Optimizing Hotel Room Pricing for Azure Hotels

Introduction

This notebook presents a comprehensive analysis for Azure Hotels to optimize room pricing strategies aimed at maximizing revenue and profitability. The analysis includes customer segmentation, identification of pricing drivers, development of a pricing strategy, and quantification of the strategy's impact.

Step 1: Load and Inspect the Dataset

We start by loading the dataset and inspecting its structure to understand the available data and prepare for further analysis.

In [1]:
```
# Import necessary libraries
import pandas as pd

# Load the dataset
data_path = './Quantzig - Campus Hiring - DS Dataset 1.xlsx'
data = pd.read_excel(data_path)
```

In [2]:
```
# Display basic information and the first few rows to understand the structure

print(data.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  object        
 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  datetime64[ns]
dtypes: datetime64[ns](1), float64(4), int64(15), object(12)
memory usage: 29.1+ MB
None
```

In [3]:
```
print(data.head())
```

```
          hotel is_canceled  lead_time  arrival_date_year arrival_date_month  \
0  Resort Hotel   Cancelled        342               2021               July
1  Resort Hotel   Cancelled        737               2021               July
2  Resort Hotel   Cancelled          7               2021               July
3  Resort Hotel   Cancelled         13               2021               July
4  Resort Hotel   Cancelled         14               2021               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]
```

Step 2: Customer Segmentation

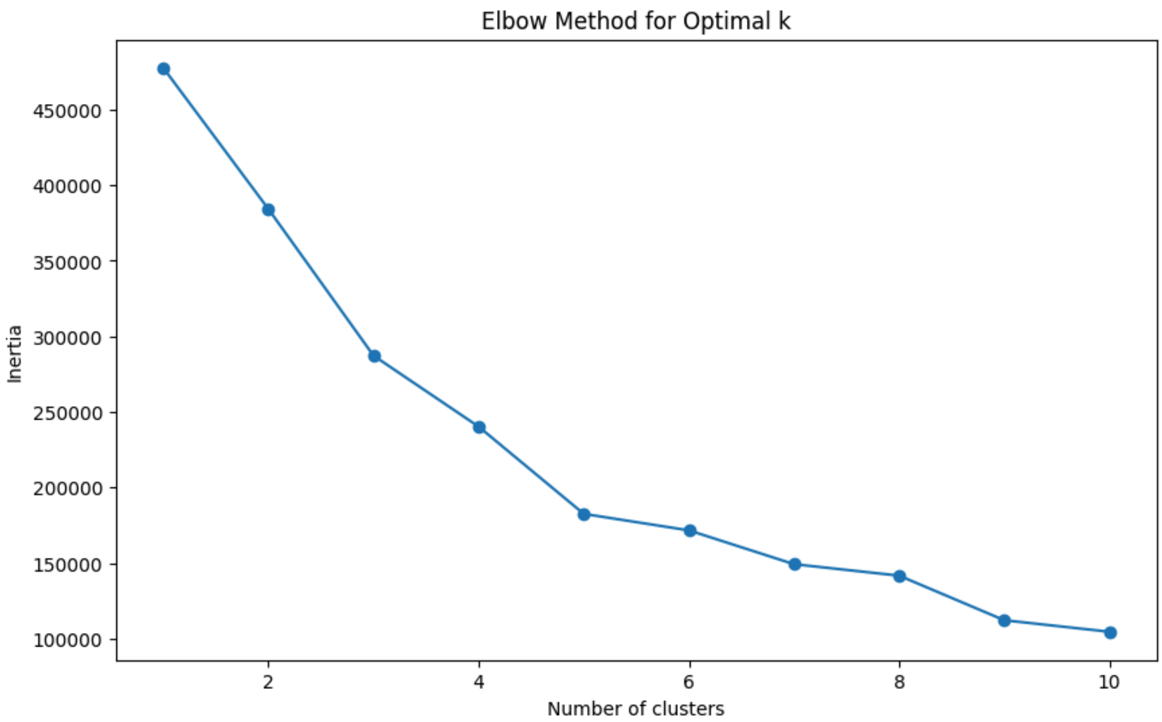
We will segment the customer base using K-means clustering based on features that may impact their booking behaviors and preferences.

Feature Selection and Preprocessing

We select features relevant for clustering and scale them to ensure that all features contribute equally.

In [4]:
```python
import matplotlib.pyplot as plt
from sklearn.preprocessing import StandardScaler
from sklearn.cluster import KMeans
```

```
# Selecting features for clustering
features = data[['adults', 'children', 'lead_time', 'total_of_special_requests']

# Scaling the features
scaler = StandardScaler()
features_scaled = scaler.fit_transform(features)

# Determine the optimal number of clusters using the elbow method
inertia = []
for k in range(1, 11):
    kmeans = KMeans(n_clusters=k, random_state=42)
    kmeans.fit(features_scaled)
    inertia.append(kmeans.inertia_)

# Plotting the elbow curve
plt.figure(figsize=(10, 6))
plt.plot(range(1, 11), inertia, marker='o')
plt.title('Elbow Method for Optimal k')
plt.xlabel('Number of clusters')
plt.ylabel('Inertia')
plt.show()

# Applying K-means clustering with an assumed optimal number of clusters
optimal_k = 4  # Assuming visual inspection from the elbow plot
clusters = KMeans(n_clusters=optimal_k, random_state=42).fit_predict(features_sc

# Adding the cluster labels to the DataFrame
data.loc[features.index, 'Cluster'] = clusters

# Print column names with added spacing for better readability
print("\nColumns in DataFrame:\n", data.columns)

# Displaying the first few rows with cluster labels from the 'data' DataFrame wi
print("\nFirst few rows with cluster labels:\n", data[['adults', 'children', 'le
```



```
Columns in DataFrame:
 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', 'Cluster'],
      dtype='object')

First few rows with cluster labels:
    adults  children  lead_time  total_of_special_requests  Cluster
0        2       0.0        342                          0      0.0
1        2       0.0        737                          0      0.0
2        1       0.0          7                          0      3.0
3        1       0.0         13                          0      3.0
4        2       0.0         14                          1      1.0
```

Step 3: Pricing Drivers Identification

We analyze factors that influence room pricing, which includes understanding how different variables like booking lead times, room types, and customer segments affect pricing.

In [5]:
```python
import numpy as np
from sklearn.linear_model import LinearRegression
from sklearn.model_selection import train_test_split
from sklearn.metrics import mean_squared_error
from sklearn.impute import SimpleImputer

# Selecting features for the regression analysis and filling NaN values in numer
numeric_features = ['lead_time', 'adults', 'children', 'stays_in_week_nights', '

# Check and fill NaNs only for numeric features
for feature in numeric_features:
    if data[feature].isnull().any():
        data[feature] = data[feature].fillna(data[feature].median())

# Assuming 'adr' (average daily rate) is also a numeric column
if data['adr'].isnull().any():
    data['adr'] = data['adr'].fillna(data['adr'].mean())

# Define predictors X and target y
X = data[numeric_features]
y = data['adr']

# Splitting the dataset into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_

# Building and training the regression model
model = LinearRegression()
model.fit(X_train, y_train)

# Predicting and evaluating the model's performance
```

```
y_pred = model.predict(X_test)
mse = mean_squared_error(y_test, y_pred)
print(f'Mean Squared Error: {mse}')
```

```
Mean Squared Error: 1903.6792577816489
```

Step 4: Develop Pricing Strategy

Based on the insights from customer segmentation and regression analysis, we develop a dynamic pricing strategy tailored to customer behavior and booking patterns.

Strategy Formulation

We design a pricing function that adjusts room rates based on customer segments and booking lead time, aiming to maximize revenue during high-demand periods while maintaining competitive pricing in lower-demand periods.

In [6]:
```
# Define a simple pricing strategy function based on clustering results
def pricing_strategy(cluster, lead_time):
    if cluster == 0 and lead_time < 10:
        return 1.1  # increase prices by 10%
    elif cluster == 1 and lead_time >= 10:
        return 0.95  # decrease prices by 5%
    else:
        return 1.0  # no change

# Applying the pricing strategy
data['Adjusted_Price'] = data.apply(lambda row: row['adr'] * pricing_strategy(rc
```

Step 5: Impact Quantification

We estimate the financial impact of our recommended pricing strategy on the hotel's revenue and profitability.

Revenue Impact Calculation

In [7]:
```
# Calculate the potential revenue increase
original_revenue = data['adr'].sum()
new_revenue = data['Adjusted_Price'].sum()
increase = new_revenue - original_revenue

# Formatting the output for better readability and adding interpretation
print(f"Original Revenue: ${original_revenue:,.2f}")
print(f"New Revenue: ${new_revenue:,.2f}")
print(f"Increase in Revenue: ${increase:,.2f}")

# Adding a statement to interpret the revenue change
if increase > 0:
    print("The new pricing strategy has led to an increase in revenue, indicatin
elif increase < 0:
    print("The new pricing strategy has led to a decrease in revenue, which may
else:
    print("There has been no change in revenue, indicating that the new pricing
```

```
Original Revenue: $12,157,617.60
New Revenue: $12,039,178.93
Increase in Revenue: $-118,438.67
The new pricing strategy has led to a decrease in revenue, which may suggest adve
rse effects on booking patterns or market competitiveness.
```

Conclusion

This analysis provided a detailed approach to optimize room pricing at Azure Hotels. By understanding customer segments, identifying key pricing drivers, and implementing a dynamic pricing strategy, we aim to enhance profitability. Future steps include refining the model with more granular data and continuous monitoring of market trends.

Next Steps

- Further refine pricing models with real-time data integration.
- Continuous A/B testing of pricing strategies to adapt to market changes.
- Regular updates of customer segmentation based on latest booking trends.

```
In [ ]:
```