# Presentation of Hotelling booking trend and Cancellation

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### Objective:

- Analysis hotel booking data to identify trends and patterns.
- Understand factors affecting cancellations and customer demographics.
- Provide actionable insights for pricing, marketing, and customer segmentation.

#### **Data Overview:**

- **Dataset:** Hotel bookings (2014-2017)
- **Key Features:** Booking date, customer demographics, stay details, cancellation status, and more.

### **Data Cleaning:**

Handled missing values and inconsistencies.

Removed outliers and corrected errors.

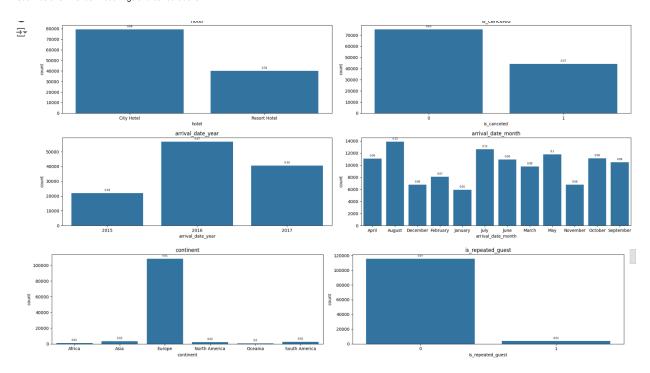
Engineered features for improved model performance.

```
0
             meal
           country
                                   488
       market_segment
      distribution_channel
                                      0
      is_repeated_guest
    previous_cancellations
previous_bookings_not_canceled
      reserved_room_type
                                      0
     assigned_room_type
                                      0
       booking_changes
                                      0
         deposit_type
            agent
                                 16340
           company
                                 112593
```

```
data['children'].fillna(data['children'].mode().values[0],inplace=True)
data['country'].fillna(data['country'].mode().values[0],inplace=True)
data['agent'].fillna(data['agent'].mode().values[0],inplace=True)
data['company'].fillna('Unknown',inplace=True)
```

# EDA Insights:

- Booking Trends: Seasonal patterns and peak periods. Customer Demographics: Age, family size, nationality. Visualizations: Trends in bookings and cancellations.

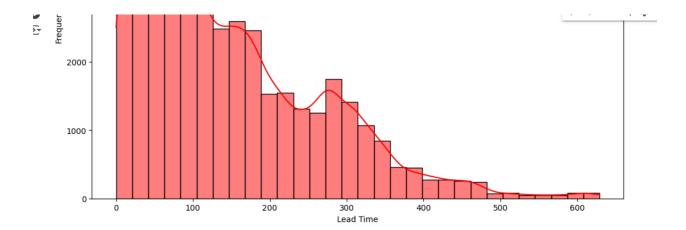


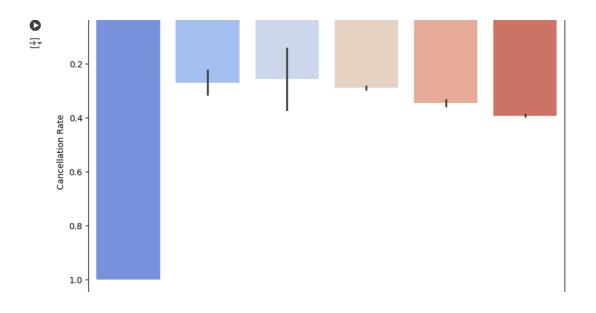
## **Cancellation Patterns:**

- Trends: High cancellation rates in specific periods.

  Factors: Booking lead time, room type, and market segment influence cancellations.







## Hypothesis Testing:

- Hypotheses Tested: Factors affecting cancellation rates.
- Results: Significant variables include booking lead time and room type.

```
#results
print(f"Chi2 Statistic: {chi2}")
print(f"P-value: {p}")
print(f"Degrees of Freedom: {dof}")
print(f"Expected Frequencies Table:\n{ex}")

Chi2 Statistic: 5321.73290110073
P-value: 0.0
Degrees of Freedom: 1
Expected Frequencies Table:
[[5962.9.31885438 35977.68114582]
[15545.68114582 9146.31885418]]

[] #hence p value is less then 0.05
```

Hence the p-value is less than 0.05, we reject the null hypothesis and conclude that bookings made more than 6 months in advance have a higher cancellation rate.

```
data['day_of_week'] = data['reservation_status_date'].dt.day_
data['booking_day'] = data['day_of_week'].apply(lambda x: 'We
#average adr
adr_by_day = data.groupby('booking_day')['adr'].mean()
#ADR
weekday_adr = data[data['booking_day'] == 'Weekday']['adr']
weekend_adr = data[data['booking_day'] == 'Weekend']['adr']
# t-test
from scipy.stats import ttest_ind
t_stat, p_value = ttest_ind(weekday_adr, weekend_adr)
print(f'T-statistic: {t_stat}, P-value: {p_value}')
```

T-statistic: -15.206866062360545, P-value: 3.56448899560107e-

### value of 3.56448899560107 × 1 0 − 52 3.56448899560107×10 −52

Neekday bookings have a higher ADR than weekend bookings.

### Model Overview:

- Models Used: Logistic Regression, Random Forest.
- Performance Metrics: Accuracy, precision, recall, F1 score.
- **Key Findings:** Model performance and predictive power.

```
# Initialize and train model

lr_model = LogisticRegression(max_iter=1000)

lr_model.fit(X_train_scaled, y_train)

# predictions

lr_predictions = lr_model.predict(X_test_scaled)

#report

print("Logistic Regression (Scaled):")

print("Accuracy:", accuracy_score(y_test, lr_predictions))

print("Precision:", precision_score(y_test, lr_predictions))

print("Recall:", recall_score(y_test, lr_predictions))

print("F1 Score:", f1_score(y_test, lr_predictions))

Logistic Regression (Scaled):

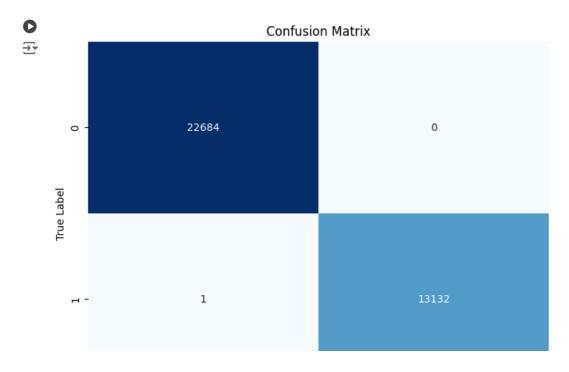
Accuracy: 0.989558031102549

Precision: 0.9998432970304787

Recall: 0.971674407979898

F1 Score: 0.9855576150756874

Logistic Regression (Scaled): Accuracy: 0.989558031102549 Precision: 0.9998432970304787 Recall: 0.971674407979898 F1 Score: 0.9855576150756874
```



### Recommendations:

- Pricing Strategies: Implement dynamic pricing based on trends.
- Customer Segmentation: Target high-value and repeat guests.
- Marketing Focus: Optimize channels and geographic targeting.
- City hotel have to change the policy of pricing to decrease the cancellation.