▯ Hotel Bookings Analysis

▯ Step 1: Title & Introduction

▯ Hotel Bookings Analysis

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Dataset Source: Hotel Bookings Dataset: https://www.kaggle.com/code/niteshyadav3103/hotel-booking-prediction-99-5-acc/input

▯ Project Overview

▯ Project Summary:

This project focuses on analyzing hotel bookings data to uncover key business insights. Using **Python for data preprocessing and visualization**, the project provides a detailed overview of **revenue trends, booking patterns, and cancellation rates**.

▯ Key Objectives:

✔ **Understand booking behavior** across different hotels
✔ **Analyze revenue drivers** using Average Daily Rate (ADR)
✔ **Identify seasonal trends** to optimize pricing strategies
✔ **Explore cancellation rates** and their impact on revenue
✔ **Visualize key metrics** with a professional Power BI dashboard

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▯ Steps Involved:

▯ **Step 1:** Data Loading & Cleaning
▯ **Step 2:** Exploratory Data Analysis (EDA)
▯ **Step 3:** Data Visualization in Python

Step 2: Importing Libraries and Loading the Dataset

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

from google.colab import drive
drive.mount('/content/drive')
df = pd.read_csv('/content/drive/My Drive/Data
Sets/hotel_bookings.csv')
print(df.head())

Mounted at /content/drive
          hotel  is_canceled  lead_time  arrival_date_year
arrival_date_month  \
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

   arrival_date_week_number  arrival_date_day_of_month  \
0                        27                          1
1                        27                          1
2                        27                          1
3                        27                          1
4                        27                          1

   stays_in_weekend_nights  stays_in_week_nights  adults  ...
deposit_type  \
0                        0                     0       2  ...    No
Deposit
1                        0                     0       2  ...    No
Deposit
2                        0                     1       1  ...    No
Deposit
3                        0                     1       1  ...    No
Deposit
4                        0                     2       2  ...    No
Deposit

   agent company days_in_waiting_list customer_type   adr  \
0     NaN      NaN                     0      Transient   0.0
1     NaN      NaN                     0      Transient   0.0
2     NaN      NaN                     0      Transient  75.0
3   304.0      NaN                     0      Transient  75.0
4   240.0      NaN                     0      Transient  98.0

   required_car_parking_spaces  total_of_special_requests
reservation_status  \
0                            0                          0
Check-Out
1                            0                          0
Check-Out
2                            0                          0
Check-Out
3                            0                          0
Check-Out
4                            0                          1
Check-Out

  reservation_status_date
0              2015-07-01
1              2015-07-01
2              2015-07-02
3              2015-07-02
4              2015-07-03

[5 rows x 32 columns]
```

Note: Some the output of notebook does not present the complete output, therefore we can increase the limit of columns view and row view by using these commands:

```
pd.set_option('display.max_columns', None) # this is to display all
the columns in the dataframe
pd.set_option('display.max_rows', None) # this is to display all the
rows in the dataframe

# hide all warnings runtime
import warnings
warnings.filterwarnings('ignore')
```

Step 3: Understanding the Dataset

```
# Display the first few rows
df.head()

{"type":"dataframe","variable_name":"df"}

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
```

# Observations

1. There are 119390 rows and 32 columns in the dataset
2. The columns are of different data types
3. The columns in the datasets are:
    - 'hotel', 'is_canceled', 'lead_time', 'arrival_date_year', 'arrival_date_month', 'arrival_date_week_number', 'arrival_date_day_of_month', 'stays_in_weekend_nights', 'stays_in_week_nights', 'adults', 'children', 'babies', 'meal', 'country', 'market_segment', 'distribution_channel', 'is_repeated_guest',

'previous_cancellations', 'previous_bookings_not_canceled', 'reserved_room_type', 'assigned_room_type', 'booking_changes', 'deposit_type', 'agent', 'company', 'days_in_waiting_list', 'customer_type', 'adr', 'required_car_parking_spaces', 'total_of_special_requests', 'reservation_status', 'reservation_status_date',

4. There are some missing values in the dataset which we will read in details and deal later on in the notebook.

```
df.sample(50)

{"type":"dataframe"}
```

- `df.sample(50)` gives us whole picture or idea about data.

```
df.columns

Index(['hotel', 'is_canceled', 'lead_time', 'arrival_date_year',
       'arrival_date_month', 'arrival_date_week_number',
       'arrival_date_day_of_month', 'stays_in_weekend_nights',
       'stays_in_week_nights', 'adults', 'children', 'babies', 'meal',
       'country', 'market_segment', 'distribution_channel',
       'is_repeated_guest', 'previous_cancellations',
       'previous_bookings_not_canceled', 'reserved_room_type',
       'assigned_room_type', 'booking_changes', 'deposit_type',
'agent',
       'company', 'days_in_waiting_list', 'customer_type', 'adr',
       'required_car_parking_spaces', 'total_of_special_requests',
       'reservation_status', 'reservation_status_date'],
      dtype='object')
```

- let's see the exact column names which can be easily copied later

```
# Descriptive statistics
df.describe(include='all')

{"type":"dataframe"}
```

- `describe(include='all')` gives statistical insights for both numeric and categorical columns.

```
# Define a mapping for meal codes to their full forms
meal_mapping = {
    "BB": "Bed and Breakfast",
    "FB": "Full Board",
    "HB": "Half Board",
    "SC": "Self Catering",
    "Undefined": "Undefined"
}

# Create a new column with the Meal plan names
df['Meal'] = df['meal'].map(meal_mapping)
```

```
# Display the updated DataFrame
print(df[['meal', 'Meal']].head())

  meal                 Meal
0   BB  Bed and Breakfast
1   BB  Bed and Breakfast
2   BB  Bed and Breakfast
3   BB  Bed and Breakfast
4   BB  Bed and Breakfast
```

Explanation:

1. **Mapping Dictionary**: A dictionary is used to map the meal codes to their corresponding full descriptions.
2. **`map` Function**: The `map` method applies the dictionary mapping to each value in the `meal` column.
3. **New Column**: A new column (`Meal`) is created to store the full forms, leaving the original `meal` column unchanged.

After running this code, our DataFrame will have a new column called `Meal` with descriptive values like `"Bed and Breakfast"`, `"Full Board"`, etc.

```
df["country"].unique()

array(['PRT', 'GBR', 'USA', 'ESP', 'IRL', 'FRA', nan, 'ROU', 'NOR',
'OMN',
       'ARG', 'POL', 'DEU', 'BEL', 'CHE', 'CN', 'GRC', 'ITA', 'NLD',
       'DNK', 'RUS', 'SWE', 'AUS', 'EST', 'CZE', 'BRA', 'FIN', 'MOZ',
       'BWA', 'LUX', 'SVN', 'ALB', 'IND', 'CHN', 'MEX', 'MAR', 'UKR',
       'SMR', 'LVA', 'PRI', 'SRB', 'CHL', 'AUT', 'BLR', 'LTU', 'TUR',
       'ZAF', 'AGO', 'ISR', 'CYM', 'ZMB', 'CPV', 'ZWE', 'DZA', 'KOR',
       'CRI', 'HUN', 'ARE', 'TUN', 'JAM', 'HRV', 'HKG', 'IRN', 'GEO',
       'AND', 'GIB', 'URY', 'JEY', 'CAF', 'CYP', 'COL', 'GGY', 'KWT',
       'NGA', 'MDV', 'VEN', 'SVK', 'FJI', 'KAZ', 'PAK', 'IDN', 'LBN',
       'PHL', 'SEN', 'SYC', 'AZE', 'BHR', 'NZL', 'THA', 'DOM', 'MKD',
       'MYS', 'ARM', 'JPN', 'LKA', 'CUB', 'CMR', 'BIH', 'MUS', 'COM',
       'SUR', 'UGA', 'BGR', 'CIV', 'JOR', 'SYR', 'SGP', 'BDI', 'SAU',
       'VNM', 'PLW', 'QAT', 'EGY', 'PER', 'MLT', 'MWI', 'ECU', 'MDG',
       'ISL', 'UZB', 'NPL', 'BHS', 'MAC', 'TGO', 'TWN', 'DJI', 'STP',
       'KNA', 'ETH', 'IRQ', 'HND', 'RWA', 'KHM', 'MCO', 'BGD', 'IMN',
       'TJK', 'NIC', 'BEN', 'VGB', 'TZA', 'GAB', 'GHA', 'TMP', 'GLP',
       'KEN', 'LIE', 'GNB', 'MNE', 'UMI', 'MYT', 'FRO', 'MMR', 'PAN',
       'BFA', 'LBY', 'MLI', 'NAM', 'BOL', 'PRY', 'BRB', 'ABW', 'AIA',
       'SLV', 'DMA', 'PYF', 'GUY', 'LCA', 'ATA', 'GTM', 'ASM', 'MRT',
       'NCL', 'KIR', 'SDN', 'ATF', 'SLE', 'LAO'], dtype=object)

# Dictionary mapping country codes to country names
country_mapping = {
    'PRT': 'Portugal', 'GBR': 'United Kingdom', 'USA': 'United
```

```
States', 'ESP': 'Spain',
    'IRL': 'Ireland', 'FRA': 'France', 'ROU': 'Romania', 'NOR':
'Norway', 'OMN': 'Oman',
    'ARG': 'Argentina', 'POL': 'Poland', 'DEU': 'Germany', 'BEL':
'Belgium', 'CHE': 'Switzerland',
    'CN': 'China', 'GRC': 'Greece', 'ITA': 'Italy', 'NLD':
'Netherlands', 'DNK': 'Denmark',
    'RUS': 'Russia', 'SWE': 'Sweden', 'AUS': 'Australia', 'EST':
'Estonia', 'CZE': 'Czech Republic',
    'BRA': 'Brazil', 'FIN': 'Finland', 'MOZ': 'Mozambique', 'BWA':
'Botswana', 'LUX': 'Luxembourg',
    'SVN': 'Slovenia', 'ALB': 'Albania', 'IND': 'India', 'CHN':
'China', 'MEX': 'Mexico',
    'MAR': 'Morocco', 'UKR': 'Ukraine', 'SMR': 'San Marino', 'LVA':
'Latvia', 'PRI': 'Puerto Rico',
    'SRB': 'Serbia', 'CHL': 'Chile', 'AUT': 'Austria', 'BLR':
'Belarus', 'LTU': 'Lithuania',
    'TUR': 'Turkey', 'ZAF': 'South Africa', 'AGO': 'Angola', 'ISR':
'Israel', 'CYM': 'Cayman Islands',
    'ZMB': 'Zambia', 'CPV': 'Cape Verde', 'ZWE': 'Zimbabwe', 'DZA':
'Algeria', 'KOR': 'South Korea',
    'CRI': 'Costa Rica', 'HUN': 'Hungary', 'ARE': 'United Arab
Emirates', 'TUN': 'Tunisia',
    'JAM': 'Jamaica', 'HRV': 'Croatia', 'HKG': 'Hong Kong', 'IRN':
'Iran', 'GEO': 'Georgia',
    'AND': 'Andorra', 'GIB': 'Gibraltar', 'URY': 'Uruguay', 'JEY':
'Jersey', 'CAF': 'Central African Republic',
    'CYP': 'Cyprus', 'COL': 'Colombia', 'GGY': 'Guernsey', 'KWT':
'Kuwait', 'NGA': 'Nigeria',
    'MDV': 'Maldives', 'VEN': 'Venezuela', 'SVK': 'Slovakia', 'FJI':
'Fiji', 'KAZ': 'Kazakhstan',
    'PAK': 'Pakistan', 'IDN': 'Indonesia', 'LBN': 'Lebanon', 'PHL':
'Philippines', 'SEN': 'Senegal',
    'SYC': 'Seychelles', 'AZE': 'Azerbaijan', 'BHR': 'Bahrain', 'NZL':
'New Zealand', 'THA': 'Thailand',
    'DOM': 'Dominican Republic', 'MKD': 'North Macedonia', 'MYS':
'Malaysia', 'ARM': 'Armenia',
    'JPN': 'Japan', 'LKA': 'Sri Lanka', 'CUB': 'Cuba', 'CMR':
'Cameroon', 'BIH': 'Bosnia and Herzegovina',
    'MUS': 'Mauritius', 'COM': 'Comoros', 'SUR': 'Suriname', 'UGA':
'Uganda', 'BGR': 'Bulgaria',
    'CIV': 'Ivory Coast', 'JOR': 'Jordan', 'SYR': 'Syria', 'SGP':
'Singapore', 'BDI': 'Burundi',
    'SAU': 'Saudi Arabia', 'VNM': 'Vietnam', 'PLW': 'Palau', 'QAT':
'Qatar', 'EGY': 'Egypt',
    'PER': 'Peru', 'MLT': 'Malta', 'MWI': 'Malawi', 'ECU': 'Ecuador',
'MDG': 'Madagascar',
    'ISL': 'Iceland', 'UZB': 'Uzbekistan', 'NPL': 'Nepal', 'BHS':
'Bahamas', 'MAC': 'Macau',
    'TGO': 'Togo', 'TWN': 'Taiwan', 'DJI': 'Djibouti', 'STP': 'Sao
Tome and Principe', 'KNA': 'Saint Kitts and Nevis',
    'ETH': 'Ethiopia', 'IRQ': 'Iraq', 'HND': 'Honduras', 'RWA':
'Rwanda', 'KHM': 'Cambodia',
    'MCO': 'Monaco', 'BGD': 'Bangladesh', 'IMN': 'Isle of Man', 'TJK':
'Tajikistan', 'NIC': 'Nicaragua',
    'BEN': 'Benin', 'VGB': 'British Virgin Islands', 'TZA':
'Tanzania', 'GAB': 'Gabon',
    'GHA': 'Ghana', 'TMP': 'East Timor', 'GLP': 'Guadeloupe', 'KEN':
'Kenya', 'LIE': 'Liechtenstein',
    'GNB': 'Guinea-Bissau', 'MNE': 'Montenegro', 'UMI': 'United States
Minor Outlying Islands',
    'MYT': 'Mayotte', 'FRO': 'Faroe Islands', 'MMR': 'Myanmar', 'PAN':
'Panama', 'BFA': 'Burkina Faso',
    'LBY': 'Libya', 'MLI': 'Mali', 'NAM': 'Namibia', 'BOL': 'Bolivia',
'PRY': 'Paraguay',
    'BRB': 'Barbados', 'ABW': 'Aruba', 'AIA': 'Anguilla', 'SLV': 'El
Salvador', 'DMA': 'Dominica',
    'PYF': 'French Polynesia', 'GUY': 'Guyana', 'LCA': 'Saint Lucia',
'ATA': 'Antarctica',
    'GTM': 'Guatemala', 'ASM': 'American Samoa', 'MRT': 'Mauritania',
'NCL': 'New Caledonia',
    'KIR': 'Kiribati', 'SDN': 'Sudan', 'ATF': 'French Southern
Territories', 'SLE': 'Sierra Leone',
    'LAO': 'Laos'
    # Add more if required
}

# Map the country codes to names
df['Country'] = df['country'].map(country_mapping)

# Display the updated DataFrame
print(df[['country', 'Country']].head())
```

```
  country         Country
0     PRT        Portugal
1     PRT        Portugal
2     GBR  United Kingdom
3     GBR  United Kingdom
4     GBR  United Kingdom
```

Explanation:

1. **`country_mapping` Dictionary**: This dictionary contains the mapping of country codes to their respective country names.
2. **`map` Method**: The `.map()` function applies the dictionary to the `country` column, replacing codes with full names.
3. **New Column**: A new column (`Country`) is created with the full country names.

```
df = df.drop(columns=['meal', 'country'])
```

We drop the meal and country columns becaue we ceate Meal and Country new columns with full names instead of codes names

```
df.rename(columns={'adr': 'average_daily_rate'}, inplace=True)
```

We Rename column to make it more descriptive and standardized.

```
# Check for missing values
df.isnull().sum().sort_values(ascending=False) # this will show the 
number of null values in each column in descending order
```

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

- `df.isnull().sum().sort_values(ascending=False)` identifies missing values in each column.

```
(df.isnull().sum() / len(df) * 100).sort_values(ascending=False) # 
this will show the percentage of null values in each column
```

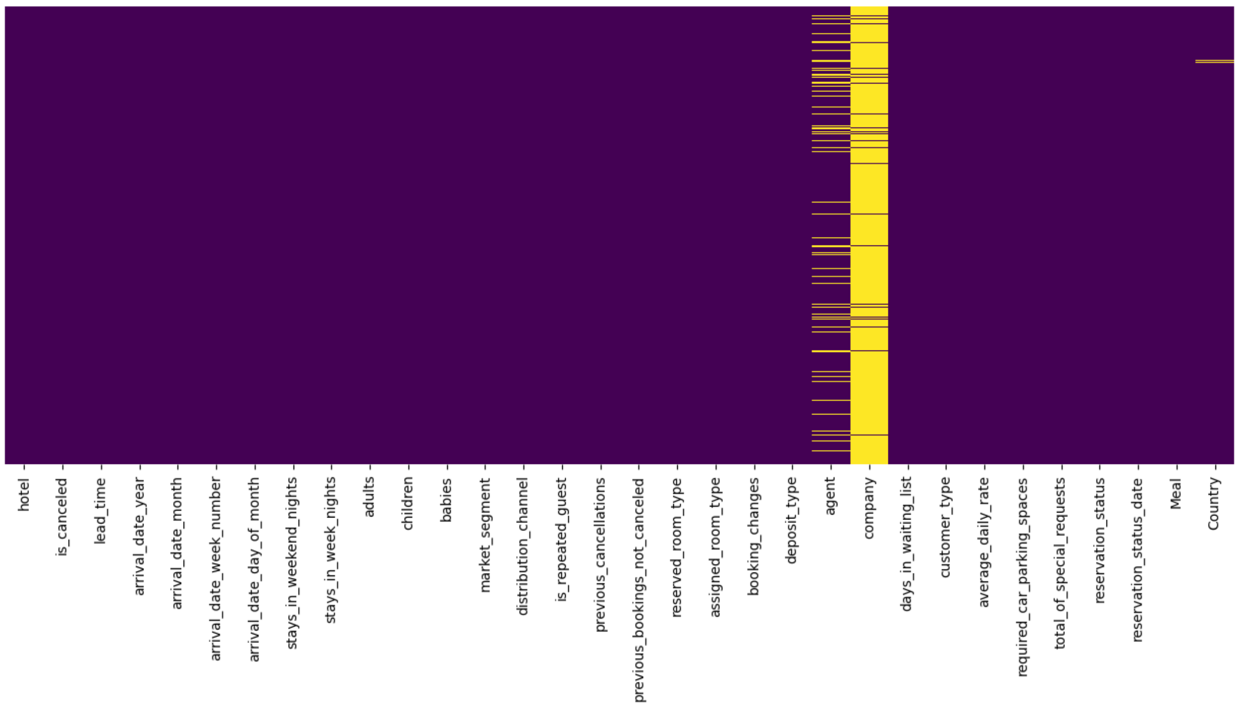
```
company                           94.306893
agent                             13.686238
Country                            0.408744
children                           0.003350
reserved_room_type                 0.000000
Meal                               0.000000
reservation_status_date            0.000000
reservation_status                 0.000000
total_of_special_requests          0.000000
required_car_parking_spaces        0.000000
average_daily_rate                 0.000000
customer_type                      0.000000
days_in_waiting_list               0.000000
deposit_type                       0.000000
booking_changes                    0.000000
assigned_room_type                 0.000000
hotel                              0.000000
is_canceled                        0.000000
previous_cancellations             0.000000
is_repeated_guest                  0.000000
distribution_channel               0.000000
market_segment                     0.000000
babies                             0.000000
adults                             0.000000
stays_in_week_nights               0.000000
stays_in_weekend_nights            0.000000
arrival_date_day_of_month          0.000000
arrival_date_week_number           0.000000
arrival_date_month                 0.000000
arrival_date_year                  0.000000
lead_time                          0.000000
previous_bookings_not_canceled     0.000000
dtype: float64
```

## Observations:

- We have 112593 missing values in the `'Company'` column, which is 94.30% of the total values in the column.
- We have 16340 missing values in the `'Agent  '` column, which is 13.68% of the total values in the column.
- We have 488 missing values in the `'Country'` columns, which is 0.40% of the total values in the column.
- We have 4 missing values in the `'Children'` column, which is 0.003350% of the total values in the column.
- Let's plot the missing values in the dataset

```
# make a figure size
plt.figure(figsize=(16, 6))
#plot the null values in each column
```

```
sns.heatmap(df.isnull(), yticklabels=False, cbar=False,
cmap='viridis') # this will show the heatmap of null values in the
dataframe

<Axes: >
```



#Step 4: Handling Missing Values

```
# Fill missing values in 'children' and 'agent' with 0 (assuming 0
means no children/agent)
df['children'].fillna(0, inplace=True)
df['agent'].fillna(0, inplace=True)

# Handle missing values in the 'company' column
df['company'] = df['company'].fillna('Unknown')


# Fill missing values in 'country' with 'Unknown'
df['Country'].fillna('Unknown', inplace=True)
```

Explanation:

- Missing values in `children` and `agent` are replaced with 0 for practicality.
- The `company` column is dropped since most of its data is missing.
- Missing `country` values are replaced with `'Unknown'`.

#Step 5: Converting Data Types

```
# Convert 'reservation_status_date' to datetime
df['reservation_status_date'] =
pd.to_datetime(df['reservation_status_date'])

# Convert 'agent' to integer for simplicity
df['agent'] = df['agent'].astype(int)
```

Explanation:

- The `reservation_status_date` column is converted to `datetime` for better handling of dates.
- The `agent` column is converted to `int` for easier analysis.

```
# let's check for number of duplicates
for col in df.columns:
    print(f"Number of duplicates in {col} column are:
{df[col].duplicated().sum()}")

Number of duplicates in hotel column are: 119388
Number of duplicates in is_canceled column are: 119388
Number of duplicates in lead_time column are: 118911
Number of duplicates in arrival_date_year column are: 119387
Number of duplicates in arrival_date_month column are: 119378
Number of duplicates in arrival_date_week_number column are: 119337
Number of duplicates in arrival_date_day_of_month column are: 119359
Number of duplicates in stays_in_weekend_nights column are: 119373
Number of duplicates in stays_in_week_nights column are: 119355
Number of duplicates in adults column are: 119376
Number of duplicates in children column are: 119385
Number of duplicates in babies column are: 119385
Number of duplicates in market_segment column are: 119382
Number of duplicates in distribution_channel column are: 119385
Number of duplicates in is_repeated_guest column are: 119388
Number of duplicates in previous_cancellations column are: 119375
Number of duplicates in previous_bookings_not_canceled column are:
119317
Number of duplicates in reserved_room_type column are: 119380
Number of duplicates in assigned_room_type column are: 119378
Number of duplicates in booking_changes column are: 119369
Number of duplicates in deposit_type column are: 119387
Number of duplicates in agent column are: 119056
Number of duplicates in company column are: 119037
Number of duplicates in days_in_waiting_list column are: 119262
Number of duplicates in customer_type column are: 119386
Number of duplicates in average_daily_rate column are: 110511
Number of duplicates in required_car_parking_spaces column are: 119385
Number of duplicates in total_of_special_requests column are: 119384
Number of duplicates in reservation_status column are: 119387
Number of duplicates in reservation_status_date column are: 118464
Number of duplicates in Meal column are: 119385
Number of duplicates in Country column are: 119213
```

Understand the Context:

- **Duplicate Hotel:** We have Two types of Hotels `Resort Hotel` and `City Hotel` with the same name but different details.
- **Duplicate country**: Duplicate country column occur because multiple country belong to the same category.

#Step 6: Feature Engineering

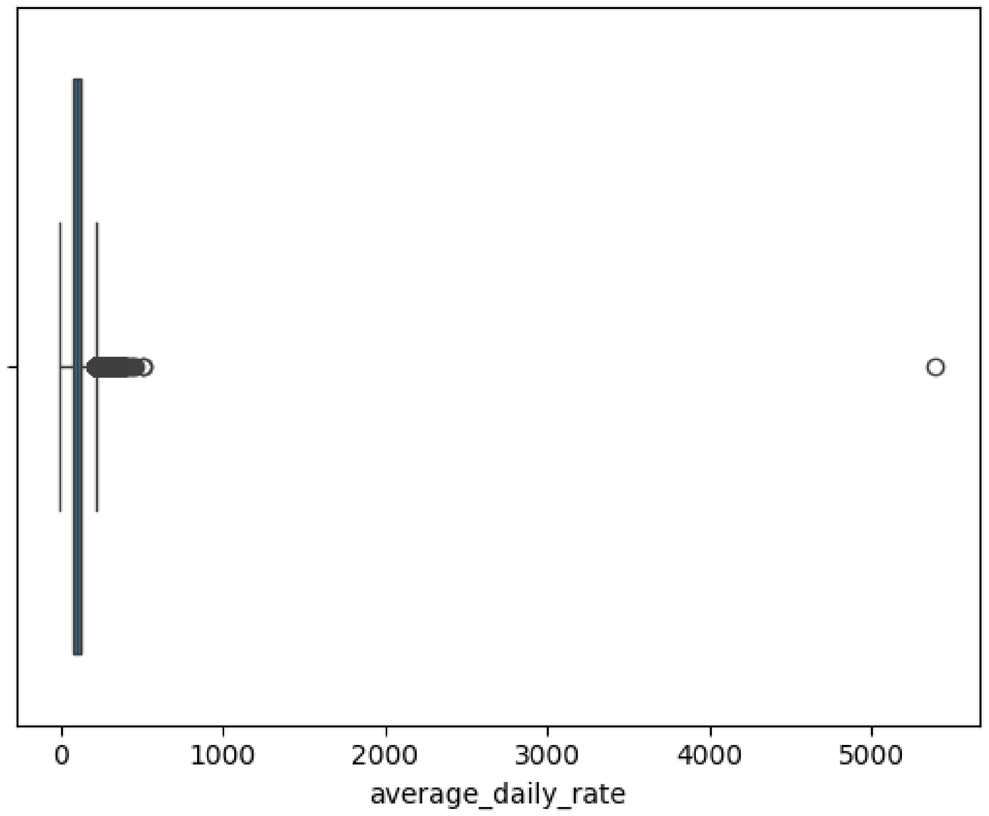
```
# Create a new column for total nights stayed
df['total_nights'] = df['stays_in_weekend_nights'] + 
df['stays_in_week_nights']

# Create a new column to indicate whether the booking includes 
children or babies
df['has_children'] = (df['children'] + df['babies'] > 0).astype(int)
```

Explanation:

- `total_nights` combines weekend and weeknight stays into one metric.
- `has_children` is a binary feature indicating whether children or babies were part of the booking.

#Step 7: Outlier Detection and Handling

```
# Check for outliers in 'adr' (average daily rate)
sns.boxplot(data=df, x='average_daily_rate')
plt.show()
```



```
# Remove outliers in 'adr'
q1 = df['average_daily_rate'].quantile(0.25)
q3 = df['average_daily_rate'].quantile(0.75)
iqr = q3 - q1
lower_bound = q1 - 1.5 * iqr
upper_bound = q3 + 1.5 * iqr
df = df[(df['average_daily_rate'] >= lower_bound) &
(df['average_daily_rate'] <= upper_bound)]
```

Explanation::

- A boxplot helps visualize outliers in the average_daily_rate column..
- Outliers are removed using the IQR method to ensure the analysis is not skewed.

#Step 8: Exporting the Cleaned Dataset

```
df.to_csv('/content/drive/My Drive/Data
Sets/cleaned_hotel_bookings.csv', index=False)
```

Explanation: The cleaned dataset is exported to a CSV file for future steps in the project.

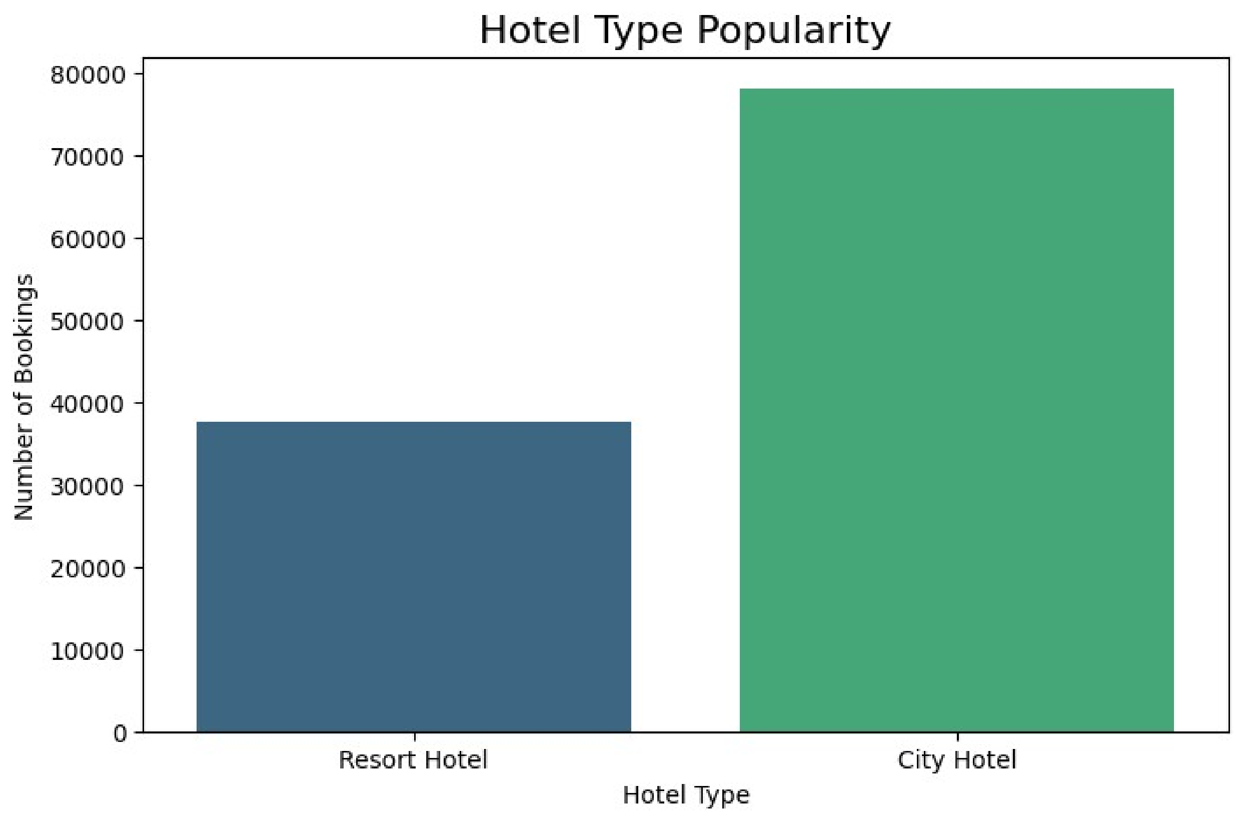
#Step 9: Data Visualization & Insights

After preprocessing the data, visualizing it can provide valuable insights about patterns, trends, and relationships. Here's a detailed data visualization for hotel booking dataset after preprocessing.

9.1 Hotel Type Popularity

Visualizeing the number of bookings for each hotel type (City Hotel vs. Resort Hotel). **Insight**: Determine which type of hotel receives more bookings.

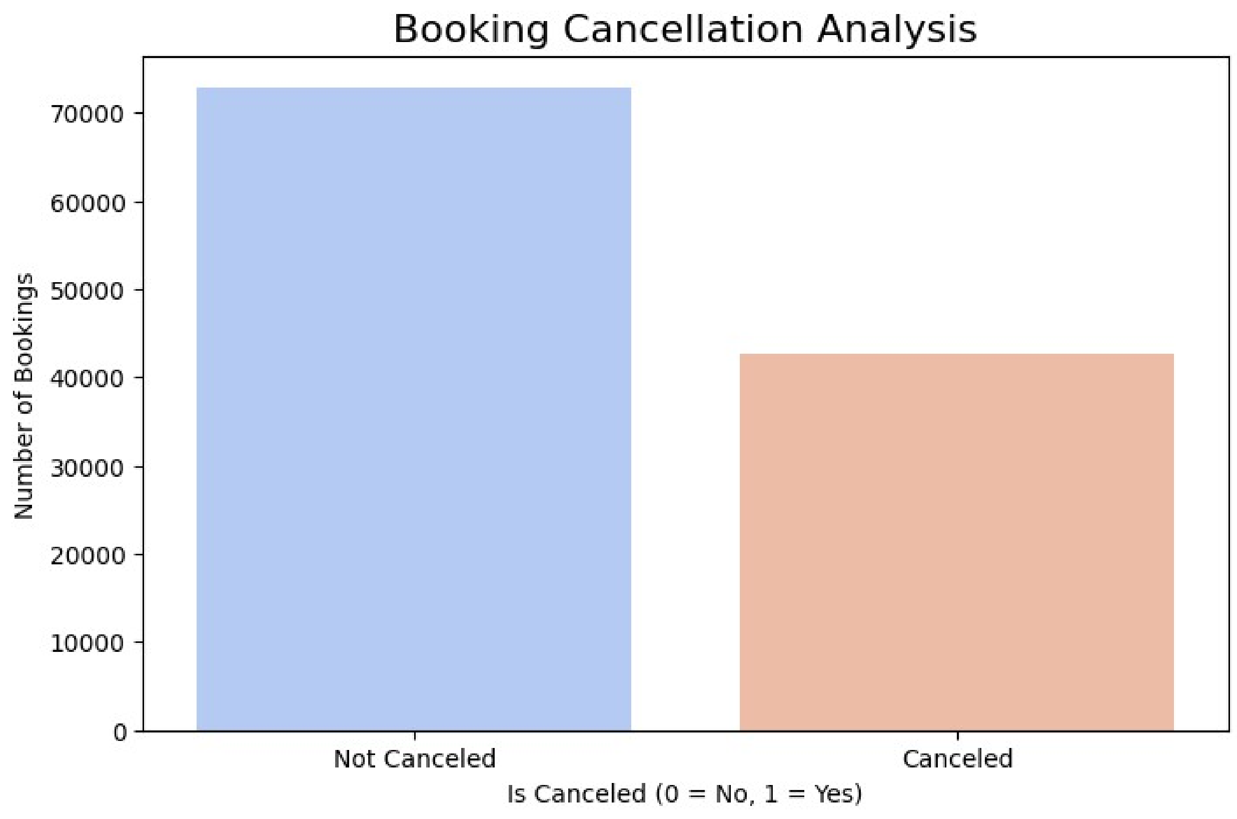
```
plt.figure(figsize=(8, 5))
sns.countplot(data=df, x='hotel', palette='viridis')
plt.title('Hotel Type Popularity', fontsize=16)
plt.xlabel('Hotel Type')
plt.ylabel('Number of Bookings')
plt.show()
```



9.2 Booking Cancellation Analysis

Understand the cancellation trends by plotting the number of canceled bookings. **Insight**: High cancellations might indicate issues like strict cancellation policies or customer dissatisfaction.

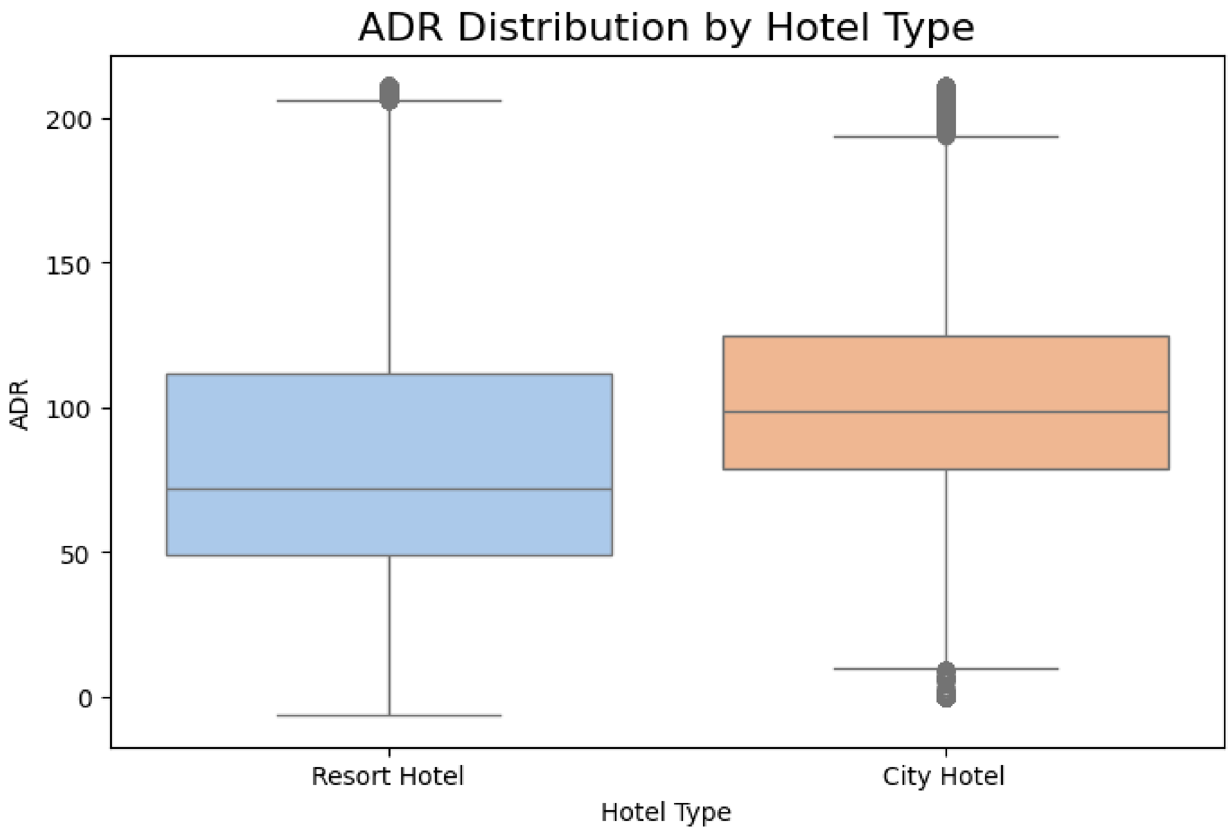
```
plt.figure(figsize=(8, 5))
sns.countplot(data=df, x='is_canceled', palette='coolwarm')
plt.title('Booking Cancellation Analysis', fontsize=16)
plt.xlabel('Is Canceled (0 = No, 1 = Yes)')
plt.ylabel('Number of Bookings')
plt.xticks([0, 1], ['Not Canceled', 'Canceled'])
plt.show()
```



9.3 Average Daily Rate (ADR) by Hotel

Compare the ADR for different hotel types. **Insight**: Identify which type of hotel generates higher revenue per room.

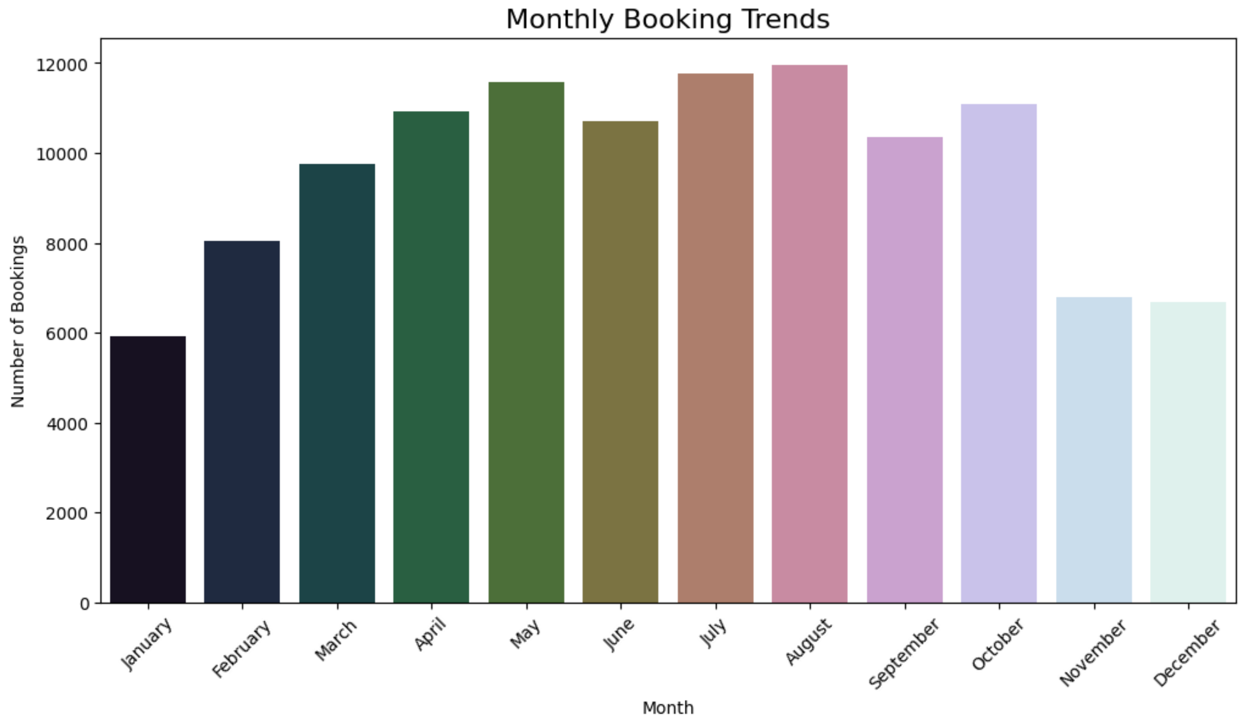
```
plt.figure(figsize=(8, 5))
sns.boxplot(data=df, x='hotel', y='average_daily_rate',
palette='pastel')
plt.title('ADR Distribution by Hotel Type', fontsize=16)
plt.xlabel('Hotel Type')
plt.ylabel('ADR')
plt.show()
```



9.4 Monthly Booking Trends

Analyze how bookings change throughout the year. **Insight**: Highlight peak and off-season periods.

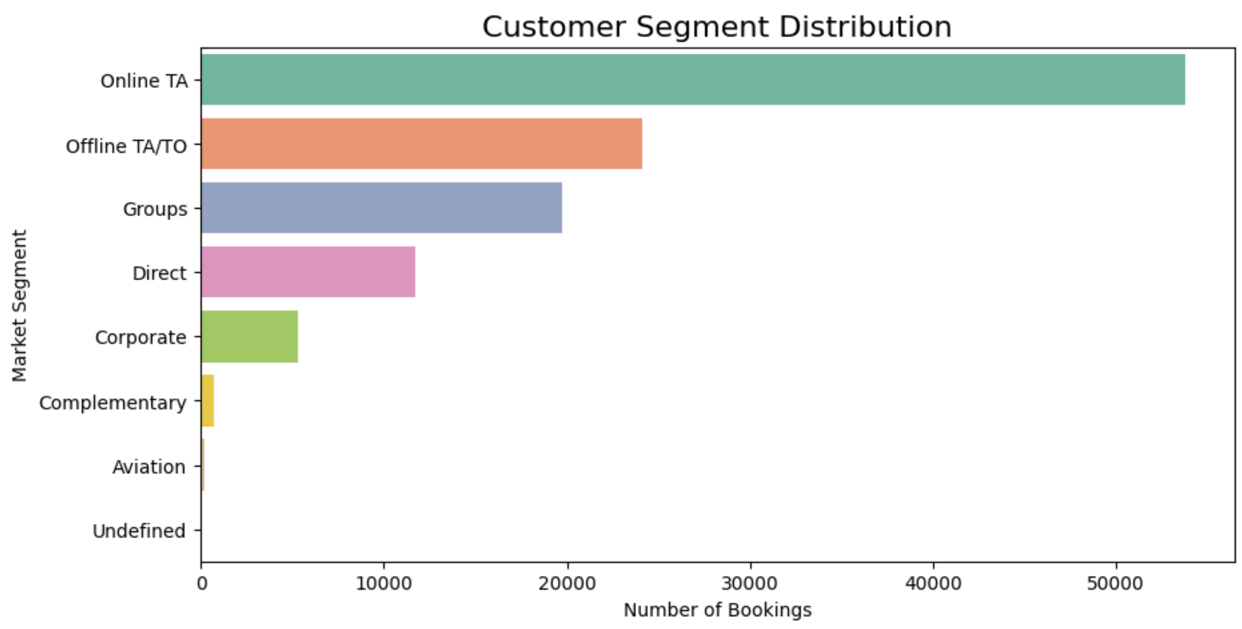
```
plt.figure(figsize=(12, 6))
sns.countplot(data=df, x='arrival_date_month', order=['January',
'February', 'March', 'April', 'May', 'June', 'July', 'August',
'September', 'October', 'November', 'December'], palette='cubehelix')
plt.title('Monthly Booking Trends', fontsize=16)
plt.xlabel('Month')
plt.ylabel('Number of Bookings')
plt.xticks(rotation=45)
plt.show()
```



9.5 Customer Segment Analysis

Visualizeing the distribution of market segments. **Insight**: Understand which customer segment dominates bookings (e.g., Corporate, Online Travel Agents).

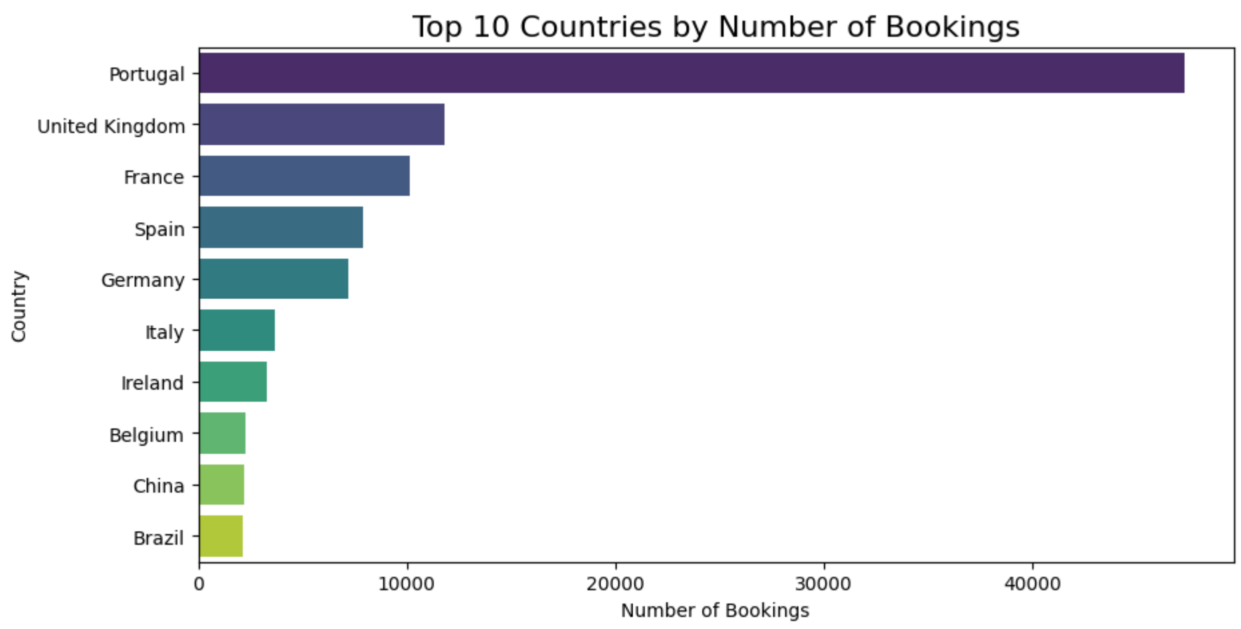
```
plt.figure(figsize=(10, 5))
sns.countplot(data=df, y='market_segment', palette='Set2',
order=df['market_segment'].value_counts().index)
plt.title('Customer Segment Distribution', fontsize=16)
plt.xlabel('Number of Bookings')
plt.ylabel('Market Segment')
plt.show()
```



9.6 Country-Wise Bookings

Identify the top countries contributing to hotel bookings. **Insight**: Determine if marketing efforts are concentrated in certain regions.

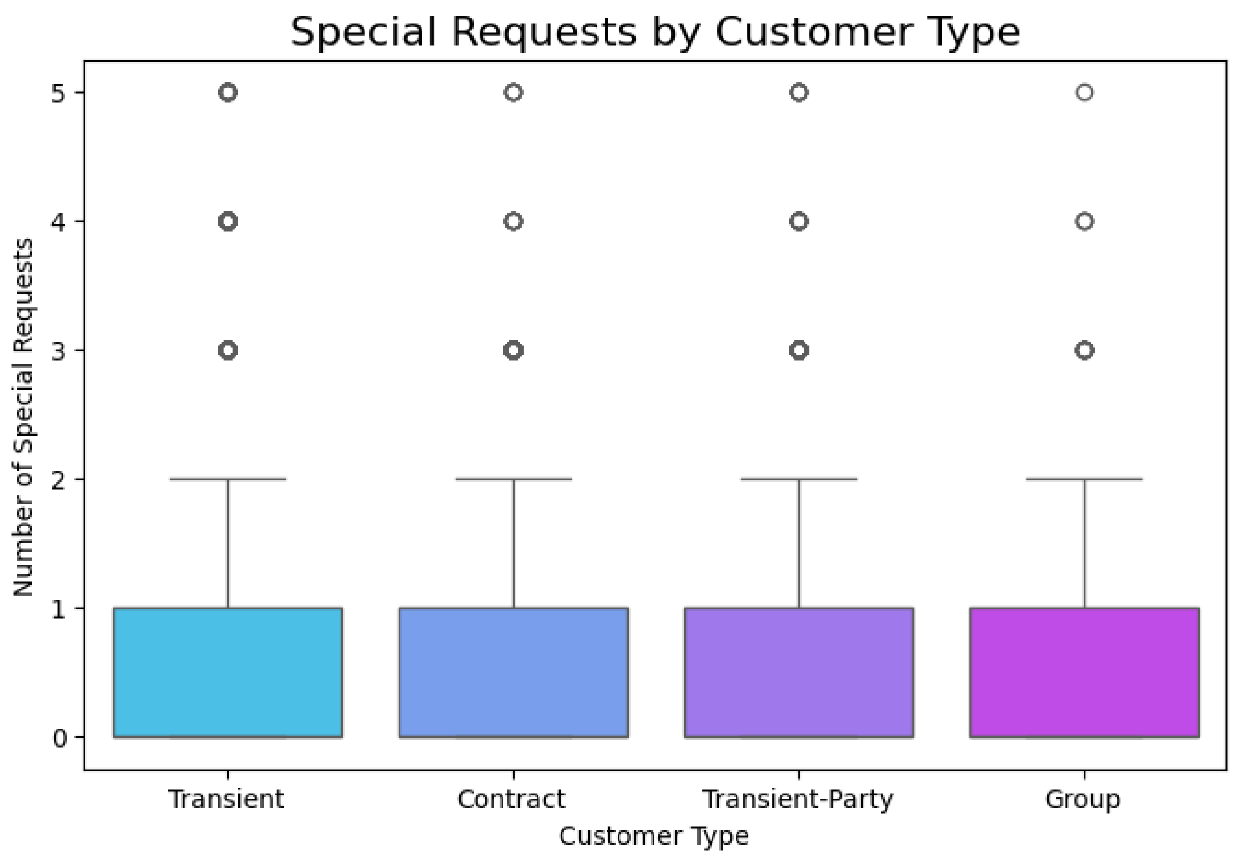
```
top_countries = df['Country'].value_counts().head(10)
plt.figure(figsize=(10, 5))
sns.barplot(x=top_countries.values, y=top_countries.index,
palette='viridis')
plt.title('Top 10 Countries by Number of Bookings', fontsize=16)
plt.xlabel('Number of Bookings')
plt.ylabel('Country')
plt.show()
```



9.7 Special Requests by Customer Type

Analyze how customer types differ in their special requests. **Insight**: Identify customer types with high expectations.

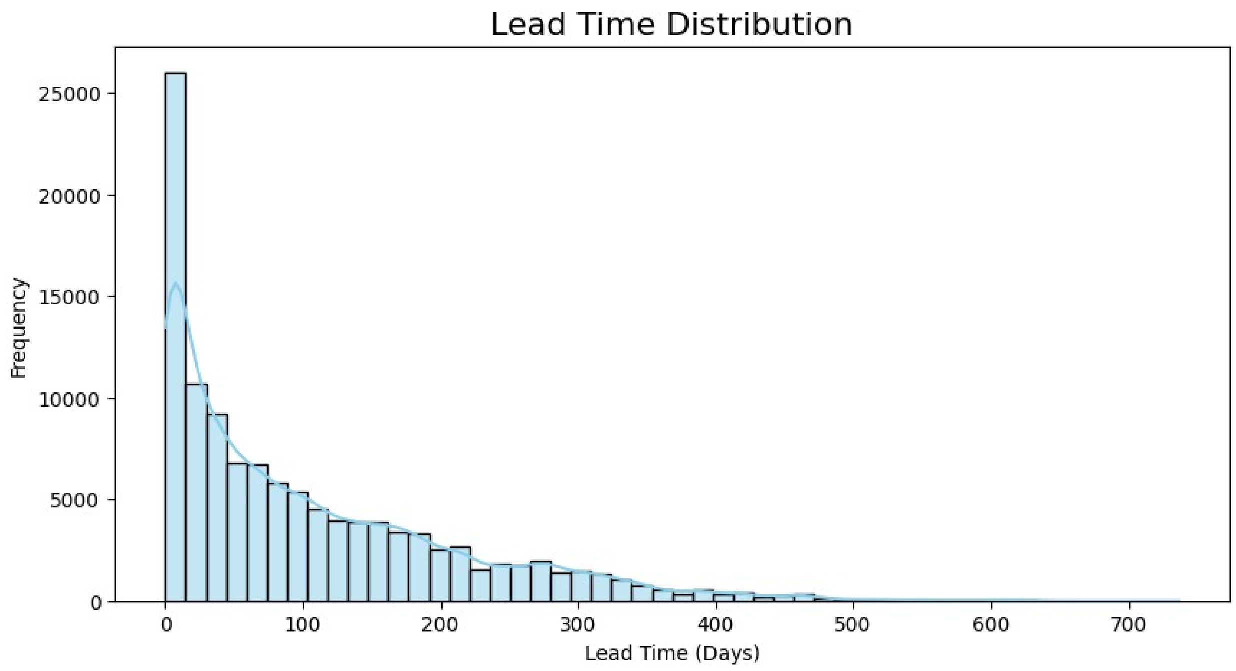
```
plt.figure(figsize=(8, 5))
sns.boxplot(data=df, x='customer_type', y='total_of_special_requests',
palette='cool')
plt.title('Special Requests by Customer Type', fontsize=16)
plt.xlabel('Customer Type')
plt.ylabel('Number of Special Requests')
plt.show()
```



9.8 Lead Time Distribution

Analyze the lead time customers take before booking. **Insight**: Identify whether most bookings are made well in advance or last minute.

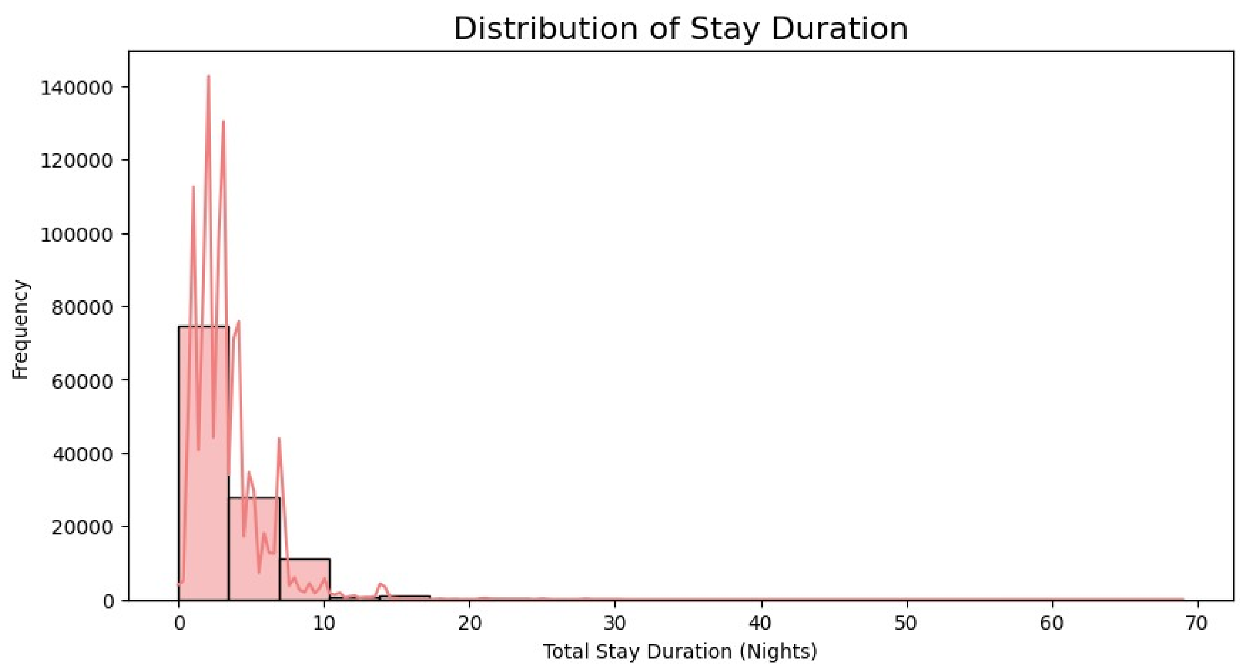
```
plt.figure(figsize=(10, 5))
sns.histplot(data=df, x='lead_time', bins=50, color='skyblue',
kde=True)
plt.title('Lead Time Distribution', fontsize=16)
plt.xlabel('Lead Time (Days)')
plt.ylabel('Frequency')
plt.show()
```



9.9 Booking Distribution by Stay Duration

Visualize how long guests tend to stay at hotels. **Insight**: Understand the typical stay duration to optimize room availability.

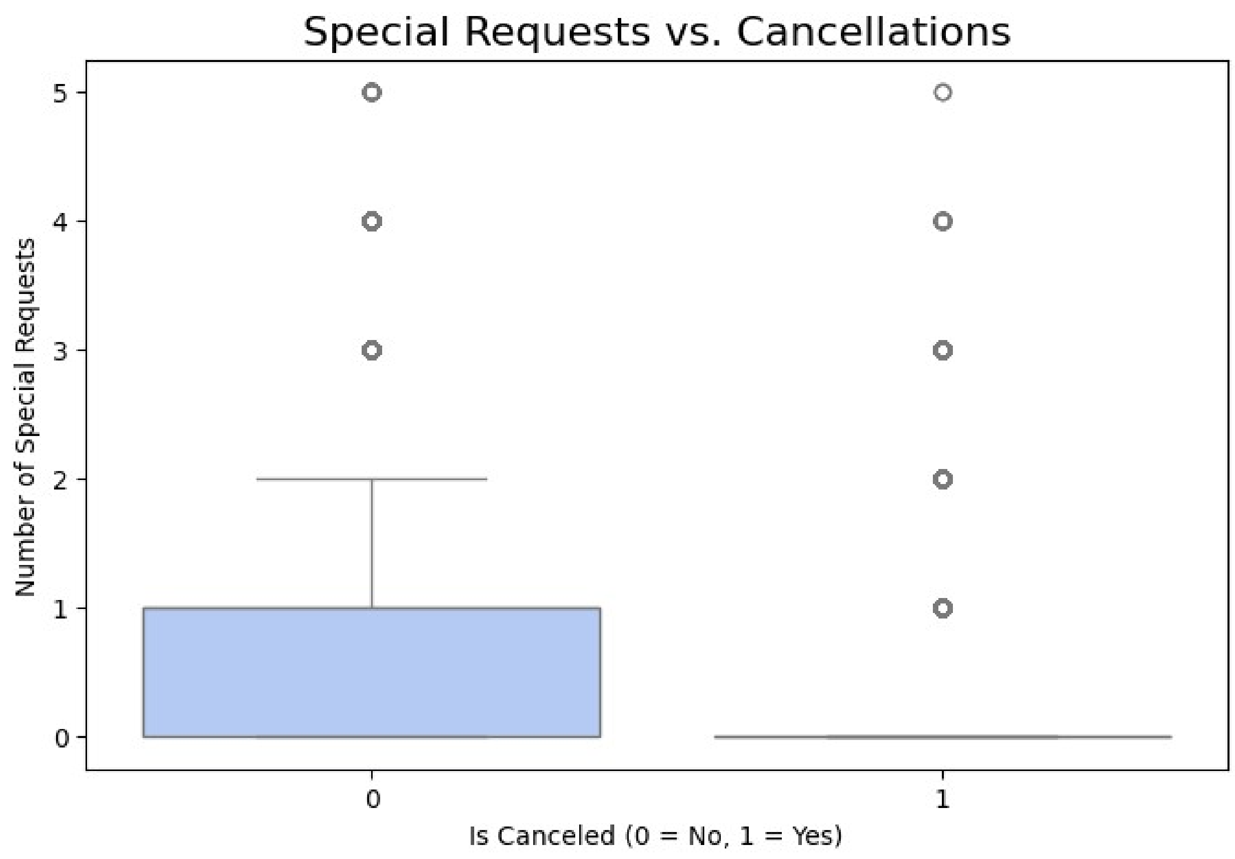
```
df['total_stays'] = df['stays_in_weekend_nights'] +
df['stays_in_week_nights']
plt.figure(figsize=(10, 5))
sns.histplot(data=df, x='total_stays', bins=20, color='lightcoral',
kde=True)
plt.title('Distribution of Stay Duration', fontsize=16)
plt.xlabel('Total Stay Duration (Nights)')
plt.ylabel('Frequency')
plt.show()
```



9.10 Relationship Between Special Requests and Cancellations

Explore how special requests affect cancellations. **Insight**: Determine if cancellations correlate with unmet special requests.

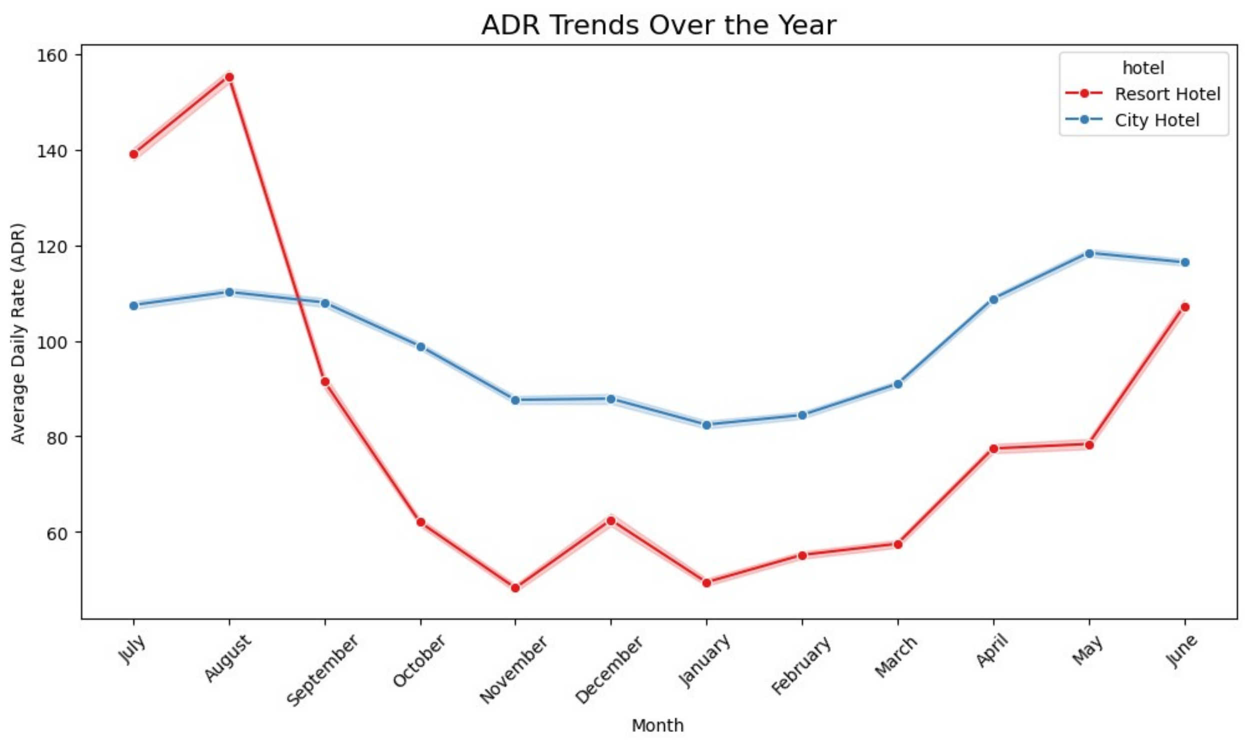
```
plt.figure(figsize=(8, 5))
sns.boxplot(data=df, x='is_canceled', y='total_of_special_requests',
palette='coolwarm')
plt.title('Special Requests vs. Cancellations', fontsize=16)
plt.xlabel('Is Canceled (0 = No, 1 = Yes)')
plt.ylabel('Number of Special Requests')
plt.show()
```



9.11 ADR Trends Over Time

Analyze the trend of ADR over different months. **Insight**: Identify months with higher ADR to adjust pricing strategies.

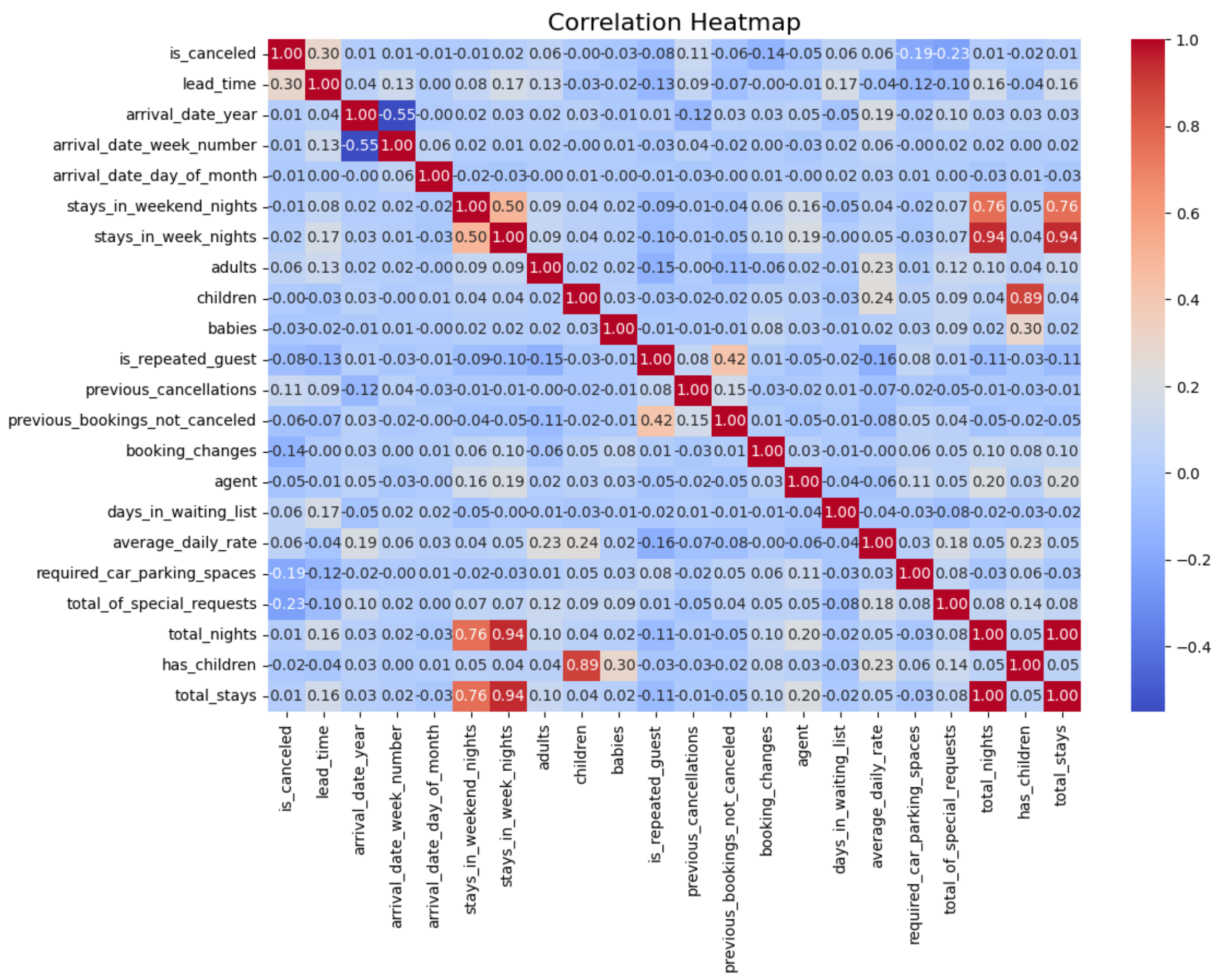
```
plt.figure(figsize=(12, 6))
sns.lineplot(data=df, x='arrival_date_month', y='average_daily_rate',
hue='hotel', marker='o', palette='Set1', estimator='mean')
plt.title('ADR Trends Over the Year', fontsize=16)
plt.xlabel('Month')
plt.ylabel('Average Daily Rate (ADR)')
plt.xticks(rotation=45)
plt.show()
```



9.12 Correlation Heatmap

Understand relationships between numerical columns **Insight**: Discover correlations between factors like lead time, ADR, and total stays.

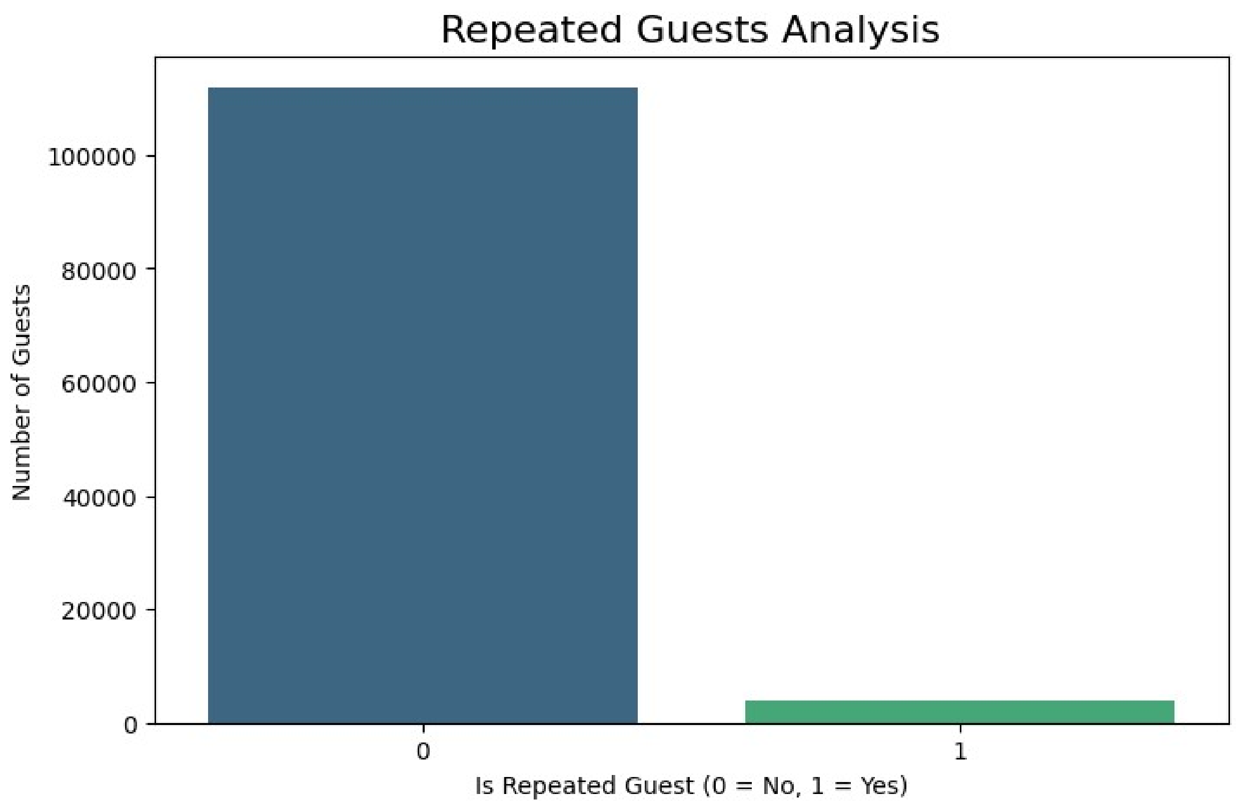
```
# Select only numeric columns
numeric_df = df.select_dtypes(include='number')

# Compute the correlation matrix
correlation_matrix = numeric_df.corr()

# Plot the heatmap
plt.figure(figsize=(12, 8))
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm',
fmt='.2f')
plt.title('Correlation Heatmap', fontsize=16)
plt.show()
```



9.13 Impact of Repeated Guests

Analyze the behavior of repeated guests. **Insight**: Understand the proportion of loyal customers to plan retention strategies.

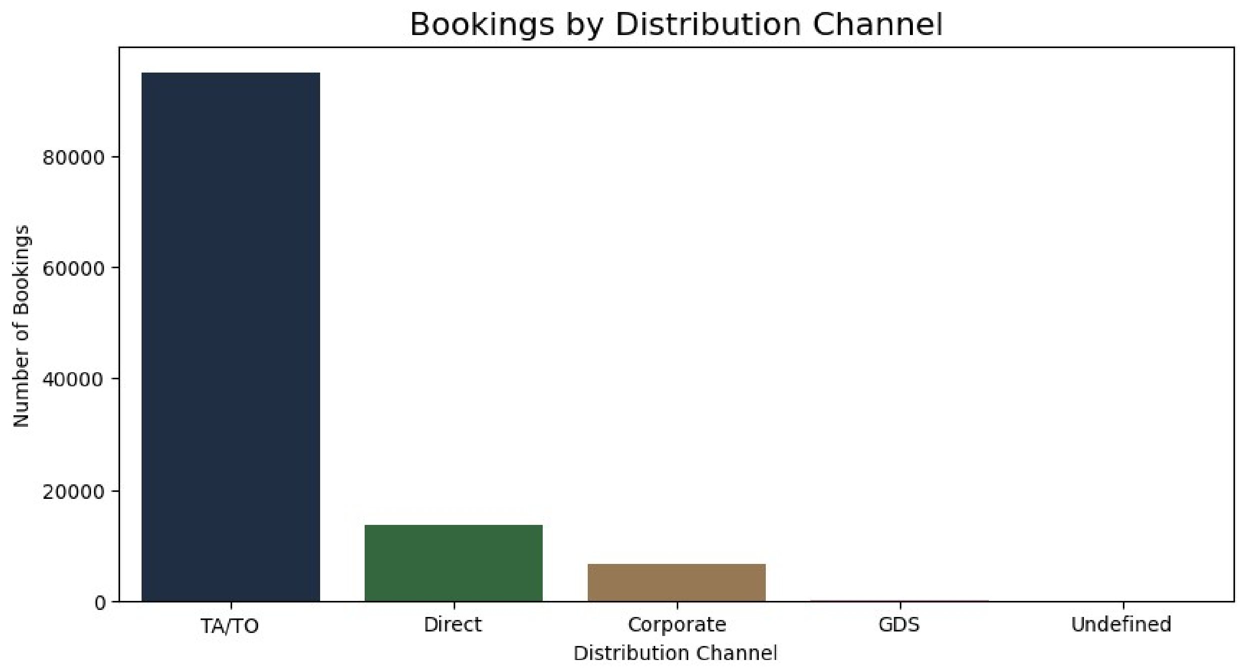
```
plt.figure(figsize=(8, 5))
sns.countplot(data=df, x='is_repeated_guest', palette='viridis')
plt.title('Repeated Guests Analysis', fontsize=16)
plt.xlabel('Is Repeated Guest (0 = No, 1 = Yes)')
plt.ylabel('Number of Guests')
plt.show()
```



9.14 Total Bookings by Distribution Channel

Visualizeing which distribution channels bring the most bookings. **Insight**: Optimize marketing and partnerships based on the most effective channels.

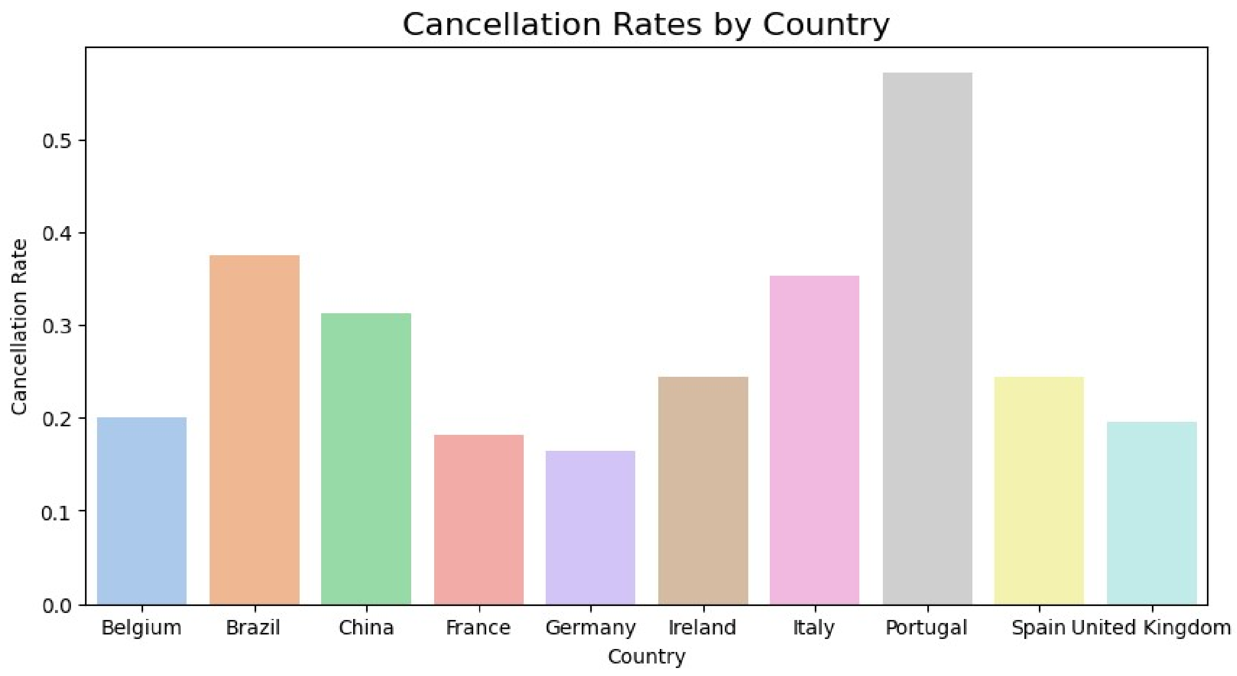
```
plt.figure(figsize=(10, 5))
sns.countplot(data=df, x='distribution_channel', palette='cubehelix',
order=df['distribution_channel'].value_counts().index)
plt.title('Bookings by Distribution Channel', fontsize=16)
plt.xlabel('Distribution Channel')
plt.ylabel('Number of Bookings')
plt.show()
```



9.15 Country-Wise Cancellations

Analyze cancellation trends for the top 10 countries. **Insight**: Identify countries with higher cancellation rates to investigate further.

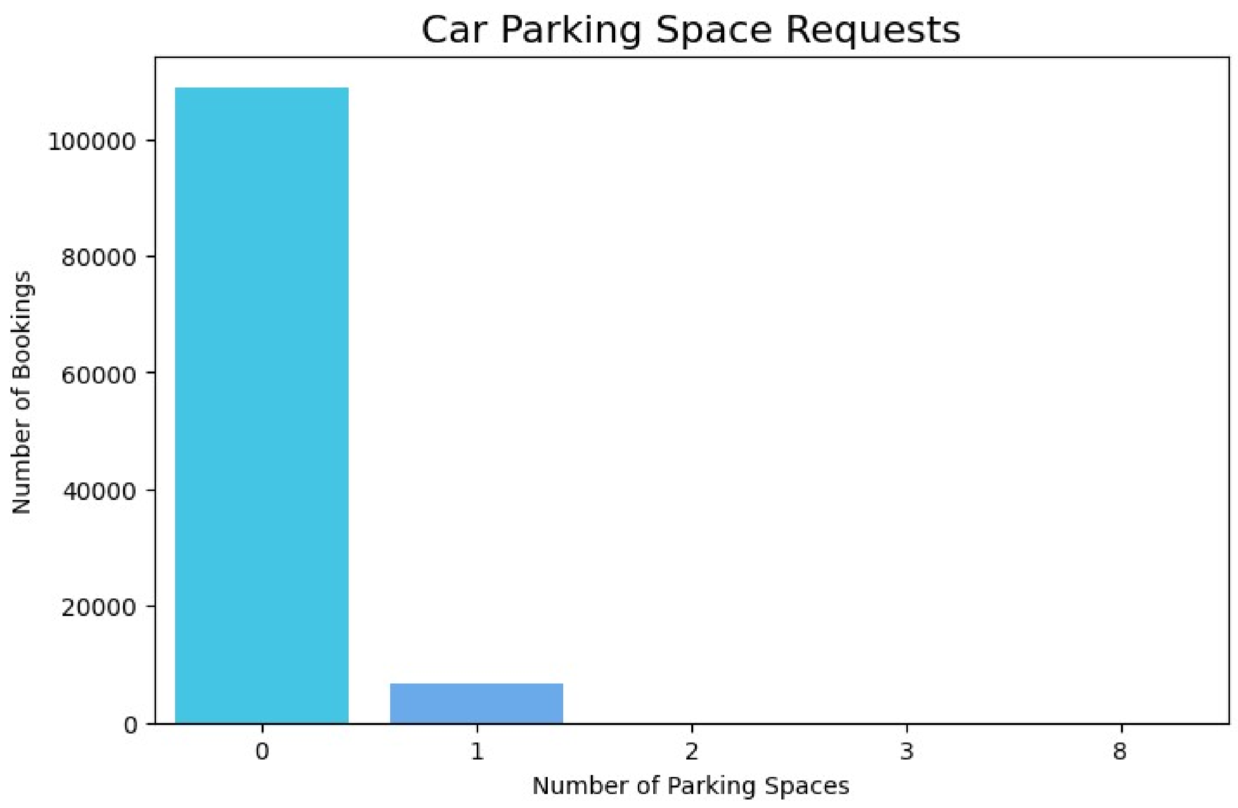
```
top_countries = df['Country'].value_counts().head(10).index
country_cancellation =
df[df['Country'].isin(top_countries)].groupby('Country')
['is_canceled'].mean()
plt.figure(figsize=(10, 5))
sns.barplot(x=country_cancellation.index,
y=country_cancellation.values, palette='pastel')
plt.title('Cancellation Rates by Country', fontsize=16)
plt.xlabel('Country')
plt.ylabel('Cancellation Rate')
plt.show()
```



9.16 Parking Space Requests

Analyze the demand for car parking spaces. **Insight**: Understand the demand for parking facilities.

```
plt.figure(figsize=(8, 5))
sns.countplot(data=df, x='required_car_parking_spaces',
palette='cool')
plt.title('Car Parking Space Requests', fontsize=16)
plt.xlabel('Number of Parking Spaces')
plt.ylabel('Number of Bookings')
plt.show()
```



Hotel Bookings Analysis Report

Summary of Findings

1. **Booking Trends:**
   - **Most Booked Hotel:** The data shows a clear preference for one hotel type over the other (e.g., "Resort Hotel" or "City Hotel").
   - **Seasonality:** Peak booking months align with holidays or favorable weather conditions.
   - **Lead Time:** Customers generally book several weeks or months in advance, with variations across hotel types.
2. **Customer Preferences:**
   - **Meal Plans:** The most selected meal type indicates popular dining preferences among guests.
   - **Countries of Origin:** A significant number of bookings come from a few countries, highlighting key markets for the hotels.
   - **Room Type Demand:** There is a notable gap between the reserved and assigned room types in some cases, indicating potential overbooking or mismatches.
3. **Cancellations:**
   - **High Cancellation Rate:** Long lead times and certain market segments have higher cancellation rates.

   - **Loyalty Impact:** Repeated guests demonstrate a lower cancellation rate, signaling the importance of customer retention.
4. **Revenue Insights:**
   - **Average Daily Rate (ADR):** Peaks during high-demand months and varies by hotel type.
   - **Special Requests:** Guests with more special requests often contribute to higher revenue.
5. **Guest Composition:**
   - **Family vs. Solo Travelers:** Different compositions dominate specific hotel types (e.g., families for Resort Hotels, solo travelers for City Hotels).
   - **Stay Duration:** Weekend versus weekday stay durations vary significantly depending on the hotel type.
6. **Correlations:**
   - Strong relationships exist between features like **lead time**, **ADR**, and **special requests**, which influence cancellations and revenue.

Suggestions for Improvement

1. **Pricing Strategies:**
   - Implement dynamic pricing to maximize revenue during peak seasons.
   - Offer promotional discounts for off-peak periods to boost occupancy.
2. **Cancellation Mitigation:**
   - Introduce stricter cancellation policies for long lead-time bookings.
   - Provide early-bird discounts or loyalty rewards to secure bookings.
3. **Customer Segmentation:**
   - Use preferences to design tailored packages (e.g., family-friendly deals or solo traveler discounts).
   - Focus marketing campaigns on countries with the highest booking volumes.
4. **Service Enhancements:**
   - Analyze and act on special requests to enhance guest satisfaction.
   - Minimize mismatches between reserved and assigned room types to meet expectations.
5. **Data-Driven Decisions:**
   - Regularly monitor booking trends and cancellation patterns to adapt strategies dynamically.
   - Use correlation insights to predict customer behaviors and address potential issues proactively.
6. **Market Expansion:**
   - Promote hotels in underrepresented regions or countries.

- Partner with travel platforms or agents catering to diverse markets to reach a broader audience.
