Data Mining Project

From Reservation to Check-In: Data-Driven Insights for Optimizing Hotel Bookings - Predicting Cancellations and Understanding Customer Preferences

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`pip install -r requirements.txt`

In [1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import plotly.express as px
import seaborn as sns
import copy
```

In [2]:
```
df = pd.read_csv("hotel_bookings_raw.csv")
```

First 5 rows

In [3]:
```
df.head()
```

Out[3]:

	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 × 43 columns

Last 10 rows

In [4]:
```
df.tail()
```

Out[4]:

	hotel	is_canceled	lead_time	arrival_date_year	arrival_date_month	arrival_date_we
119385	City Hotel	0	23	2017	August	
119386	City Hotel	0	102	2017	August	
119387	City Hotel	0	34	2017	August	
119388	City Hotel	0	109	2017	August	
119389	City Hotel	0	205	2017	August	

5 rows × 43 columns

In [5]:
```
df.shape
```

Out[5]: (119390, 43)

Hotel Booking Dataset Column Descriptions

1. Booking Status and Basic Information

- `hotel` : Type of hotel
- `is_canceled` : Whether the booking was canceled (binary: 0/1)
- `reservation_status` : Current status of the reservation
- `reservation_status_date` : Date of the last status update

2. Temporal Information

- `lead_time` : Number of days between booking and arrival date
- `arrival_date_year` : Year of arrival
- `arrival_date_month` : Month of arrival
- `arrival_date_week_number` : Week number of arrival
- `arrival_date_day_of_month` : Day of month of arrival
- `MO_YR` : Month and year combined

3. Stay Details

- `stays_in_weekend_nights` : Number of weekend nights booked
- `stays_in_week_nights` : Number of weekday nights booked
- `adults` : Number of adults
- `children` : Number of children
- `babies` : Number of babies

4. Room and Service Information

- `meal` : Type of meal plan
- `reserved_room_type` : Type of room reserved
- `assigned_room_type` : Type of room actually assigned
- `required_car_parking_spaces` : Number of parking spaces needed
- `total_of_special_requests` : Number of special requests made

5. Customer Information

- `country` : Country of origin
- `is_repeated_guest` : Whether the guest has stayed before
- `previous_cancellations` : Number of previous cancellations
- `previous_bookings_not_canceled` : Number of previous non-canceled bookings
- `customer_type` : Type of customer

6. Business/Distribution Information

- `market_segment` : Market segment (e.g., direct, corporate)
- `distribution_channel` : Booking distribution channel
- `agent` : ID of the travel agency
- `booking_changes` : Number of changes made to the booking
- `deposit_type` : Type of deposit made
- `adr` : Average Daily Rate
- `days_in_waiting_list` : Days spent on waiting list

7. Economic Indicators

- `CPI_AVG` : Consumer Price Index average
- `INFLATION` : Inflation rate
- `INFLATION_CHG` : Change in inflation
- `CSMR_SENT` : Consumer sentiment
- `UNRATE` : Unemployment rate
- `INTRSRT` : Interest rate

- `GDP` : Gross Domestic Product
- `FUEL_PRCS` : Fuel prices
- `CPI_HOTELS` : CPI specific to hotels
- `US_GINI` : Gini coefficient (income inequality measure)
- `DIS_INC` : Disposable income

In [6]:
```
df.columns
```

Out[6]:
```
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',
       'days_in_waiting_list', 'customer_type', 'adr',
       'required_car_parking_spaces', 'total_of_special_requests',
       'reservation_status', 'reservation_status_date', 'MO_YR', 'CPI_AVG',
       'INFLATION', 'INFLATION_CHG', 'CSMR_SENT', 'UNRATE', 'INTRSRT', 'GDP',
       'FUEL_PRCS', 'CPI_HOTELS', 'US_GINI', 'DIS_INC'],
      dtype='object')
```

In [7]:
```
df.dtypes
```

Out[7]:
```
hotel                              object
is_canceled                         int64
lead_time                           int64
arrival_date_year                   int64
arrival_date_month                 object
arrival_date_week_number            int64
arrival_date_day_of_month           int64
stays_in_weekend_nights             int64
stays_in_week_nights                int64
adults                              int64
children                          float64
babies                              int64
meal                               object
country                            object
market_segment                     object
distribution_channel               object
is_repeated_guest                   int64
previous_cancellations              int64
previous_bookings_not_canceled      int64
reserved_room_type                 object
assigned_room_type                 object
booking_changes                     int64
deposit_type                       object
agent                             float64
days_in_waiting_list                int64
customer_type                      object
adr                               float64
required_car_parking_spaces         int64
total_of_special_requests           int64
reservation_status                 object
reservation_status_date            object
MO_YR                              object
CPI_AVG                           float64
INFLATION                         float64
INFLATION_CHG                     float64
CSMR_SENT                         float64
UNRATE                            float64
INTRSRT                           float64
GDP                               float64
FUEL_PRCS                         float64
CPI_HOTELS                        float64
US_GINI                           float64
DIS_INC                           float64
dtype: object
```

In [8]:
```
df['agent'] = df['agent'].astype('Int64')
```

In [9]:
```
binary_columns = ['is_canceled', 'is_repeated_guest']

# Date columns
date_columns = [
    'reservation_status_date'
]

# Numeric columns
```

```
numeric_columns = [
    'lead_time',
    'arrival_date_year',
    'arrival_date_week_number',
    'arrival_date_day_of_month',
    'stays_in_weekend_nights',
    'stays_in_week_nights',
    'adults',
    'children',
    'babies',
    'is_repeated_guest',
    'previous_cancellations',
    'previous_bookings_not_canceled',
    'booking_changes',
    'days_in_waiting_list',
    'adr',
    'required_car_parking_spaces',
    'total_of_special_requests',
    'CPI_AVG',
    'INFLATION',
    'INFLATION_CHG',
    'CSMR_SENT',
    'UNRATE',
    'INTRSRT',
    'GDP',
    'FUEL_PRCS',
    'CPI_HOTELS',
    'US_GINI',
    'DIS_INC'
]

# Categorical columns
categorical_columns = [
    'hotel',
    'arrival_date_month',
    'meal',
    'country',
    'market_segment',
    'distribution_channel',
    'reserved_room_type',
    'assigned_room_type',
    'deposit_type',
    'customer_type',
    'reservation_status',
    'agent'
]
```

In [10]:

```
def fix_datatypes(df):
    # Make a copy to avoid modifying the original dataframe
    df = copy.deepcopy(df)

    # Convert dates
    for col in date_columns:
        df[col] = pd.to_datetime(df[col])

    # Convert numeric columns
```

```
    for col in numeric_columns:
        df[col] = pd.to_numeric(df[col], errors='coerce')

    # Convert categorical columns
    for col in categorical_columns:
        df[col] = df[col].astype('category')

    # Convert binary columns
    for col in binary_columns:
        df[col] = df[col].astype('bool')
    # Handle 'MO_YR' as string
    df['MO_YR'] = df['MO_YR'].astype(str)

    return df
```

In [11]:
```
df = fix_datatypes(df)
df.dtypes
```

Out[11]:
```
hotel                                   category
is_canceled                                 bool
lead_time                                  int64
arrival_date_year                          int64
arrival_date_month                      category
arrival_date_week_number                   int64
arrival_date_day_of_month                  int64
stays_in_weekend_nights                    int64
stays_in_week_nights                       int64
adults                                     int64
children                                 float64
babies                                     int64
meal                                    category
country                                 category
market_segment                          category
distribution_channel                    category
is_repeated_guest                           bool
previous_cancellations                     int64
previous_bookings_not_canceled             int64
reserved_room_type                      category
assigned_room_type                      category
booking_changes                            int64
deposit_type                            category
agent                                   category
days_in_waiting_list                       int64
customer_type                           category
adr                                      float64
required_car_parking_spaces                int64
total_of_special_requests                  int64
reservation_status                      category
reservation_status_date           datetime64[ns]
MO_YR                                     object
CPI_AVG                                  float64
INFLATION                                float64
INFLATION_CHG                            float64
CSMR_SENT                                float64
UNRATE                                   float64
INTRSRT                                  float64
GDP                                      float64
FUEL_PRCS                                float64
CPI_HOTELS                               float64
US_GINI                                  float64
DIS_INC                                  float64
dtype: object
```

In [12]:
```python
booking_by_month = df.groupby(['arrival_date_month', 'hotel']).size()
booking_by_month
```

```
C:\Users\asifm\AppData\Local\Temp\ipykernel_16660\3460393484.py:1: FutureWarning: Th
e default of observed=False is deprecated and will be changed to True in a future ve
rsion of pandas. Pass observed=False to retain current behavior or observed=True to
adopt the future default and silence this warning.
  booking_by_month = df.groupby(['arrival_date_month', 'hotel']).size()
```

Out[12]:
```
arrival_date_month  hotel
April               City Hotel      7480
                    Resort Hotel    3609
August              City Hotel      8983
                    Resort Hotel    4894
December            City Hotel      4132
                    Resort Hotel    2648
February            City Hotel      4965
                    Resort Hotel    3103
January             City Hotel      3736
                    Resort Hotel    2193
July                City Hotel      8088
                    Resort Hotel    4573
June                City Hotel      7894
                    Resort Hotel    3045
March               City Hotel      6458
                    Resort Hotel    3336
May                 City Hotel      8232
                    Resort Hotel    3559
November            City Hotel      4357
                    Resort Hotel    2437
October             City Hotel      7605
                    Resort Hotel    3555
September           City Hotel      7400
                    Resort Hotel    3108
dtype: int64
```

In [13]:
```
import plotly.express as px
import plotly.graph_objects as go
from plotly.subplots import make_subplots
fig = go.Figure()

# Add traces, one for each hotel
for hotel_type in df['hotel'].unique():
    hotel_data = df[df['hotel'] == hotel_type]
    monthly_counts = hotel_data['arrival_date_month'].value_counts().reset_index()
    monthly_counts.columns = ['Month', 'Bookings']

    # Define month order
    month_order = ['January', 'February', 'March', 'April', 'May', 'June',
                   'July', 'August', 'September', 'October', 'November', 'December'

    monthly_counts['Month'] = pd.Categorical(monthly_counts['Month'],
                                             categories=month_order,
                                             ordered=True)
    monthly_counts = monthly_counts.sort_values('Month')

    fig.add_trace(
        go.Bar(
            name=hotel_type,
            x=monthly_counts['Month'],
            y=monthly_counts['Bookings'],
            visible=True
        )
    )
```

```
# Add buttons for hotel selection
fig.update_layout(
    updatemenus=[
        dict(
            type="buttons",
            direction="right",
            x=0.7,
            y=1.2,
            showactive=True,
            buttons=list([
                dict(
                    label="All Hotels",
                    method="update",
                    args=[{"visible": [True, True]},
                          {"title": "All Hotels Booking Distribution"}]),
                dict(
                    label="Resort Hotel",
                    method="update",
                    args=[{"visible": [True, False]},
                          {"title": "Resort Hotel Booking Distribution"}]),
                dict(
                    label="City Hotel",
                    method="update",
                    args=[{"visible": [False, True]},
                          {"title": "City Hotel Booking Distribution"}])
            ]),
        )
    ]
)

# Update layout
fig.update_layout(
    title="Hotel Bookings Distribution",
    xaxis_title="Month",
    yaxis_title="Number of Bookings",
    barmode='group',
    height=600,
    width=1000,
    showlegend=True
)

fig.show()
```

Dealing with missing values

In [14]:

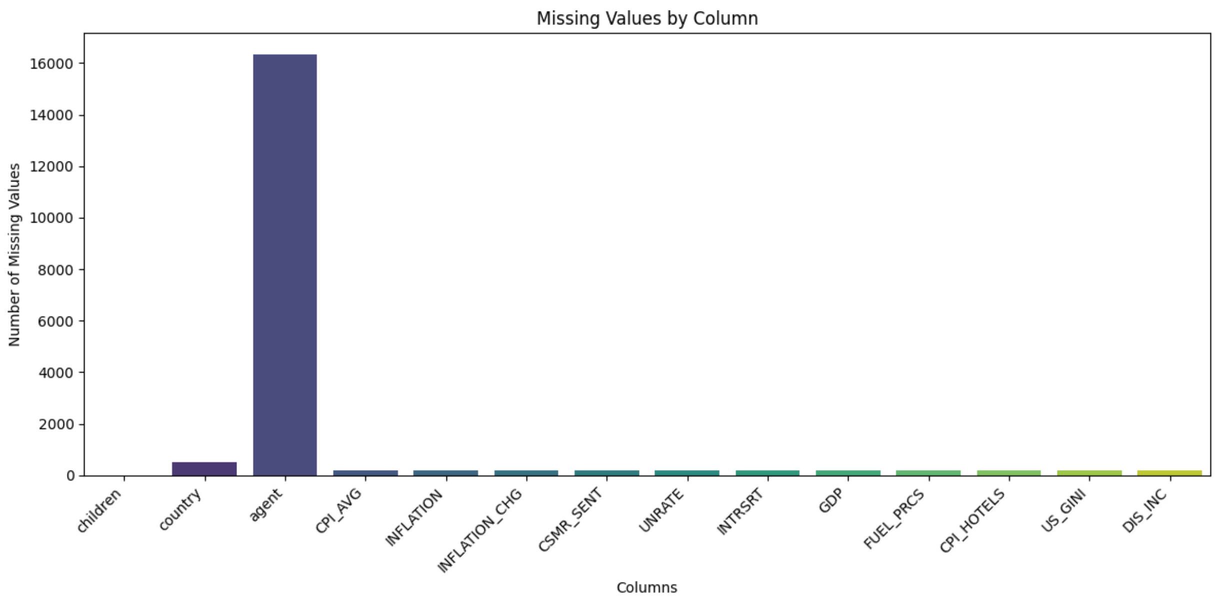
```
missing_values_count = df.isnull().sum()[df.isnull().sum()>0]
total_missing = df.isnull().sum().sum()

print("Missing values per column:\n", missing_values_count)
print("Total missing values:", total_missing)
```

```
Missing values per column:
 children            4
country           488
agent           16340
CPI_AVG           181
INFLATION         181
INFLATION_CHG     181
CSMR_SENT         181
UNRATE            181
INTRSRT           181
GDP               181
FUEL_PRCS         181
CPI_HOTELS        181
US_GINI           181
DIS_INC           181
dtype: int64
Total missing values: 18823
```

Visualizing missing values in a column

In [15]:

```
# Create figure with specified size
plt.figure(figsize=(12, 6))

# Create bar plot
sns.barplot(x=missing_values_count.index,
            y=missing_values_count.values,
            hue=missing_values_count.index,
            palette='viridis')

# Customize the plot
plt.xticks(rotation=45, ha='right')
plt.title('Missing Values by Column')
plt.xlabel('Columns')
plt.ylabel('Number of Missing Values')

# Adjust layout to prevent label cutoff
plt.tight_layout()

# Show the plot
plt.show()
```



- The children column contains the number of children the guest will bring
- We will asssume the null value means the guest has no children

Children Missing

In [16]:
```
# Fill children column missing values
# df['children'].fillna(0, inplace=True)
df['children'] = df['children'].fillna(0)
```

Country missing

In [17]:
```
# Replace missing values with the mode of the column country
mode_country = df['country'].mode()[0]
print(mode_country)
df['country'] = df['country'].fillna(mode_country)
```

```
PRT
```

Agent Missing

In [18]:
```
df['agent'] = df['agent'].astype('object')  # temporarily convert to object
df['agent'] = df['agent'].fillna(0)

df['agent'] = df['agent'].astype('category')
```

```
C:\Users\asifm\AppData\Local\Temp\ipykernel_16660\2899670480.py:2: FutureWarning:

Downcasting object dtype arrays on .fillna, .ffill, .bfill is deprecated and will ch
ange in a future version. Call result.infer_objects(copy=False) instead. To opt-in t
o the future behavior, set `pd.set_option('future.no_silent_downcasting', True)`
```

In [19]:
```python
df[['agent']].head()
```

Out[19]:

	agent
0	0
1	0
2	0
3	304
4	240

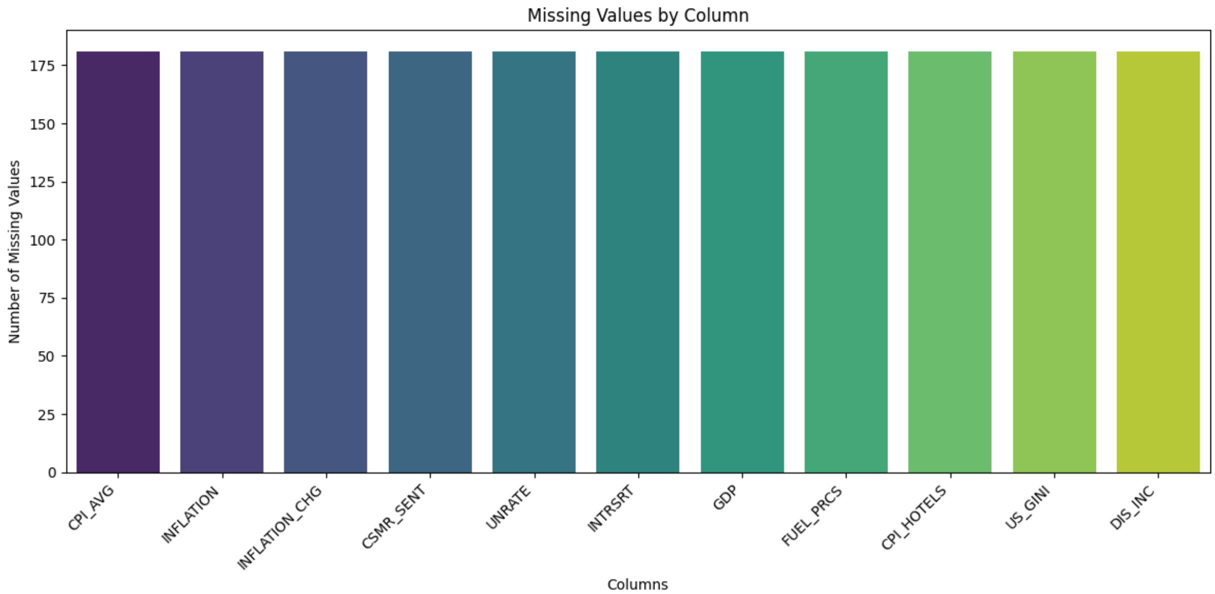
Replacing missing values with '0' of the column Agent as it states that no agent was involved in the booking

In [20]:
```python
missing_values_count = df.isnull().sum()[df.isnull().sum()>0]
total_missing = df.isnull().sum().sum()

print("Missing values per column:\n", missing_values_count)
print("Total missing values:", total_missing)
```

```
Missing values per column:
 CPI_AVG          181
INFLATION        181
INFLATION_CHG    181
CSMR_SENT        181
UNRATE           181
INTRSRT          181
GDP              181
FUEL_PRCS        181
CPI_HOTELS       181
US_GINI          181
DIS_INC          181
dtype: int64
Total missing values: 1991
```

In [21]:
```python
# Create figure with specified size
plt.figure(figsize=(12, 6))

# Create bar plot
sns.barplot(x=missing_values_count.index,
            y=missing_values_count.values,
            hue=missing_values_count.index,
            palette='viridis')

# Customize the plot
plt.xticks(rotation=45, ha='right')
plt.title('Missing Values by Column')
plt.xlabel('Columns')
plt.ylabel('Number of Missing Values')

# Adjust layout to prevent label cutoff
plt.tight_layout()
```

```python
# Show the plot
plt.show()
```



CPI_AVG

- replacing the null values in the CPI_AVG columns that indicates consumer price index average with mean as it maintains the dataset's overall balance and avoids skewing results

In [22]:
```python
mean_CPI = df['CPI_AVG'].mean()
print(mean_CPI)
df['CPI_AVG'] = df['CPI_AVG'].fillna(mean_CPI)
```

```
240.78065240879465
```

Inflation

- replacing null values in the Inflation column with Interpolation as it Estimates missing values based on surrounding data points, preserving the column’s natural trends over time

In [23]:
```python
df['INFLATION'] = df['INFLATION'].interpolate(method='linear')
print(df['INFLATION'].isnull().sum())
```

```
0
```

CSMR_SENT (costumer sentiment)

In [24]:
```python
# Replace missing values with the mode of the column CSMR_SENT
mode_csmr = df['CSMR_SENT'].mode()[0]
```

```
print(mode_csmr)
df['CSMR_SENT'] = df['CSMR_SENT'].fillna(mode_csmr)
```

```
90.0
```

UNRATE (Unemployment rate)

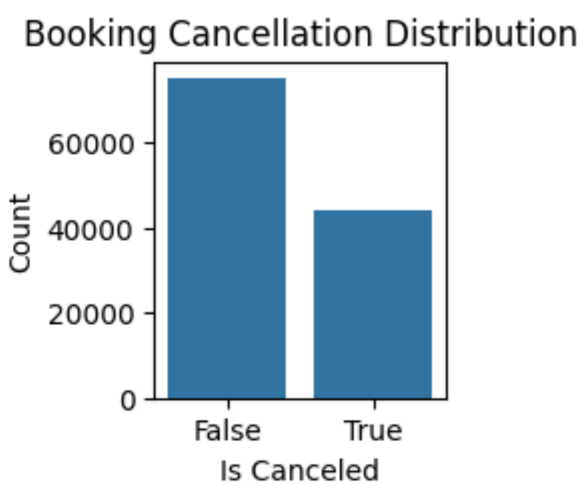
- replacing the null values in the UNRATE column that indicates Unemployment rate with mean as it maintains the dataset's overall balance and avoids skewing results

In [25]:
```
Unrate_Mean = df['UNRATE'].mean()
print(Unrate_Mean)
df['UNRATE'] = df['UNRATE'].fillna(Unrate_Mean)
```

```
4.827967687003499
```

In [26]:
```
plt.subplot(2, 3, 1)
sns.countplot(data=df, x='is_canceled')
plt.title('Booking Cancellation Distribution')
plt.xlabel('Is Canceled')
plt.ylabel('Count')
```

Out[26]: `Text(0, 0.5, 'Count')`

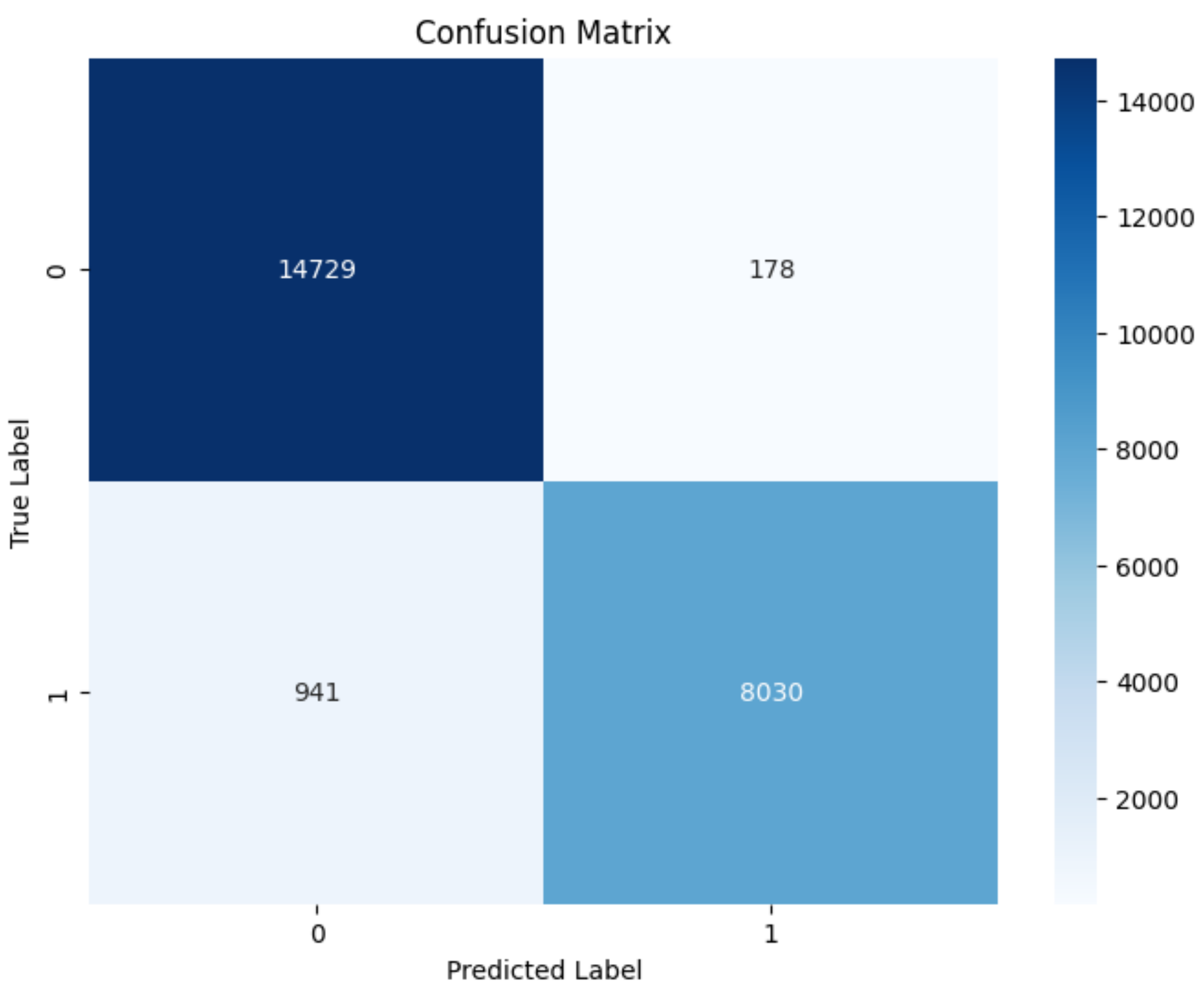


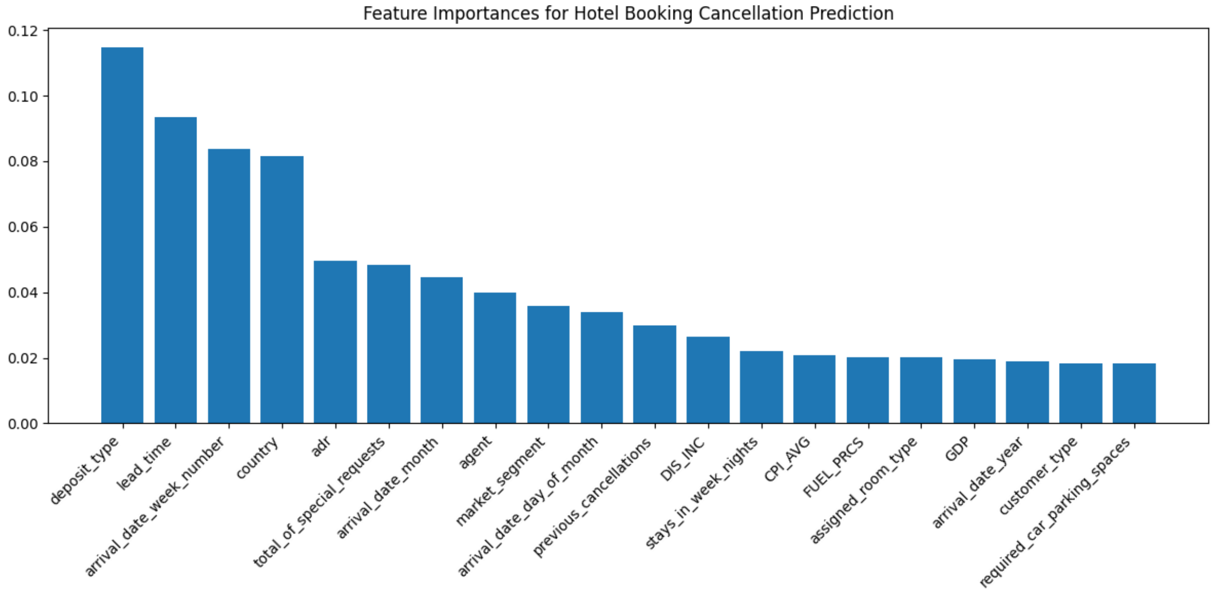
In [27]:
```
import pandas as pd
import numpy as np
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestClassifier
from sklearn.preprocessing import LabelEncoder
from sklearn.metrics import classification_report, confusion_matrix
import matplotlib.pyplot as plt
import seaborn as sns

def prepare_data(df):
    # Create a copy to avoid modifying the original dataframe
    df_model = df.copy()

    # Drop columns that shouldn't be used for prediction
    columns_to_drop = ['reservation_status', 'reservation_status_date', 'MO_YR']
```

```
    df_model = df_model.drop(columns=columns_to_drop, errors='ignore')


    # Encode categorical variables
    le = LabelEncoder()
    for column in categorical_columns:
        if column in df_model.columns:
            df_model[column] = le.fit_transform(df_model[column].astype(str))

    return df_model

def train_random_forest(X, y):
    # Split the data
    X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random

    # Create and train the model
    rf = RandomForestClassifier(n_estimators=100, random_state=42)
    rf.fit(X_train, y_train)

    # Make predictions
    y_pred = rf.predict(X_test)

    return rf, X_train, X_test, y_train, y_test, y_pred

def plot_feature_importance(rf, feature_names):
    # Get feature importance
    importances = rf.feature_importances_
    indices = np.argsort(importances)[::-1]

    # Plot the feature importances
    plt.figure(figsize=(12, 6))
    plt.title("Feature Importances for Hotel Booking Cancellation Prediction")
    plt.bar(range(20), importances[indices][:20])
    plt.xticks(range(20), [feature_names[i] for i in indices][:20], rotation=45, ha
    plt.tight_layout()
    plt.show()

    # Print numerical values
    print("\nTop 20 Most Important Features:")
    for i in range(20):
        print(f"{feature_names[indices[i]]}: {importances[indices[i]]:.4f}")

def analyze_cancellations():
    # Prepare the data
    df_model = prepare_data(df)

    # Separate features and target
    X = df_model.drop('is_canceled', axis=1)
    y = df_model['is_canceled']

    # Train the model and get predictions
    rf, X_train, X_test, y_train, y_test, y_pred = train_random_forest(X, y)

    # Print model performance
    print("Classification Report:")
    print(classification_report(y_test, y_pred))
```

```python
    # Plot confusion matrix
    plt.figure(figsize=(8, 6))
    sns.heatmap(confusion_matrix(y_test, y_pred), annot=True, fmt='d', cmap='Blues'
    plt.title('Confusion Matrix')
    plt.ylabel('True Label')
    plt.xlabel('Predicted Label')
    plt.show()

    # Plot feature importance
    plot_feature_importance(rf, X.columns)

    return rf, X, y

# Run the analysis
rf_model, X, y = analyze_cancellations()
```

```
Classification Report:
              precision    recall  f1-score   support

       False       0.94      0.99      0.96     14907
        True       0.98      0.90      0.93      8971

    accuracy                           0.95     23878
   macro avg       0.96      0.94      0.95     23878
weighted avg       0.95      0.95      0.95     23878
```





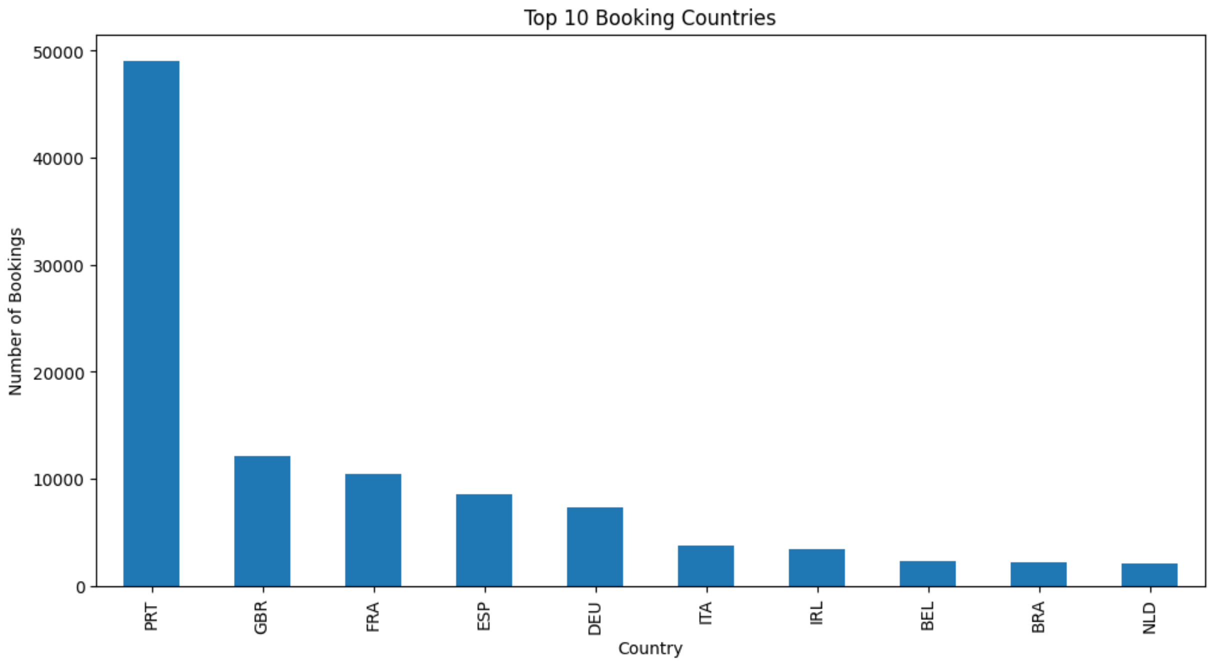

```
Top 20 Most Important Features:
deposit_type: 0.1149
lead_time: 0.0934
arrival_date_week_number: 0.0837
country: 0.0817
adr: 0.0498
total_of_special_requests: 0.0485
arrival_date_month: 0.0446
agent: 0.0398
market_segment: 0.0360
arrival_date_day_of_month: 0.0340
previous_cancellations: 0.0299
DIS_INC: 0.0263
stays_in_week_nights: 0.0221
CPI_AVG: 0.0208
FUEL_PRCS: 0.0201
assigned_room_type: 0.0200
GDP: 0.0194
arrival_date_year: 0.0188
customer_type: 0.0183
required_car_parking_spaces: 0.0182
```

Customer Segmentation

Country of origin (top booking countries)

In [28]:
```
def country_analysis(dataframe):
    # Count bookings by country
    country_counts = dataframe['country'].value_counts().head(10)

    plt.figure(figsize=(12,6))
    country_counts.plot(kind='bar')
    plt.title('Top 10 Booking Countries')
    plt.xlabel('Country')
    plt.ylabel('Number of Bookings')
```

```
    plt.show()

    return country_counts
country_analysis(df)
```



Out[28]:
```
country
PRT    49078
GBR    12129
FRA    10415
ESP     8568
DEU     7287
ITA     3766
IRL     3375
BEL     2342
BRA     2224
NLD     2104
Name: count, dtype: int64
```

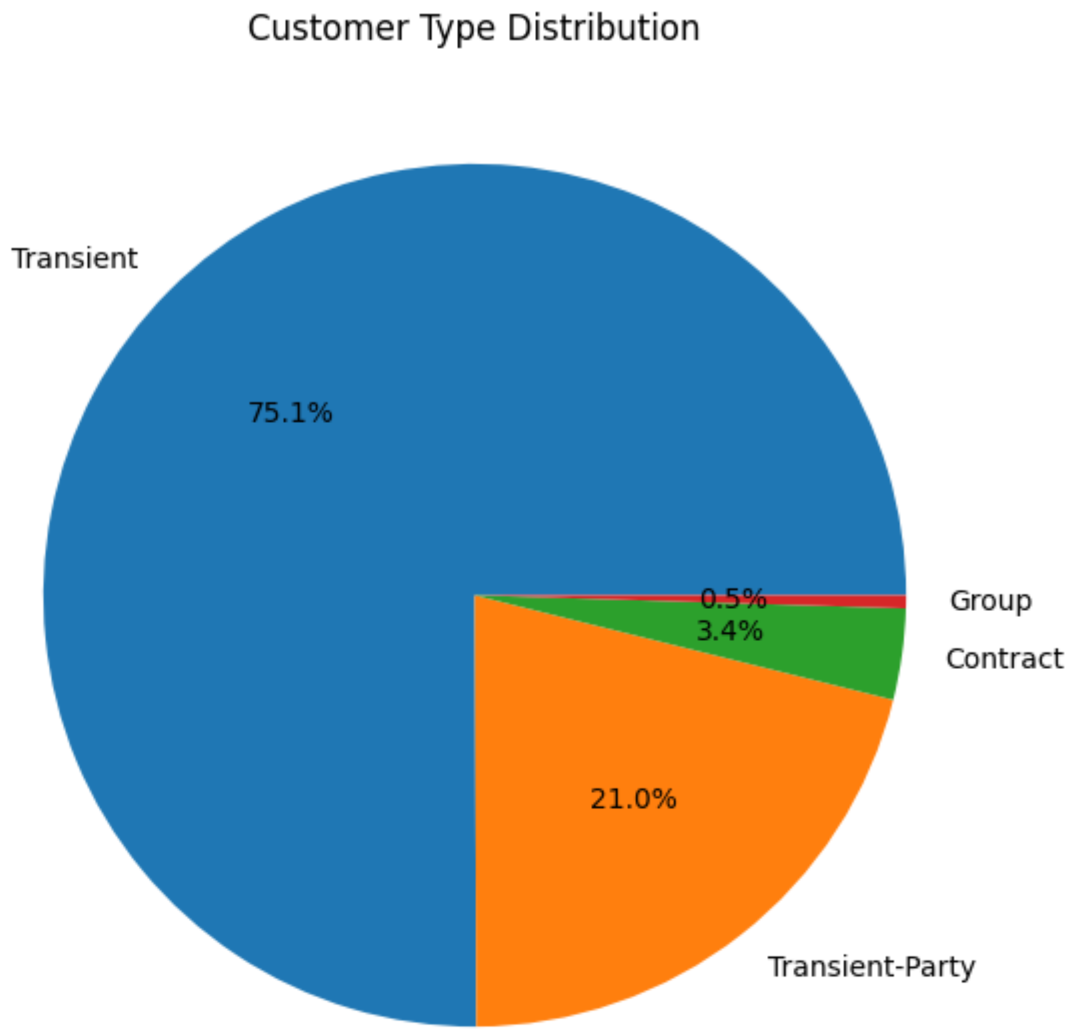
Customer type

- There are 4 types of Customer :

1. Transient: Individual or small group travelers booking short stays that its mostly for business.
2. Transient Party: Similar to Transient but refers to a smaller group travelling together
3. Contract: Guests whos stays depending on a pre-negotiated agreements for example airline crews
4. Group: Larger groups of people booking for an event that its often multiple rooms and services

In [29]:
```
def customer_type_analysis(df):
    customer_type_dist = df['customer_type'].value_counts()
```

```
    plt.figure(figsize=(10,7))
    customer_type_dist.plot(kind='pie', autopct='%1.1f%%')
    plt.title('Customer Type Distribution')
    plt.ylabel('')
    plt.show()

    return customer_type_dist

customer_type_analysis(df)
```



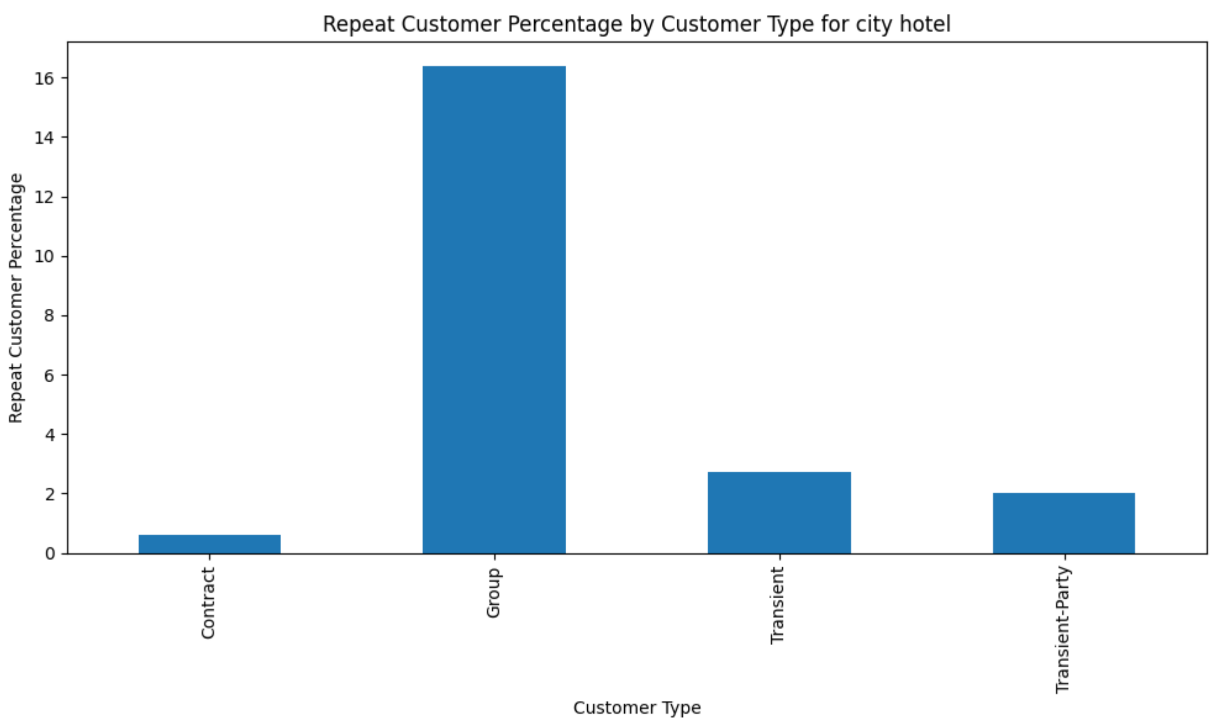
Out[29]:
```
customer_type
Transient          89613
Transient-Party    25124
Contract            4076
Group                577
Name: count, dtype: int64
```

Repeat vs. new customers

In [30]:
```
def city_repeat_customer_analysis(df):
    city_hotel = df[df['hotel']=='City Hotel']
```

```
    city_repeat_customers = city_hotel.groupby('customer_type')['is_repeated_guest'

    plt.figure(figsize=(10,6))
    city_repeat_customers.plot(kind='bar')
    plt.title('Repeat Customer Percentage by Customer Type for city hotel')
    plt.xlabel('Customer Type')
    plt.ylabel('Repeat Customer Percentage')
    plt.tight_layout()
    plt.show()

    return city_repeat_customers

city_repeat_customers = city_repeat_customer_analysis(df)
```

```
C:\Users\asifm\AppData\Local\Temp\ipykernel_16660\2356061341.py:4: FutureWarning:

The default of observed=False is deprecated and will be changed to True in a future
version of pandas. Pass observed=False to retain current behavior or observed=True t
o adopt the future default and silence this warning.
```



In [31]:
```
def resort_repeat_customer_analysis(df):
    resort_hotel = df[df['hotel']=='Resort Hotel']

    resort_repeat_customers = resort_hotel.groupby('customer_type')['is_repeated_gu

    plt.figure(figsize=(10,6))
    resort_repeat_customers.plot(kind='bar')
    plt.title('Repeat Customer Percentage by Customer Type for Resort hotel ')
    plt.xlabel('Customer Type')
    plt.ylabel('Repeat Customer Percentage')
    plt.tight_layout()
    plt.show()
```

```
    return resort_repeat_customers

resort_repeat_customers = resort_repeat_customer_analysis(df)
```

```
C:\Users\asifm\AppData\Local\Temp\ipykernel_16660\4095704785.py:4: FutureWarning:

The default of observed=False is deprecated and will be changed to True in a future
version of pandas. Pass observed=False to retain current behavior or observed=True t
o adopt the future default and silence this warning.
```

In [32]:
```
df_family = df.copy()
df_family
```

Out[32]:

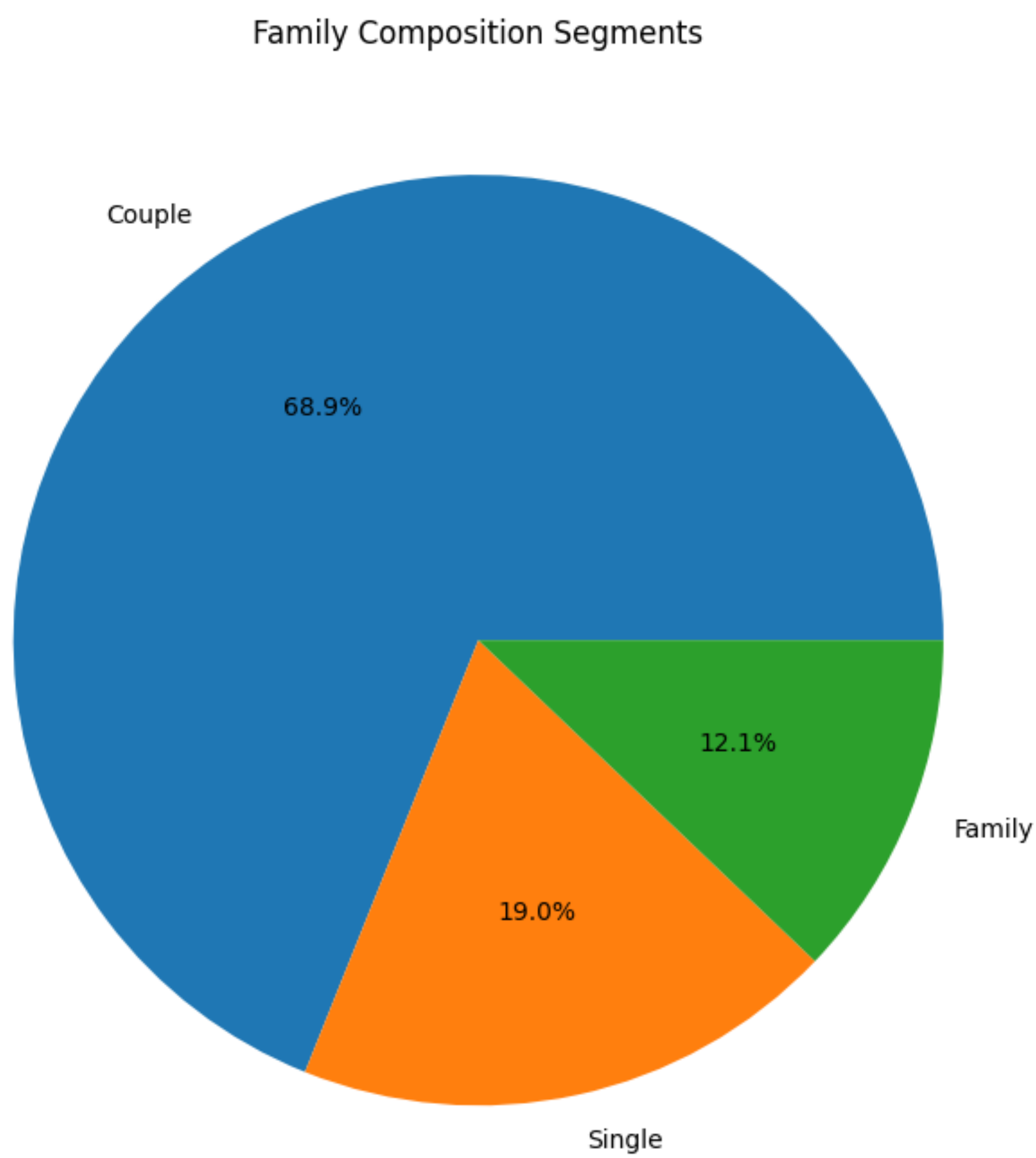
	hotel	is_canceled	lead_time	arrival_date_year	arrival_date_month	arrival_date_w
0	Resort Hotel	False	342	2015	July	
1	Resort Hotel	False	737	2015	July	
2	Resort Hotel	False	7	2015	July	
3	Resort Hotel	False	13	2015	July	
4	Resort Hotel	False	14	2015	July	
...	...	...	...	...	...	
119385	City Hotel	False	23	2017	August	
119386	City Hotel	False	102	2017	August	
119387	City Hotel	False	34	2017	August	
119388	City Hotel	False	109	2017	August	
119389	City Hotel	False	205	2017	August	

119390 rows × 43 columns

Family Composition Analysis

In [33]:

```
def family_Composition(df_family):
    df_family["Total_Guests"] = df_family["adults"] + df_family["children"] + df_fa
    family_count = pd.cut(df_family['Total_Guests'],bins=[0,1,2,4],labels=['Single'
    family_distrbution = family_count.value_counts()
    plt.figure(figsize=(10,7))
    plt.pie(family_distrbution.values, labels= family_distrbution.index,autopct='%1
    plt.title('Family Composition Segments')
    plt.ylabel('')
    plt.tight_layout()
    plt.show()

    return family_distrbution

family_Composition(df_family)
```

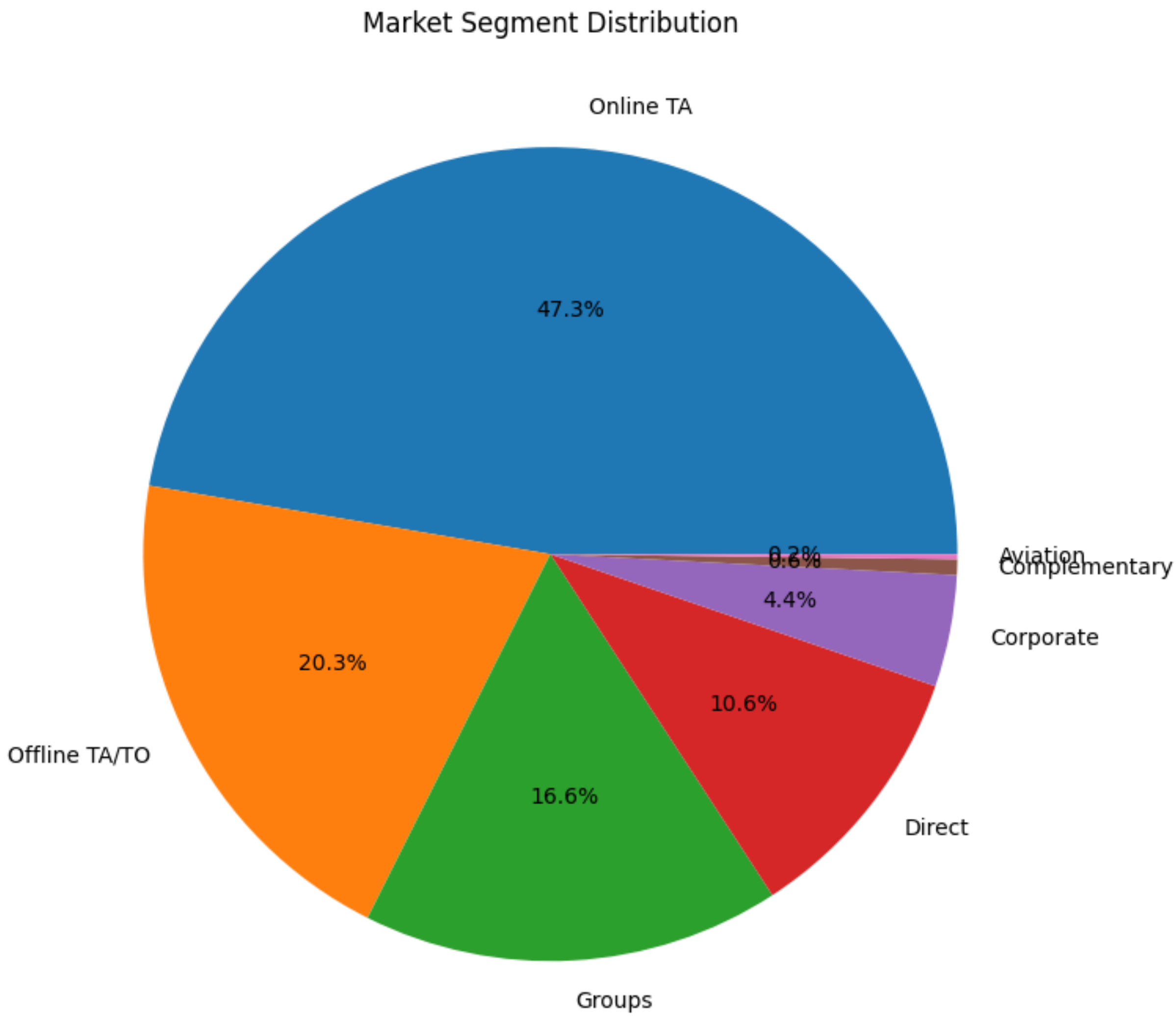



```
Out[33]: Total_Guests
         Couple     82051
         Single     22581
         Family     14424
         Name: count, dtype: int64
```

Market Segment distribution

```
In [34]: def market_segment_analysis(df):
             market_segment_dist = df['market_segment'].value_counts()
             market_segment_dist = market_segment_dist.drop("Undefined")

             plt.figure(figsize=(10,7))
             plt.pie(market_segment_dist.values, labels= market_segment_dist.index,autopct='
             plt.title('Market Segment Distribution')
             plt.ylabel('')
             plt.tight_layout()
```

```
    plt.show()
    return market_segment_dist

market_segment_analysis(df_family)
```

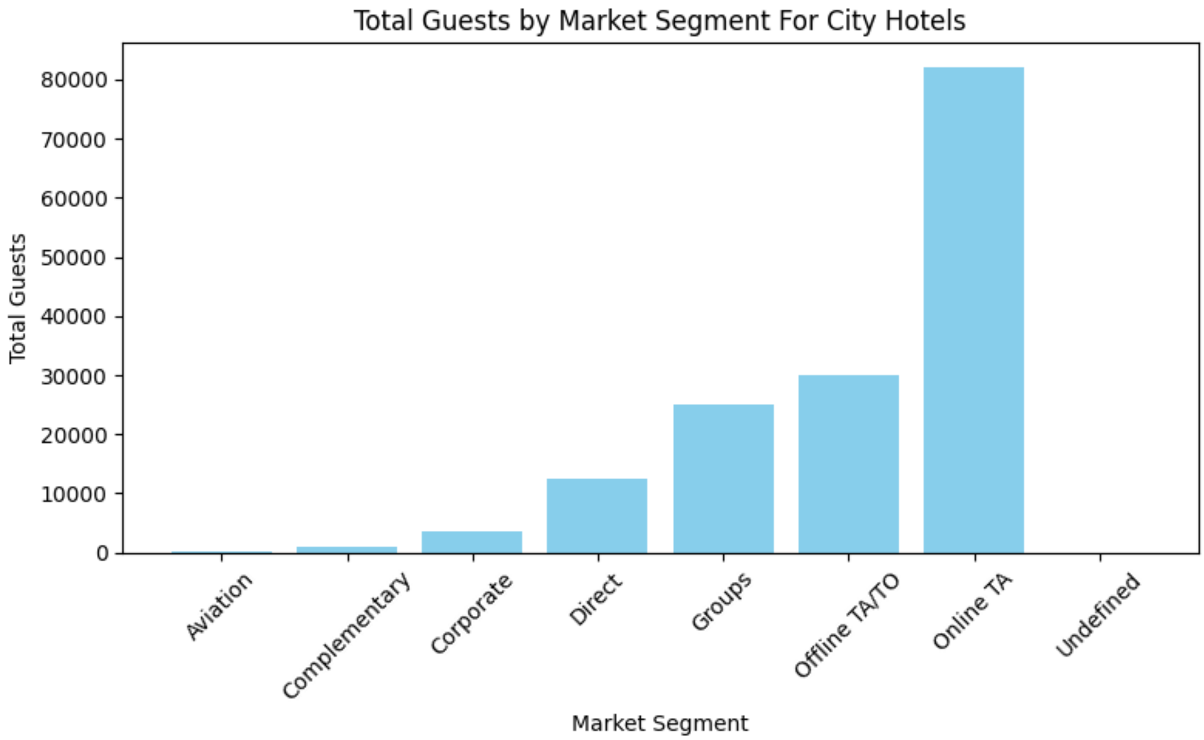



```
Out[34]: market_segment
         Online TA        56477
         Offline TA/TO    24219
         Groups           19811
         Direct           12606
         Corporate         5295
         Complementary      743
         Aviation           237
         Name: count, dtype: int64
```

```
In [35]: def city_travelers_market_analysis(df_family):
             city_hotel = df_family[df_family['hotel']=='City Hotel']
             group_market_dist = city_hotel.groupby('market_segment')['Total_Guests'].sum().
             plt.figure(figsize=(8, 5))
             plt.bar(group_market_dist['market_segment'], group_market_dist['Total_Guests'],
             plt.title('Total Guests by Market Segment For City Hotels')
             plt.xlabel('Market Segment')
             plt.ylabel('Total Guests')
```

```
    plt.xticks(rotation=45)
    plt.tight_layout()
    plt.show()
    return group_market_dist
city_travelers_market_analysis(df_family)
```

```
C:\Users\asifm\AppData\Local\Temp\ipykernel_16660\3674355011.py:3: FutureWarning:

The default of observed=False is deprecated and will be changed to True in a future
version of pandas. Pass observed=False to retain current behavior or observed=True t
o adopt the future default and silence this warning.
```



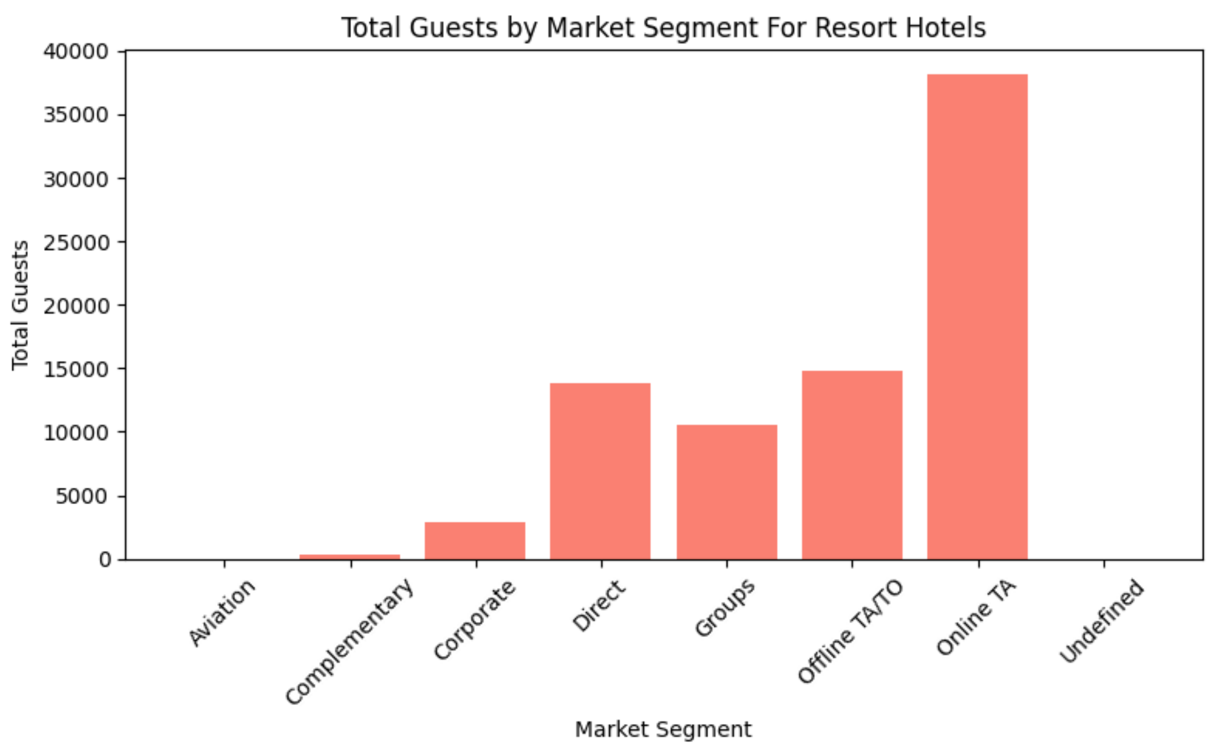
Out[35]:

	market_segment	Total_Guests
0	Aviation	238.0
1	Complementary	851.0
2	Corporate	3689.0
3	Direct	12414.0
4	Groups	25110.0
5	Offline TA/TO	30117.0
6	Online TA	82054.0
7	Undefined	5.0

In [36]:
```
def resort_travelers_market_analysis(df_family):
    Resort_hotel = df_family[df_family['hotel']=='Resort Hotel']
    group_market_dist = Resort_hotel.groupby('market_segment')['Total_Guests'].sum(
```

```
    plt.figure(figsize=(8, 5))
    plt.bar(group_market_dist['market_segment'], group_market_dist['Total_Guests'],
    plt.title('Total Guests by Market Segment For Resort Hotels')
    plt.xlabel('Market Segment')
    plt.ylabel('Total Guests')
    plt.xticks(rotation=45)
    plt.tight_layout()
    plt.show()
    return group_market_dist
resort_travelers_market_analysis(df_family)
```

```
C:\Users\asifm\AppData\Local\Temp\ipykernel_16660\1798386414.py:3: FutureWarning:

The default of observed=False is deprecated and will be changed to True in a future
version of pandas. Pass observed=False to retain current behavior or observed=True t
o adopt the future default and silence this warning.
```



Out[36]:

	market_segment	Total_Guests
0	Aviation	0.0
1	Complementary	336.0
2	Corporate	2925.0
3	Direct	13768.0
4	Groups	10559.0
5	Offline TA/TO	14774.0
6	Online TA	38148.0
7	Undefined	0.0

Stay Duration Analysis

In [37]:
```
def calculate_total_stay_nights(df):
    """Calculate total nights stayed per booking by adding a new column"""
    df['total_nights'] = df['stays_in_weekend_nights'] + df['stays_in_week_nights']
    return df

def analyze_stay_duration(df):
    """Analyze various aspects of stay duration"""
    stats = {
        'Average total nights': df['total_nights'].mean(),
        'Median total nights': df['total_nights'].median(),
        'Most common duration': df['total_nights'].mode().iloc[0],
        'Max stay duration': df['total_nights'].max(),
        'Min stay duration': df['total_nights'].min()
    }
    print("\nStay Duration Statistics:")
    for metric, value in stats.items():
        print(f"{metric}: {value:.2f} days")

def analyze_weekend_vs_weekday(df):
    """Analyze weekend vs weekday stay patterns"""

    # Calculate averages by hotel type
    hotel_stays = df.groupby('hotel').agg({
        'stays_in_weekend_nights': 'mean',
        'stays_in_week_nights': 'mean',
        'total_nights': 'mean'
    }).round(2)

    print("\nAverage Stays by Hotel Type:")
    print(hotel_stays)

    # Calculate weekend vs weekday ratio
    df['weekend_ratio'] = df['stays_in_weekend_nights'] / df['total_nights']
    avg_weekend_ratio = df['weekend_ratio'].mean()

    print(f"\nAverage proportion of weekend nights for both hotels: {avg_weekend_ra

def analyze_seasonal_patterns(df):
    """Analyze stay duration patterns by season/month for each hotel type"""

    # Create month order for consistent sorting
    month_order = ['January', 'February', 'March', 'April', 'May', 'June',
                   'July', 'August', 'September', 'October', 'November', 'December'

    # Calculate average stay duration by month and hotel type
    monthly_stays = df.groupby(['arrival_date_month', 'hotel'])['total_nights'].mea
    monthly_stays = monthly_stays.reindex(month_order)

    # Calculate total nights stayed by month and hotel type
    monthly_total_stays = df.groupby(['arrival_date_month', 'hotel'])['total_nights
    monthly_total_stays = monthly_total_stays.reindex(month_order)
```

```
    print("\nAverage Stay Duration by Month and Hotel Type (nights per booking):")
    print(monthly_stays.round(2))

    print("\nTotal Nights Stayed by Month and Hotel Type:")
    print(monthly_total_stays.round(2))

    # Calculate total nights for each hotel type
    total_nights_by_hotel = df.groupby('hotel')['total_nights'].sum()
    print("\nTotal Nights Stayed at Each Hotel:")
    print(total_nights_by_hotel)

    # Analyze patterns for City Hotel
    city_peak_month = monthly_stays['City Hotel'].idxmax()
    city_low_month = monthly_stays['City Hotel'].idxmin()
    city_peak_value = monthly_stays['City Hotel'].max()
    city_low_value = monthly_stays['City Hotel'].min()

    # Analyze patterns for Resort Hotel
    resort_peak_month = monthly_stays['Resort Hotel'].idxmax()
    resort_low_month = monthly_stays['Resort Hotel'].idxmin()
    resort_peak_value = monthly_stays['Resort Hotel'].max()
    resort_low_value = monthly_stays['Resort Hotel'].min()

    print("\nCity Hotel Seasonal Patterns:")
    print(f"Peak month: {city_peak_month}")
    print(f"- Average stay: {city_peak_value:.2f} nights per booking")
    print(f"- Total nights: {monthly_total_stays.loc[city_peak_month, 'City Hotel']
    print(f"Low month: {city_low_month}")
    print(f"- Average stay: {city_low_value:.2f} nights per booking")
    print(f"- Total nights: {monthly_total_stays.loc[city_low_month, 'City Hotel']:

    print("\nResort Hotel Seasonal Patterns:")
    print(f"Peak month: {resort_peak_month}")
    print(f"- Average stay: {resort_peak_value:.2f} nights per booking")
    print(f"- Total nights: {monthly_total_stays.loc[resort_peak_month, 'Resort Hot
    print(f"Low month: {resort_low_month}")
    print(f"- Average stay: {resort_low_value:.2f} nights per booking")
    print(f"- Total nights: {monthly_total_stays.loc[resort_low_month, 'Resort Hote

    # Calculate and display year-round statistics
    hotel_stats = df.groupby('hotel').agg({
        'total_nights': ['mean', 'sum', 'count']
    })
    hotel_stats.columns = ['Average Stay', 'Total Nights', 'Number of Bookings']

    print("\nYear-round Statistics by Hotel Type:")
    print(hotel_stats.round(2))

    # Calculate monthly share of total nights for each hotel
    print("\nMonthly Share of Total Nights (%):")
    monthly_share = monthly_total_stays.div(monthly_total_stays.sum()) * 100
    print(monthly_share.round(2))
```

In [38]:
```
# Calculate total nights for each booking
df_copy = df.copy()
```

```
df_copy = calculate_total_stay_nights(df_copy)
# # Run all analyses
print("=== Hotel Stay Duration Analysis ===")
analyze_stay_duration(df_copy)
analyze_weekend_vs_weekday(df_copy)
analyze_seasonal_patterns(df_copy)
# analyze_stay_distribution(df)
```

```
=== Hotel Stay Duration Analysis ===

Stay Duration Statistics:
Average total nights: 3.43 days
Median total nights: 3.00 days
Most common duration: 2.00 days
Max stay duration: 69.00 days
Min stay duration: 0.00 days

Average Stays by Hotel Type:
              stays_in_weekend_nights  stays_in_week_nights  total_nights
hotel
City Hotel                       0.80                  2.18          2.98
Resort Hotel                     1.19                  3.13          4.32

Average proportion of weekend nights for both hotels: 25.47%

Average Stay Duration by Month and Hotel Type (nights per booking):
hotel              City Hotel  Resort Hotel
arrival_date_month
January                  3.01          2.91
February                 2.99          3.10
March                    3.05          4.13
April                    3.05          4.03
May                      2.84          4.29
June                     2.89          5.37
July                     3.14          5.31
August                   3.16          5.25
September                2.80          5.06
October                  2.75          3.94
November                 2.97          3.58
December                 3.20          3.25

Total Nights Stayed by Month and Hotel Type:
hotel              City Hotel  Resort Hotel
arrival_date_month
January                 11233          6385
February                14825          9630
March                   19719         13770
April                   22789         14546
May                     23367         15267
June                    22778         16338
July                    25400         24305
August                  28391         25686
September               20692         15733
October                 20885         14002
November                12940          8727
December                13237          8612

Total Nights Stayed at Each Hotel:
hotel
City Hotel      236256
Resort Hotel    173001
Name: total_nights, dtype: int64

City Hotel Seasonal Patterns:
```

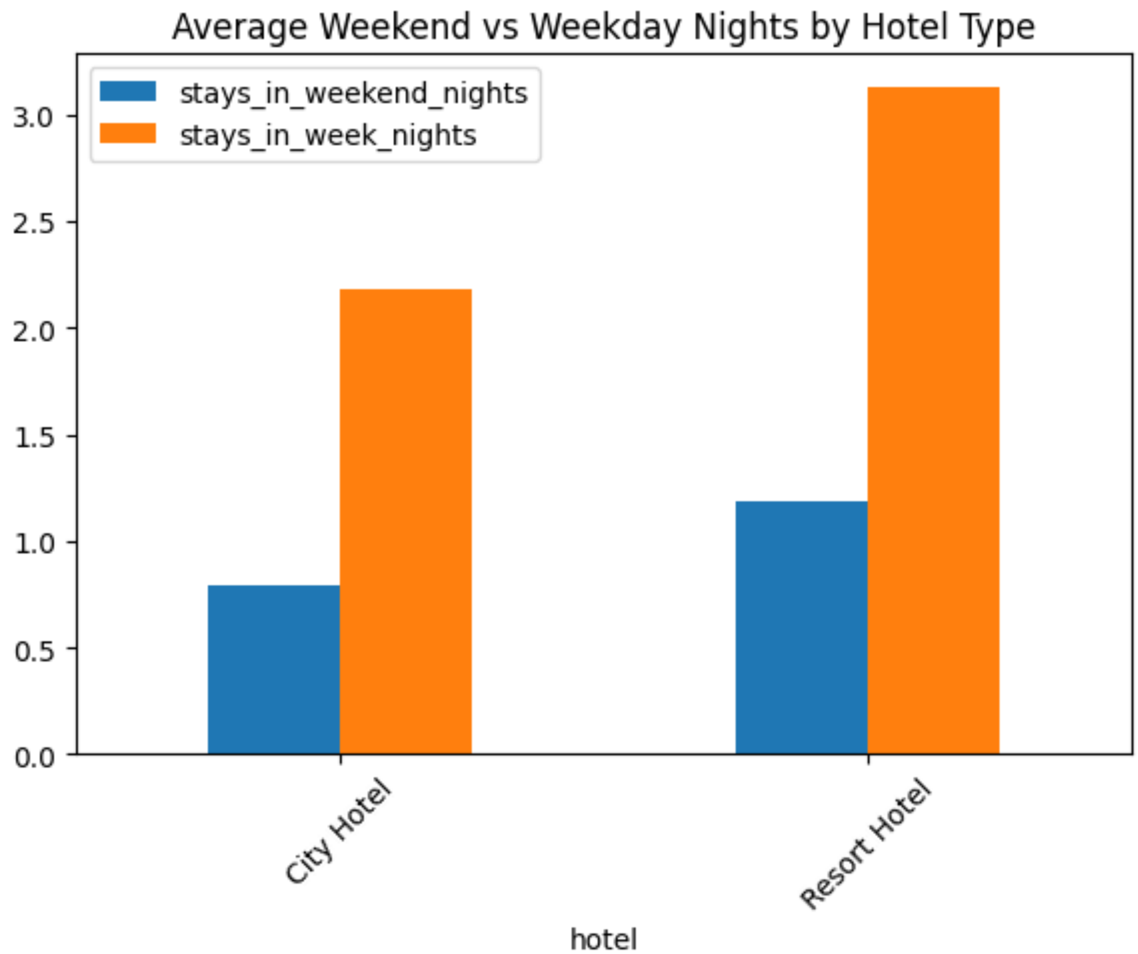
```
Peak month: December
- Average stay: 3.20 nights per booking
- Total nights: 13237 nights
Low month: October
- Average stay: 2.75 nights per booking
- Total nights: 20885 nights

Resort Hotel Seasonal Patterns:
Peak month: June
- Average stay: 5.37 nights per booking
- Total nights: 16338 nights
Low month: January
- Average stay: 2.91 nights per booking
- Total nights: 6385 nights

Year-round Statistics by Hotel Type:
              Average Stay  Total Nights  Number of Bookings
hotel
City Hotel            2.98        236256               79330
Resort Hotel          4.32        173001               40060

Monthly Share of Total Nights (%):
hotel               City Hotel  Resort Hotel
arrival_date_month
January                   4.75          3.69
February                  6.27          5.57
March                     8.35          7.96
April                     9.65          8.41
May                       9.89          8.82
June                      9.64          9.44
July                     10.75         14.05
August                   12.02         14.85
September                 8.76          9.09
October                   8.84          8.09
November                  5.48          5.04
December                  5.60          4.98
```

```
C:\Users\asifm\AppData\Local\Temp\ipykernel_16660\2576096640.py:23: FutureWarning:

The default of observed=False is deprecated and will be changed to True in a future
version of pandas. Pass observed=False to retain current behavior or observed=True t
o adopt the future default and silence this warning.

C:\Users\asifm\AppData\Local\Temp\ipykernel_16660\2576096640.py:46: FutureWarning:

The default of observed=False is deprecated and will be changed to True in a future
version of pandas. Pass observed=False to retain current behavior or observed=True t
o adopt the future default and silence this warning.

C:\Users\asifm\AppData\Local\Temp\ipykernel_16660\2576096640.py:50: FutureWarning:

The default of observed=False is deprecated and will be changed to True in a future
version of pandas. Pass observed=False to retain current behavior or observed=True t
o adopt the future default and silence this warning.

C:\Users\asifm\AppData\Local\Temp\ipykernel_16660\2576096640.py:60: FutureWarning:

The default of observed=False is deprecated and will be changed to True in a future
version of pandas. Pass observed=False to retain current behavior or observed=True t
o adopt the future default and silence this warning.

C:\Users\asifm\AppData\Local\Temp\ipykernel_16660\2576096640.py:93: FutureWarning:

The default of observed=False is deprecated and will be changed to True in a future
version of pandas. Pass observed=False to retain current behavior or observed=True t
o adopt the future default and silence this warning.
```

In [39]:

```python
plt.figure(figsize=(15, 10))
plt.subplot(2, 2, 1)
weekend_weekday = df.groupby('hotel')[['stays_in_weekend_nights', 'stays_in_week_ni
weekend_weekday.plot(kind='bar', ax=plt.gca())
plt.title('Average Weekend vs Weekday Nights by Hotel Type')
plt.xticks(rotation=45)
plt.show()
```

```
C:\Users\asifm\AppData\Local\Temp\ipykernel_16660\2198894593.py:3: FutureWarning:

The default of observed=False is deprecated and will be changed to True in a future
version of pandas. Pass observed=False to retain current behavior or observed=True t
o adopt the future default and silence this warning.
```

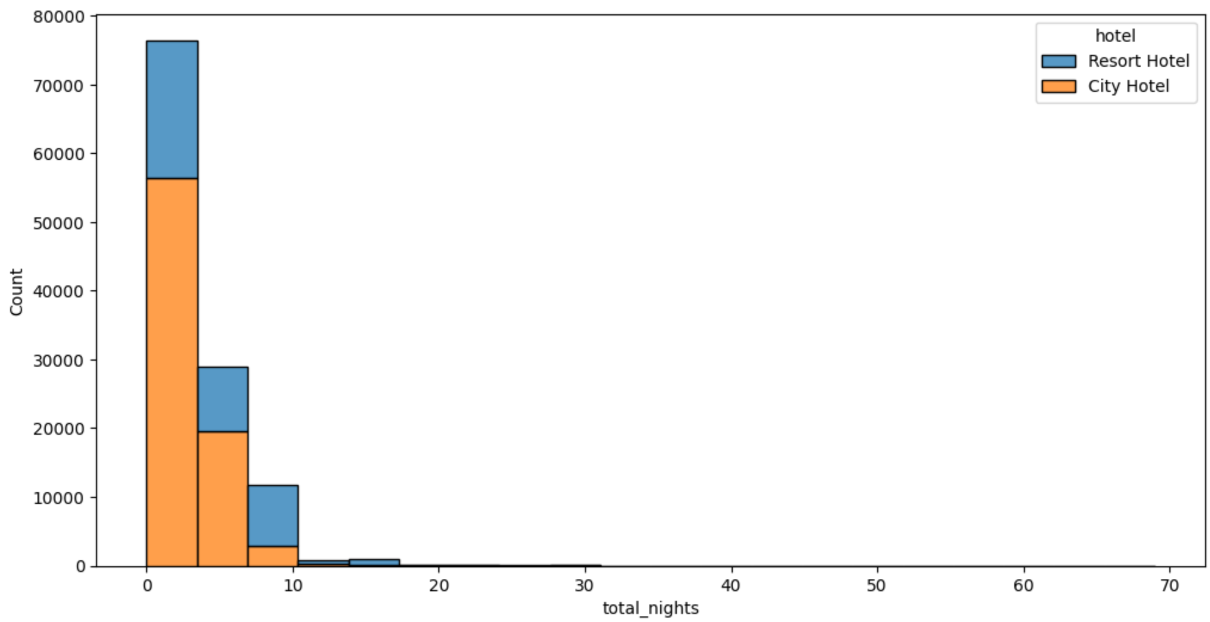


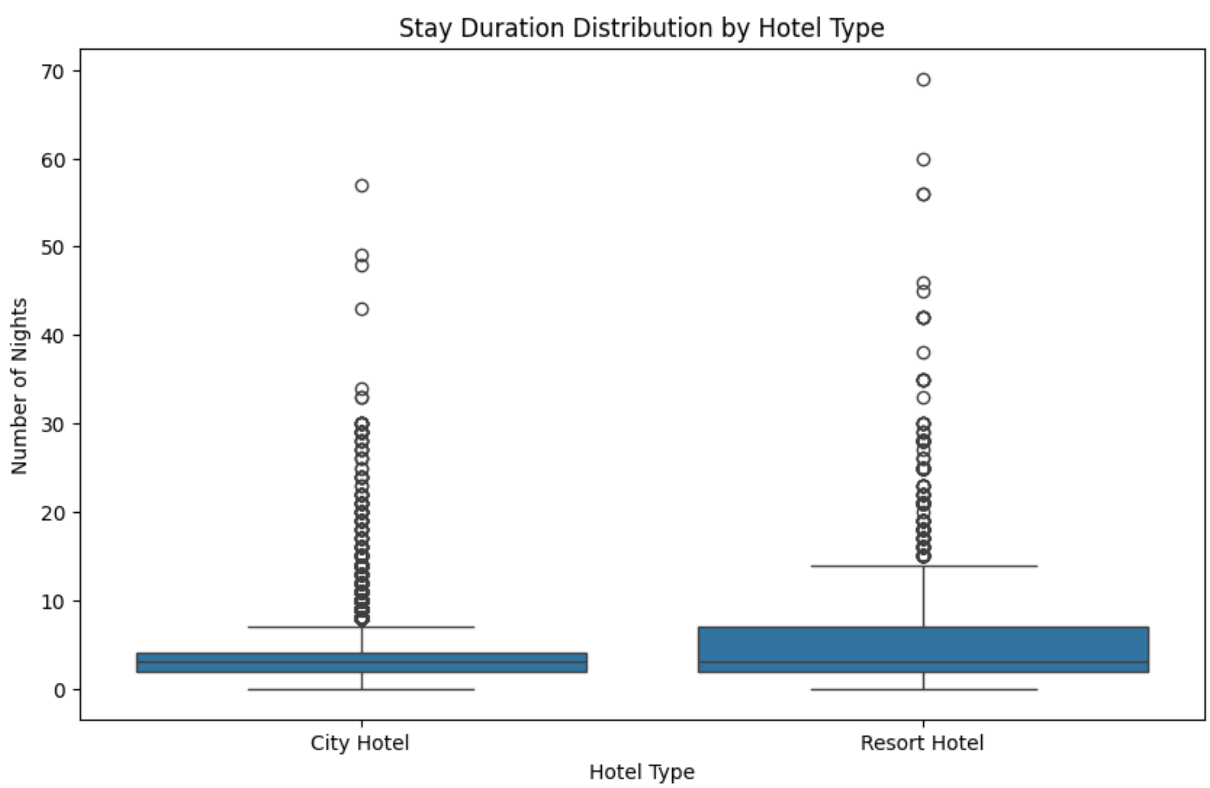
In [40]:
```
def print_summary_statistics(df):
    """Print summary statistics for stay duration by hotel type"""
    summary_stats = df.groupby('hotel').agg({
        'total_nights': ['count', 'mean', 'median', 'std', 'min', 'max']
    }).round(2)
    summary_stats.columns = ['Total Bookings', 'Average Stay', 'Median Stay',
                             'Std Dev', 'Min Stay', 'Max Stay']
    print("\nSummary Statistics by Hotel Type:")
    print(summary_stats)
```

Distribution of stay durations by hotel type

In [41]:
```
def plot_stay_duration_distribution(df):
    """Plot the distribution of stay durations by hotel type"""
    plt.figure(figsize=(12, 6))


    sns.histplot(data=df,
                 x='total_nights',
                 hue='hotel',
                 multiple="stack",
                 bins=20,  # Light salmon for Resort, Light blue for City
                 hue_order=['Resort Hotel', 'City Hotel'])
```

```python
def plot_stay_duration_boxplot(df):
    """Plot box plot of stay durations by hotel type"""
    plt.figure(figsize=(10, 6))
    sns.boxplot(data=df, x='hotel', y='total_nights')
    plt.title('Stay Duration Distribution by Hotel Type')
    plt.xlabel('Hotel Type')
    plt.ylabel('Number of Nights')
    plt.show()

plot_stay_duration_distribution(df_copy)
plot_stay_duration_boxplot(df_copy)
```





Analysis

Distribution Shape

The data reveals a highly right-skewed (positively skewed) distribution, with a strong concentration of short stays ranging from 0-3 nights. The distribution shows a long tail extending to approximately 20 nights, though there are very few stays that extend beyond this duration.

Pattern Recognition

Analysis shows a clear dominance of short-duration stays across the dataset. The data follows an exponential decay pattern in stay duration, with notable differences emerging between City and Resort hotels when examining the stacked color distributions.

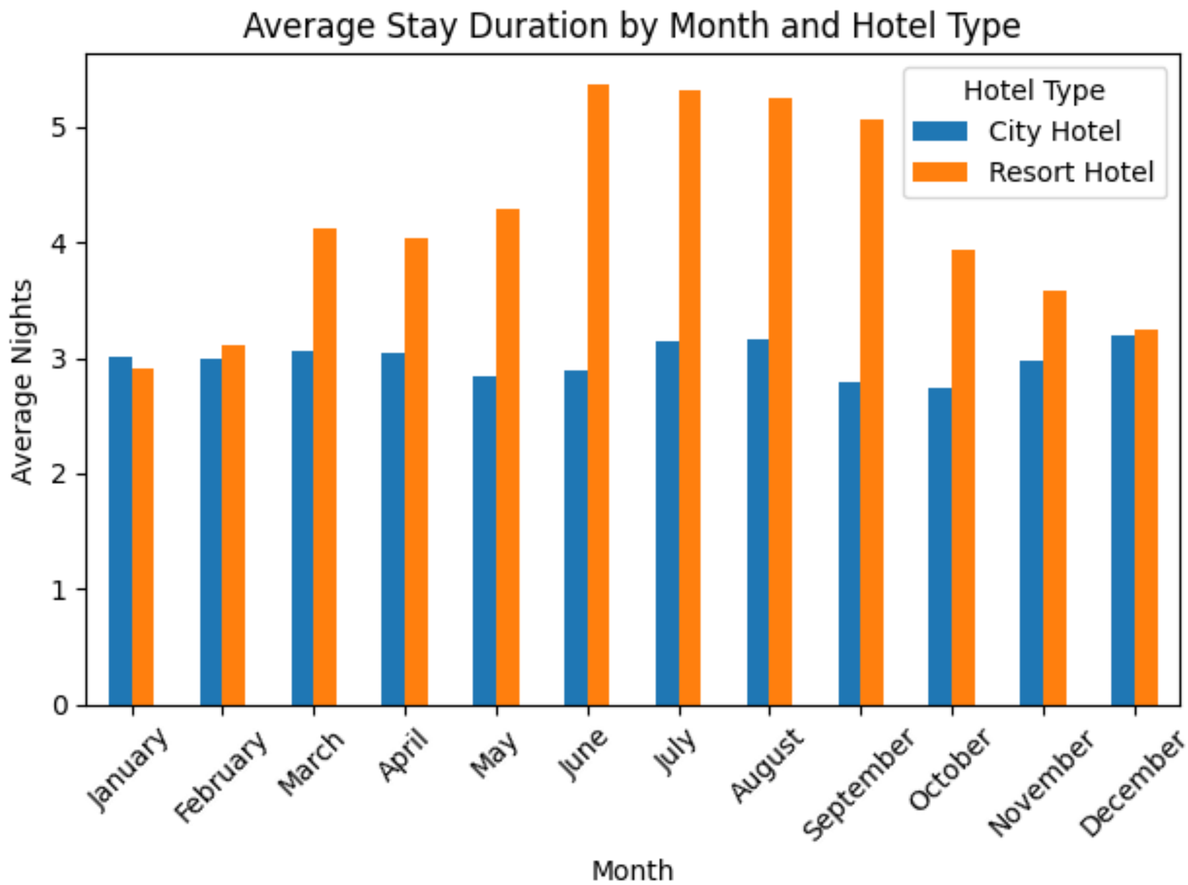
Business Implications

The high turnover rate, evidenced by the predominance of short stays, suggests a need for highly efficient check-in and check-out processes. This pattern has significant implications for room cleaning and maintenance scheduling, while also presenting various opportunities for revenue optimization strategies.

Average stay duration by month and hotel type

In [42]:
```
def plot_monthly_average_stays(df):
    """Plot average stay duration by month and hotel type"""
    plt.figure(figsize=(12, 6))
    month_order = ['January', 'February', 'March', 'April', 'May', 'June',
                   'July', 'August', 'September', 'October', 'November', 'December'
    monthly_avg = df.groupby(['arrival_date_month', 'hotel'])['total_nights'].mean(
    monthly_avg = monthly_avg.reindex(month_order)
    monthly_avg.plot(kind='bar')
    plt.title('Average Stay Duration by Month and Hotel Type')
    plt.xlabel('Month')
    plt.ylabel('Average Nights')
    plt.xticks(rotation=45)
    plt.legend(title='Hotel Type')
    plt.tight_layout()
    plt.show()
plot_monthly_average_stays(df_copy)
```

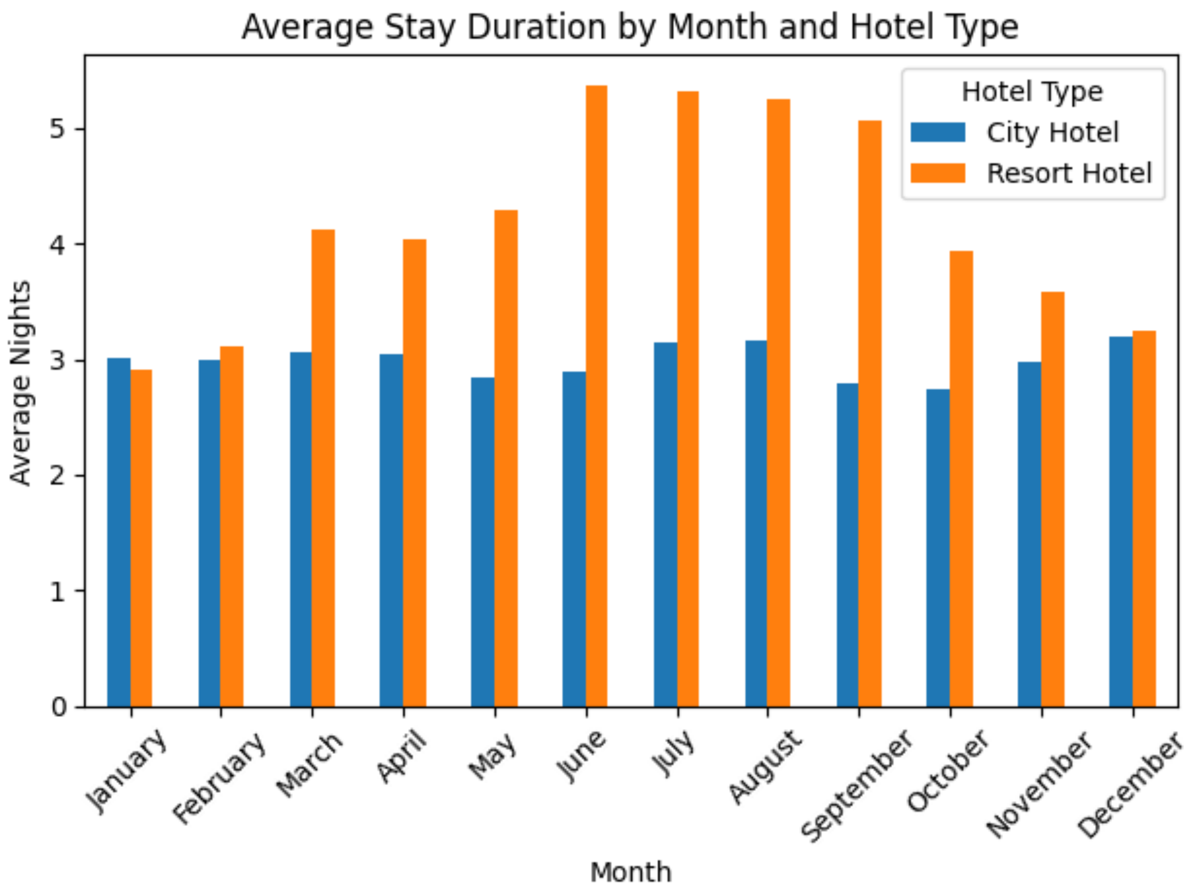
```
C:\Users\asifm\AppData\Local\Temp\ipykernel_16660\3804584767.py:6: FutureWarning:

The default of observed=False is deprecated and will be changed to True in a future
version of pandas. Pass observed=False to retain current behavior or observed=True t
o adopt the future default and silence this warning.

<Figure size 1200x600 with 0 Axes>
```



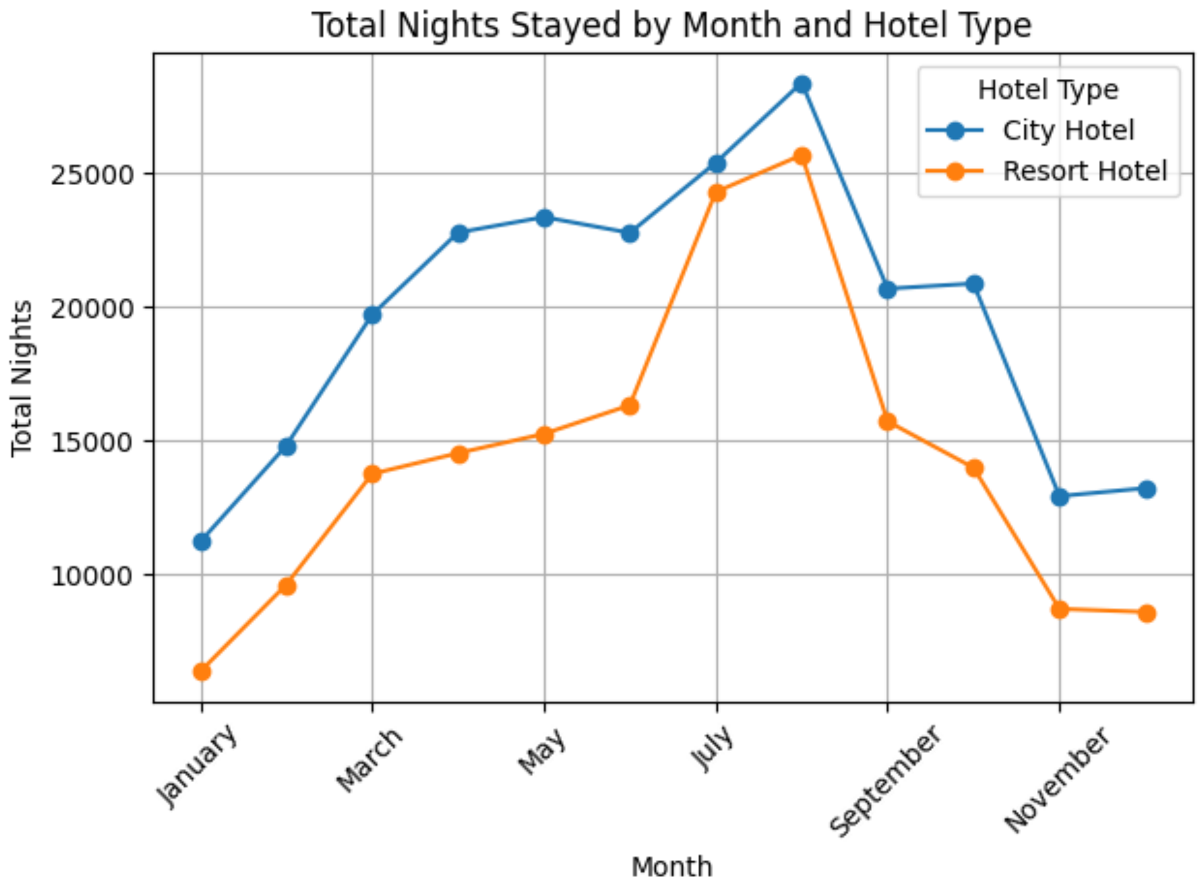
In [43]:
```
def plot_total_nights_by_month(df):
    """Plot total nights stayed by month and hotel type"""
    plt.figure(figsize=(15, 10))
    month_order = ['January', 'February', 'March', 'April', 'May', 'June',
                   'July', 'August', 'September', 'October', 'November', 'December'
    total_nights_by_hotel = df.groupby(['arrival_date_month', 'hotel'])['total_nigh
    total_nights_by_hotel = total_nights_by_hotel.reindex(month_order)
    total_nights_by_hotel.plot(kind='line', marker='o')
    plt.title('Total Nights Stayed by Month and Hotel Type')
    plt.xlabel('Month')
    plt.ylabel('Total Nights')
    plt.xticks(rotation=45)
    plt.legend(title='Hotel Type')
    plt.grid(True)
    plt.tight_layout()
    plt.show()

def plot_monthly_average_stays(df):
    """Plot average stay duration by month and hotel type"""
    plt.figure(figsize=(12, 6))
    month_order = ['January', 'February', 'March', 'April', 'May', 'June',
                   'July', 'August', 'September', 'October', 'November', 'December'
    monthly_avg = df.groupby(['arrival_date_month', 'hotel'])['total_nights'].mean(
    monthly_avg = monthly_avg.reindex(month_order)
    monthly_avg.plot(kind='bar')
    plt.title('Average Stay Duration by Month and Hotel Type')
    plt.xlabel('Month')
    plt.ylabel('Average Nights')
```

```
    plt.xticks(rotation=45)
    plt.legend(title='Hotel Type')
    plt.tight_layout()
    plt.show()
plot_monthly_average_stays(df_copy)
plot_total_nights_by_month(df_copy)
```

```
C:\Users\asifm\AppData\Local\Temp\ipykernel_16660\271762834.py:23: FutureWarning:

The default of observed=False is deprecated and will be changed to True in a future
version of pandas. Pass observed=False to retain current behavior or observed=True t
o adopt the future default and silence this warning.

<Figure size 1200x600 with 0 Axes>
```




```
C:\Users\asifm\AppData\Local\Temp\ipykernel_16660\271762834.py:6: FutureWarning:

The default of observed=False is deprecated and will be changed to True in a future
version of pandas. Pass observed=False to retain current behavior or observed=True t
o adopt the future default and silence this warning.

<Figure size 1500x1000 with 0 Axes>
```



Seasonal Patterns

Peak Season (June-August)

- **City Hotels**
  - Highest total nights (~28,000 nights in August)
  - Consistent average stay duration (~3 nights)
  - Strong business performance despite shorter stays
- **Resort Hotels**
  - Peak total nights (~25,000 in July)
  - Longest average stays (~5.3 nights)
  - Clear summer vacation pattern

Off-Peak Season (November-January)

- **City Hotels**
  - Lowest total nights (~13,000)
  - Stable average duration (~3 nights)
  - Maintains business consistency
- **Resort Hotels**

- Minimum total nights (~7,000)
- Shorter average stays (~3 nights)
- Converges with city hotel patterns

Key Trends

Total Nights Pattern

1. **Seasonal Variation**
   - Both types show strong seasonality
   - City hotels consistently higher volume
   - Resort hotels show more dramatic fluctuation
2. **Volume Leadership**
   - City hotels maintain higher total nights year-round
   - Gap narrows significantly in summer months
   - Maximum difference in winter months

Stay Duration Insights

1. **City Hotels**
   - Remarkably stable duration (~2.8-3.2 nights)
   - Minimal seasonal impact on stay length
   - Suggests consistent business travel base
2. **Resort Hotels**
   - High seasonal variation in duration
   - Summer stays almost double winter stays
   - Clear leisure travel pattern

Business Implications

Revenue Optimization

1. **City Hotels**
   - Focus on volume in peak seasons
   - Maintain consistent pricing strategy
   - Target business travelers year-round
2. **Resort Hotels**
   - Aggressive summer premium pricing
   - Winter package deals to increase stays
   - Focus on extending shoulder season stays

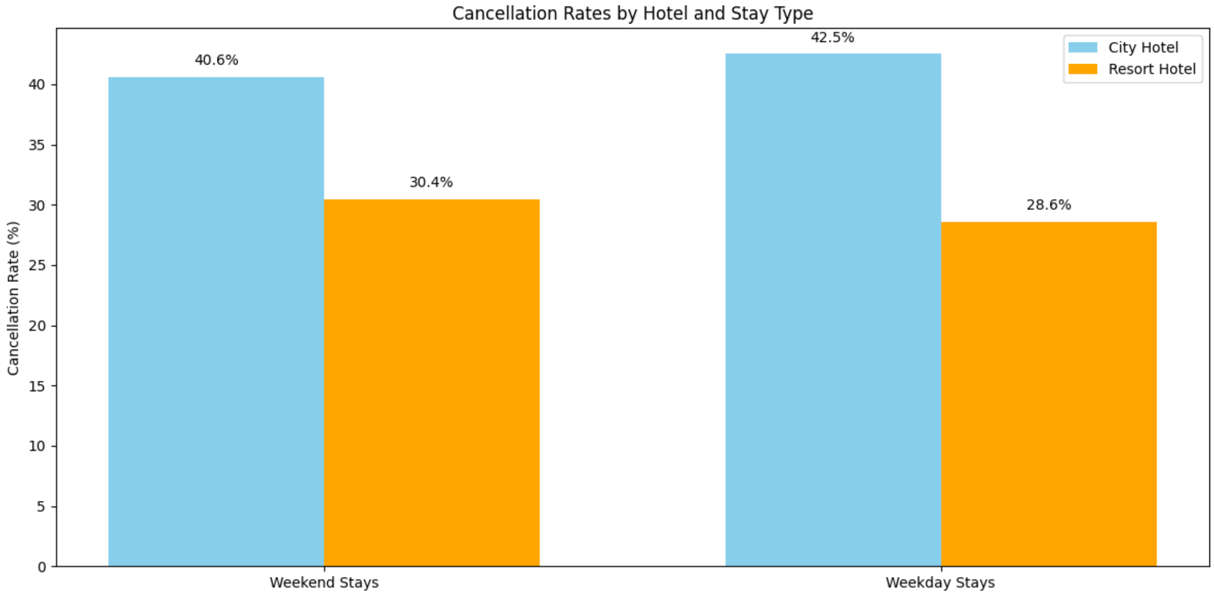
Strategic Recommendations

1. Target shoulder seasons for growth
2. Develop season-specific pricing strategies
3. Optimize operational efficiency based on stay patterns
4. Create targeted marketing campaigns by season

Comparison of weekend vs weekday stays

In [44]:
```
def plot_cancellation_rates_by_hotel(df):
    """
    Create a single plot showing cancellation rates by hotel type and stay type

    Parameters:
    df (pandas.DataFrame): DataFrame containing hotel booking data
    """
    # Initialize figure
    plt.figure(figsize=(12, 6))

    # Calculate cancellation rates for each hotel type
    hotel_cancellation_rates = {}

    for hotel_type in df['hotel'].unique():
        hotel_data = df[df['hotel'] == hotel_type]

        weekend_stays = hotel_data[hotel_data['stays_in_weekend_nights'] > 0]
        weekday_stays = hotel_data[hotel_data['stays_in_week_nights'] > 0]

        hotel_cancellation_rates[hotel_type] = {
            'Weekend': (weekend_stays['is_canceled'].mean() * 100),
            'Weekday': (weekday_stays['is_canceled'].mean() * 100)
        }

    # Set up bar positions
    x = np.arange(2)
    width = 0.35

    # Create bars
    plt.bar(x - width/2,
            [hotel_cancellation_rates['City Hotel']['Weekend'],
             hotel_cancellation_rates['City Hotel']['Weekday']],
            width,
            label='City Hotel',
            color='skyblue')

    plt.bar(x + width/2,
            [hotel_cancellation_rates['Resort Hotel']['Weekend'],
             hotel_cancellation_rates['Resort Hotel']['Weekday']],
            width,
            label='Resort Hotel',
            color='orange')
```

```
    # Customize plot
    plt.ylabel('Cancellation Rate (%)')
    plt.title('Cancellation Rates by Hotel and Stay Type')
    plt.xticks(x, ['Weekend Stays', 'Weekday Stays'])
    plt.legend()

    # Add percentage labels on bars
    for i, hotel_type in enumerate(['City Hotel', 'Resort Hotel']):
        for j, stay_type in enumerate(['Weekend', 'Weekday']):
            value = hotel_cancellation_rates[hotel_type][stay_type]
            plt.text(j + (width if i else -width)/2, value + 1,
                    f'{value:.1f}%',
                    ha='center')

    plt.tight_layout()

    # Return statistics
    stats = {
        'Cancellation Rates': hotel_cancellation_rates,
        'Total Bookings': {
            'City Hotel': {
                'Weekend': len(df[(df['hotel'] == 'City Hotel') &
                                (df['stays_in_weekend_nights'] > 0)]),
                'Weekday': len(df[(df['hotel'] == 'City Hotel') &
                                 (df['stays_in_week_nights'] > 0)])
            },
            'Resort Hotel': {
                'Weekend': len(df[(df['hotel'] == 'Resort Hotel') &
                                (df['stays_in_weekend_nights'] > 0)]),
                'Weekday': len(df[(df['hotel'] == 'Resort Hotel') &
                                 (df['stays_in_week_nights'] > 0)])
            }
        }
    }

    return stats

# Example usage:
stats = plot_cancellation_rates_by_hotel(df)
plt.show()

# Print summary
for hotel in ['City Hotel', 'Resort Hotel']:
    print(f"\n{hotel}:")
    print(f"Weekend Cancellation Rate: {stats['Cancellation Rates'][hotel]['Weekend
    print(f"Weekday Cancellation Rate: {stats['Cancellation Rates'][hotel]['Weekday
    print(f"Total Weekend Bookings: {stats['Total Bookings'][hotel]['Weekend']}")
    print(f"Total Weekday Bookings: {stats['Total Bookings'][hotel]['Weekday']}")
```




```
City Hotel:
Weekend Cancellation Rate: 40.6%
Weekday Cancellation Rate: 42.5%
Total Weekend Bookings: 41513
Total Weekday Bookings: 74367

Resort Hotel:
Weekend Cancellation Rate: 30.4%
Weekday Cancellation Rate: 28.6%
Total Weekend Bookings: 25879
Total Weekday Bookings: 37378
```

In [50]:
```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import numpy as np

def plot_simple_cancellation_rates(df):
    """
    Create a simple bar plot showing cancellation rates by stay type

    Parameters:
    df (pandas.DataFrame): DataFrame containing hotel booking data
    """
    # Calculate cancellation rates
    weekend_stays = df[df['stays_in_weekend_nights'] > 0]
    weekday_stays = df[df['stays_in_week_nights'] > 0]

    cancellation_rates = {
        'Weekend': (weekend_stays['is_canceled'].mean() * 100),
        'Weekday': (weekday_stays['is_canceled'].mean() * 100)
    }

    # Create plot
    plt.figure(figsize=(10, 6))
    bars = plt.bar(['Weekend Stays', 'Weekday Stays'],
                   [cancellation_rates['Weekend'], cancellation_rates['Weekday']],
                   color=['lightblue', 'orange'])
```

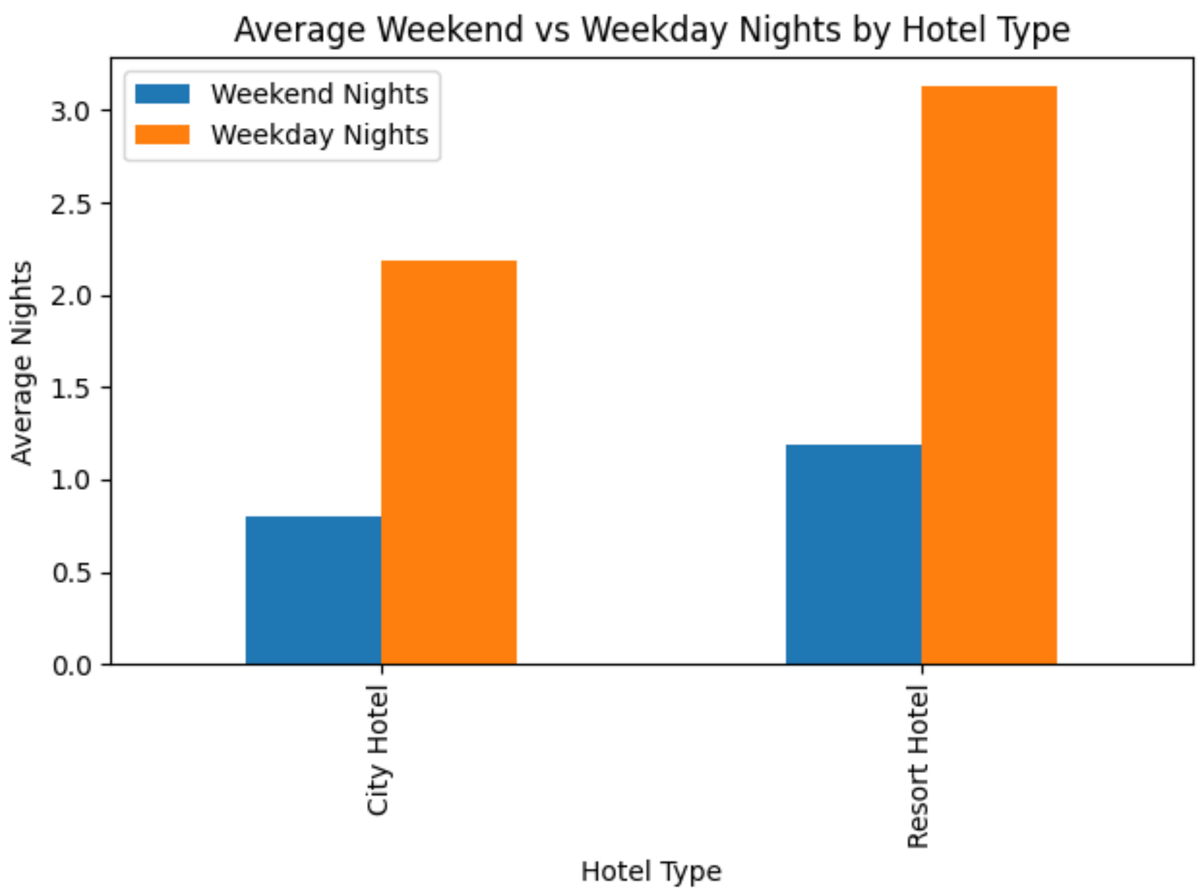
```
    # Customize plot
    plt.ylabel('Cancellation Rate (%)')
    plt.title('Cancellation Rates by Stay Type')

    # Add percentage labels on top of bars
    for bar in bars:
        height = bar.get_height()
        plt.text(bar.get_x() + bar.get_width()/2, height + 0.5,
                f'{height:.1f}%',
                ha='center', va='bottom')

    # Clean up layout
    plt.tight_layout()

    return cancellation_rates

def analyze_cancellations_by_hotel_and_day(df):
    """
    Analyze and visualize booking cancellations by hotel type for weekend vs weekda

    Parameters:
    df (pandas.DataFrame): DataFrame containing hotel booking data

    Returns:
    tuple: (figure, cancellation_stats)
    """
    # Calculate total nights for each booking
    df['total_nights'] = df['stays_in_weekend_nights'] + df['stays_in_week_nights']

    # Create statistics dictionary for each hotel type
    stats = {}
    for hotel_type in df['hotel'].unique():
        hotel_data = df[df['hotel'] == hotel_type]

        cancelled = hotel_data[hotel_data['is_canceled'] == True]
        not_cancelled = hotel_data[hotel_data['is_canceled'] == False]

        stats[hotel_type] = {
            'Cancelled': {
                'Weekend': cancelled['stays_in_weekend_nights'].mean(),
                'Weekday': cancelled['stays_in_week_nights'].mean(),
                'Total': len(cancelled)
            },
            'Not Cancelled': {
                'Weekend': not_cancelled['stays_in_weekend_nights'].mean(),
                'Weekday': not_cancelled['stays_in_week_nights'].mean(),
                'Total': len(not_cancelled)
            }
        }

    # Create visualization with subplots
    fig = plt.figure(figsize=(20, 10))
    gs = fig.add_gridspec(2, 2)

    # Plot 1: Average nights comparison for City Hotel
```

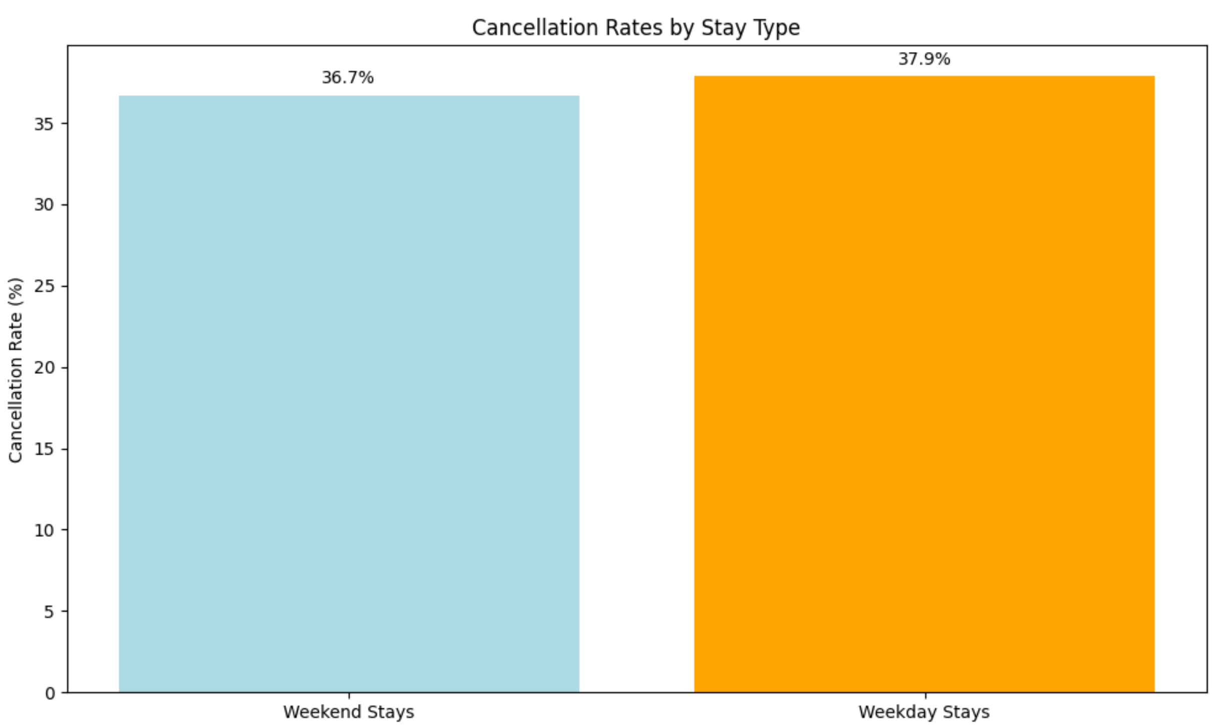
```
ax1 = fig.add_subplot(gs[0, 0])
width = 0.35
x = np.arange(2)

ax1.bar(x - width/2,
        [stats['City Hotel']['Cancelled']['Weekend'],
         stats['City Hotel']['Cancelled']['Weekday']],
        width, label='Cancelled', color='red', alpha=0.6)
ax1.bar(x + width/2,
        [stats['City Hotel']['Not Cancelled']['Weekend'],
         stats['City Hotel']['Not Cancelled']['Weekday']],
        width, label='Not Cancelled', color='green', alpha=0.6)

ax1.set_xticks(x)
ax1.set_xticklabels(['Weekend Nights', 'Weekday Nights'])
ax1.set_ylabel('Average Nights')
ax1.set_title('City Hotel: Average Stay Duration')
ax1.legend()

# Plot 2: Average nights comparison for Resort Hotel
ax2 = fig.add_subplot(gs[0, 1])

ax2.bar(x - width/2,
        [stats['Resort Hotel']['Cancelled']['Weekend'],
         stats['Resort Hotel']['Cancelled']['Weekday']],
        width, label='Cancelled', color='red', alpha=0.6)
ax2.bar(x + width/2,
        [stats['Resort Hotel']['Not Cancelled']['Weekend'],
         stats['Resort Hotel']['Not Cancelled']['Weekday']],
        width, label='Not Cancelled', color='green', alpha=0.6)

ax2.set_xticks(x)
ax2.set_xticklabels(['Weekend Nights', 'Weekday Nights'])
ax2.set_ylabel('Average Nights')
ax2.set_title('Resort Hotel: Average Stay Duration')
ax2.legend()

# Plot 3: Cancellation rates comparison
ax3 = fig.add_subplot(gs[1, :])

cancellation_rates = {}
for hotel_type in ['City Hotel', 'Resort Hotel']:
    hotel_data = df[df['hotel'] == hotel_type]
    weekend_stays = hotel_data[hotel_data['stays_in_weekend_nights'] > 0]
    weekday_stays = hotel_data[hotel_data['stays_in_week_nights'] > 0]

    cancellation_rates[hotel_type] = {
        'Weekend': (weekend_stays['is_canceled'].mean() * 100),
        'Weekday': (weekday_stays['is_canceled'].mean() * 100)
    }

# Create grouped bar chart for cancellation rates
x = np.arange(2)
width = 0.35

ax3.bar(x - width/2,
```

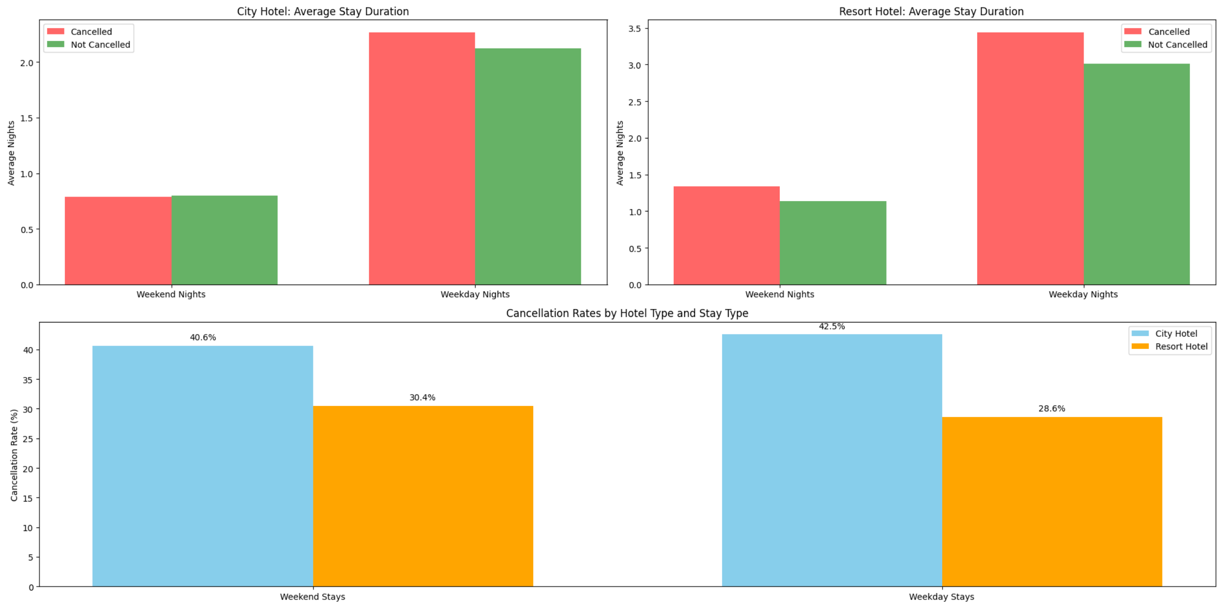
```
            [cancellation_rates['City Hotel']['Weekend'],
             cancellation_rates['City Hotel']['Weekday']],
            width, label='City Hotel', color='skyblue')
    ax3.bar(x + width/2,
            [cancellation_rates['Resort Hotel']['Weekend'],
             cancellation_rates['Resort Hotel']['Weekday']],
            width, label='Resort Hotel', color='orange')

    ax3.set_xticks(x)
    ax3.set_xticklabels(['Weekend Stays', 'Weekday Stays'])
    ax3.set_ylabel('Cancellation Rate (%)')
    ax3.set_title('Cancellation Rates by Hotel Type and Stay Type')
    ax3.legend()

    # Add percentage labels
    for i, hotel_type in enumerate(['City Hotel', 'Resort Hotel']):
        for j, stay_type in enumerate(['Weekend', 'Weekday']):
            value = cancellation_rates[hotel_type][stay_type]
            ax3.text(j + (width if i else -width)/2, value + 1,
                    f'{value:.1f}%', ha='center')

    plt.tight_layout()
```

In [51]:
```
def plot_weekend_weekday_comparison(df):
    """Plot comparison of weekend vs weekday stays"""
    plt.figure(figsize=(10, 6))
    weekend_weekday = df.groupby('hotel').agg({
        'stays_in_weekend_nights': 'mean',
        'stays_in_week_nights': 'mean'
    })
    weekend_weekday.plot(kind='bar')
    plt.title('Average Weekend vs Weekday Nights by Hotel Type')
    plt.xlabel('Hotel Type')
    plt.ylabel('Average Nights')
    plt.legend(['Weekend Nights', 'Weekday Nights'])
    plt.tight_layout()
    plt.show()

plot_weekend_weekday_comparison(df_copy)
plt.show()
plot_simple_cancellation_rates(df_copy)
plt.show()
analyze_cancellations_by_hotel_and_day(df_copy)
plt.show()
```

```
C:\Users\asifm\AppData\Local\Temp\ipykernel_16660\504322050.py:4: FutureWarning:

The default of observed=False is deprecated and will be changed to True in a future
version of pandas. Pass observed=False to retain current behavior or observed=True t
o adopt the future default and silence this warning.

<Figure size 1000x600 with 0 Axes>
```


Average Weekend vs Weekday Nights by Hotel Type
Weekend Nights
Weekday Nights
Average Nights
0.0
0.5
1.0
1.5
2.0
2.5
3.0
City Hotel
Resort Hotel
Hotel Type


Cancellation Rates by Stay Type
36.7%
37.9%
Cancellation Rate (%)
0
5
10
15
20
25
30
35
Weekend Stays
Weekday Stays



Hotel stay analysis for weekdays vs weekends

City Hotels

- Lower average stay duration overall
- Weekend nights: ~0.8 nights average
- Weekday nights: ~2.2 nights average
- Clear preference for weekday stays (2.75x higher than weekends)

Resort Hotels

- Higher average stay duration compared to city hotels
- Weekend nights: ~1.2 nights average
- Weekday nights: ~3.1 nights average
- Strongest weekday preference (2.6x higher than weekends)

Cancellation Analysis

Overall Patterns

- Weekday stays show slightly higher cancellation rates (37.9%) compared to weekend stays (36.7%)
- Minimal difference (~1.2%) between weekend and weekday cancellation rates
- Both types show significant cancellation rates >35%

Hotel-Specific Cancellation Patterns

1. **City Hotels**
    - Weekend cancellation rate: 40.6%
    - Weekday cancellation rate: 42.5%

- Consistently higher cancellation rates than resort hotels
- Higher volatility between cancelled and non-cancelled bookings

2. **Resort Hotels**

- Weekend cancellation rate: 30.4%
- Weekday cancellation rate: 28.6%
- More stable cancellation pattern
- Generally lower cancellation rates (~12% lower than city hotels)

Key Business Insights

1. **Booking Stability**

- Resort hotels demonstrate more stable booking patterns
- City hotels face higher cancellation risk
- Weekend bookings slightly more reliable overall

2. **Duration Strategy**

- Both hotel types should focus on extending weekend stays
- Resort hotels have better success with longer stays
- Weekday stays dominate in terms of duration

3. **Risk Management**

- City hotels should implement stronger cancellation policies
- Focus on converting weekend bookings to longer stays
- Consider different deposit requirements based on hotel type and stay duration

Recommendations

1. **For City Hotels**

- Implement stricter cancellation policies for weekday bookings
- Develop weekend packages to increase duration
- Consider loyalty programs to reduce cancellation rates

2. **For Resort Hotels**

- Focus on maintaining lower cancellation rates
- Develop extended stay promotions
- Leverage successful weekday booking patterns

3. **General Strategies**

- Differentiated pricing for weekend vs weekday stays
- Length-of-stay incentives
- targeted marketing based on stay patterns

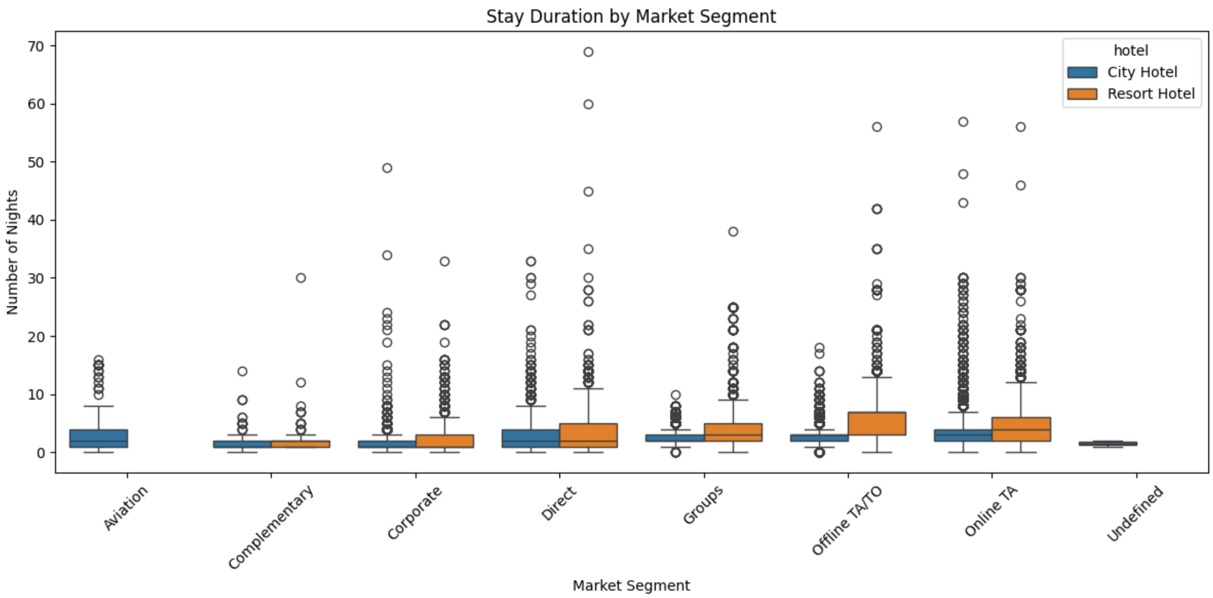
In [ ]:
```
def plot_total_nights_by_month(df):
    """Plot total nights stayed by month and hotel type"""
    plt.figure(figsize=(12, 6))
    month_order = ['January', 'February', 'March', 'April', 'May', 'June',
                   'July', 'August', 'September', 'October', 'November', 'December'
    total_nights_by_hotel = df.groupby(['arrival_date_month', 'hotel'])['total_nigh
    total_nights_by_hotel = total_nights_by_hotel.reindex(month_order)
    total_nights_by_hotel.plot(kind='line', marker='o')
    plt.title('Total Nights Stayed by Month and Hotel Type')
    plt.xlabel('Month')
    plt.ylabel('Total Nights')
    plt.xticks(rotation=45)
    plt.legend(title='Hotel Type')
    plt.grid(True)
    plt.tight_layout()
    plt.show()
```

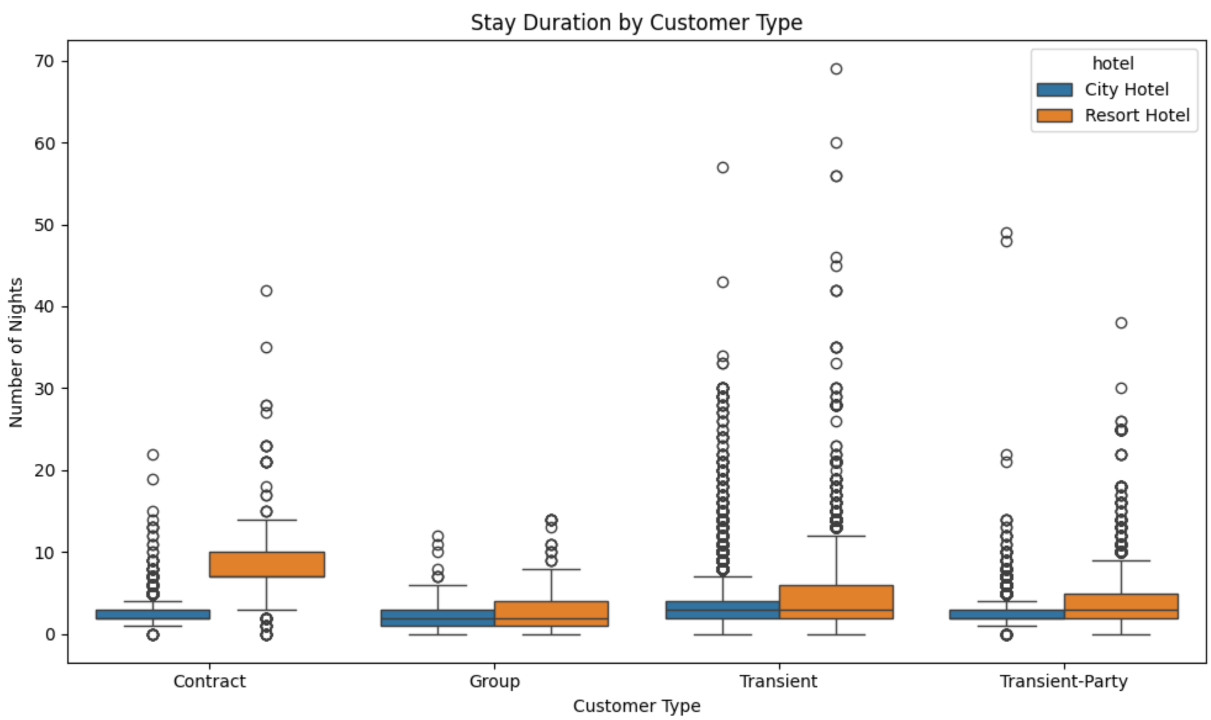
Stay duration by Market segment, Customer types and room Types

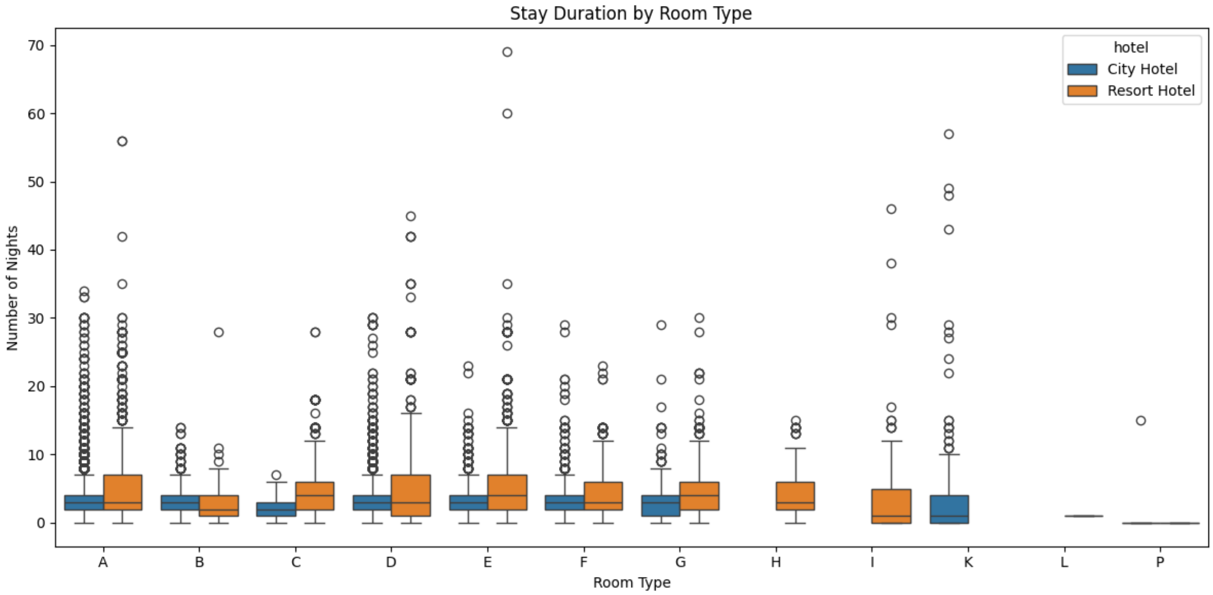
In [ ]:
```
def plot_stay_duration_by_market_segment(df):
    """Plot stay duration by market segment"""
    plt.figure(figsize=(12, 6))
    sns.boxplot(data=df, x='market_segment', y='total_nights', hue='hotel')
    plt.title('Stay Duration by Market Segment')
    plt.xlabel('Market Segment')
    plt.ylabel('Number of Nights')
    plt.xticks(rotation=45)
    plt.tight_layout()
    plt.show()

def plot_stay_duration_by_customer_type(df):
    """Plot stay duration by customer type"""
    plt.figure(figsize=(10, 6))
    sns.boxplot(data=df, x='customer_type', y='total_nights', hue='hotel')
    plt.title('Stay Duration by Customer Type')
    plt.xlabel('Customer Type')
    plt.ylabel('Number of Nights')
    plt.tight_layout()
    plt.show()

def plot_stay_duration_by_room_type(df):
    """Plot stay duration by room type"""
    plt.figure(figsize=(12, 6))
    sns.boxplot(data=df, x='assigned_room_type', y='total_nights', hue='hotel')
    plt.title('Stay Duration by Room Type')
    plt.xlabel('Room Type')
    plt.ylabel('Number of Nights')
    plt.tight_layout()
    plt.show()
```

In [ ]:
```
plot_stay_duration_by_market_segment(df_copy)
plot_stay_duration_by_customer_type(df_copy)
```

```
plot_stay_duration_by_room_type(df_copy)
```







Market Segment Analysis

Online and Offline Travel Agencies (TA)

- Highest median stay duration for both hotel types
- Resort hotels show greater variance in stay length
- Online TA bookings typically longer than offline
- More outliers indicating extended stays (up to 60 nights)

Corporate and Direct Bookings

- More consistent stay durations
- City hotels show tighter distribution
- Direct bookings slightly longer than corporate
- Fewer extreme outliers

Aviation and Complementary

- Shortest average stays
- Limited variance in duration
- Minimal difference between hotel types
- Few outliers

Customer Type Analysis

Contract Customers

- Resort hotels show significantly longer stays
- Highest median duration among all customer types
- Large variance in stay length

- Median stay ~8 nights for resort hotels

Transient Customers

- Most common customer type
- Similar patterns between city and resort hotels
- More outliers in resort hotels
- Median stay 2-3 nights

Group and Transient-Party

- Moderate stay durations
- Resort hotels show slightly longer stays
- More consistent patterns than contract customers
- Less variance in stay duration

Room Type Patterns

Type A and D Rooms

- Most popular room types
- Highest number of bookings
- Greater variance in stay duration
- More outliers in both hotel types

Premium Rooms (B, C, F)

- Shorter average stays
- More consistent duration patterns
- Fewer extreme outliers
- Similar patterns across hotel types

Specialized Rooms (H, I, K)

- Limited availability in city hotels
- Resort-specific room types show unique patterns
- More variable stay durations
- Higher proportion of extended stays

Business Implications

Marketing Strategy

1. **Target Segmentation**

    - Focus on Online TA for longer stays

- Develop corporate packages for consistent occupancy
- Special rates for contract customers in resort hotels

2. **Room Allocation**

- Optimize Type A and D room inventory
- Consider converting less popular room types
- Balance premium room availability with demand

Operational Planning

1. **Resource Management**

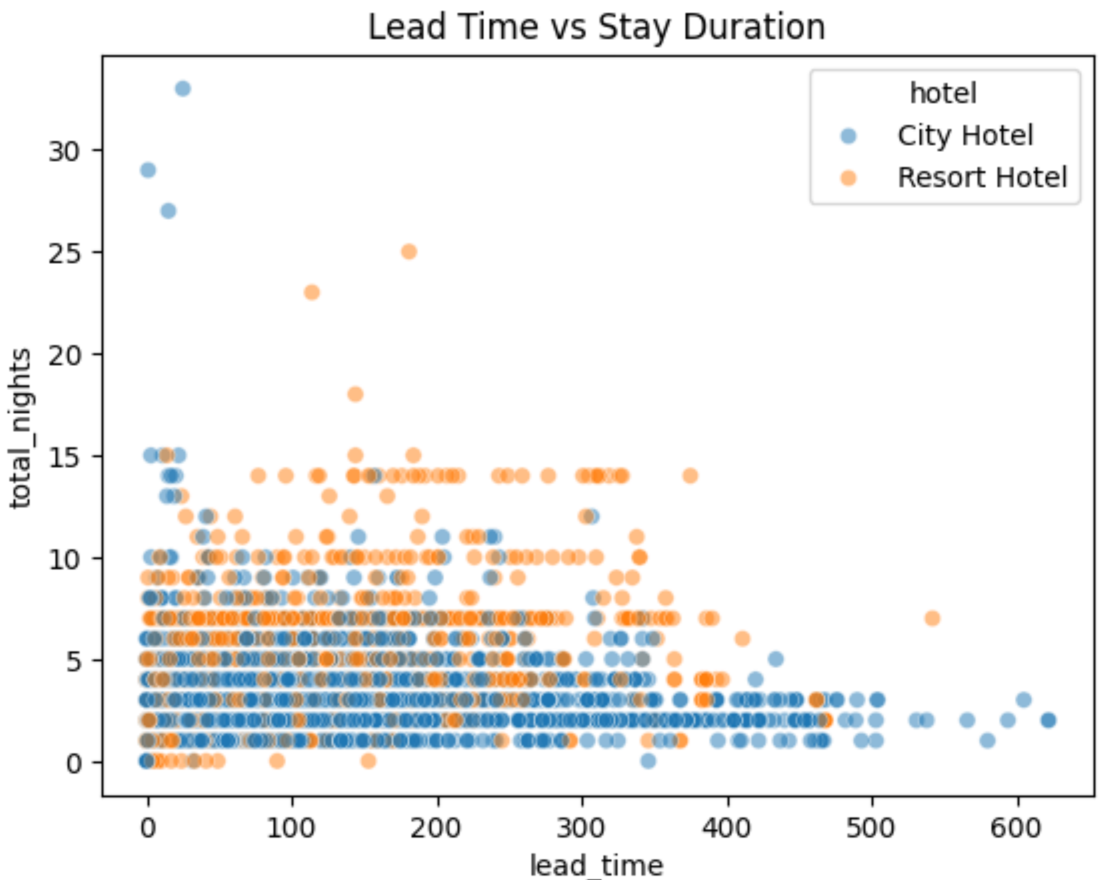
- Plan staffing based on customer type mix
- Adjust housekeeping schedules for varying durations
- Optimize room turnover processes

2. **Revenue Optimization**

- Dynamic pricing by market segment
- Length-of-stay incentives for preferred segments
- Premium pricing for high-demand room types

Lead time vs Stay Duration

In [ ]:
```
def lead_time_vs_stay_duration(df):
    sns.scatterplot(data=df.sample(5000), x='lead_time', y='total_nights',
                    hue='hotel', alpha=0.5)
    plt.title('Lead Time vs Stay Duration')
    plt.show()
lead_time_vs_stay_duration(df_copy)
```



General Pattern

- Most bookings concentrate in the shorter stay duration range (1-5 nights)
- Lead times spread from immediate (0 days) to approximately 600 days in advance
- The pattern forms a dense cluster at the bottom of the plot, showing that shorter stays are most common regardless of lead time

Hotel Type Differences

- City Hotels (blue dots) show more concentration in shorter stays
- Resort Hotels (orange dots) have more scattered points in longer stay durations
- Resort Hotels appear to have more longer-duration bookings (10+ nights)

Lead Time Patterns

- Short stays (1-5 nights) occur across all lead times
- Longer stays (>10 nights) tend to have more varied lead times
- Very long stays (>20 nights) are rare and appear sporadically

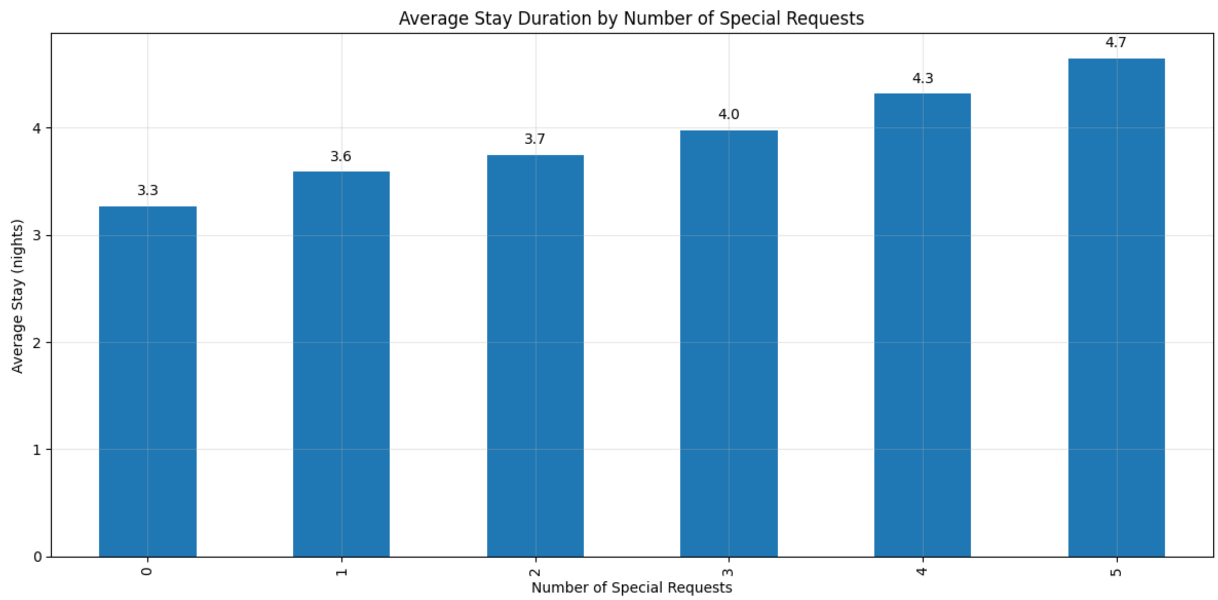
Notable Insights

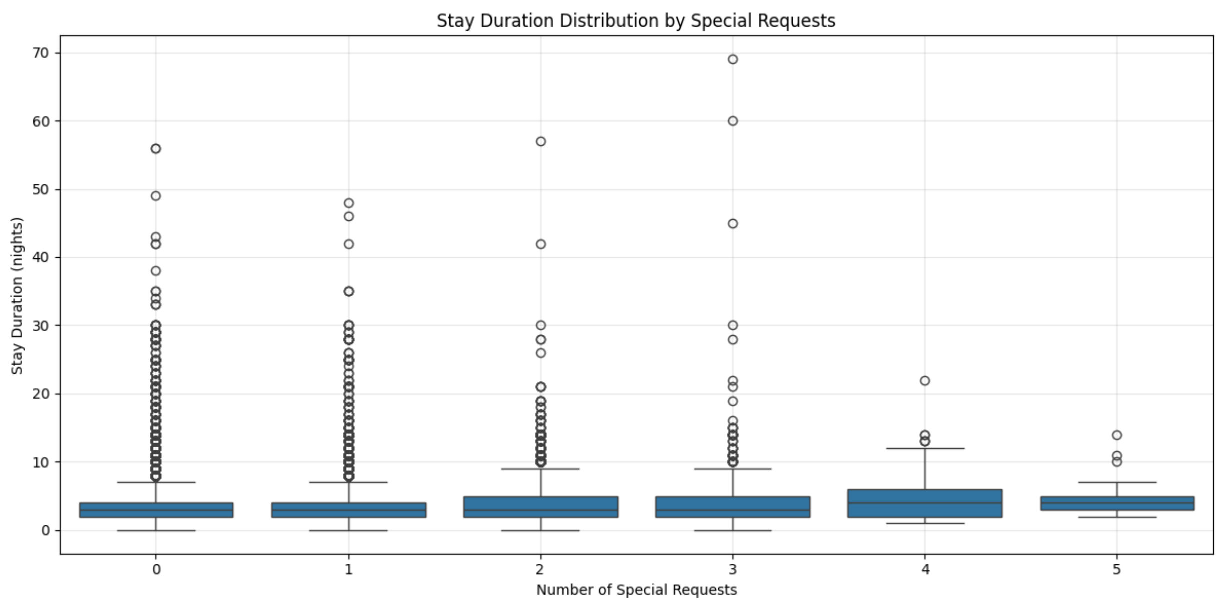
- No strong linear relationship between lead time and stay duration

- Maximum stay duration appears to be around 30 nights
- Both hotel types show similar patterns in short-term bookings
- Resort Hotels have slightly more extended-stay bookings with longer lead times

No. of Special Requests vs Stay Duration

In [ ]:
```
def analyze_stay_duration_requests(df):
    """
    Analyze stay duration vs special requests with two focused visualizations

    Parameters:
    df (pandas.DataFrame): DataFrame containing hotel booking data
    """
    # Calculate total stay duration if not already present
    df['total_stay'] = df['stays_in_week_nights'] + df['stays_in_weekend_nights']

    # 1. Average stay duration plot
    plt.figure(figsize=(12, 6))
    avg_stay_by_requests = df.groupby('total_of_special_requests')['total_stay'].me
    avg_stay_by_requests.plot(kind='bar')
    plt.title('Average Stay Duration by Number of Special Requests', fontsize=12)
    plt.xlabel('Number of Special Requests', fontsize=10)
    plt.ylabel('Average Stay (nights)', fontsize=10)
    plt.grid(True, alpha=0.3)

    # Add value labels on top of each bar
    for i, v in enumerate(avg_stay_by_requests):
        plt.text(i, v + 0.1, f'{v:.1f}', ha='center')

    plt.tight_layout()
    plt.show()

    # 2. Box plot distribution
    plt.figure(figsize=(12, 6))
    sns.boxplot(data=df, x='total_of_special_requests', y='total_stay')
    plt.title('Stay Duration Distribution by Special Requests', fontsize=12)
    plt.xlabel('Number of Special Requests', fontsize=10)
    plt.ylabel('Stay Duration (nights)', fontsize=10)
    plt.grid(True, alpha=0.3)
    plt.tight_layout()
    plt.show()

    # Print summary statistics
    print("\nAverage stay duration by number of special requests:")
    summary = df.groupby('total_of_special_requests')['total_stay'].agg(['mean', 'c
    summary.columns = ['Average Stay (nights)', 'Number of Bookings']
    print(summary)


analyze_stay_duration_requests(df_copy)
```





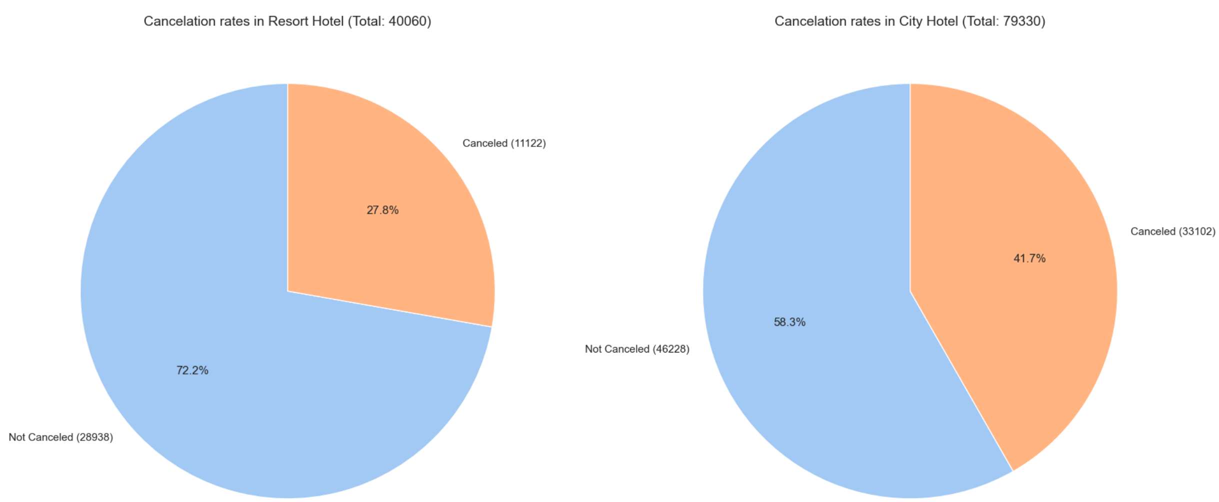

```
Average stay duration by number of special requests:
                          Average Stay (nights)  Number of Bookings
total_of_special_requests
0                                          3.27               70318
1                                          3.59               33226
2                                          3.75               12969
3                                          3.98                2497
4                                          4.32                 340
5                                          4.65                  40
```

Cancelation Analysis

1) Cancelation by Hotel type

In [ ]:
```python
# Calculate the total counts for each hotel type
hotel_counts = df.groupby(['hotel', 'is_canceled']).size().unstack(fill_value=0)
hotel_totals = hotel_counts.sum(axis=1)
```

```
# Create two pie charts for Resort Hotel and City Hotel
fig, axes = plt.subplots(1, 2, figsize=(18, 8))

# Pie chart for Resort Hotel
resort_data = hotel_counts.loc['Resort Hotel']
axes[0].pie(
    resort_data,
    labels=[f"Not Canceled ({resort_data[0]})", f"Canceled ({resort_data[1]})"],
    autopct=lambda p: f"{p:.1f}%",
    startangle=90,
    colors=sns.color_palette("pastel"))
axes[0].set_title(f"Cancelation rates in Resort Hotel (Total: {hotel_totals['Resort

# Pie chart for City Hotel
city_data = hotel_counts.loc['City Hotel']
axes[1].pie(
    city_data,
    labels=[f"Not Canceled ({city_data[0]})", f"Canceled ({city_data[1]})"],
    autopct=lambda p: f"{p:.1f}%",
    startangle=90,
    colors=sns.color_palette("pastel"))
axes[1].set_title(f"Cancelation rates in City Hotel (Total: {hotel_totals['City Hot

plt.tight_layout()
plt.show()
```

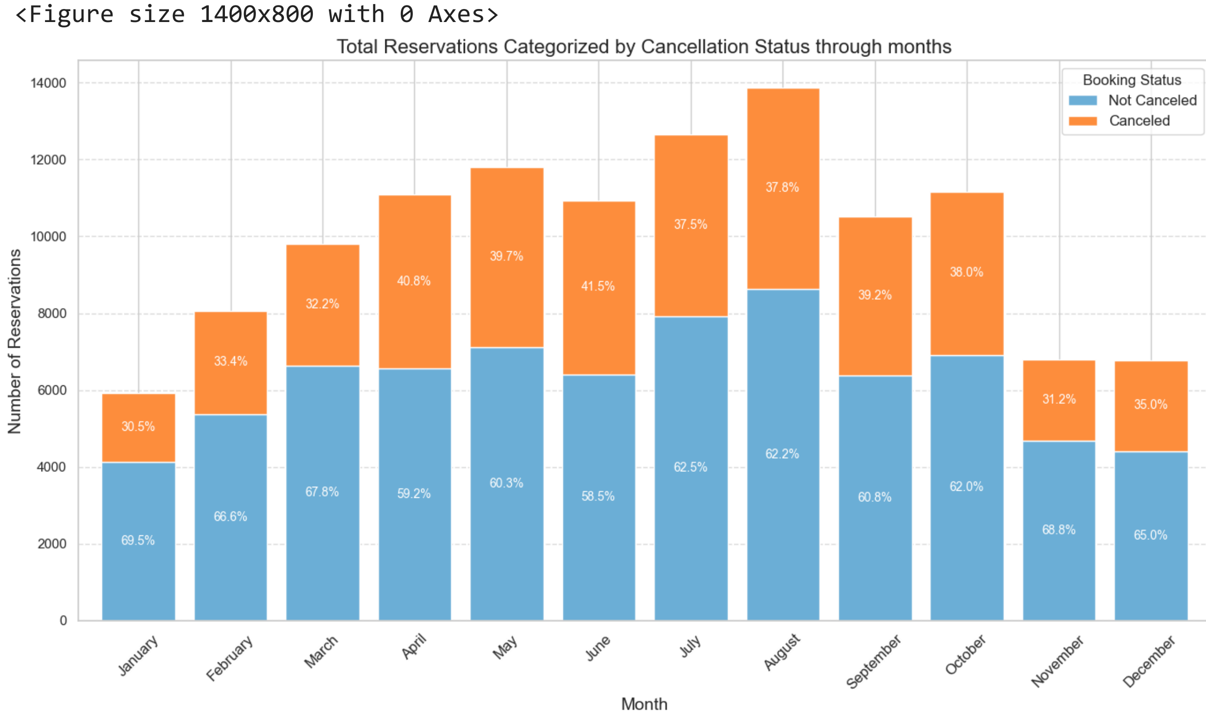


2) Cancelation by Month

In [ ]:
```
# Order months
months_order = ["January", "February", "March", "April", "May", "June",
                "July", "August", "September", "October", "November", "December"]

# Group data by month and cancellation status
monthly_data = df.groupby(['arrival_date_month', 'is_canceled']).size().unstack(fil

# Normalize data to percentages
monthly_percent = monthly_data.div(monthly_data.sum(axis=1), axis=0) * 100
```

```
# Plot a stacked bar chart
plt.figure(figsize=(14, 8))
monthly_data.plot(kind='bar', stacked=True, width=0.8, color=['#6baed6', '#fd8d3c']

# Adding labels and title
plt.title("Total Reservations Categorized by Cancellation Status through months", f
plt.xlabel("Month", fontsize=14)
plt.ylabel("Number of Reservations", fontsize=14)
plt.xticks(rotation=45, fontsize=12)
plt.legend(["Not Canceled", "Canceled"], title="Booking Status", fontsize=12)

# Add percentage labels on the bars
for i, (index, row) in enumerate(monthly_percent.iterrows()):
    for j, value in enumerate(row):
        if value > 0:  # Avoid plotting percentages for 0
            plt.text(
                i,
                monthly_data.iloc[i].cumsum()[j] - (monthly_data.iloc[i, j] / 2),
                f"{value:.1f}%",
                ha="center",
                va="center",
                color="white",
                fontsize=10
            )

plt.grid(axis='y', linestyle='--', alpha=0.7)
plt.tight_layout()
plt.show()
```

```
<Figure size 1400x800 with 0 Axes>
```

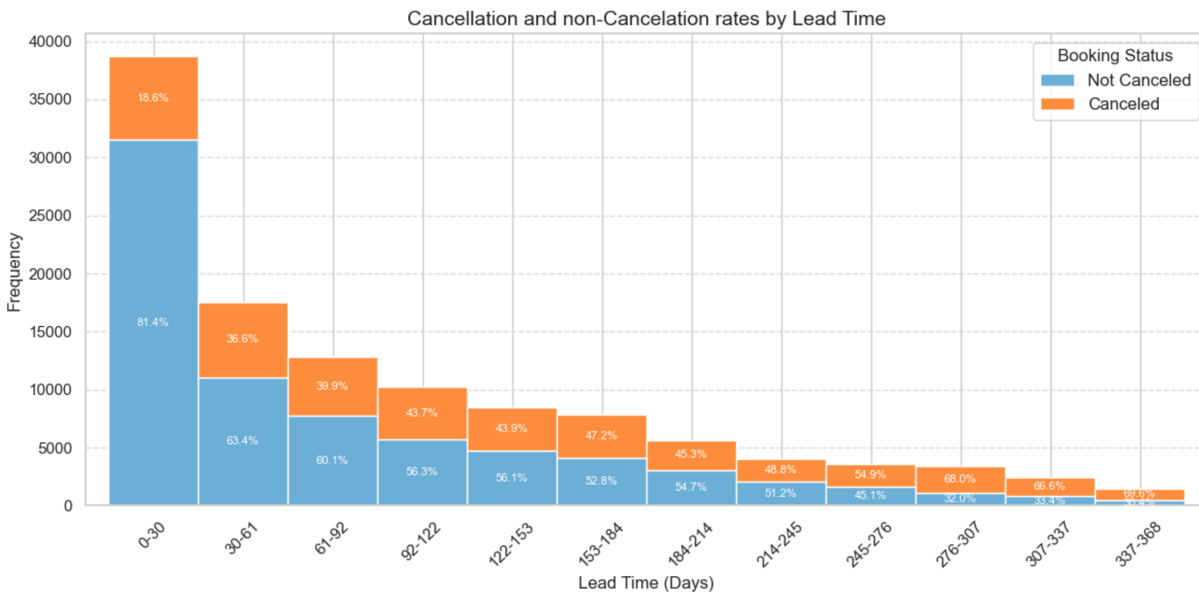


3) Cancelation by Lead Time

In [ ]:
```
# Define the bins for lead time
```

```
bins = 24
bin_edges = np.histogram_bin_edges(df['lead_time'], bins=bins)

# Calculate the histogram counts for each category
hist_data = pd.DataFrame({
    'Not Canceled': np.histogram(df[df['is_canceled'] == 0]['lead_time'], bins=bin_
    'Canceled': np.histogram(df[df['is_canceled'] == 1]['lead_time'], bins=bin_edge
}, index=pd.IntervalIndex.from_breaks(bin_edges, closed='left'))

# Normalize to percentages
hist_percent = hist_data.div(hist_data.sum(axis=1), axis=0) * 100

# Filter out bins with fewer than 1000 total data points
valid_bins = hist_data.sum(axis=1) >= 1000
filtered_hist_data = hist_data[valid_bins]
filtered_hist_percent = hist_percent[valid_bins]

# Plot the histogram
plt.figure(figsize=(12, 6))
ax = filtered_hist_data.plot(kind='bar', stacked=True, color=['#6baed6', '#fd8d3c']

# Add percentage labels for bins with sufficient data
for i, (index, row) in enumerate(filtered_hist_percent.iterrows()):
    for j, value in enumerate(row):
        if value > 0:  # Avoid plotting percentages for 0
            plt.text(
                i,
                filtered_hist_data.iloc[i].cumsum()[j] - (filtered_hist_data.iloc[i
                f"{value:.1f}%",
                ha="center",
                va="center",
                color="white",
                fontsize=8  # Smaller font size
            )

# Customize plot
plt.title("Cancellation and non-Cancelation rates by Lead Time", fontsize=14)
plt.xlabel("Lead Time (Days)", fontsize=12)
plt.ylabel("Frequency", fontsize=12)
plt.legend(["Not Canceled", "Canceled"], title="Booking Status", fontsize=12)
plt.xticks(
    ticks=range(len(filtered_hist_data)),
    labels=[f"{int(interval.left)}-{int(interval.right)}" for interval in filtered_
    rotation=45
)
plt.grid(axis='y', linestyle='--', alpha=0.7)
plt.tight_layout()
plt.show()
```

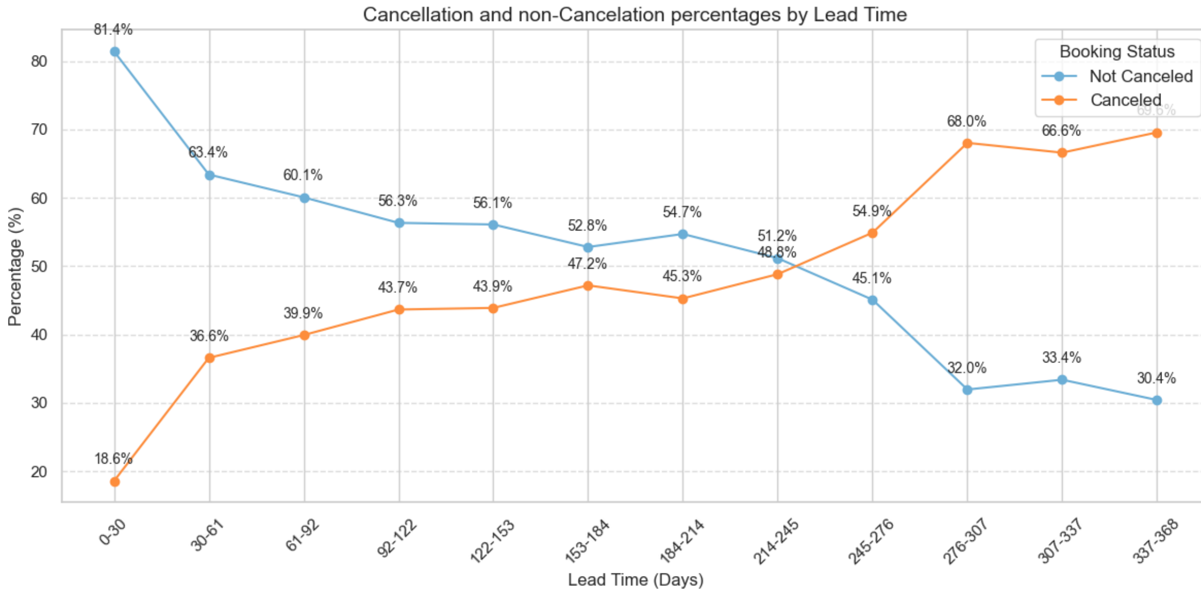
```
<Figure size 1200x600 with 0 Axes>
```



In [ ]:

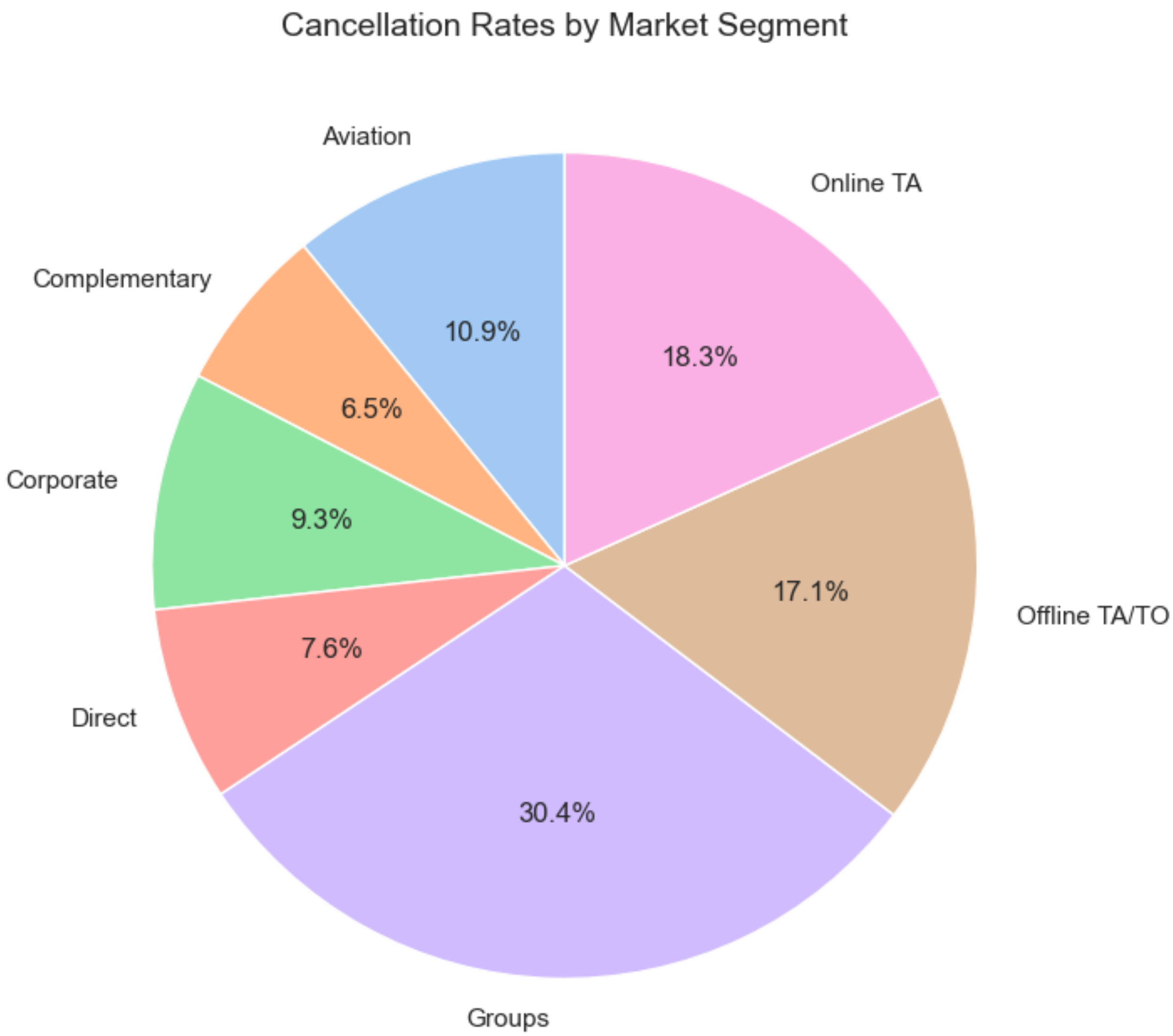
```
# Define the bins for lead time
bins = 24
bin_edges = np.histogram_bin_edges(df['lead_time'], bins=bins)

# Calculate the histogram counts for each category
hist_data = pd.DataFrame({
    'Not Canceled': np.histogram(df[df['is_canceled'] == 0]['lead_time'], bins=bin_
    'Canceled': np.histogram(df[df['is_canceled'] == 1]['lead_time'], bins=bin_edge
}, index=pd.IntervalIndex.from_breaks(bin_edges, closed='left'))

# Normalize to percentages
hist_percent = hist_data.div(hist_data.sum(axis=1), axis=0) * 100

# Filter out bins with fewer than 1000 total data points
valid_bins = hist_data.sum(axis=1) >= 1000
filtered_hist_percent = hist_percent[valid_bins]

# Round the bin edges to remove unnecessary decimals
rounded_bins = [f"{int(bin.left)}-{int(bin.right)}" for bin in filtered_hist_percen

# Plot the line chart
plt.figure(figsize=(12, 6))

# Plot each category as a line
plt.plot(rounded_bins, filtered_hist_percent['Not Canceled'], label="Not Canceled",
plt.plot(rounded_bins, filtered_hist_percent['Canceled'], label="Canceled", color='

# Add percentage labels on the lines
for i, (index, row) in enumerate(filtered_hist_percent.iterrows()):
    plt.text(i, row['Not Canceled'] + 2, f"{row['Not Canceled']:.1f}%", ha="center"
    plt.text(i, row['Canceled'] + 2, f"{row['Canceled']:.1f}%", ha="center", va="bo

# Customize plot
plt.title("Cancellation and non-Cancelation percentages by Lead Time", fontsize=14)
plt.xlabel("Lead Time (Days)", fontsize=12)
plt.ylabel("Percentage (%)", fontsize=12)
plt.xticks(rotation=45)
```

```
plt.legend(title="Booking Status", fontsize=12)
plt.grid(axis='y', linestyle='--', alpha=0.7)
plt.tight_layout()
plt.show()
```



4) Cancelation by Market Segment

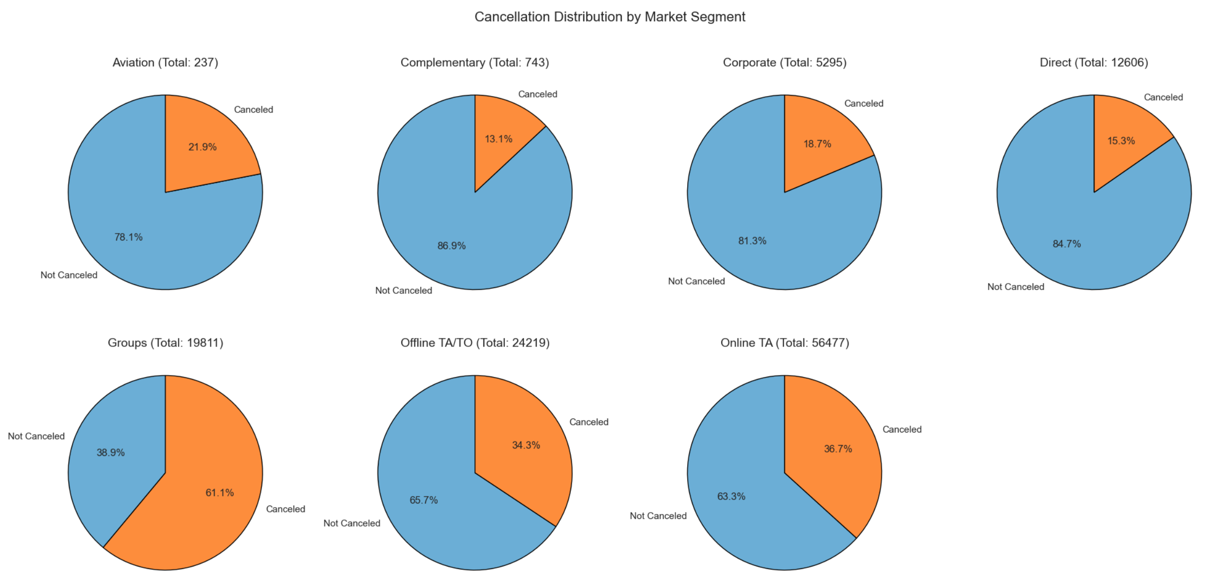
In [ ]:
```
# Calculate cancellation rates by market segment
market_segment_cancellation_rates = df.groupby('market_segment')['is_canceled'].mea

# Exclude the 'Undefined' market segment (it should not appear in the pie chart)
market_segment_cancellation_rates = market_segment_cancellation_rates[market_segmen

# Plot as a pie chart
plt.figure(figsize=(8, 8))
plt.pie(market_segment_cancellation_rates,
        labels=market_segment_cancellation_rates.index,
        autopct='%1.1f%%',
        startangle=90,
        colors=sns.color_palette("pastel", n_colors=len(market_segment_cancellation
plt.title("Cancellation Rates by Market Segment", fontsize=14)
plt.show()
```



In [ ]:

```
# Group by market_segment and cancellation status, then calculate the counts
market_segment_cancellation = df.groupby(['market_segment', 'is_canceled']).size().

# Exclude the 'undefined' market segment if it exists
market_segment_cancellation = market_segment_cancellation[market_segment_cancellati

# Prepare the figure for a 2x4 grid of pie charts
fig, axes = plt.subplots(nrows=2, ncols=4, figsize=(20, 10))

# Flatten axes to make indexing easier
axes = axes.flatten()

# Loop through each market segment and plot a pie chart
for i, (segment, row) in enumerate(market_segment_cancellation.iterrows()):
    total = row.sum()  # Total number of reservations in this market segment
    canceled_count = row[1]  # Number of canceled reservations
    not_canceled_count = row[0]  # Number of non-canceled reservations

    # Create the pie chart for each market segment
    axes[i].pie([not_canceled_count, canceled_count],
                labels=["Not Canceled", "Canceled"],
                autopct='%1.1f%%',
```

```
                startangle=90,
                colors=['#6baed6', '#fd8d3c'],
                wedgeprops={'edgecolor': 'black'})

    # Set title for each pie chart
    axes[i].set_title(f"{segment} (Total: {total})", fontsize=14)

# Remove empty subplots (if any)
for j in range(i + 1, len(axes)):
    axes[j].axis('off')

# Set the title for the entire grid
fig.suptitle("Cancellation Distribution by Market Segment", fontsize=16)

# Adjust layout to avoid overlap
plt.tight_layout()
plt.subplots_adjust(top=0.9)  # Adjust the top to make space for the figure title
plt.show()
```

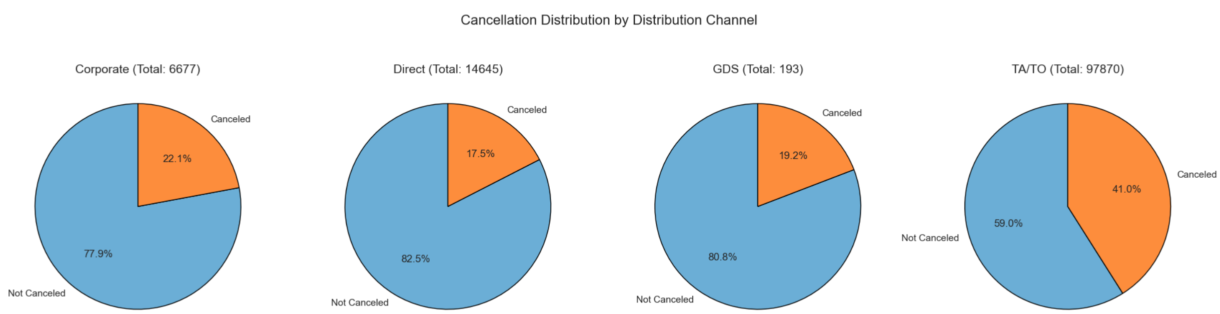


5) Cancelation by Distribution channel

In [ ]:

```
# Group by distribution_channel and cancellation status, then calculate the counts
distribution_channel_cancellation = df.groupby(['distribution_channel', 'is_cancele

# Exclude the 'Undefined' distribution channel if it exists
distribution_channel_cancellation = distribution_channel_cancellation[distribution_

# Prepare the figure for a 1x4 grid of pie charts
fig, axes = plt.subplots(nrows=1, ncols=4, figsize=(20, 6))

# Flatten axes to make indexing easier
axes = axes.flatten()

# Loop through each distribution channel and plot a pie chart
for i, (channel, row) in enumerate(distribution_channel_cancellation.iterrows()):
    total = row.sum()  # Total number of reservations in this distribution channel
```

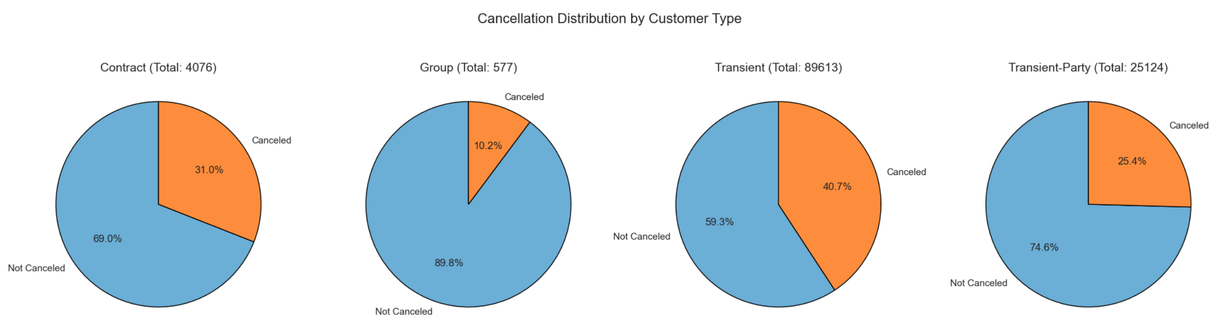
```
    canceled_count = row[1]  # Number of canceled reservations
    not_canceled_count = row[0]  # Number of non-canceled reservations

    # Create the pie chart for each distribution channel
    axes[i].pie([not_canceled_count, canceled_count],
                labels=["Not Canceled", "Canceled"],
                autopct='%1.1f%%',
                startangle=90,
                colors=['#6baed6', '#fd8d3c'],
                wedgeprops={'edgecolor': 'black'})

    # Set title for each pie chart
    axes[i].set_title(f"{channel} (Total: {total})", fontsize=14)

# Remove empty subplots (if any)
for j in range(i + 1, len(axes)):
    axes[j].axis('off')

# Set the title for the entire grid
fig.suptitle("Cancellation Distribution by Distribution Channel", fontsize=16)

# Adjust layout to avoid overlap
plt.tight_layout()
plt.subplots_adjust(top=0.9)  # Adjust the top to make space for the figure title
plt.show()
```



6) Cancelation by Customer type

In [ ]:
```
# Group by customer_type and cancellation status, then calculate the counts
customer_type_cancellation = df.groupby(['customer_type', 'is_canceled']).size().un

# Prepare the figure for a 1x4 grid of pie charts
fig, axes = plt.subplots(nrows=1, ncols=4, figsize=(20, 6))

# Flatten axes to make indexing easier
axes = axes.flatten()

# Loop through each customer type and plot a pie chart
for i, (customer, row) in enumerate(customer_type_cancellation.iterrows()):
    total = row.sum()  # Total number of reservations for this customer type
    canceled_count = row[1]  # Number of canceled reservations
    not_canceled_count = row[0]  # Number of non-canceled reservations

    # Create the pie chart for each customer type
```

```
    axes[i].pie([not_canceled_count, canceled_count],
                labels=["Not Canceled", "Canceled"],
                autopct='%1.1f%%',
                startangle=90,
                colors=['#6baed6', '#fd8d3c'],
                wedgeprops={'edgecolor': 'black'})

    # Set title for each pie chart
    axes[i].set_title(f"{customer} (Total: {total})", fontsize=14)

# Remove empty subplots (if any)
for j in range(i + 1, len(axes)):
    axes[j].axis('off')

# Set the title for the entire grid
fig.suptitle("Cancellation Distribution by Customer Type", fontsize=16)

# Adjust layout to avoid overlap
plt.tight_layout()
plt.subplots_adjust(top=0.9)  # Adjust the top to make space for the figure title
plt.show()
```

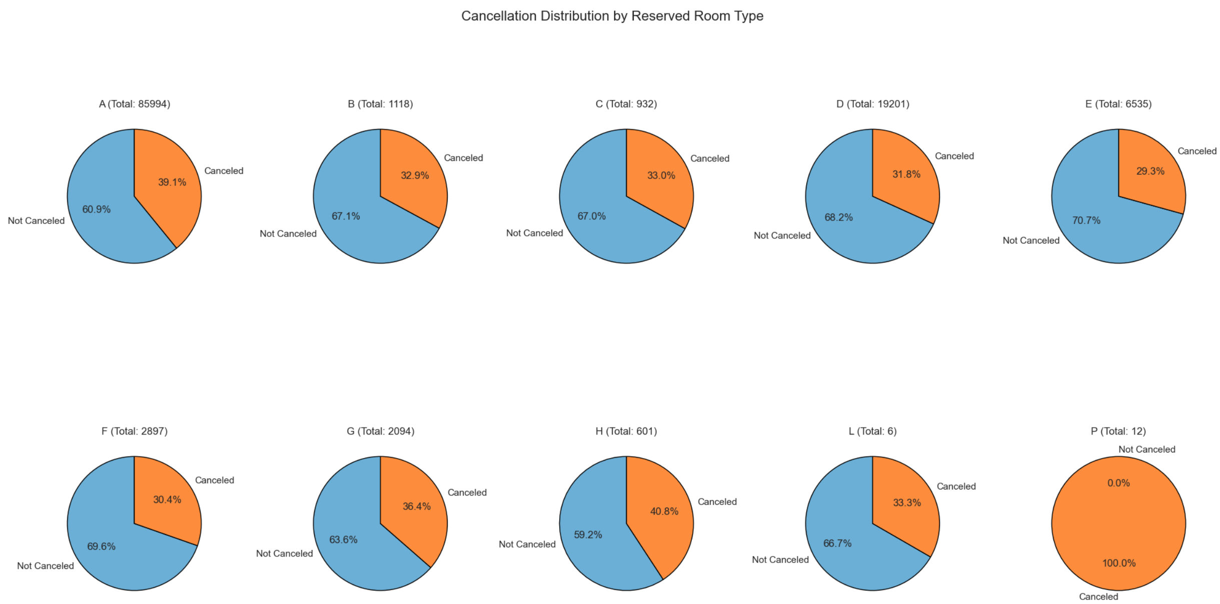


7) Cancelation by Room type

In [ ]:

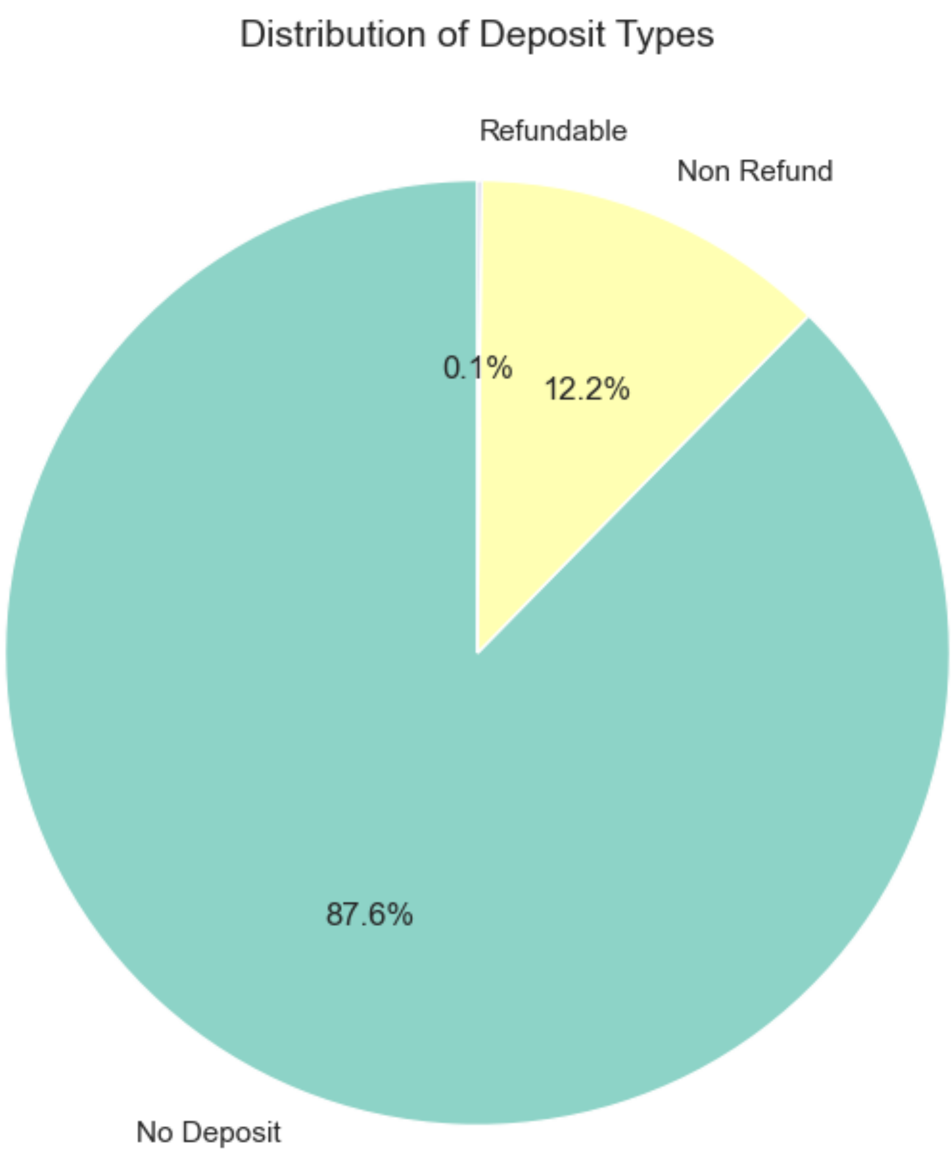
```
# Group by reserved_room_type and cancellation status, then calculate the counts
reserved_room_type_cancellation = df.groupby(['reserved_room_type', 'is_canceled'])

# Prepare the figure for a 2x5 grid of pie charts
fig, axes = plt.subplots(nrows=2, ncols=5, figsize=(20, 12))

# Flatten axes to make indexing easier
axes = axes.flatten()

# Loop through each reserved room type and plot a pie chart
for i, (room_type, row) in enumerate(reserved_room_type_cancellation.iterrows()):
    total = row.sum()  # Total number of reservations for this room type
    canceled_count = row[1]  # Number of canceled reservations
    not_canceled_count = row[0]  # Number of non-canceled reservations

    # Create the pie chart for each reserved room type
    axes[i].pie([not_canceled_count, canceled_count],
                labels=["Not Canceled", "Canceled"],
                autopct='%1.1f%%',
                startangle=90,
                colors=['#6baed6', '#fd8d3c'],
```

```
                wedgeprops={'edgecolor': 'black'})

    # Set title for each pie chart
    axes[i].set_title(f"{room_type} (Total: {total})", fontsize=12)

# Remove empty subplots (if any)
for j in range(i + 1, len(axes)):
    axes[j].axis('off')

# Set the title for the entire grid
fig.suptitle("Cancellation Distribution by Reserved Room Type", fontsize=16)

# Adjust layout to avoid overlap
plt.tight_layout()
plt.subplots_adjust(top=1)  # Adjust the top to make space for the figure title
plt.show()
```



8) Cancelation by Deposit type

In [ ]:
```
deposit_type_counts = df['deposit_type'].value_counts()

# Plot the pie chart
plt.figure(figsize=(8, 8))
plt.pie(deposit_type_counts,
        labels=deposit_type_counts.index,
        autopct='%1.1f%%',
        startangle=90,
        colors=sns.color_palette("Set3", n_colors=len(deposit_type_counts)))
plt.title("Distribution of Deposit Types", fontsize=14)
plt.show()
```



In [ ]:

```
# Group by deposit_type and cancellation status, then calculate the counts
deposit_type_cancellation = df.groupby(['deposit_type', 'is_canceled']).size().unst

# Prepare the figure for a 1x3 grid of pie charts
fig, axes = plt.subplots(nrows=1, ncols=3, figsize=(18, 6))

# Flatten axes to make indexing easier
axes = axes.flatten()

# Loop through each deposit type and plot a pie chart
for i, (deposit, row) in enumerate(deposit_type_cancellation.iterrows()):
    total = row.sum()  # Total number of reservations for this deposit type
    canceled_count = row[1]  # Number of canceled reservations
    not_canceled_count = row[0]  # Number of non-canceled reservations

    # Create the pie chart for each deposit type
    axes[i].pie([not_canceled_count, canceled_count],
                labels=["Not Canceled", "Canceled"],
```

```
                autopct='%1.1f%%',
                startangle=90,
                colors=['#6baed6', '#fd8d3c'],
                wedgeprops={'edgecolor': 'black'})

    # Set title for each pie chart
    axes[i].set_title(f"{deposit} (Total: {total})", fontsize=12)

# Remove empty subplots (if any)
for j in range(i + 1, len(axes)):
    axes[j].axis('off')

# Set the title for the entire grid
fig.suptitle("Cancellation Distribution by Deposit Type", fontsize=16)

# Adjust layout to avoid overlap
plt.tight_layout()
plt.subplots_adjust(top=0.9)  # Adjust the top to make space for the figure title
plt.show()
```