Hotel Booking Cancellations — Project Overview

Objective: Predict hotel booking cancellations and identify the main factors that influence cancellations so business stakeholders can reduce revenue loss.

What this notebook contains:

- Data loading and initial checks
- Exploratory Data Analysis (EDA) with visualizations
- Data cleaning and feature engineering
- Model training (Logistic Regression, Random Forest)
- Model evaluation and business recommendations

In [243…

```
import numpy as np
import pandas as pd
import seaborn as sns
```

In [244…

```
df=pd.read_csv("hotel.csv")
```

Data Loading & Description

We load the dataset here. Key notes:

- Source file: `hotel.csv` (raw data snapshot)
- Important columns: `is_canceled` (target), `lead_time` , `adr` (average daily rate), guest counts, arrival date components, deposit_type, market_segment, and customer_type.

understanding the raw columns helps guide cleaning and feature engineering decisions.

In [245…

```
df.head()
```

Out[245…

	hotel	is_canceled	lead_time	arrival_date_year	arrival_date_month	arrival_date_week_nu
0	Resort Hotel	0	342	2015	July	
1	Resort Hotel	0	737	2015	July	
2	Resort Hotel	0	7	2015	July	
3	Resort Hotel	0	13	2015	July	
4	Resort Hotel	0	14	2015	July	

5 rows × 32 columns

In [246…

```
df.shape
```

Out[246…

```
(119390, 32)
```

In [247…

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 119390 entries, 0 to 119389
Data columns (total 32 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_week_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  country                         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  reserved_room_type              119390 non-null  object 
 20  assigned_room_type              119390 non-null  object 
 21  booking_changes                 119390 non-null  int64  
 22  deposit_type                    119390 non-null  object 
 23  agent                           103050 non-null  float64
 24  company                         6797 non-null    float64
 25  days_in_waiting_list            119390 non-null  int64  
 26  customer_type                   119390 non-null  object 
 27  adr                             119390 non-null  float64
 28  required_car_parking_spaces     119390 non-null  int64  
 29  total_of_special_requests       119390 non-null  int64  
 30  reservation_status              119390 non-null  object 
 31  reservation_status_date         119390 non-null  object 
dtypes: float64(4), int64(16), object(12)
memory usage: 29.1+ MB
```

In [248…

```
df.describe()
```

Out[248…

	is_canceled	lead_time	arrival_date_year	arrival_date_week_number	arrival_d
count	119390.000000	119390.000000	119390.000000	119390.000000	
mean	0.370416	104.011416	2016.156554	27.165173	
std	0.482918	106.863097	0.707476	13.605138	
min	0.000000	0.000000	2015.000000	1.000000	
25%	0.000000	18.000000	2016.000000	16.000000	
50%	0.000000	69.000000	2016.000000	28.000000	
75%	1.000000	160.000000	2017.000000	38.000000	
max	1.000000	737.000000	2017.000000	53.000000	

In [249…

```
df['is_canceled'].value_counts(normalize=True)*100
```

Out[249…

```
is_canceled
0    62.958372
1    37.041628
Name: proportion, dtype: float64
```

In [250…

```
df.isnull().sum().sort_values(ascending=False)
```

Out[250…

```
company                           112593
agent                              16340
country                              488
children                               4
arrival_date_month                     0
arrival_date_week_number               0
hotel                                  0
is_canceled                            0
stays_in_weekend_nights                0
arrival_date_day_of_month              0
adults                                 0
stays_in_week_nights                   0
babies                                 0
meal                                   0
lead_time                              0
arrival_date_year                      0
distribution_channel                   0
market_segment                         0
previous_bookings_not_canceled         0
is_repeated_guest                      0
reserved_room_type                     0
assigned_room_type                     0
booking_changes                        0
previous_cancellations                 0
deposit_type                           0
days_in_waiting_list                   0
customer_type                          0
adr                                    0
required_car_parking_spaces            0
total_of_special_requests              0
reservation_status                     0
reservation_status_date                0
dtype: int64
```

Initial EDA — What to look for

Run these checks to get a quick sense of the data:

- `df.head()` shows sample rows and column types
- `df.shape` gives the dataset size (rows × columns)
- `df.info()` shows missing values and data types
- `df.isnull().sum()` highlights columns needing cleaning

In [251…

```
df['children'] = df['children'].fillna(0)
```

Missing Values — Strategy & Rationale

We fill missing values with domain-aware defaults:

- `children` filled with `0` because a missing value usually implies no children recorded
- `country` filled with the mode (most common) to avoid adding rare categories

- `agent` and `company` set to `0` where missing because they are ID fields and `0` indicates 'no agent/company'

In [252…

```
df['country'] = df['country'].fillna(df['country'].mode()[0])
```

In [253…

```
df['agent'] = df['agent'].fillna(0)
df['company'] = df['company'].fillna(0)
```

In [254…

```
df[(df['adults'] + df['children'] + df['babies']) == 0].shape
```

Out[254…

```
(180, 32)
```

In [255…

```
df['hotel'].value_counts()
```

Out[255…

```
hotel
City Hotel      79330
Resort Hotel    40060
Name: count, dtype: int64
```

In [256…

```
df['market_segment'].value_counts()
```

Out[256…

```
market_segment
Online TA        56477
Offline TA/TO    24219
Groups           19811
Direct           12606
Corporate         5295
Complementary      743
Aviation           237
Undefined            2
Name: count, dtype: int64
```

In [257…

```
df['deposit_type'].value_counts()
```

Out[257…

```
deposit_type
No Deposit    104641
Non Refund     14587
Refundable       162
Name: count, dtype: int64
```

Which hotel type has the higher cancellation rate?

We compare cancellation rates between hotel categories using a normalized crosstab and a stacked bar chart. Interpret the bars as the percentage of bookings that were canceled vs. not canceled for each hotel type — this highlights which hotel types are at higher risk.

In [258…

```
pd.crosstab(df['hotel'], df['is_canceled'], normalize='index')*100
```

Out[258...

is_canceled	0	1
hotel		
City Hotel	58.273037	41.726963
Resort Hotel	72.236645	27.763355

In [259...

```
df.corr(numeric_only=True)['is_canceled'].sort_values(ascending=False)*100
```

Out[259...

```
is_canceled                       100.000000
lead_time                          29.312336
previous_cancellations             11.013281
adults                              6.001721
days_in_waiting_list                5.418582
adr                                 4.755660
stays_in_week_nights                2.476463
arrival_date_year                   1.665986
arrival_date_week_number            0.814807
children                            0.503625
stays_in_weekend_nights            -0.179108
arrival_date_day_of_month          -0.613008
babies                             -3.249109
agent                              -4.652945
previous_bookings_not_canceled     -5.735772
company                            -8.299480
is_repeated_guest                  -8.479342
booking_changes                   -14.438099
required_car_parking_spaces       -19.549782
total_of_special_requests         -23.465777
Name: is_canceled, dtype: float64
```

Initial exploratory data analysis (EDA) was performed to:

- Identify missing values and data types
- Detect outliers and unusual records
- Check class balance of the target (`is_canceled`) and other key distributions

These checks guide later cleaning and modeling choices.

Booking counts by hotel type

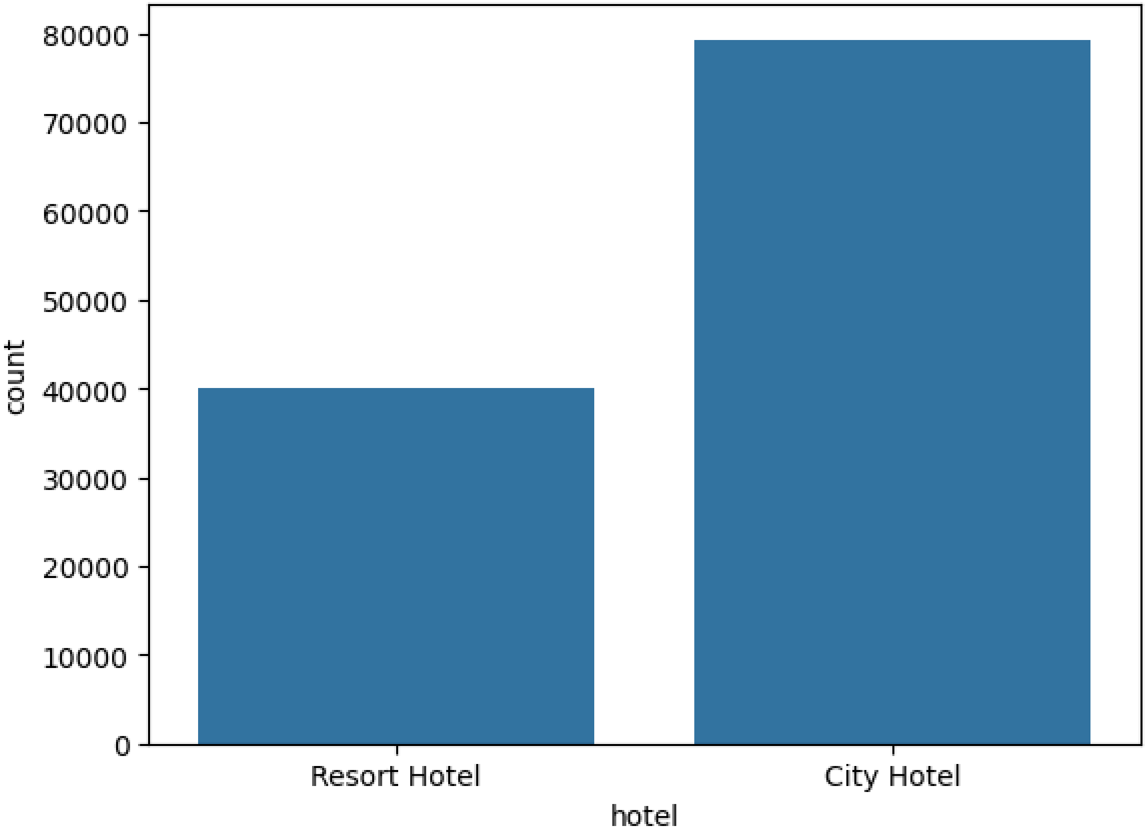
Use the bar chart to see how bookings are distributed across hotel categories (e.g., City vs. Resort). This helps verify whether the dataset is balanced and if sampling adjustments will be needed for modeling.

In [260...

```
sns.countplot(x='hotel', data=df)
```

Out[260...

```
<Axes: xlabel='hotel', ylabel='count'>
```

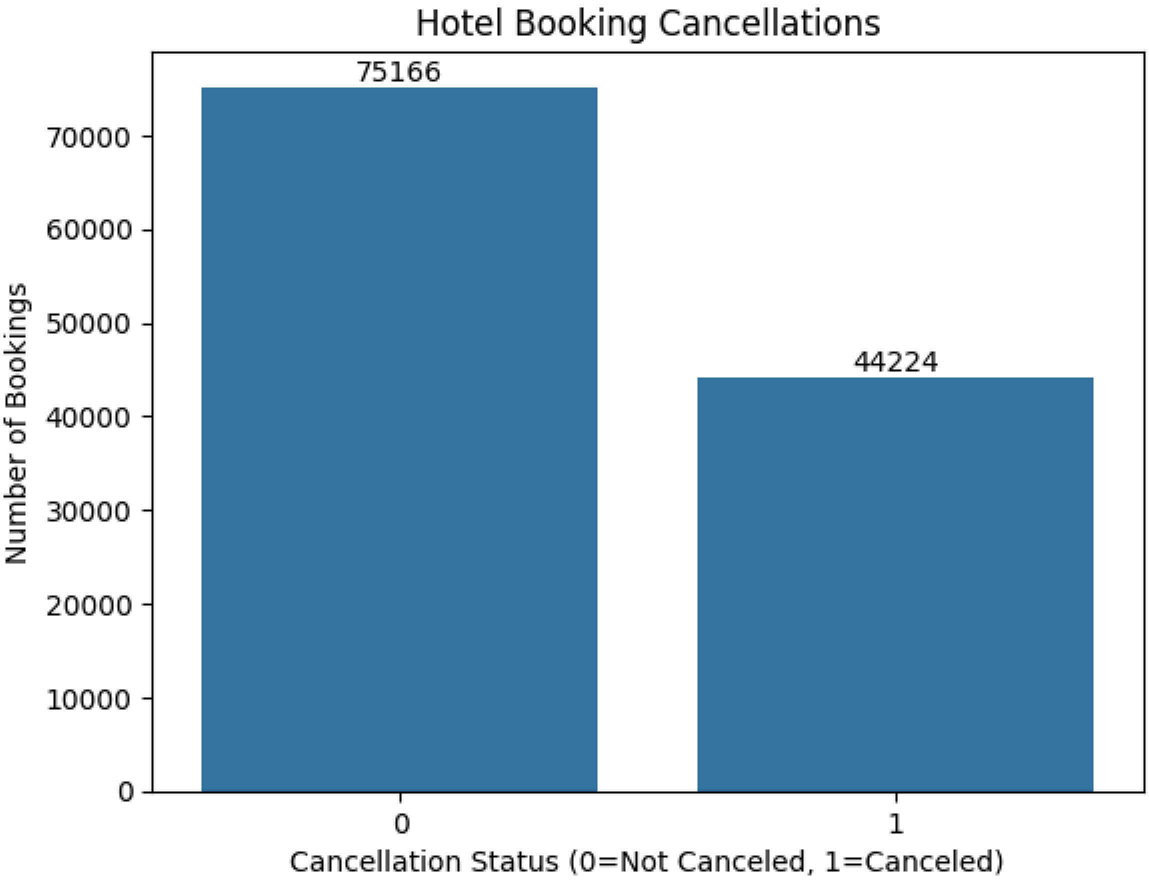


Cancellation rate — overall percentage

Visualize the proportion of canceled vs. non-canceled bookings. Use percentages to assess class imbalance and decide whether to apply class weights or resampling in the modeling step.

In [261…

```
import matplotlib.pyplot as plt
ax=sns.countplot(x='is_canceled', data=df)
plt.xlabel('Cancellation Status (0=Not Canceled, 1=Canceled)')
plt.ylabel('Number of Bookings')
plt.title('Hotel Booking Cancellations')
for container in ax.containers:
    ax.bar_label(container)
plt.show()
```

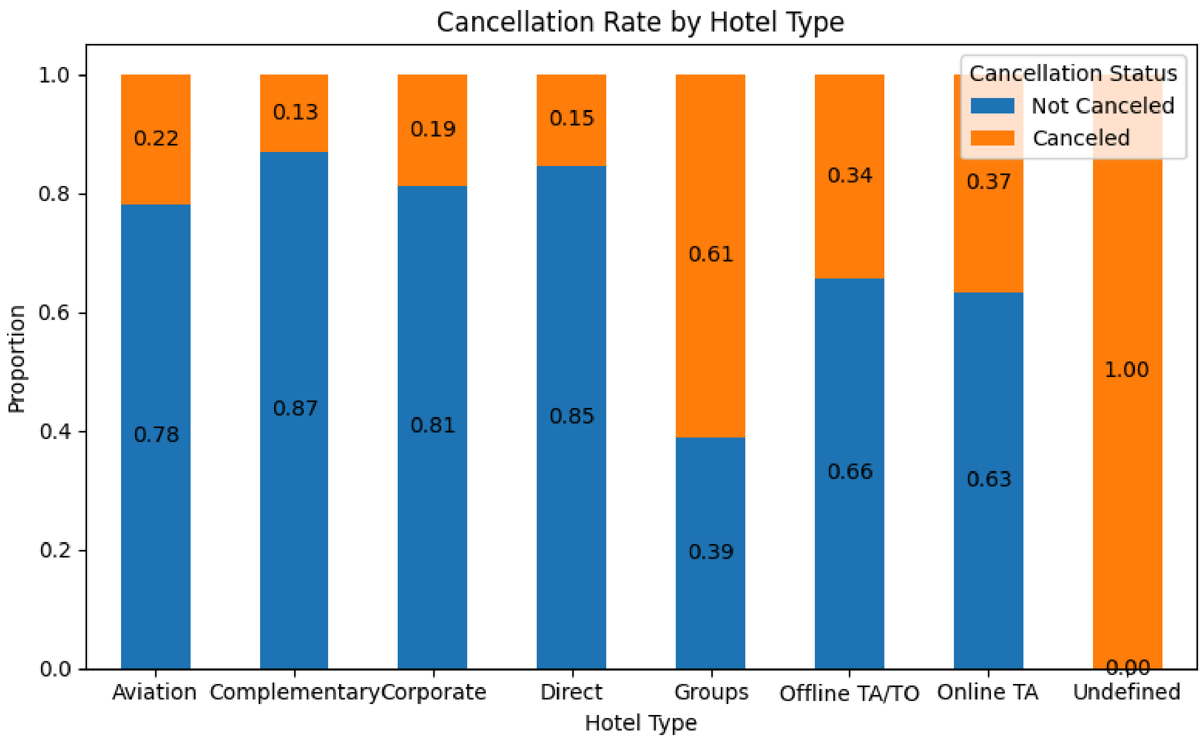


Cancellation rate by hotel type

Compare cancellation percentages by hotel type with a stacked bar chart. This reveals whether certain hotel types have systematically higher cancellation risks and may need targeted actions.

In [262…

```
crosstab_result= pd.crosstab(df['market_segment'], df['is_canceled'], normalize='in
ax=crosstab_result.plot(kind='bar', stacked=True,figsize=(8,5))
plt.xlabel('Hotel Type')
plt.ylabel('Proportion')
plt.title('Cancellation Rate by Hotel Type')
plt.legend(title='Cancellation Status', labels=['Not Canceled', 'Canceled'], loc='u
for container in ax.containers:
    ax.bar_label(container, fmt='%.2f', label_type='center')
plt.xticks(rotation=0)
plt.tight_layout()
plt.show()
```



Does lead time affect cancellation?

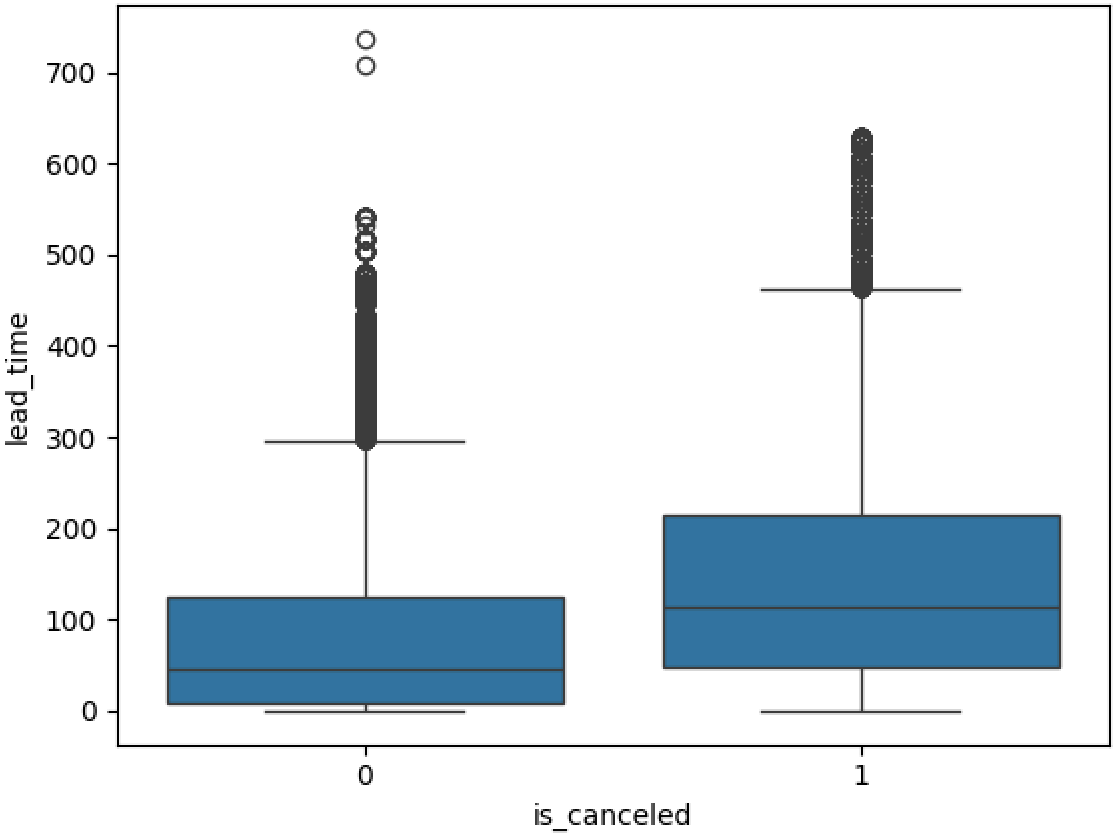
Use a boxplot to compare `lead_time` distributions for canceled vs. non-canceled bookings. Longer lead times can indicate higher cancellation risk — interpret differences in medians and spread.

In [263…

```
sns.boxplot(x='is_canceled', y='lead_time', data=df)
```

Out[263…

```
<Axes: xlabel='is_canceled', ylabel='lead_time'>
```



Outlier handling — lead time and ADR

We observed extreme values in `lead_time` and `adr`. To reduce variance and improve model stability we cap `lead_time` at 180 days and remove unrealistic ADR values (e.g., ADR ≥ 1000).

Keep a record of any removed rows so results remain reproducible.

In [264…

```
df=df[df['lead_time']<=180]
df.shape
```

Out[264…

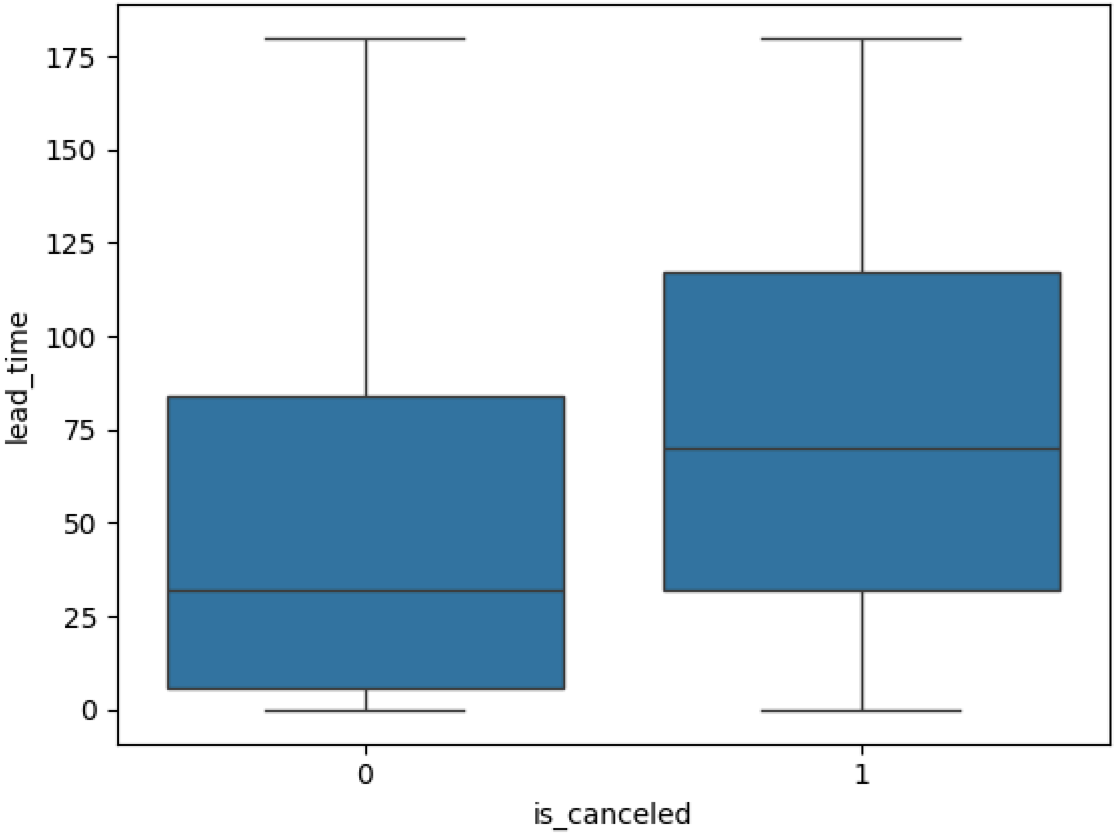
```
(94698, 32)
```

In [265…

```
sns.boxplot(x='is_canceled', y='lead_time', data=df)
```

Out[265…

```
<Axes: xlabel='is_canceled', ylabel='lead_time'>
```



Does deposit type reduce cancellations?

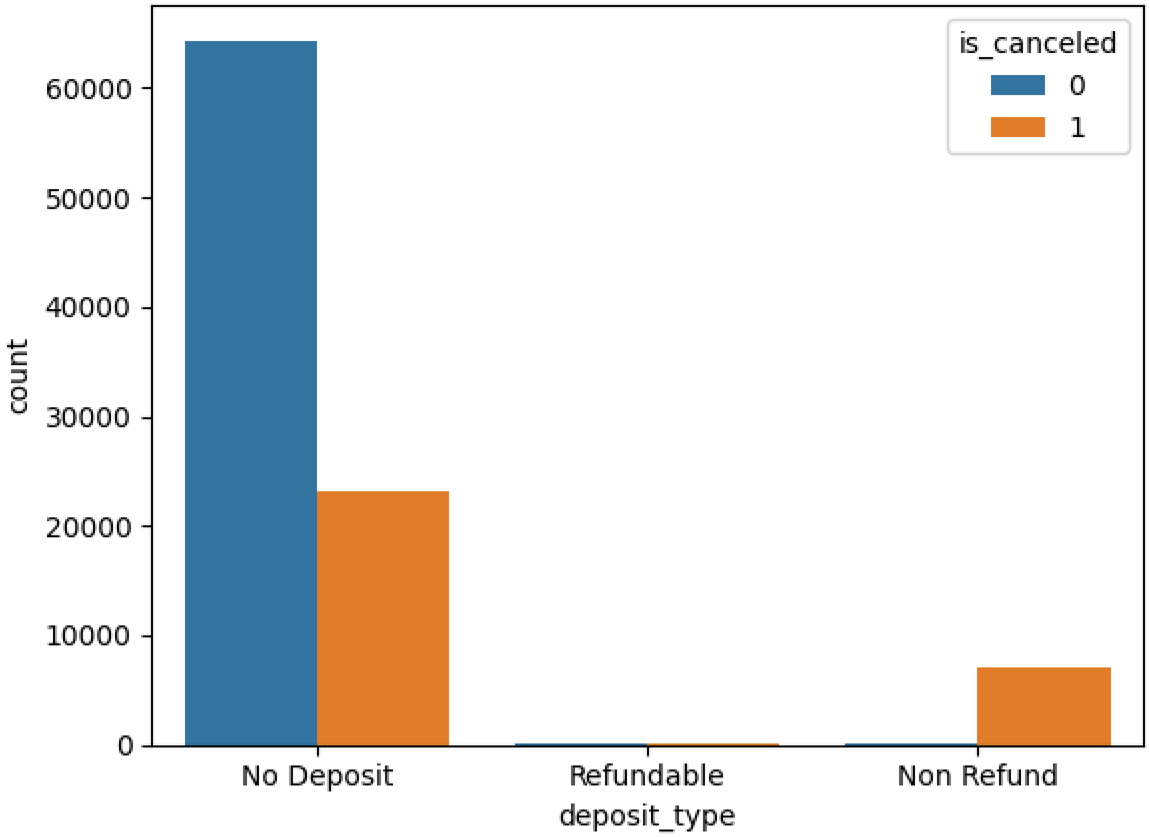
Visualize cancellations by `deposit_type` to see if bookings with deposits are less likely to cancel. Translate results into business action: deposits can be a lever to reduce cancellations if a clear association exists.

In [266…

```
sns.countplot(x='deposit_type', hue='is_canceled', data=df)
```

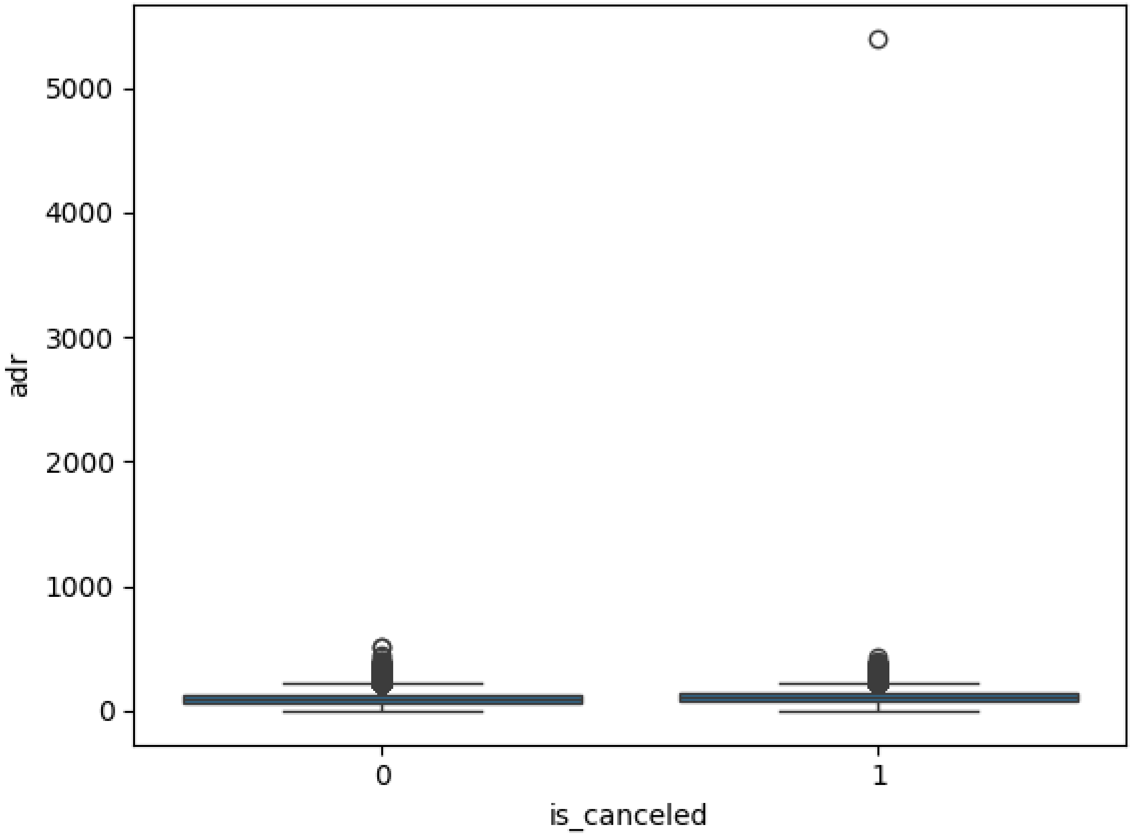
Out[266…

```
<Axes: xlabel='deposit_type', ylabel='count'>
```



```
In [267…: sns.boxplot(x='is_canceled', y='adr', data=df)
```

```
Out[267…: <Axes: xlabel='is_canceled', ylabel='adr'>
```



When do most cancellations occur?

Aggregate cancellations by month to detect seasonality and trends. Use the time-series plot to identify months with unusually high cancellations and consider targeted interventions during those periods.

In [268…

```
df['arrival_date'] = pd.to_datetime(
    df['arrival_date_year'].astype(str) + '-' +
    df['arrival_date_month'] + '-' +
    df['arrival_date_day_of_month'].astype(str)
)
```

In [269…

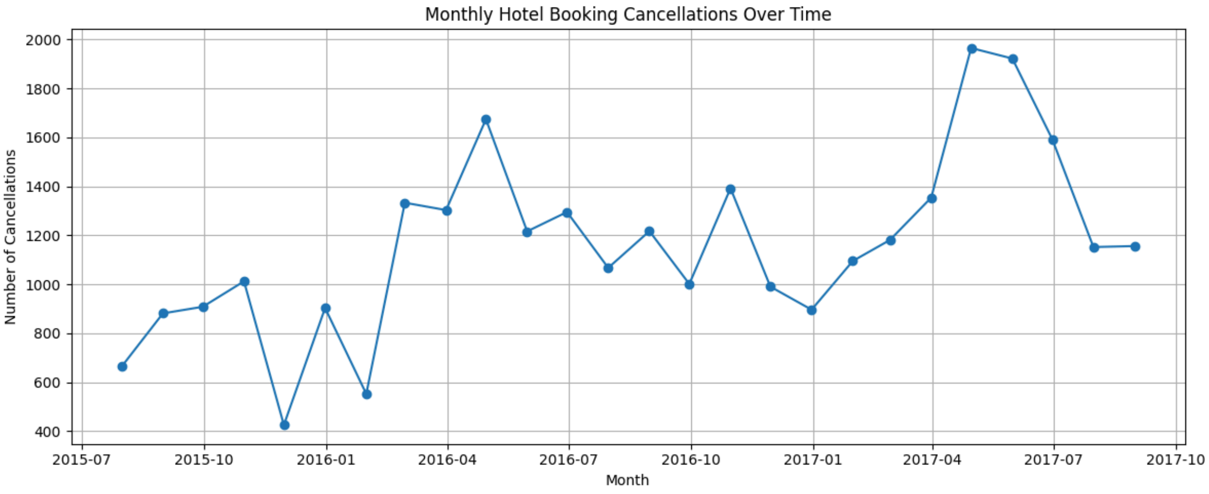
```
canceled_df = df[df['is_canceled'] == 1]
```

In [270…

```
monthly_cancellations = (
    canceled_df
    .groupby(pd.Grouper(key='arrival_date', freq='ME'))
    .size()
    .reset_index(name='cancellation_count')
)
```

In [271…

```
import matplotlib.pyplot as plt

plt.figure(figsize=(12,5))
plt.plot(
    monthly_cancellations['arrival_date'],
    monthly_cancellations['cancellation_count'],
    marker='o'
)

plt.title('Monthly Hotel Booking Cancellations Over Time')
plt.xlabel('Month')
plt.ylabel('Number of Cancellations')
plt.grid(True)
plt.tight_layout()
plt.show()
```



Observed trend and recommendation

The time-series shows an upward trend in cancellations in recent periods. Recommendation: investigate peak months, and test targeted policies (e.g., deposits or promotions) during those high-risk windows.

In [272…

```
invalid_bookings = df[(df['adults'] + df['children'] + df['babies']) == 0]
invalid_bookings.shape
```

Out[272…

```
(169, 33)
```

In [273…

```
df.isnull().sum().sort_values(ascending=False)
```

Out[273…

```
hotel                             0
is_canceled                       0
lead_time                         0
arrival_date_year                 0
arrival_date_month                0
arrival_date_week_number          0
arrival_date_day_of_month         0
stays_in_weekend_nights           0
stays_in_week_nights              0
adults                            0
children                          0
babies                            0
meal                              0
country                           0
market_segment                    0
distribution_channel              0
is_repeated_guest                 0
previous_cancellations            0
previous_bookings_not_canceled    0
reserved_room_type                0
assigned_room_type                0
booking_changes                   0
deposit_type                      0
agent                             0
company                           0
days_in_waiting_list              0
customer_type                     0
adr                               0
required_car_parking_spaces       0
total_of_special_requests         0
reservation_status                0
reservation_status_date           0
arrival_date                      0
dtype: int64
```

In [274…

```
df_clean = df.copy()
```

In [275…

```
df_clean['children'] = df_clean['children'].fillna(0)
```

In [276…

```
df_clean['country'] = df_clean['country'].fillna(df_clean['country'].mode()[0])
```

In [277…

```
df_clean['agent'] = df_clean['agent'].fillna(0)
df_clean['company'] = df_clean['company'].fillna(0)
```

In [278…

```
df_clean = df_clean[
    (df_clean['adults'] + df_clean['children'] + df_clean['babies']) > 0
]
```

Why remove bookings with zero guests?

Bookings with zero guests are invalid records and can distort analyses and model training. Removing them improves data quality and prevents misleading metrics.

In [279…

```
df_clean = df_clean[df_clean['adr'] < 1000]
```

In [280…

```
df_clean['children'] = df_clean['children'].astype(int)
df_clean['agent'] = df_clean['agent'].astype(int)
df_clean['company'] = df_clean['company'].astype(int)
df_clean.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 94528 entries, 2 to 119388
Data columns (total 33 columns):
 #   Column                          Non-Null Count  Dtype         
---  ------                          --------------  -----         
 0   hotel                           94528 non-null  object        
 1   is_canceled                     94528 non-null  int64         
 2   lead_time                       94528 non-null  int64         
 3   arrival_date_year               94528 non-null  int64         
 4   arrival_date_month              94528 non-null  object        
 5   arrival_date_week_number        94528 non-null  int64         
 6   arrival_date_day_of_month       94528 non-null  int64         
 7   stays_in_weekend_nights         94528 non-null  int64         
 8   stays_in_week_nights            94528 non-null  int64         
 9   adults                          94528 non-null  int64         
 10  children                        94528 non-null  int64         
 11  babies                          94528 non-null  int64         
 12  meal                            94528 non-null  object        
 13  country                         94528 non-null  object        
 14  market_segment                  94528 non-null  object        
 15  distribution_channel            94528 non-null  object        
 16  is_repeated_guest               94528 non-null  int64         
 17  previous_cancellations          94528 non-null  int64         
 18  previous_bookings_not_canceled  94528 non-null  int64         
 19  reserved_room_type              94528 non-null  object        
 20  assigned_room_type              94528 non-null  object        
 21  booking_changes                 94528 non-null  int64         
 22  deposit_type                    94528 non-null  object        
 23  agent                           94528 non-null  int64         
 24  company                         94528 non-null  int64         
 25  days_in_waiting_list            94528 non-null  int64         
 26  customer_type                   94528 non-null  object        
 27  adr                             94528 non-null  float64       
 28  required_car_parking_spaces     94528 non-null  int64         
 29  total_of_special_requests       94528 non-null  int64         
 30  reservation_status              94528 non-null  object        
 31  reservation_status_date         94528 non-null  object        
 32  arrival_date                    94528 non-null  datetime64[ns]
dtypes: datetime64[ns](1), float64(1), int64(19), object(12)
memory usage: 24.5+ MB
```

In [281…

```python
df_clean['total_guests'] = (
    df_clean['adults'] + df_clean['children'] + df_clean['babies']
)
df_clean.head()
```

Out[281…

	hotel	is_canceled	lead_time	arrival_date_year	arrival_date_month	arrival_date_week_n
2	Resort Hotel	0	7	2015	July	
3	Resort Hotel	0	13	2015	July	
4	Resort Hotel	0	14	2015	July	
5	Resort Hotel	0	14	2015	July	
6	Resort Hotel	0	0	2015	July	

5 rows × 34 columns

In [282…

```
df_clean['total_nights'] = (
    df_clean['stays_in_week_nights'] +
    df_clean['stays_in_weekend_nights']
)
```

In [283…

```
df_clean = df_clean.drop(
    columns=['reservation_status', 'reservation_status_date']
)
```

Why drop reservation status columns?

reservation_status and **reservation_status_date** reflect post-booking outcomes (future information) and would leak the target into the features. Dropping them prevents target leakage and preserves realistic model performance.

In [284…

```
df_clean.shape
```

Out[284…

```
(94528, 33)
```

In [285…

```
df_clean.to_csv("hotel_bookings_cleaned.csv", index=False)
```

Data Cleaning Summary & Feature Engineering

What we created and why:

- **total_guests** = adults + children + babies — captures booking size
- **total_nights** = stays_in_week_nights + stays_in_weekend_nights — total stay length
- Removed **reservation_status** columns to prevent future-data leakage
- Saved cleaned dataset to **hotel_bookings_cleaned.csv** for reproducibility

Based on EDA, I handled missing values logically, removed invalid bookings, treated pricing outliers, engineered new features, and eliminated data leakage before modeling.

In [286…

```
features = [
    'lead_time', 'adr', 'total_guests', 'total_nights',
    'previous_cancellations', 'booking_changes',
    'days_in_waiting_list', 'required_car_parking_spaces',
    'total_of_special_requests',
    'hotel', 'deposit_type', 'market_segment', 'customer_type'
]

X = df_clean[features]
y = df_clean['is_canceled']
```

In [287…

```
X = pd.get_dummies(X, drop_first=True)
```

Train-test split — preserving class balance

We split the data into training and test sets while preserving the target distribution using *stratify=y*. This ensures the test set reflects the same class proportions as the training data for fair evaluation.

Modeling Pipeline & Preprocessing 🔧

Steps performed before modeling:

- Selected features and encoded categorical variables (one-hot encoding)
- Scaled numerical features with *StandardScaler*
- Used *train_test_split* with stratification to preserve class balance

Model choices:

- **Logistic Regression**: baseline, interpretable
- **Random Forest**: more flexible, can capture non-linear interactions

In [288…

```
from sklearn.model_selection import train_test_split

X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size=0.2, random_state=42, stratify=y
)
```

In [289…

```
from sklearn.preprocessing import StandardScaler
```

In [290…

```
num_cols = [
    'lead_time', 'adr', 'total_guests', 'total_nights',
    'previous_cancellations', 'booking_changes',
    'days_in_waiting_list', 'required_car_parking_spaces',
    'total_of_special_requests'
]
```

```
scaler = StandardScaler()

X_train[num_cols] = scaler.fit_transform(X_train[num_cols])
X_test[num_cols] = scaler.transform(X_test[num_cols])
```

In [291…

```
log_model = LogisticRegression(max_iter=1000)
log_model.fit(X_train, y_train)
```

Out[291…

▾ LogisticRegression

▶ Parameters

Evaluate Logistic Regression

Report accuracy, confusion matrix, and precision/recall/F1 scores to assess classification performance. Consider business implications of different error types (e.g., false negatives vs. false positives) when choosing a final metric.

Evaluation — How to read the numbers 📊

- **Accuracy:** overall fraction of correct predictions (can be misleading for imbalanced data)
- **Confusion matrix:** shows true positives, false positives, true negatives, false negatives — use it to see which error types dominate
- **Precision / Recall / F1-score:** use these for class-specific performance (e.g., recall for canceled bookings if catching cancellations is highest priority)

In [292…

```
from sklearn.metrics import accuracy_score, confusion_matrix, classification_report

print("Logistic Regression Accuracy:", accuracy_score(y_test, y_pred_log)*100)
print(confusion_matrix(y_test, y_pred_log)*1)
print(classification_report(y_test, y_pred_log))
```

```
Logistic Regression Accuracy: 79.1230297260129
[[12137   743]
 [ 3204  2822]]
              precision    recall  f1-score   support

           0       0.79      0.94      0.86     12880
           1       0.79      0.47      0.59      6026

    accuracy                           0.79     18906
   macro avg       0.79      0.71      0.72     18906
weighted avg       0.79      0.79      0.77     18906
```

In [293…

```
from sklearn.ensemble import RandomForestClassifier

rf_model = RandomForestClassifier(
    n_estimators=100,
    random_state=42,
    class_weight='balanced'
)

rf_model.fit(X_train, y_train)

y_pred_rf = rf_model.predict(X_test)
```

Evaluate Random Forest

Use the same metrics as for Logistic Regression to compare performance. Also inspect feature importances to explain which attributes drive predictions and guide business actions.

In [294…

```
print("Random Forest Accuracy:", accuracy_score(y_test, y_pred_rf))
print(confusion_matrix(y_test, y_pred_rf))
print(classification_report(y_test, y_pred_rf))
```

```
Random Forest Accuracy: 0.8351845974822808
[[11667  1213]
 [ 1903  4123]]
              precision    recall  f1-score   support

           0       0.86      0.91      0.88     12880
           1       0.77      0.68      0.73      6026

    accuracy                           0.84     18906
   macro avg       0.82      0.80      0.80     18906
weighted avg       0.83      0.84      0.83     18906
```

In [295…

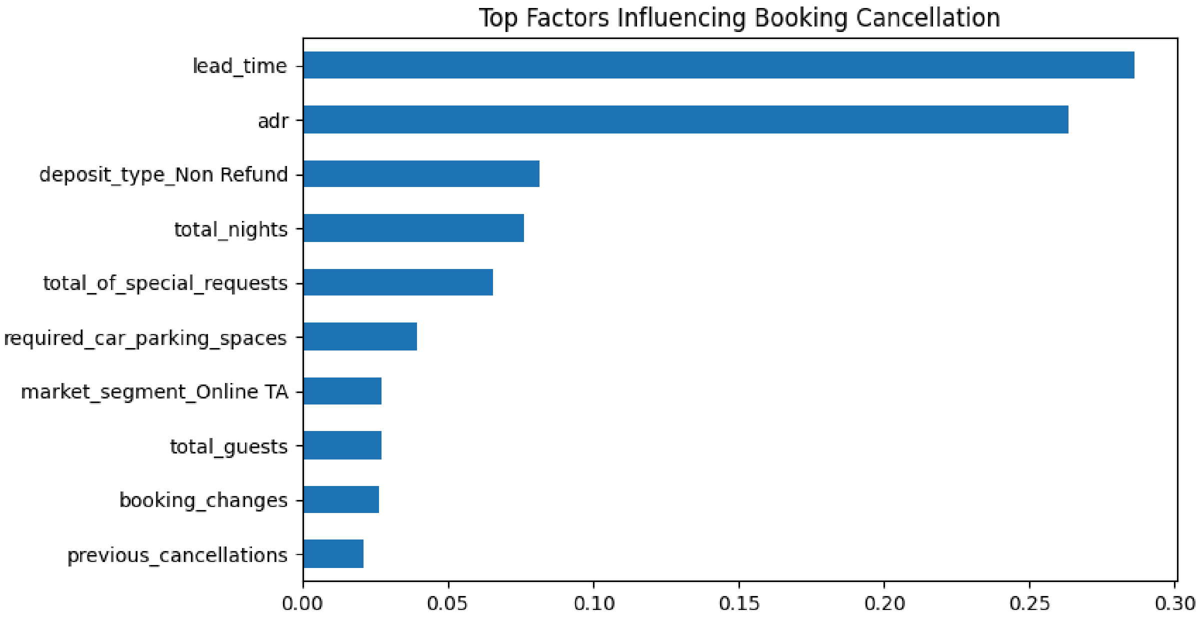
```
feature_importance = pd.Series(
    rf_model.feature_importances_,
    index=X.columns
).sort_values(ascending=False)

feature_importance.head(10)
```

Out[295…

```
lead_time                         0.286416
adr                               0.263682
deposit_type_Non Refund           0.081557
total_nights                      0.076019
total_of_special_requests         0.065497
required_car_parking_spaces       0.039483
market_segment_Online TA          0.027362
total_guests                      0.027258
booking_changes                   0.026507
previous_cancellations            0.020995
dtype: float64
```

In [296…

```
feature_importance.head(10).plot(
    kind='barh', figsize=(8,5)
)
plt.title("Top Factors Influencing Booking Cancellation")
plt.gca().invert_yaxis()
plt.show()
```



Conclusion & Recommendations

Summary: Random Forest performed better than Logistic Regression in our experiments. The most influential features for cancellations were `lead_time`, `deposit_type`, and `total_of_special_requests`.

Business recommendations:

- **Require deposits** for bookings deemed high-risk to reduce no-shows.
- **Use dynamic pricing and targeted offers** during months with higher cancellation rates.
- **Monitor long lead-time bookings** and consider flexible policies or incentives to reduce cancellations.