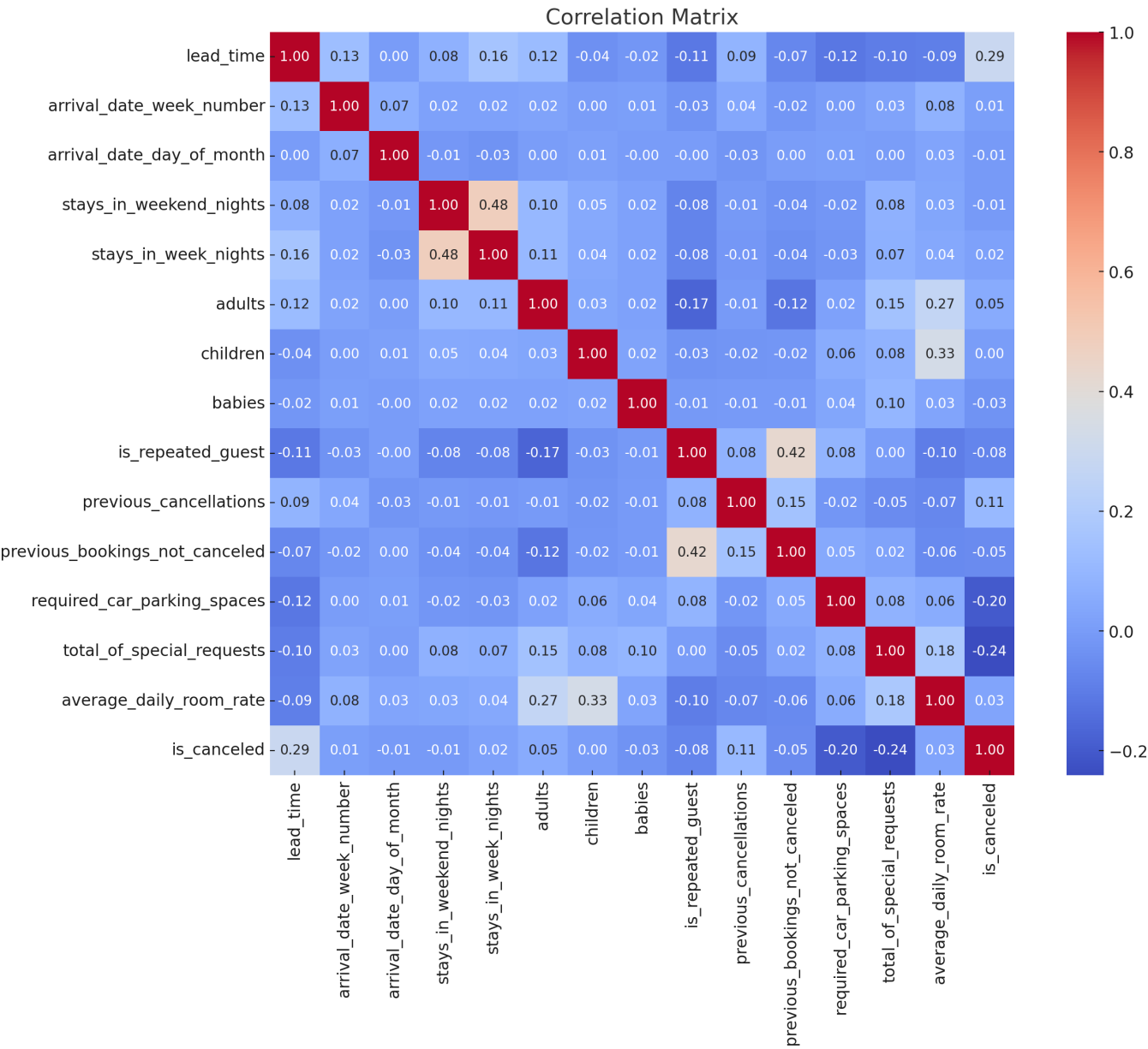
- **No Deposit** is chosen by the vast majority (~90%+).
- **Non-Refund** deposit policies significantly reduce cancellations but also reduce booking volume if the cost is high.

8. Customer Type

- **Transient** (individual travel) is the largest category, followed by **Transient-Party** or **Group**. Groups tend to have different booking/cancellation patterns due to corporate or organized tours.

Correlation Analysis Insights

To identify numerical relationships, we analyze the correlation matrix among key numerical features and the target variable (**is_canceled**):



1. Key Positive Correlations with Cancellation

- **Lead Time (0.39):** Longer lead times correlate with higher cancellations. Far-in-advance bookings have more time for plans to change.
- **Previous Cancellations (0.15):** A history of past cancellations strongly signals the likelihood of canceling again.

2. Key Negative Correlations

- **Special Requests (-0.11):** Guests who invest effort in making specific requests are more likely to commit to their stay.
- **Required Car Parking Spaces (-0.11):** Bookings indicating the need for a car parking space are less likely to cancel, possibly due to more concrete travel arrangements.

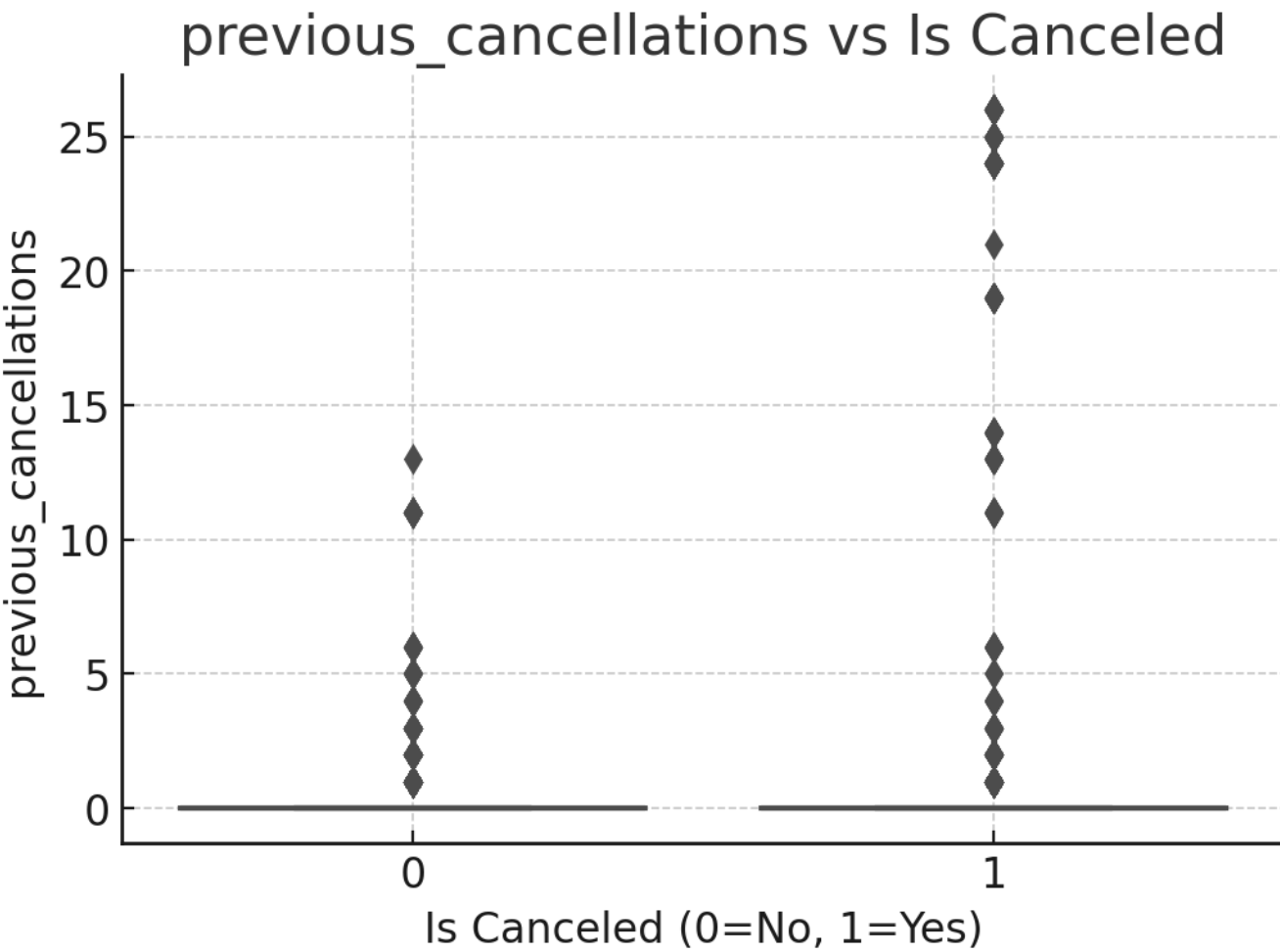
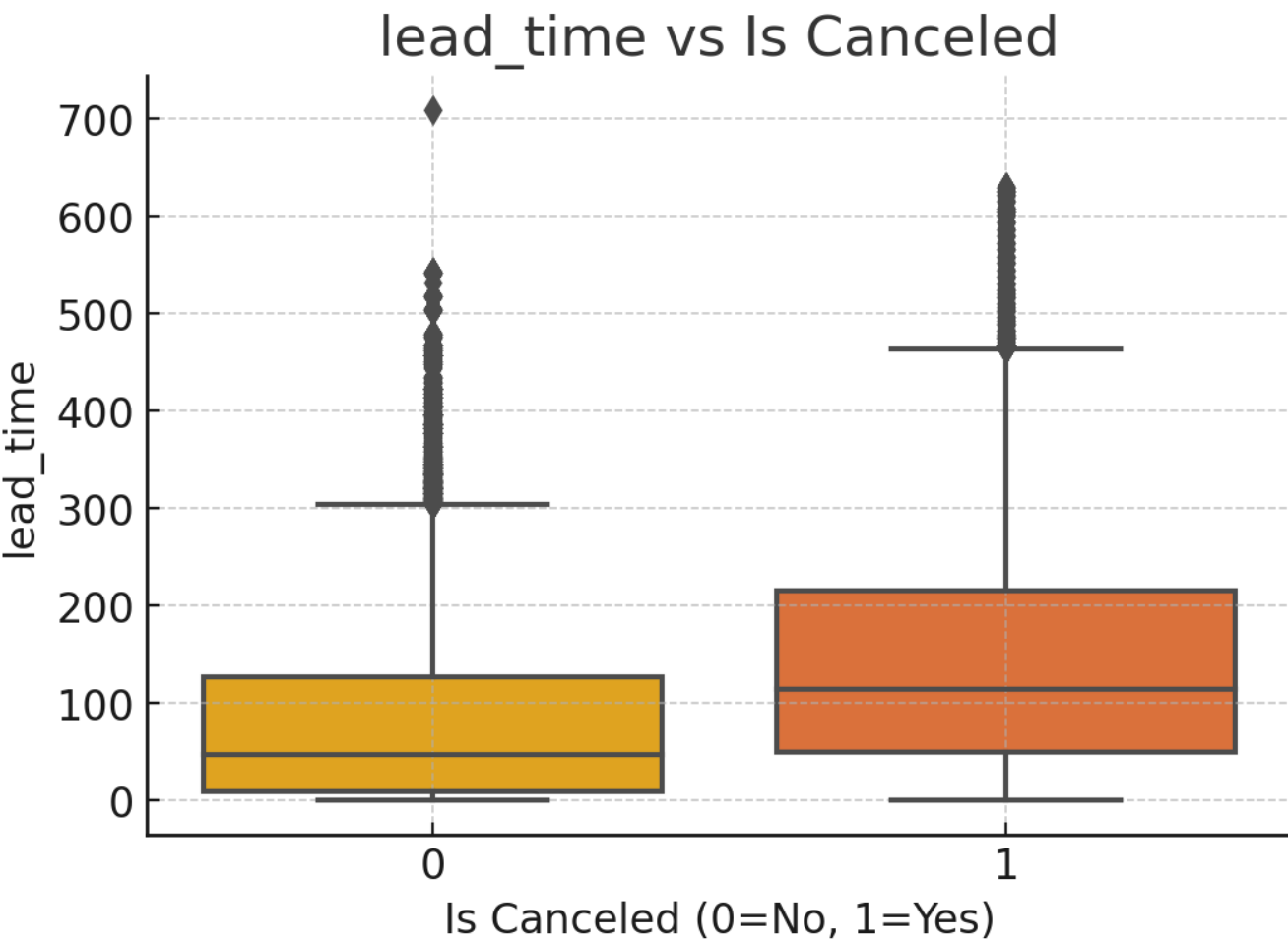
3. Weak Correlations

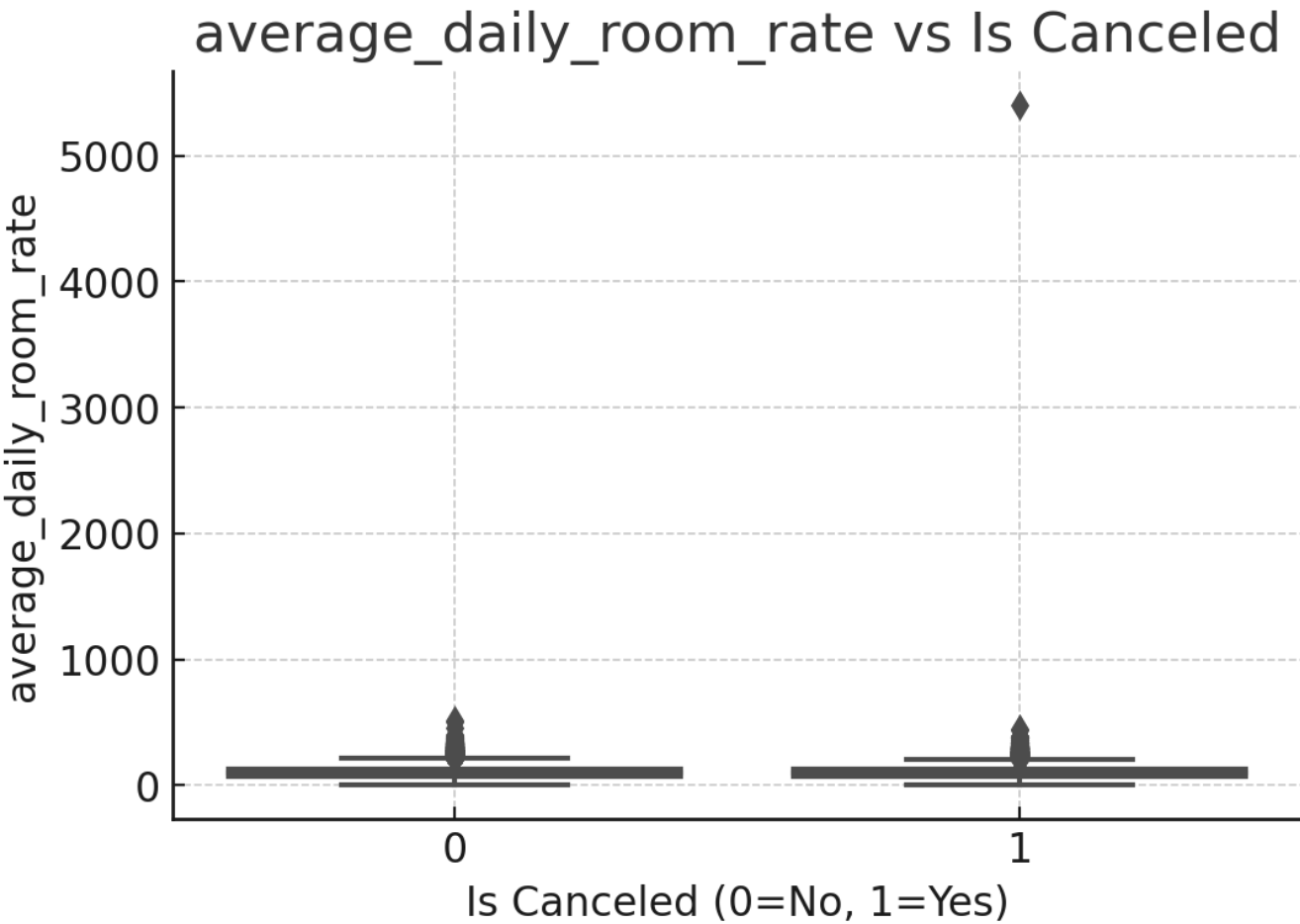
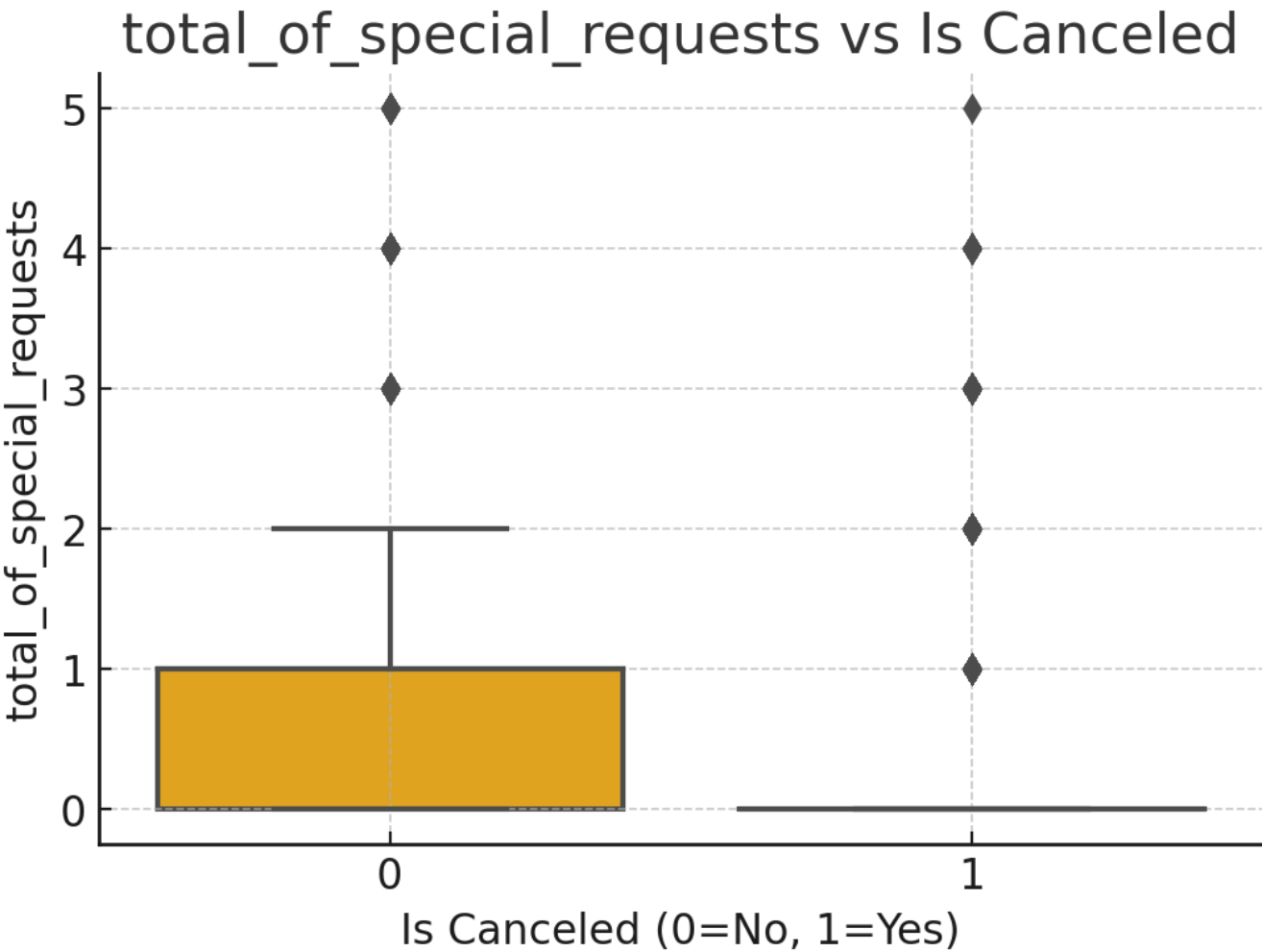
- Most other features have weak linear correlations. This suggests that **categorical interactions** and **non-linear relationships** (e.g., seasonal effects, distribution channels, dynamic pricing) might be critical to predicting cancellations.

While correlation helps highlight linear patterns, many important signals for cancellation may lie within categorical variables and interactions. Thus, advanced modeling techniques (like tree-based methods) or feature engineering (like grouping by arrival month or distribution channel) can be more revealing.

Feature Relationships Insights

To dive deeper, we plot key numerical features against **is_canceled** to see how they influence cancellation probability:





1. Lead Time vs. Cancellation

- Cancellations increase with longer lead times. Guests booking ~6 months or more in advance are more prone to changing or canceling plans.

2. Previous Cancellations vs. Cancellation

- A notable trend: guests with even a single previous cancellation are more likely to cancel again.
- Repeated cancelers (5+ cancellations) almost always show a high cancellation propensity.

3. Special Requests vs. Cancellation

- The relationship is **inversely** correlated. Guests who make 2 or more special requests show lower cancellation rates, possibly indicating stronger commitment or more specific reasons for their stay (e.g., anniversaries, events, conferences).

4. Room Rate vs. Cancellation

- Slight uptick in cancellations for very high rates, indicating price sensitivity.
- Some cancellation behavior might also relate to promotional rates versus standard rates.

Outlier Detection Insights

Boxplots of key numerical features help pinpoint extreme values that could distort analysis:

 Box Plot 1

 Box Plot 2

 Box Plot 3

 Box Plot 4

 Box Plot 5

 Box Plot 6

 Box Plot 7

 Box Plot 8

1. Lead Time

- Some lead times exceed **500 days**, which are genuine but extreme.
- These outliers may heavily influence correlation and model coefficients if not properly handled.

2. Stay Duration

- Outliers over **20 nights** or up to **41 nights** represent extended stays—common in resort settings but unusual for city hotels.

3. Adults

- Some bookings show **0 adults**, which could be data errors or an unconventional input for group travelers.

4. Children & Babies

- Large numbers (5+) might indicate group or family reservations.

- Hotels often have policies limiting maximum occupancy, so these outliers can be legitimate but rare.

5. Previous Cancellations

- Up to **26** cancellations from a single guest suggests repeated booking/cancel patterns, possibly to hold rooms or exploit certain policies.

6. Room Rate

- Outliers exceed **\$1,000/night** (and up to \$5,400). Such luxury bookings have different cancellation dynamics.
- Could also be suite reservations, corporate packages, or erroneous data entries.

Approach:

- **Retain outliers** if they represent real-world scenarios (e.g., early group bookings, luxury reservations).
- **Transform** heavily skewed features (e.g., log transform lead time, room rate) to reduce the impact on model training.
- **Investigate** suspicious values (e.g., 0 adults, extremely large children counts) to confirm data validity.

Key Insights Summary

1. Lead Time is Critical

- Strongest numerical predictor for cancellation. Long lead times permit changes in personal travel plans or re-booking at cheaper rates.

2. Behavioral Patterns

- Guests with **previous cancellations** have a significant propensity to cancel again. Potential strategies include deposit requirements or targeted marketing to reduce frequent cancelers.

3. Guest Commitment Indicators

- **Special requests** and **parking space requirements** correlate with lower cancellation rates, signifying more definite travel plans.

4. Data Anomalies & Outliers

- **High room rates**, extremely long stays, and zero adult bookings may require special handling.
- Legitimate but extreme values (e.g., 500+ day lead times) should be considered carefully, as they can skew model behavior.

5. Seasonality & Booking Channel Effects

- While not directly numeric correlation, the presence of strong seasonal patterns (peak months) and dominant booking channels (Online TA) suggests that combining or engineering these features could enhance predictive power.

Recommendations for Classification Modeling

Given the binary target (**is_canceled**), we suggest a structured approach:

Preprocessing Steps

1. Feature Scaling

- **Normalize** or **standardize** continuous variables like **lead time** and **average daily rate**. This can benefit models sensitive to feature magnitude (e.g., logistic regression, neural networks).

2. Outlier Treatment

- Consider **capping** extremely high room rates or lead times at a certain percentile (e.g., 99th percentile) if those outliers are rare and cause instability in models.
- Alternatively, use **robust models** (e.g., tree-based methods) that are inherently less sensitive to outliers.

3. Feature Engineering

- **Seasonality Indicators**: Create binary or cyclical variables for peak vs. off-peak months.
- **Interaction Terms**: For instance, lead time × (market segment) or lead time × is_repeated_guest, which could capture nuanced behaviors.
- **Aggregated Features**: Distinguish short stays (1-2 nights) from medium (3-5 nights) and long stays (6+ nights) to see if cancellation patterns differ.

4. Handling Imbalance

- Although 37.7% cancellations is not extremely imbalanced, it's still substantial. Use techniques like **class weight adjustments** (in logistic regression, random forests) or oversampling (e.g., **SMOTE**) to refine performance metrics like precision and recall.

Modeling Approaches

1. Baseline Model: Logistic Regression

- Quick to train and interpret, providing insight into which features (e.g., lead time, previous cancellations) are most impactful.

2. Advanced Tree-Based Models

- **Random Forest** or **Gradient Boosting** (XGBoost, LightGBM) handle non-linearities and interactions automatically.
- Typically yield higher accuracy in complex datasets with many categorical variables.

3. Support Vector Machines (SVM)

- Potentially powerful, but can be slower to train on very large datasets.
- May require careful parameter tuning (kernel choice, C parameter) to handle the dataset's size.

4. Neural Networks

- Usually considered if there's sufficient complexity in interactions.
- May be overkill if simpler models already achieve strong performance.

Model Evaluation

1. F1-Score

- Balances **precision** and **recall**, essential if the cost of misclassification (especially false negatives vs. false positives) is significant.

2. ROC-AUC

- Good measure for how well the model distinguishes between canceled vs. not canceled across different probability thresholds.

3. Confusion Matrix

- Helps visualize actual vs. predicted classifications, revealing if the model struggles with false positives (predicting cancellations that don't happen) or false negatives (failing to predict actual cancellations).

4. Stratified Cross-Validation

- Ensures each fold has the same proportion of cancellations vs. non-cancellations, providing a robust performance estimate.

Conclusion

The analysis of this hotel booking dataset reveals that **lead time**, **previous cancellations**, **special requests**, and **room rates** are pivotal to understanding cancellation behavior. On the categorical front, **market segments**, **arrival months**, and **hotel types** exhibit patterns aligning with industry expectations—online travel agents see higher cancellation rates, summer months have more bookings (and possibly cancellations due to changed vacation plans), and city hotels attract different behaviors than resort properties.

By combining robust data preprocessing (handling outliers, skewed distributions) and advanced modeling techniques (tree-based methods, feature engineering), hotels can significantly improve their ability to **anticipate cancellations**. This predictive power translates into more effective **inventory management**, **dynamic pricing**, and targeted **customer engagement strategies**. Ultimately, this leads to increased revenue and a better overall guest experience.

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