Import Libraries

In [1]:

```python
import pandas as pd
from sklearn.preprocessing import OneHotEncoder, LabelEncoder, PowerTransf
from sklearn.compose import ColumnTransformer
import warnings
warnings.filterwarnings('ignore')
```

Read the hotel dataset

In [2]:

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

In [3]:

```python
hotel.shape
```

Out[3]:

```
(119390, 32)
```

In [4]:

```python
hotel.head()
```

Out[4]:

	hotel	is_canceled	lead_time	arrival_date_year	arrival_date_month	arrival_date_week_numbe
0	Resort Hotel	0	342	2015	July	27
1	Resort Hotel	0	737	2015	July	27
2	Resort Hotel	0	7	2015	July	27
3	Resort Hotel	0	13	2015	July	27
4	Resort Hotel	0	14	2015	July	27

5 rows × 32 columns

Handle Missing Values

In [5]:

```
hotel.isnull().sum()
```

Out[5]:

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

In [6]:

```
hotel.describe().T
```

Out[6]:

	count	mean	std	min	25%	50%
is_canceled	119390.0	0.370416	0.482918	0.00	0.00	0.000
lead_time	119390.0	104.011416	106.863097	0.00	18.00	69.000
arrival_date_year	119390.0	2016.156554	0.707476	2015.00	2016.00	2016.000
arrival_date_week_number	119390.0	27.165173	13.605138	1.00	16.00	28.000
arrival_date_day_of_month	119390.0	15.798241	8.780829	1.00	8.00	16.000
stays_in_weekend_nights	119390.0	0.927599	0.998613	0.00	0.00	1.000
stays_in_week_nights	119390.0	2.500302	1.908286	0.00	1.00	2.000
adults	119390.0	1.856403	0.579261	0.00	2.00	2.000
children	119386.0	0.103890	0.398561	0.00	0.00	0.000
babies	119390.0	0.007949	0.097436	0.00	0.00	0.000
is_repeated_guest	119390.0	0.031912	0.175767	0.00	0.00	0.000
previous_cancellations	119390.0	0.087118	0.844336	0.00	0.00	0.000
previous_bookings_not_canceled	119390.0	0.137097	1.497437	0.00	0.00	0.000
booking_changes	119390.0	0.221124	0.652306	0.00	0.00	0.000
agent	103050.0	86.693382	110.774548	1.00	9.00	14.000
company	6797.0	189.266735	131.655015	6.00	62.00	179.000
days_in_waiting_list	119390.0	2.321149	17.594721	0.00	0.00	0.000
adr	119390.0	101.831122	50.535790	-6.38	69.29	94.575
required_car_parking_spaces	119390.0	0.062518	0.245291	0.00	0.00	0.000
total_of_special_requests	119390.0	0.571363	0.792798	0.00	0.00	0.000

Exploratory Data Analysis

In [7]:

```
import matplotlib.pyplot as plt
import seaborn as sns
```

In [8]:

```
### Let's look at missing data
```

In [9]:

```
hotel.isnull().sum()
```

Out[9]:

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

In [10]:

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

Out[10]:

```
children
0.0     110796
1.0       4861
2.0       3652
3.0         76
10.0         1
Name: count, dtype: int64
```

In [11]:

```
hotel['children'].fillna(0,inplace=True)
```

In [12]:

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

Out[12]:

```
country
PRT    48590
GBR    12129
FRA    10415
ESP     8568
DEU     7287
       ...  
DJI        1
BWA        1
HND        1
VGB        1
NAM        1
Name: count, Length: 177, dtype: int64
```

In [13]:

```
hotel['country'].fillna('PRT', inplace = True)
```

In [14]:

```
hotel.drop(['agent','company'], axis = 1, inplace = True)
```

In [15]:

```
hotel.isnull().any()
```

Out[15]:

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

In [16]:

```python
hotel.shape
```

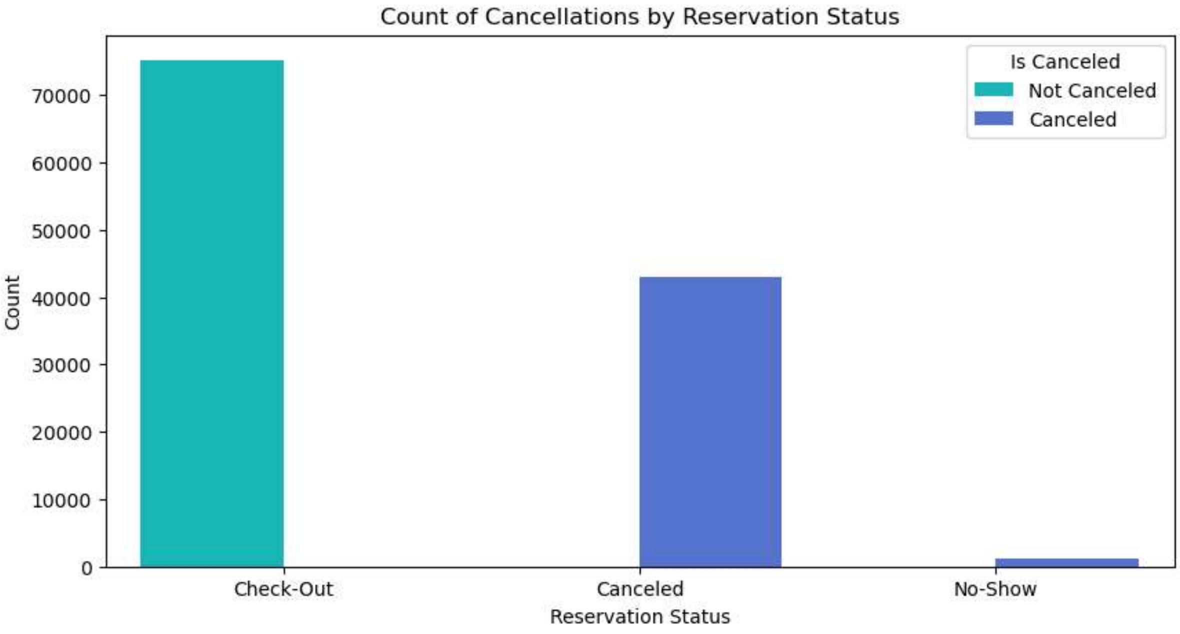
Out[16]:

```
(119390, 30)
```

Removing Directly Related Features

In [17]:

```python
# Bivariate bar plot of 'is_canceled' vs 'reservation_status' with specifi
plt.figure(figsize=(10, 5))
sns.countplot(x='reservation_status', hue='is_canceled', data=hotel, palet
plt.title('Count of Cancellations by Reservation Status')
plt.xlabel('Reservation Status')
plt.ylabel('Count')
plt.legend(title='Is Canceled', labels=['Not Canceled', 'Canceled'])
plt.show()
```



In [18]:

```python
hotel.groupby('reservation_status')['is_canceled'].mean()
```

Out[18]:

```
reservation_status
Canceled      1.0
Check-Out     0.0
No-Show       1.0
Name: is_canceled, dtype: float64
```

In [19]:

```python
hotel.drop(['reservation_status','reservation_status_date', 'assigned_room
```

In [20]:

```python
### Drop irrelavant features
```

In [21]:

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

Out[21]:

```
arrival_date_year
2016    56707
2017    40687
2015    21996
Name: count, dtype: int64
```

In [22]:

```
# Drop the `arrival_date_year` feature
hotel.drop(['arrival_date_year'], axis=1, inplace=True)
```

In [23]:

```
# Analyze noisy data
noisy_data = {
    'adr':      hotel[hotel['adr'] < 0],
    'adults':   hotel[hotel['adults'] == 0],
    'children': hotel[hotel['children'] == 10],
    'babies':   hotel[hotel['babies'] == 10],
}

noisy_data_count = {key: len(value) for key, value in noisy_data.items()}
noisy_data_count
```

Out[23]:

```
{'adr': 1, 'adults': 403, 'children': 1, 'babies': 1}
```

In [24]:

```
# Replace negative adr with median of adr column
hotel.loc[hotel['adr'] < 0, 'adr'] = hotel['adr'].median()

# Remove rows with 0 adults
hotel = hotel[hotel['adults'] != 0]

# Remove rows with 10 children or 10 babies
hotel = hotel[hotel['children'] != 10]
hotel = hotel[hotel['babies'] != 10]

# Reset the index
hotel.reset_index(drop=True, inplace=True)

# Check if the noisy data has been handled
noisy_data_handled = {
    'adr': hotel[hotel['adr'] < 0],
    'adults': hotel[hotel['adults'] == 0],
    'children': hotel[hotel['children'] == 10],
    'babies': hotel[hotel['babies'] == 10],
}

noisy_data_handled_count = {key: len(value) for key, value in noisy_data_h
noisy_data_handled_count
```

Out[24]:

```
{'adr': 0, 'adults': 0, 'children': 0, 'babies': 0}
```

In [ ]:

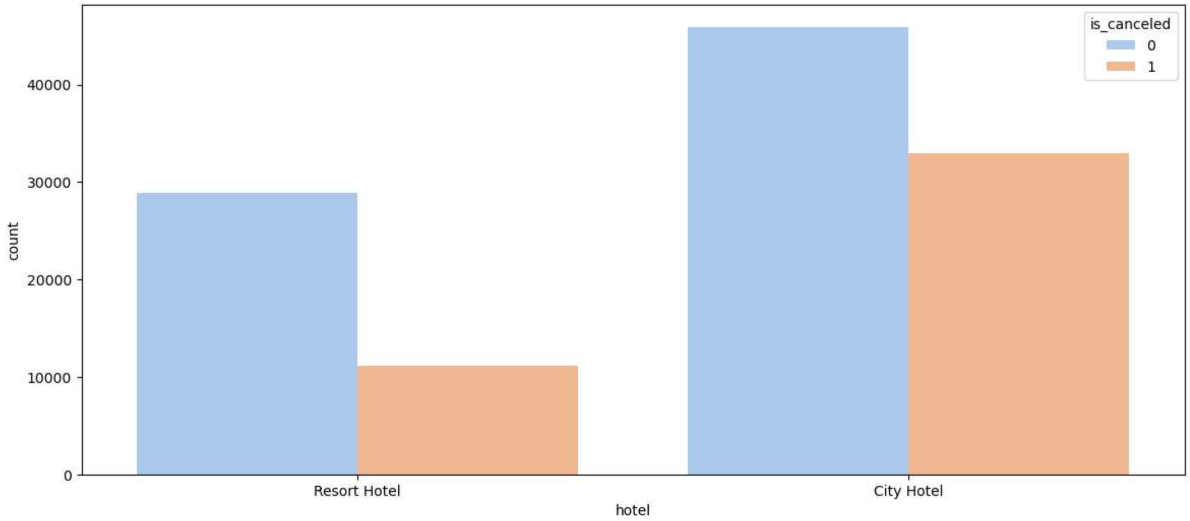
```

```

Data Visualization

In [25]:

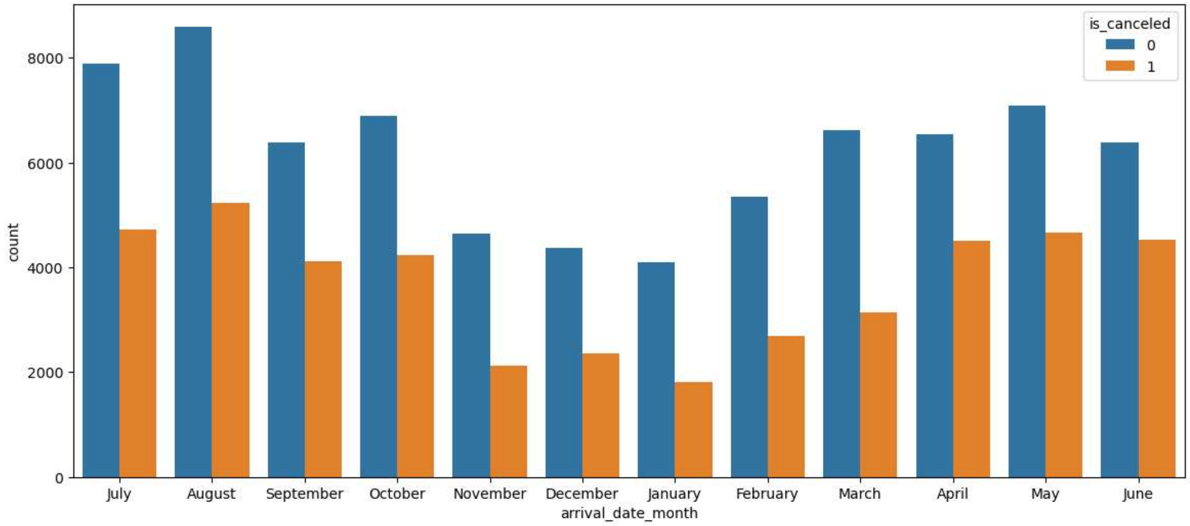
```
plt.figure(figsize=(14,6))
sns.countplot(x='hotel',data=hotel,hue='is_canceled',palette='pastel')
plt.show()
```



From above chart we can say that city hotel has highest cancellation

In [26]:

```
plt.figure(figsize=(14,6))
sns.countplot(x='arrival_date_month',data=hotel,hue='is_canceled')
plt.show()
```



Cancellations were high from month April to August

In [27]:

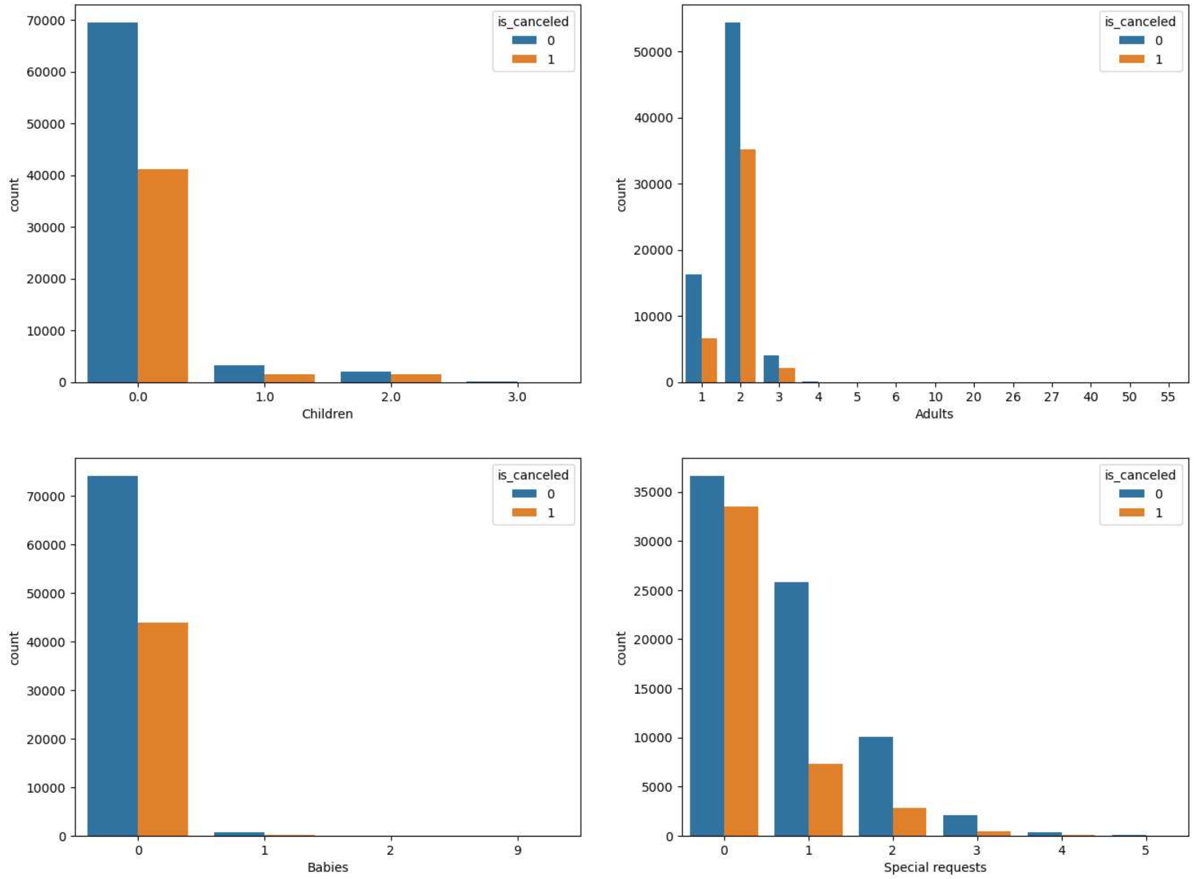
```python
hotel.columns
```

Out[27]:

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

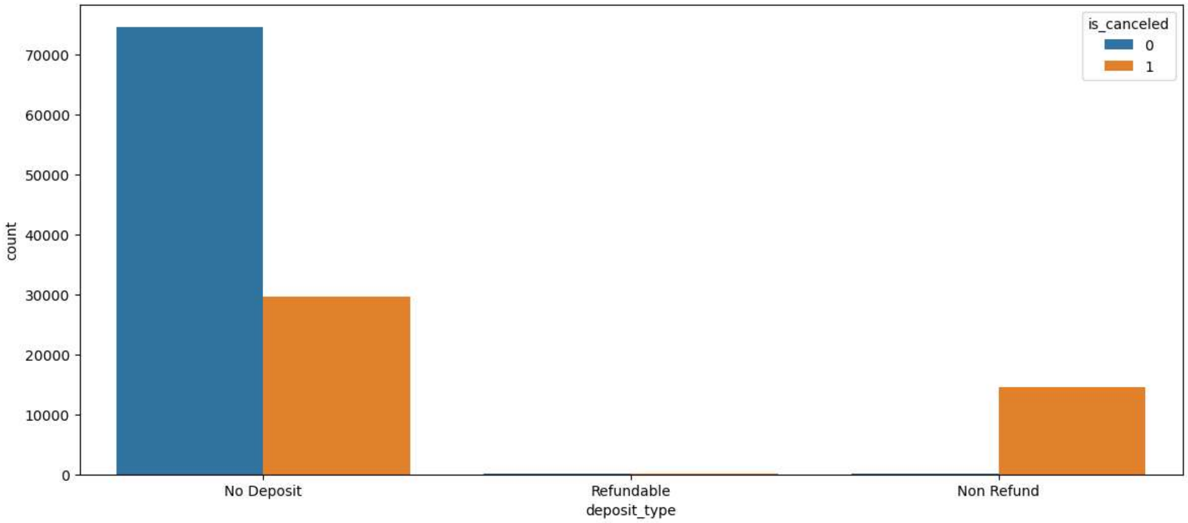
In [28]:

```python
plt.figure(figsize=(16,12))
plt.subplot(221)
sns.countplot(data= hotel,x ="children" , hue=hotel['is_canceled'])
plt.xlabel('Children')
plt.subplot(222)
sns.countplot(data= hotel,x='adults', hue=hotel['is_canceled'])
plt.xlabel('Adults')
plt.subplot(223)
sns.countplot(data= hotel,x='babies', hue=hotel['is_canceled'])
plt.xlabel('Babies')
plt.subplot(224)
sns.countplot(data= hotel,x='total_of_special_requests', hue=hotel['is_can
plt.xlabel('Special requests')
plt.show()
```



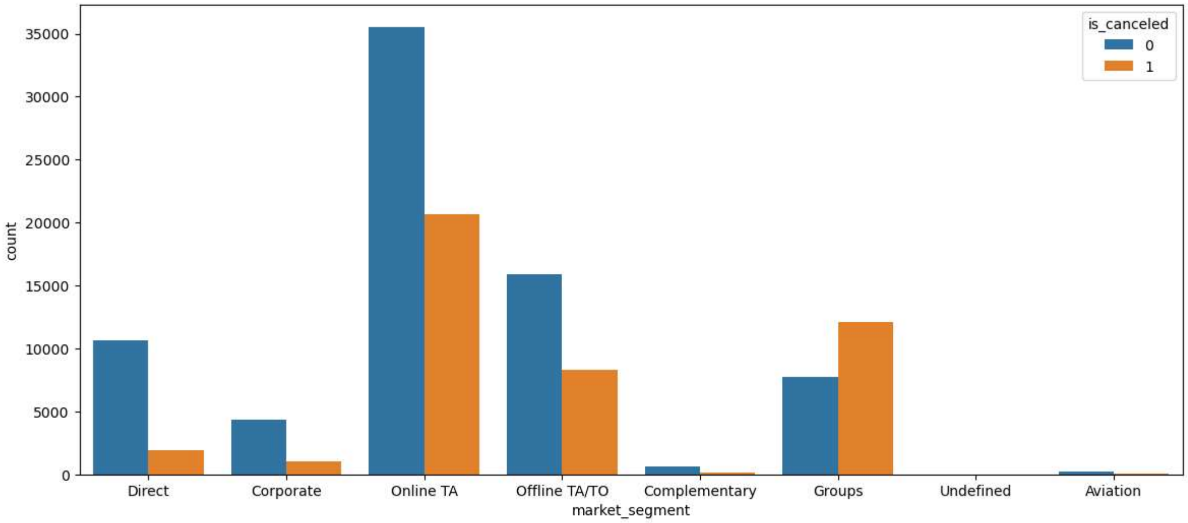
In [29]:

```python
plt.figure(figsize=(14,6))
sns.countplot(x='deposit_type',data=hotel,hue='is_canceled')
plt.show()
```



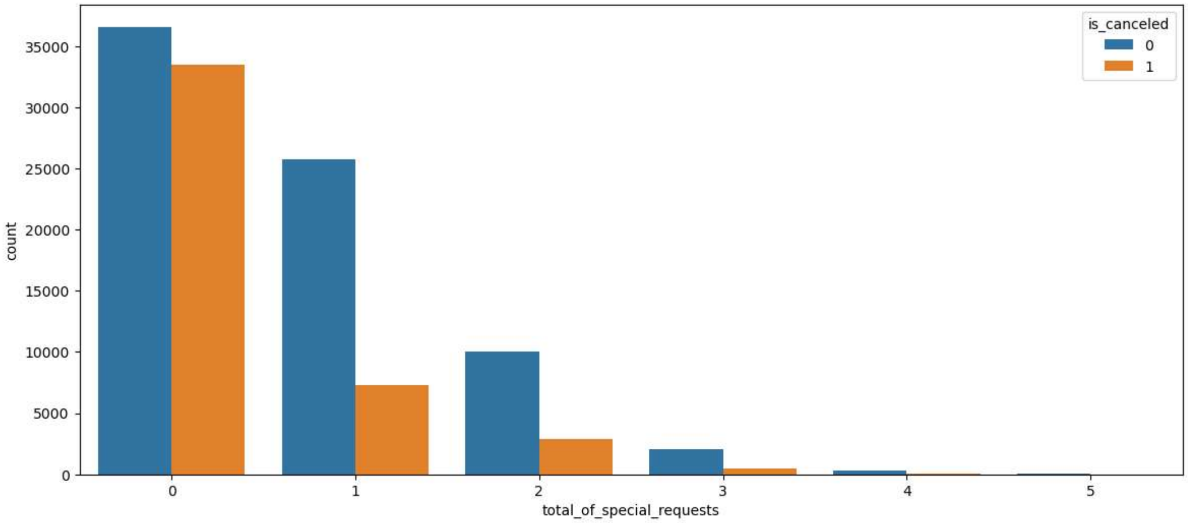
In [30]:

```python
plt.figure(figsize=(14,6))
sns.countplot(x='market_segment',data=hotel,hue='is_canceled')
plt.show()
```



In [31]:

```
plt.figure(figsize=(14,6))
sns.countplot(x='total_of_special_requests',data=hotel,hue='is_canceled')
plt.show()
```

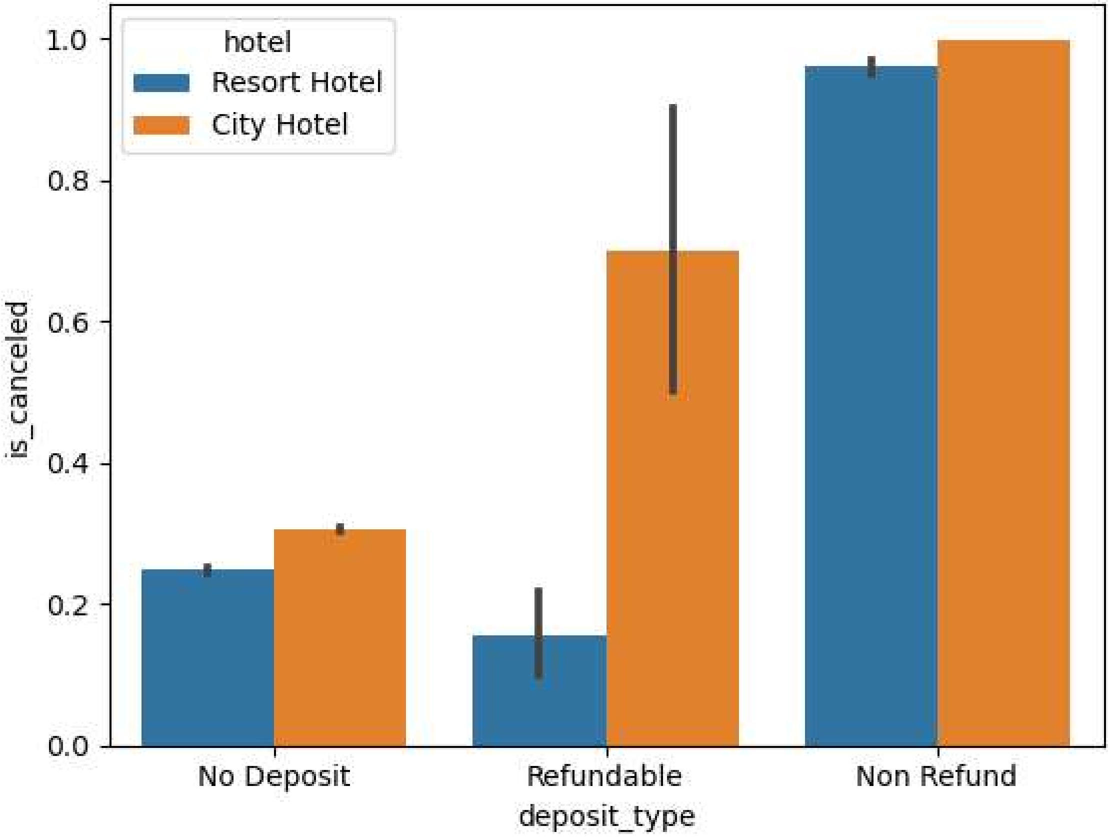


In [32]:

```
sns.barplot(data=hotel, x= 'deposit_type', y='is_canceled', hue = 'hotel')
```

Out[32]:

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

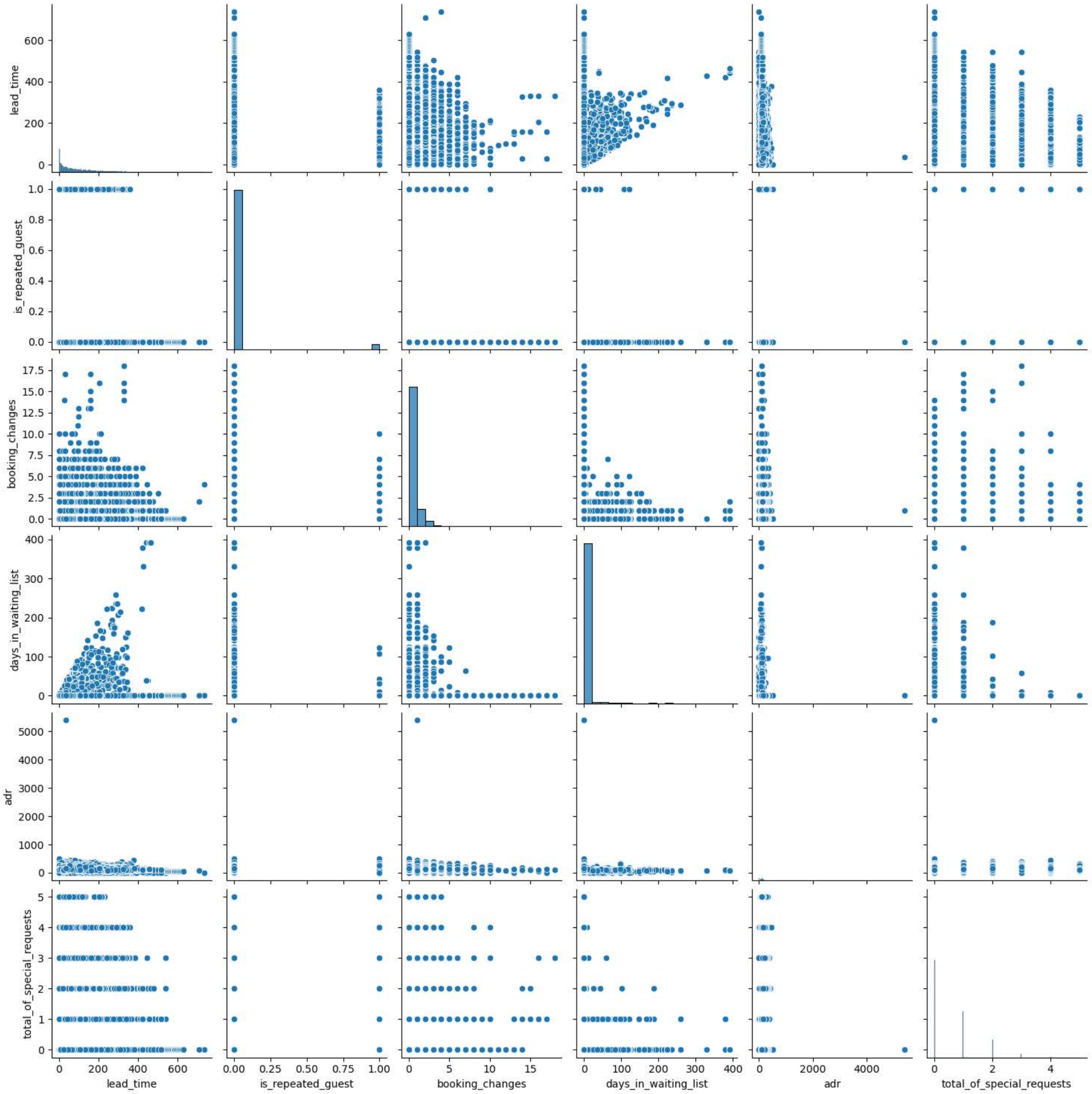


In [33]:

```python
sns.pairplot(hotel[['lead_time',
 'is_repeated_guest',
 'booking_changes',
 'days_in_waiting_list',
 'adr',
 'total_of_special_requests']])
```

Out[33]:

```
<seaborn.axisgrid.PairGrid at 0x29e6bf71fc0>
```



Feature Engineering

In [34]:

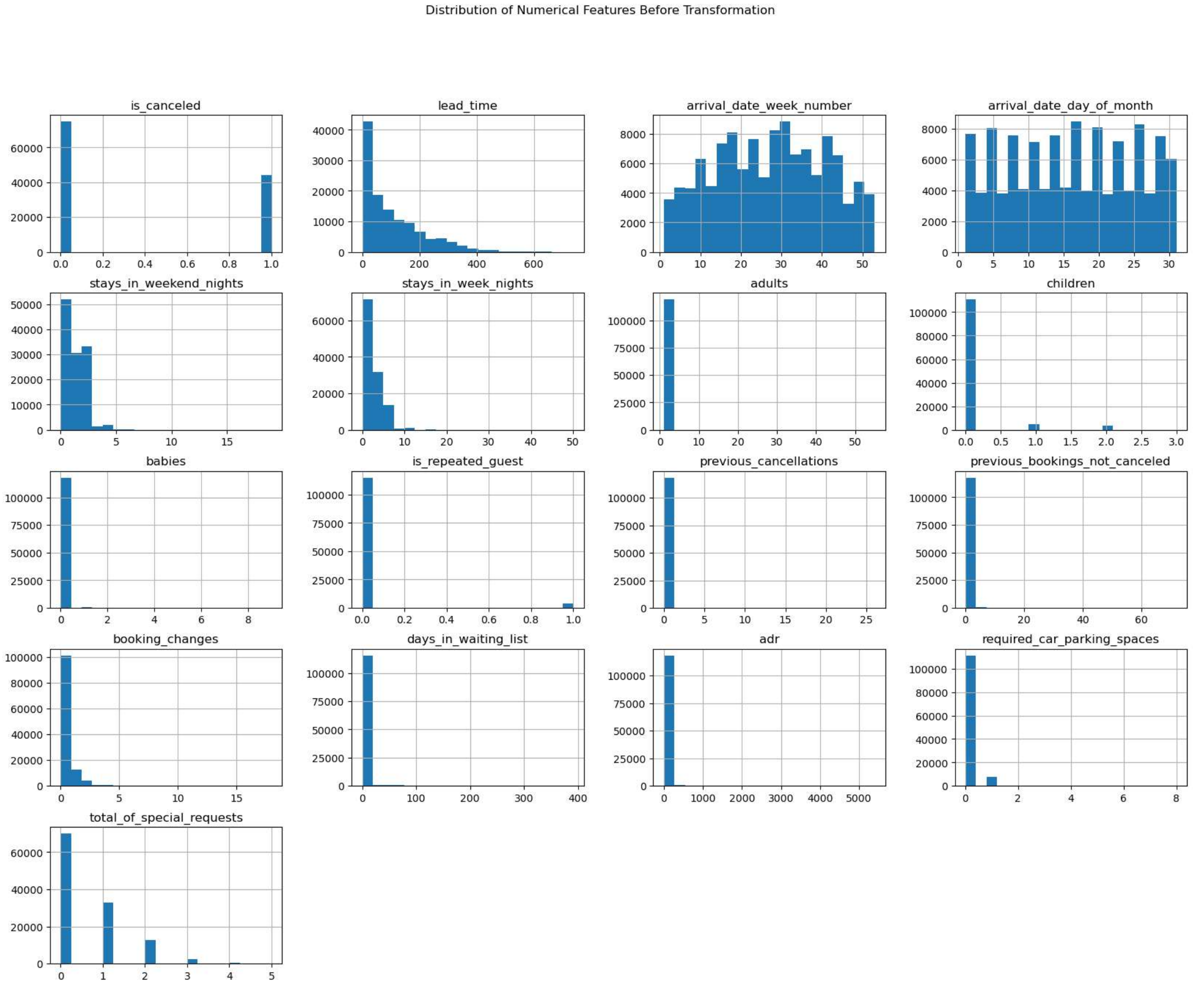
```python
### Analyze Categorical Data
from sklearn.preprocessing import StandardScaler
```

In [35]:
```
# Separating the numerical and categorical columns

def data_type(dataset):
    """
    Function to identify the numerical and categorical data columns
    :param dataset: Dataframe
    :return: list of numerical and categorical columns
    """
    numerical = []
    categorical = []
    for i in dataset.columns:
        if dataset[i].dtype == 'int64' or dataset[i].dtype == 'float64':
            numerical.append(i)
        else:
            categorical.append(i)
    return numerical, categorical
```

In [36]:
```
numerical, categorical = data_type(hotel)
```

In [37]:
```
hotel[numerical].hist(bins=20, figsize=(20, 15))
plt.suptitle('Distribution of Numerical Features Before Transformation')
plt.show()
```



In [38]:

```python
## Identifying the binary columns and ignoring them from scaling
import numpy as np
def binary_columns(df):
    """
    Generates a list of binary columns in a dataframe.
    """
    binary_cols = []
    for col in df.select_dtypes(include=['int', 'float']).columns:
        unique_values = df[col].unique()
        if np.in1d(unique_values, [0, 1]).all():
            binary_cols.append(col)
    return binary_cols

binary_cols = binary_columns(hotel)
```

In [39]:

```python
binary_cols
```

Out[39]:

```
['is_canceled', 'is_repeated_guest']
```

In [40]:

```python
# Remove the binary columns from the numerical columns
numerical = [i for i in numerical if i not in binary_cols]

```

In [41]:

```python
numerical
```

Out[41]:

```
['lead_time',
 'arrival_date_week_number',
 'arrival_date_day_of_month',
 'stays_in_weekend_nights',
 'stays_in_week_nights',
 'adults',
 'children',
 'babies',
 'previous_cancellations',
 'previous_bookings_not_canceled',
 'booking_changes',
 'days_in_waiting_list',
 'adr',
 'required_car_parking_spaces',
 'total_of_special_requests']
```

In [42]:

```python
binary_cols
```

Out[42]:

```
['is_canceled', 'is_repeated_guest']
```

Encoding

In [43]:

```python
labelencoder = LabelEncoder()
```

In [44]:
```
# Convert 'arrival_date_month' to numerical values
hotel['arrival_date_month'] = labelencoder.fit_transform(hotel['arrival_da
```

In [45]:
```
hotel
```

Out[45]:

	hotel	is_canceled	lead_time	arrival_date_month	arrival_date_week_number	arrival_dat
0	Resort Hotel	0	342	5	27	
1	Resort Hotel	0	737	5	27	
2	Resort Hotel	0	7	5	27	
3	Resort Hotel	0	13	5	27	
4	Resort Hotel	0	14	5	27	
...	...	...	...	...	...	
118980	City Hotel	0	23	1	35	
118981	City Hotel	0	102	1	35	
118982	City Hotel	0	34	1	35	
118983	City Hotel	0	109	1	35	
118984	City Hotel	0	205	1	35	

118985 rows × 26 columns

In [46]:
```
# One-hot encode the specified columns
one_hot_cols = ['hotel','country', 'meal', 'market_segment', 'distribution
df = pd.get_dummies(hotel, columns=one_hot_cols, drop_first=True)

df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 118985 entries, 0 to 118984
Columns: 223 entries, is_canceled to customer_type_Transient-Party
dtypes: bool(205), float64(2), int32(1), int64(15)
memory usage: 39.1 MB
```

In [47]:
```
bool_columns = df.select_dtypes(include='bool').columns
# Convert boolean columns to unsigned integers
df[bool_columns] = df[bool_columns].astype('uint')
```

In [48]:

```
df
```

Out[48]:

```
        is_canceled  lead_time  arrival_date_month  arrival_date_week_number  arrival_date_day_o
     0            0        342                   5                        27
     1            0        737                   5                        27
     2            0          7                   5                        27
     3            0         13                   5                        27
     4            0         14                   5                        27
   ...          ...        ...                 ...                       ...
118980            0         23                   1                        35
118981            0        102                   1                        35
118982            0         34                   1                        35
118983            0        109                   1                        35
118984            0        205                   1                        35

118985 rows × 223 columns
```

In [49]:

```
### Check Imbalanced Data
```

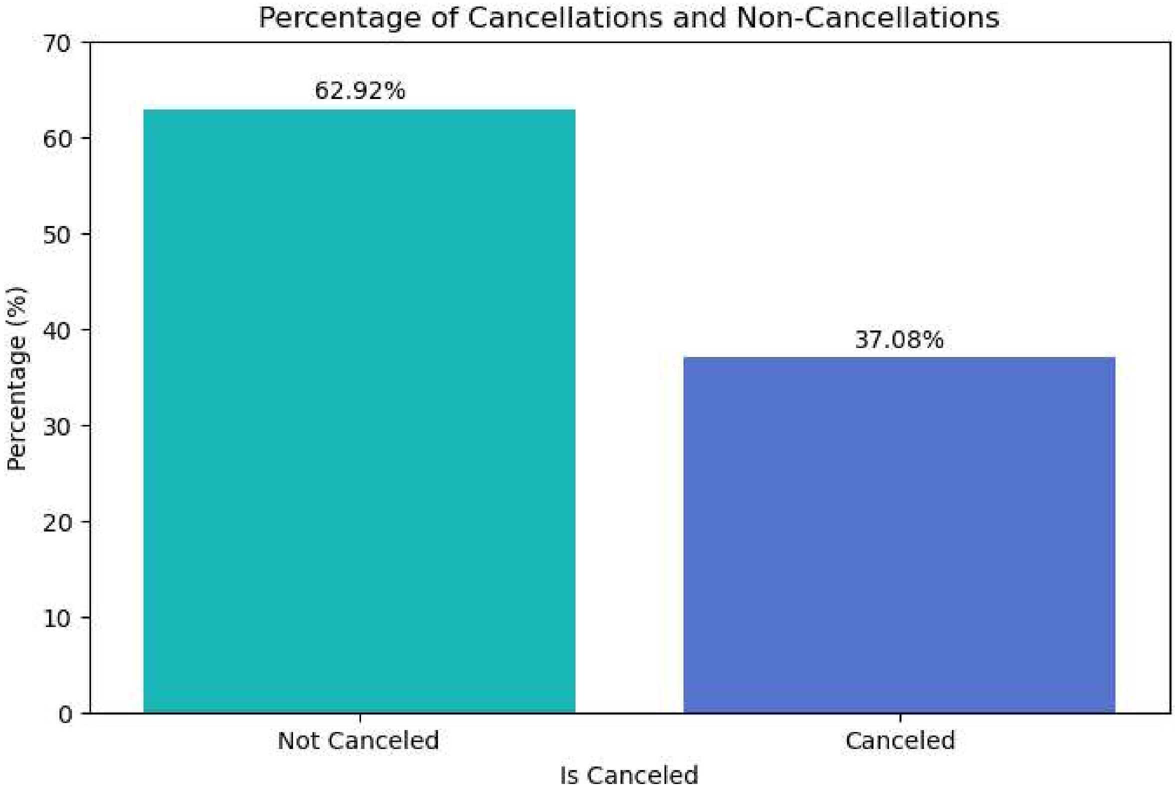
In [50]:

```
# Calculating the percentage of each class
percentage = df['is_canceled'].value_counts(normalize=True) * 100

# Plotting the percentage of each class
plt.figure(figsize=(8, 5))
ax = sns.barplot(x=percentage.index, y=percentage, palette=['darkturquoise
plt.title('Percentage of Cancellations and Non-Cancellations')
plt.xlabel('Is Canceled')
plt.ylabel('Percentage (%)')
plt.xticks(ticks=[0, 1], labels=['Not Canceled', 'Canceled'])
plt.yticks(ticks=range(0,80,10))

# Displaying the percentage on the bars
for i, p in enumerate(percentage):
    ax.text(i, p + 0.5, f'{p:.2f}%', ha='center', va='bottom')

plt.show()
```



Feature Scaling

In [51]:

```
def feature_scaling(dataset, numerical):
    """
    Function to automate the process of feature scaling the numerical data
    :param dataset: Dataframe
    :param numerical: List of numerical columns
    :return: Dataframe
    """
    sc_x = StandardScaler()
    dataset[numerical] = sc_x.fit_transform(dataset[numerical])
    return dataset
```

In [52]:

```
df = feature_scaling(df, numerical)

df
```

Out[52]:

	is_canceled	lead_time	arrival_date_month	arrival_date_week_number	arrival_date_day_o
0	0	2.225899	5	-0.012084	-1
1	0	5.921254	5	-0.012084	-1
2	0	-0.908136	5	-0.012084	-1
3	0	-0.852004	5	-0.012084	-1
4	0	-0.842649	5	-0.012084	-1
...	...	...	...	...	
118980	0	-0.758451	1	0.576208	1
118981	0	-0.019380	1	0.576208	1
118982	0	-0.655542	1	0.576208	1
118983	0	0.046108	1	0.576208	1
118984	0	0.944219	1	0.576208	1

118985 rows × 223 columns

In [53]:

```
def power_transform(dataset, numerical):
    """
    Function to automate the process of feature scaling the numerical data
    :param dataset: Dataframe
    :param numerical: List of numerical columns
    :return: Dataframe
    """
    power_transformer = PowerTransformer(method='yeo-johnson', standardize
    # You can also use 'yeo-johnson' for Yeo-Johnson transform
    dataset[numerical] = power_transformer.fit_transform(dataset[numerical
    return dataset
```

In [54]:

```python
hotel_trans = power_transform(df, numerical)
```

In [55]:

```python
hotel_trans
```

Out[55]:

	is_canceled	lead_time	arrival_date_month	arrival_date_week_number	arrival_date_day_o
0	0	1.704708	5	-0.016292	-1
1	0	2.539828	5	-0.016292	-1
2	0	-1.189414	5	-0.016292	-1
3	0	-1.063373	5	-0.016292	-1
4	0	-1.042747	5	-0.016292	-1
...	...	...	...	...	
118980	0	-0.861996	1	0.573644	1
118981	0	0.349765	1	0.573644	1
118982	0	-0.653005	1	0.573644	1
118983	0	0.424997	1	0.573644	1
118984	0	1.136467	1	0.573644	1

118985 rows × 223 columns

Split Test and Train Data

In [56]:

```python
#Splitting all the independent variables in one array
X = hotel_trans.drop('is_canceled', axis = 1)
```

In [57]:

```python
#Splitting the dependent variable in one array
y = hotel_trans['is_canceled']
```

In [58]:

```python
#Splitting the dataset into train and test based on the 70-30 ratio

from sklearn.model_selection import train_test_split

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, r

```

In [59]:

```python
print(X_train.shape)
print(y_train.shape)
print(X_test.shape)
print(y_test.shape)
```

```
(83289, 222)
(83289,)
(35696, 222)
(35696,)
```

Creating the model on training dataset

In [61]:

```
!pip install xgboost

```

```
Collecting xgboost
  Downloading xgboost-2.0.3-py3-none-win_amd64.whl (99.8 MB)
     ---------------------------------------- 99.8/99.8 MB 4.2 MB/s eta 0:00:
00
Requirement already satisfied: scipy in c:\users\user\anaconda3\lib\site-pack
ages (from xgboost) (1.10.0)
Requirement already satisfied: numpy in c:\users\user\anaconda3\lib\site-pack
ages (from xgboost) (1.23.5)
Installing collected packages: xgboost
Successfully installed xgboost-2.0.3
```

In [62]:

```
import xgboost as xgb
```

In [63]:

```
# create an XG Boost classifier
xg_reg = xgb.XGBClassifier( n_estimators = 10)
```

Run the model on the Test Dataset

In [64]:

```
#Running the model on the test dataset
# Fit and predict from the model
xg_reg.fit(X_train,y_train)

preds = xg_reg.predict(X_test)
```

Check the accuracy of the model

In [65]:

```
#Importing all the functions to for checking the accuracies
from sklearn.metrics import classification_report,confusion_matrix,accurac
```

Accuracy Score

In [68]:

```
#Using accuracy score we are checking the accuracy on the testing dataset
accuracy_score(y_test,preds)
```

Out[68]:

```
0.8312415956969968
```

ROC curve and ROC area

In [70]:

```
### Compute ROC curve and ROC area
fpr, tpr, _ = roc_curve(y_test,preds)
roc_auc = auc(fpr, tpr)
```

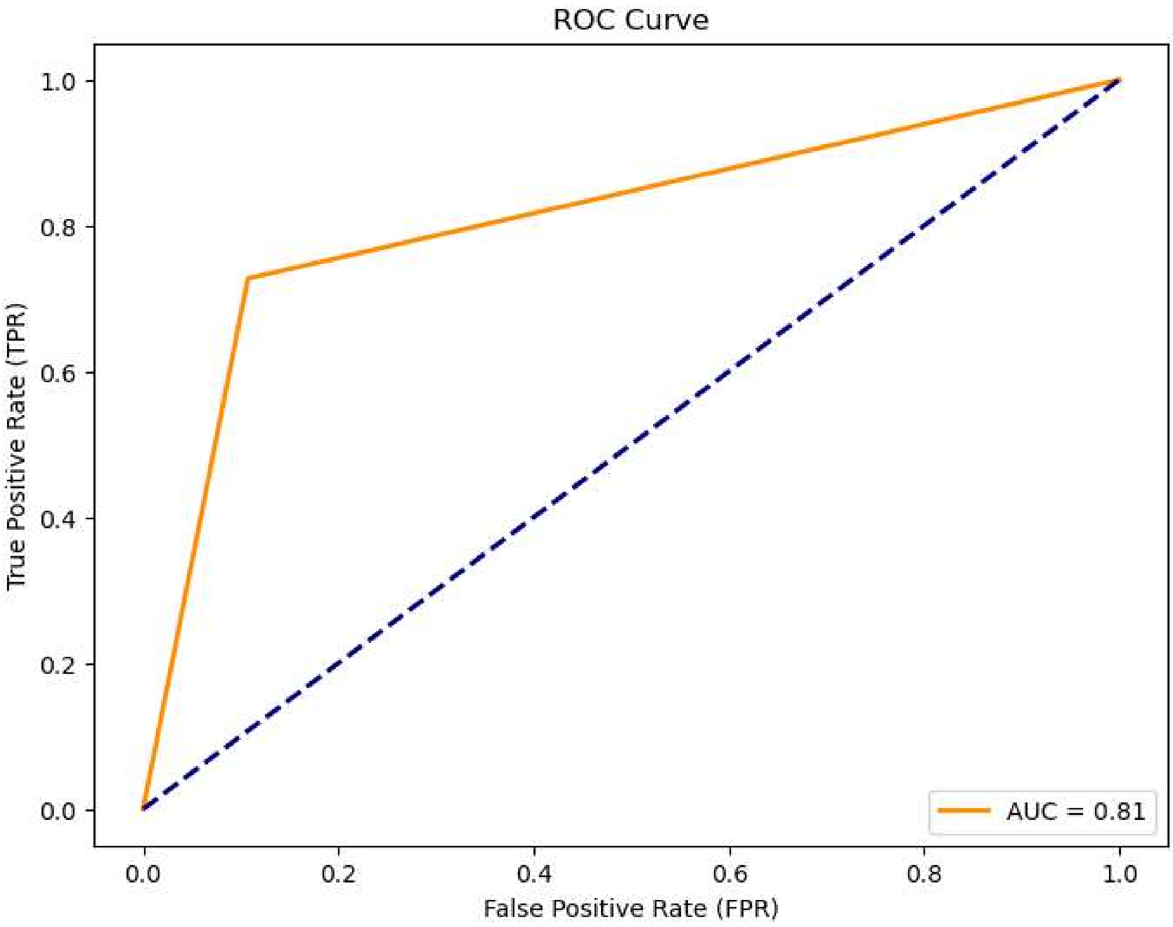
In [72]:

```
print(roc_auc_score(y_test,preds))
```

```
0.8100182358718034
```

In [73]:

```
# Plot ROC curve
plt.figure(figsize=(8, 6))
plt.plot(fpr, tpr, color='darkorange', lw=2, label=f'AUC = {roc_auc:.2f}')
plt.plot([0, 1], [0, 1], color='navy', lw=2, linestyle='--')
plt.xlabel('False Positive Rate (FPR)')
plt.ylabel('True Positive Rate (TPR)')
plt.title('ROC Curve')
plt.legend(loc='lower right')
plt.show()
```



AUC > 0.8: The model has good discrimination abilities.

Log Loss

In [74]:

```
logloss = log_loss(y_test, preds)
print("\nLog Loss:", logloss)
```

```
Log Loss: 6.0826694311979415
```

Confusion Matrix

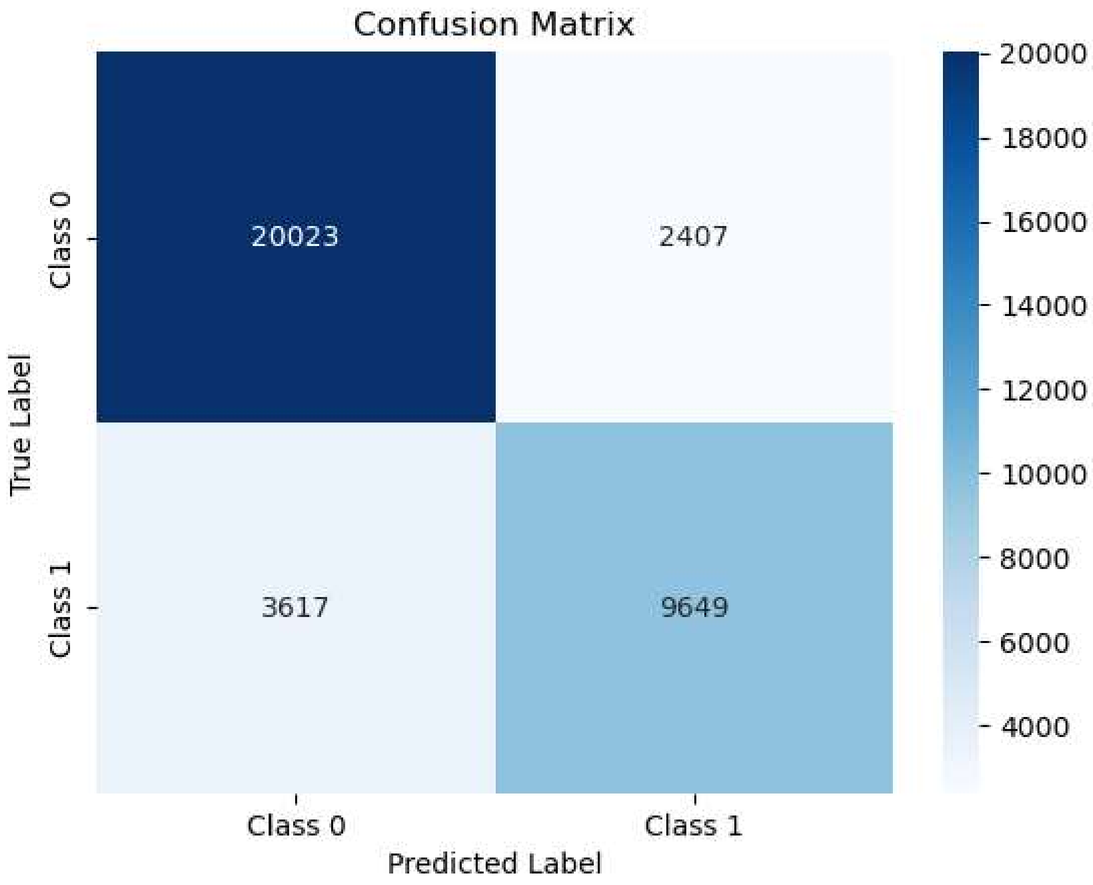
In [75]:

```
conf_matrix = confusion_matrix(y_test, preds)
print("Confusion Matrix:")
print(conf_matrix)
```

```
Confusion Matrix:
[[20023  2407]
 [ 3617  9649]]
```

In [76]:

```
sns.heatmap(conf_matrix, annot=True, fmt="d", cmap="Blues", xticklabels=["
plt.title("Confusion Matrix")
plt.xlabel("Predicted Label")
plt.ylabel("True Label")
plt.show()
```



Classification Report

In [77]:
```
print(classification_report(y_test,preds))
```

```
              precision    recall  f1-score   support

           0       0.85      0.89      0.87     22430
           1       0.80      0.73      0.76     13266

    accuracy                           0.83     35696
   macro avg       0.82      0.81      0.82     35696
weighted avg       0.83      0.83      0.83     35696
```

Comparing the Training and Testing Accuracies

In [80]:
```
#Storing the predicted values of training dataset in y_pred_train
y_pred_train = xg_reg.predict(X_train)
```

In [81]:
```
#Checking the accuracy of training dataset
accuracy_score(y_train,y_pred_train)
```

Out[81]:
```
0.8320786658502323
```

In [83]:
```
#Checking the accuracy of testing dataset
accuracy_score(y_test,preds)
```

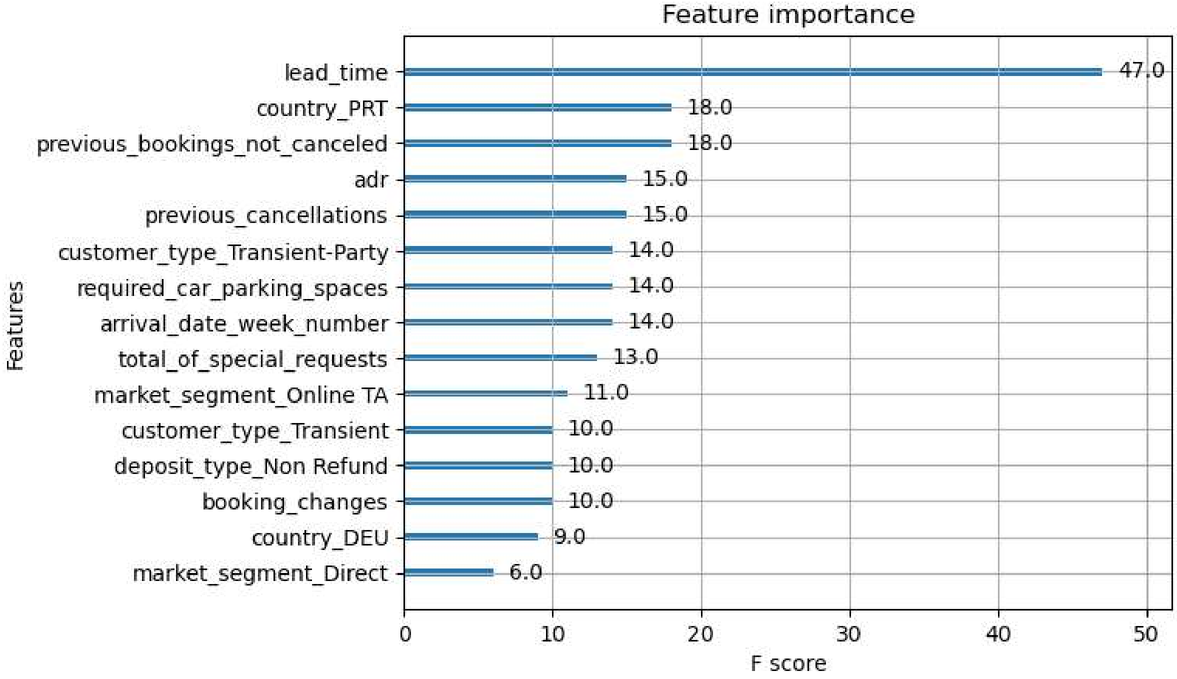
Out[83]:
```
0.8312415956969968
```

Conclusion: As there is very less difference between the accuracy of training and testing dataset we are good to go with the model

Visualizing the Feature Importance

In [89]:

```
xgb.plot_importance(xg_reg, max_num_features=15, importance_type='weight')
plt.show()
```



In [ ]:

```

```