Hotel Bookings Cancellation Prediction

- Predicting Hotel Booking Cancellation in Portugal is a machine learning classification project that will try to predict whether a booking will be cancelled or not using machine learning models based on historical data.
- The data for this project is from Hotel Booking Demand Dataset Sciencedirect. This data was acquired by extraction from hotel's Property management system from 2015 to 2017 from hotel in Region Algarve and Lisbon.

Importing necessary libraries

In [1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns


import warnings
warnings.filterwarnings('ignore')

pd.set_option('display.max_columns', 60)
```

Loading the dataset

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

Out[2]:

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

Shape of the dataset

In [3]:
```
1 df.shape
```

Out[3]:
```
(119390, 32)
```

In [4]:
```
1 # There are 119390 rows and 32 columns present in the dataset
```

Columns of the dataset

In [5]:
```
1 df.columns
```

Out[5]:
```
Index(['hotel', 'is_canceled', 'lead_time', 'arrival_date_year',
       'arrival_date_month', 'arrival_date_week_number',
       'arrival_date_day_of_month', 'stays_in_weekend_nights',
       'stays_in_week_nights', 'adults', 'children', 'babies', 'meal',
       'country', 'market_segment', 'distribution_channel',
       'is_repeated_guest', 'previous_cancellations',
       'previous_bookings_not_canceled', 'reserved_room_type',
       'assigned_room_type', 'booking_changes', 'deposit_type', 'agent',
       'company', 'days_in_waiting_list', 'customer_type', 'adr',
       'required_car_parking_spaces', 'total_of_special_requests',
       'reservation_status', 'reservation_status_date'],
      dtype='object')
```

Basic information about the dataset

In [6]:
```
1 df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 119390 entries, 0 to 119389
Data columns (total 32 columns):
 #   Column                          Non-Null Count   Dtype
---  ------                          --------------   -----
 0   hotel                           119390 non-null  object
 1   is_canceled                     119390 non-null  int64
 2   lead_time                       119390 non-null  int64
 3   arrival_date_year               119390 non-null  int64
 4   arrival_date_month              119390 non-null  object
 5   arrival_date_week_number        119390 non-null  int64
 6   arrival_date_day_of_month       119390 non-null  int64
 7   stays_in_weekend_nights         119390 non-null  int64
 8   stays_in_week_nights            119390 non-null  int64
 9   adults                          119390 non-null  int64
 10  children                        119386 non-null  float64
 11  babies                          119390 non-null  int64
 12  meal                            119390 non-null  object
 13  country                         118902 non-null  object
 14  market_segment                  119390 non-null  object
 15  distribution_channel            119390 non-null  object
 16  is_repeated_guest               119390 non-null  int64
 17  previous_cancellations          119390 non-null  int64
 18  previous_bookings_not_canceled  119390 non-null  int64
 19  reserved_room_type              119390 non-null  object
 20  assigned_room_type              119390 non-null  object
 21  booking_changes                 119390 non-null  int64
 22  deposit_type                    119390 non-null  object
 23  agent                           103050 non-null  float64
 24  company                         6797 non-null    float64
 25  days_in_waiting_list            119390 non-null  int64
 26  customer_type                   119390 non-null  object
 27  adr                             119390 non-null  float64
 28  required_car_parking_spaces     119390 non-null  int64
 29  total_of_special_requests       119390 non-null  int64
 30  reservation_status              119390 non-null  object
 31  reservation_status_date         119390 non-null  object
dtypes: float64(4), int64(16), object(12)
memory usage: 29.1+ MB
```

In [7]:
```
# Object columns = hotel, arrival_date_month, meal, country, market_segment, distribution_channel, rese
#                  assigned_room_type, deposit_type, customer_type, reservation_status, reservation_sta

# Numeric columns = is_canceled, lead_time, arrival_date_year, arrival_date_week_number, arrival_date_d
#                   stays_in_weekend_nights, stays_in_week_night, adults, children, babies, is_repeated_
#                   previous_cancellations, previous_bookings_not_canceled, booking_changes, agent, com
#                   days_in_waiting_list, adr, required_car_parking_spaces, total_of_special_requests.

```

Number of unique values per column

In [8]:
```
df.nunique()
```

Out[8]:
```
hotel                               2
is_canceled                         2
lead_time                         479
arrival_date_year                   3
arrival_date_month                 12
arrival_date_week_number           53
arrival_date_day_of_month          31
stays_in_weekend_nights            17
stays_in_week_nights               35
adults                             14
children                            5
babies                              5
meal                                5
country                           177
market_segment                      8
distribution_channel                5
is_repeated_guest                   2
previous_cancellations             15
previous_bookings_not_canceled     73
reserved_room_type                 10
assigned_room_type                 12
booking_changes                    21
deposit_type                        3
agent                             333
company                           352
days_in_waiting_list              128
customer_type                       4
adr                              8879
required_car_parking_spaces         5
total_of_special_requests           6
reservation_status                  3
reservation_status_date           926
dtype: int64
```

Statistical Summary

In [9]:
```
df.describe()
```

Out[9]:

	is_canceled	lead_time	arrival_date_year	arrival_date_week_number	arrival_date_day_of_month	stays_in_weekend_night
count	119390.000000	119390.000000	119390.000000	119390.000000	119390.000000	119390.00000
mean	0.370416	104.011416	2016.156554	27.165173	15.798241	0.92759
std	0.482918	106.863097	0.707476	13.605138	8.780829	0.99861
min	0.000000	0.000000	2015.000000	1.000000	1.000000	0.00000
25%	0.000000	18.000000	2016.000000	16.000000	8.000000	0.00000
50%	0.000000	69.000000	2016.000000	28.000000	16.000000	1.00000
75%	1.000000	160.000000	2017.000000	38.000000	23.000000	2.00000
max	1.000000	737.000000	2017.000000	53.000000	31.000000	19.00000

In [10]:
```
df.describe(include = "object")
```

Out[10]:

	hotel	arrival_date_month	meal	country	market_segment	distribution_channel	reserved_room_type	assigned_room_type
count	119390	119390	119390	118902	119390	119390	119390	119390
unique	2	12	5	177	8	5	10	12
top	City Hotel	August	BB	PRT	Online TA	TA/TO	A	A
freq	79330	13877	92310	48590	56477	97870	85994	74053

Exploratory Data Analysis

Checking for duplicate records

In [11]:
```
1 df.duplicated().sum()
```

Out[11]: 31994

In [12]:
```
1 # There are 31994 duplicate records and it is better to get rid of them.
```

Checking for null values

In [13]:
```
1 df.isna().sum()
```

Out[13]:
```
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 [14]:
```
1 # Null values are present in 4 columns : children, country, agent, and company
```

Percentage of null values

In [15]:
```
df.isna().sum()/len(df) * 100
```

Out[15]:
```
hotel                           0.000000
is_canceled                     0.000000
lead_time                       0.000000
arrival_date_year               0.000000
arrival_date_month              0.000000
arrival_date_week_number        0.000000
arrival_date_day_of_month       0.000000
stays_in_weekend_nights         0.000000
stays_in_week_nights            0.000000
adults                          0.000000
children                        0.003350
babies                          0.000000
meal                            0.000000
country                         0.408744
market_segment                  0.000000
distribution_channel            0.000000
is_repeated_guest               0.000000
previous_cancellations          0.000000
previous_bookings_not_canceled  0.000000
reserved_room_type              0.000000
assigned_room_type              0.000000
booking_changes                 0.000000
deposit_type                    0.000000
agent                          13.686238
company                        94.306893
days_in_waiting_list            0.000000
customer_type                   0.000000
adr                             0.000000
required_car_parking_spaces     0.000000
total_of_special_requests       0.000000
reservation_status              0.000000
reservation_status_date         0.000000
dtype: float64
```

In [16]:
```
# As 94% of the values in company column are missing. Therefore, it is better to drop that column.
# Other columns have sufficiently less number of missing values and hence, can be imputed through appro
```

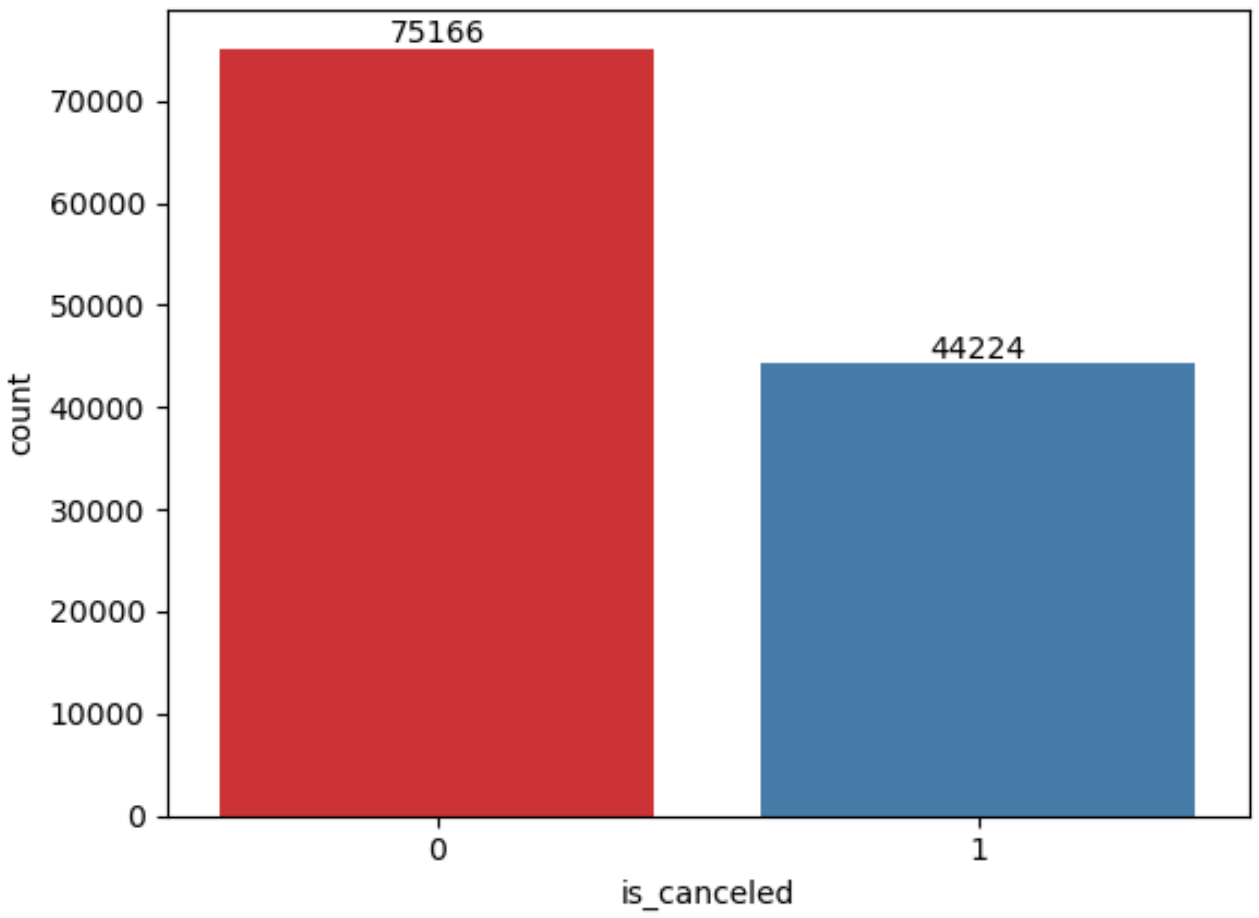
Univariate Analysis

Booking cancellation rate

In [17]:
```
rate = len(df[df['is_canceled']==1]) / len(df) * 100
print(f"Booking cancellation rate = {round(rate,2)} %")
```

```
Booking cancellation rate = 37.04 %
```

In [18]:
```
ax=sns.countplot(x = 'is_canceled', data = df, palette = 'Set1')

for i in ax.containers:
    ax.bar_label(i)
plt.show()
```



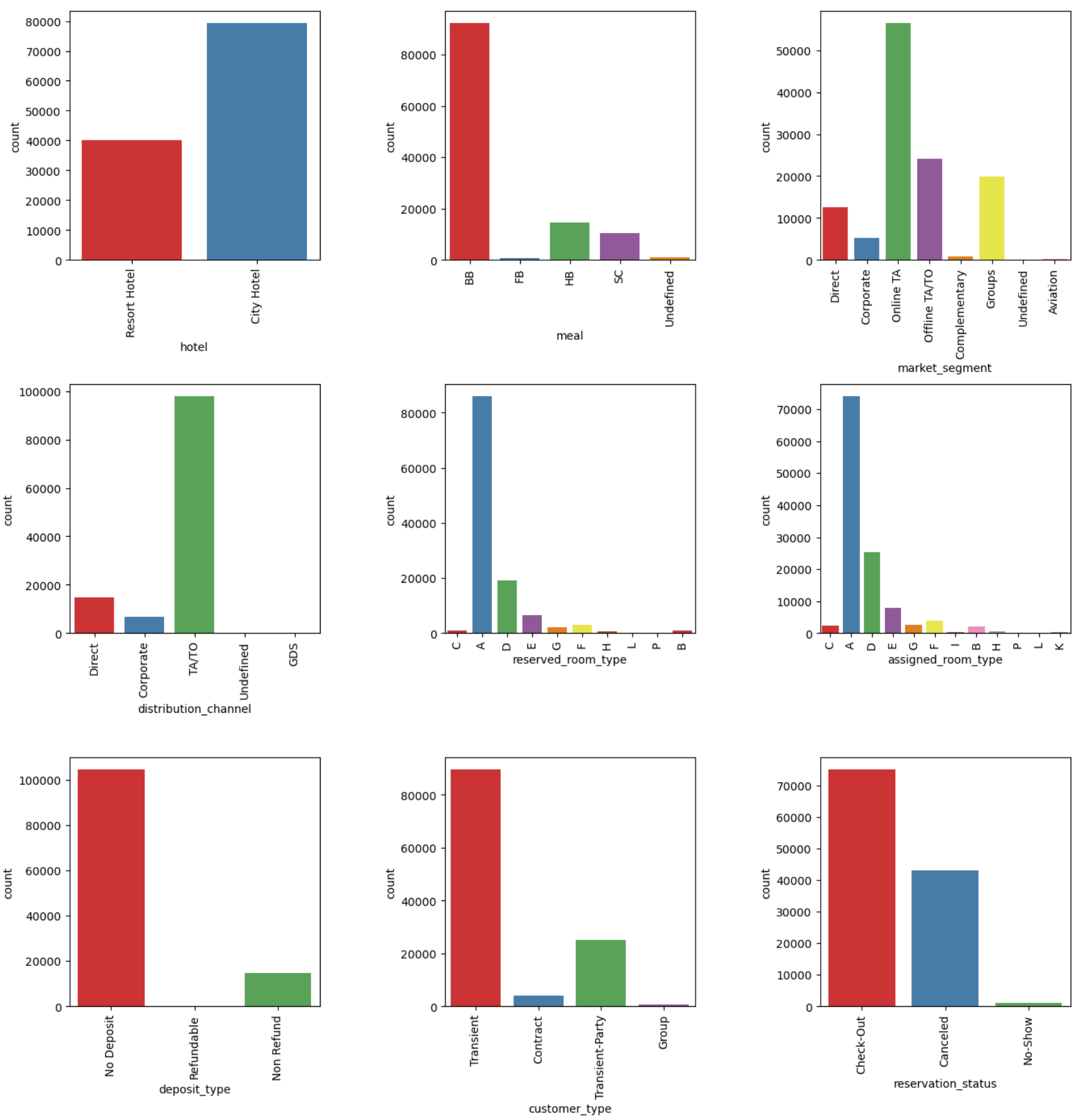
In [19]:
```
#Out of 119390 bookings, 44224 (37.04%) bookings have been canceled.
```

Analysis of each feature

In [20]:
```
obj_col_list = list(df[["hotel", "meal","market_segment", "distribution_channel", "reserved_room_type",
```

In [21]:

```
plt.figure(figsize = (16,16))
plt.subplots_adjust(hspace = 0.50, wspace = 0.50)

for i in range(len(obj_col_list)):
    plt.subplot(3,3,i+1)
    plt.xticks(rotation=90)
    sns.countplot(df[obj_col_list[i]], palette = 'Set1')

plt.show()
```



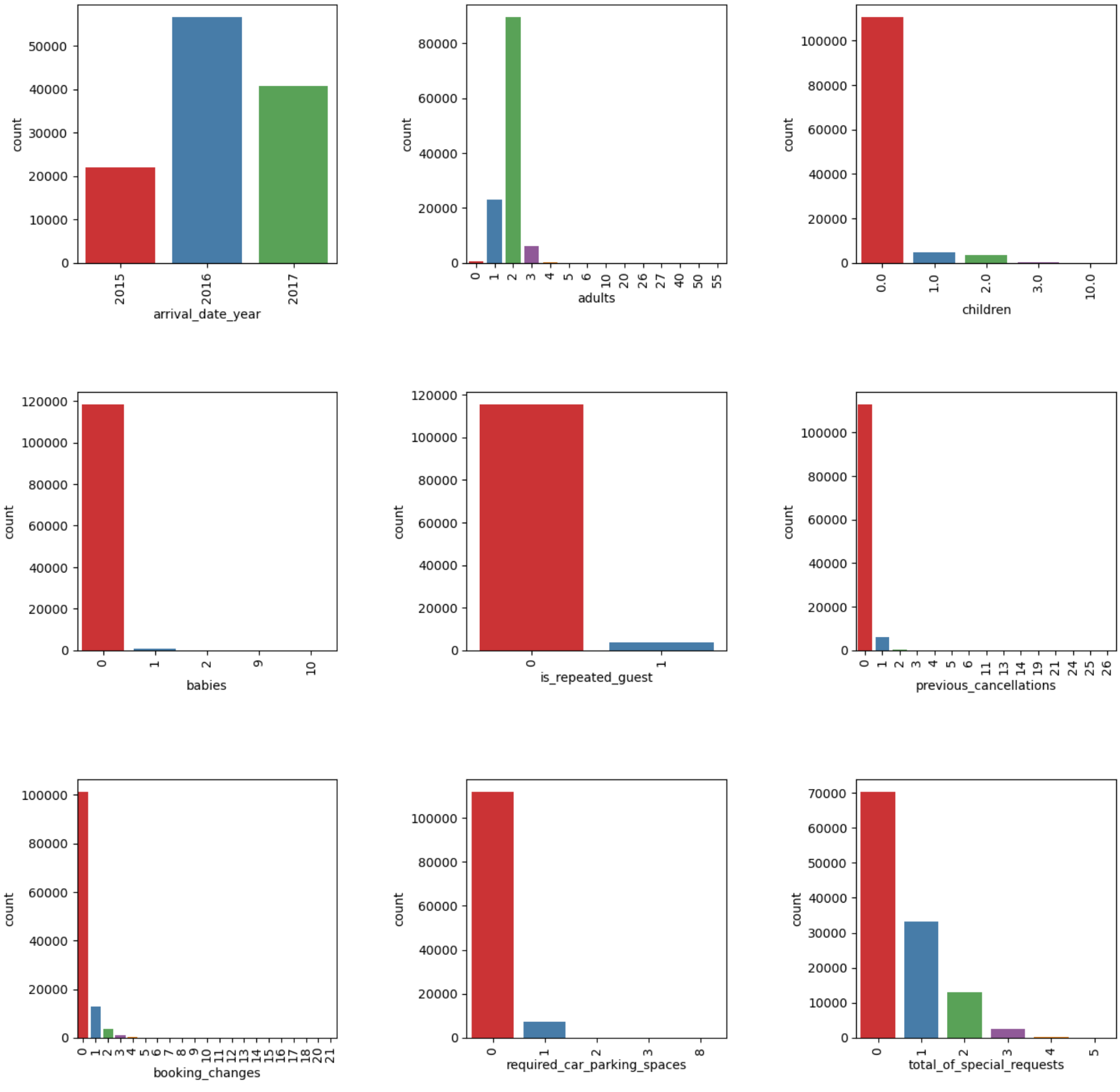
Analysis:

1. The number of bookings in City Hotel are more than the number of bookings in Resort Hotel.
2. Most of the customers prefer 'BB' type of meal.
3. Maximum number of bookings have been done through 'online TA' market segment as well as 'TA/TO' distribution channel.
4. The most number of bookings have been made for 'A' room_type , followed by 'D' room type. Same pattern can also be seen while assigning room type to the customers.
5. Most of the customers prefer to book rooms without any deposit.
6. Maximum number of bookings have been done by Transient customers, followed by Transient party type. There are very few bookings made by Groups.
7. A very few number of customers did not show up after booking their rooms.

In [22]:

```
num_col_list = list(df[["arrival_date_year", "adults", "children", "babies", "is_repeated_guest", "prev
```

In [23]:
```
plt.figure(figsize = (15,15))
plt.subplots_adjust(hspace = 0.50, wspace = 0.50)

for i in range(len(num_col_list)):
    plt.subplot(3,3,i+1)
    plt.xticks(rotation=90)
    sns.countplot(df[num_col_list[i]], palette = 'Set1')

plt.show()
```

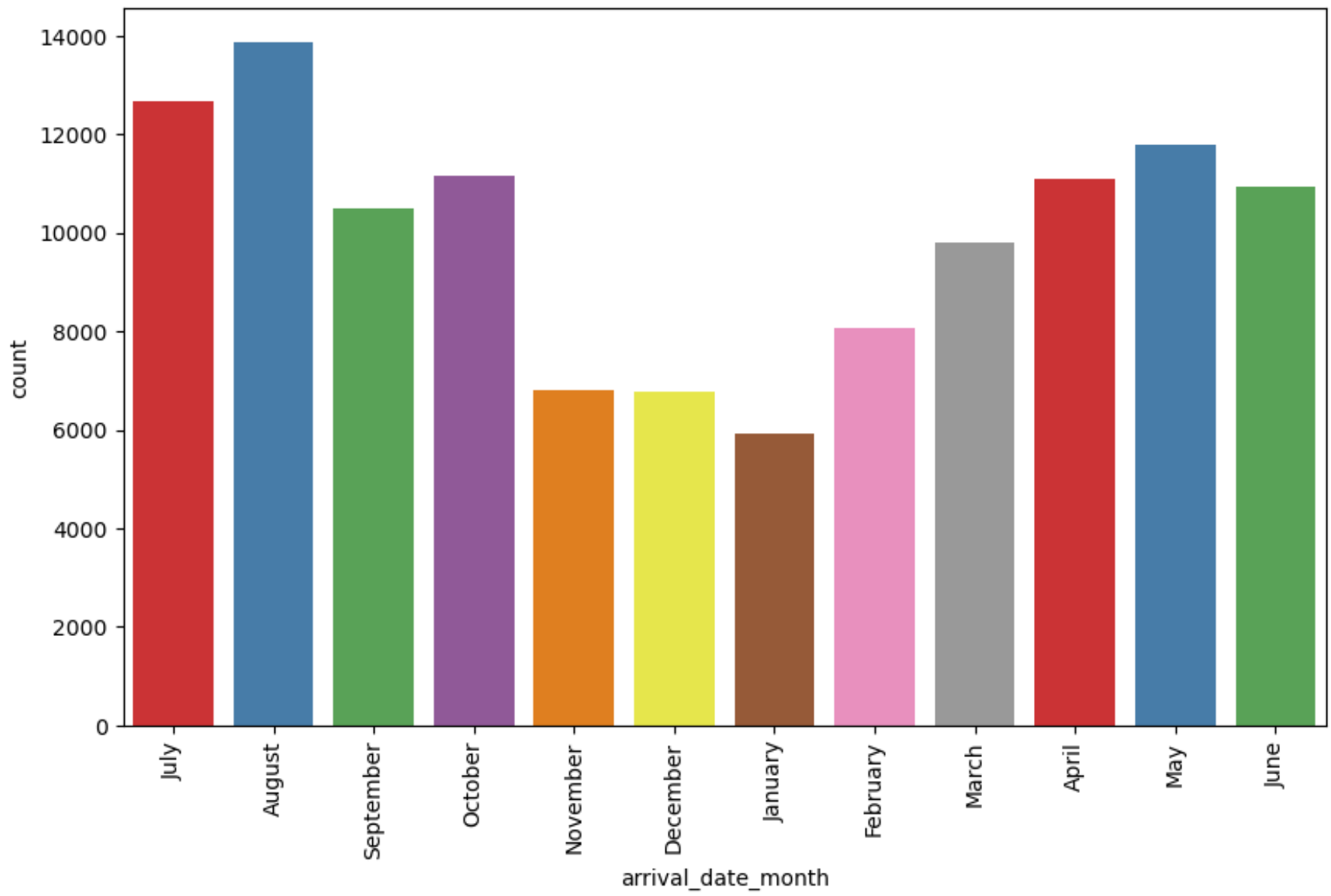


Analysis:

1. Maximum number of bookings have been done in 2016, followed by 2017.
2. Maximum number of bookings have been done by adults, probably couples having no child.
3. There are very few number of repeated customers. Most of them are new comers.
4. Most of the customers have not done any previous cancellations and booking changes. Very few have done booking changes and previous cancellations only once.
5. Most of the customers do not require car parking space.
6. Similarly, most of the customers have not made any special requests, followed by 1 or 2 special request.

Monthly analysis

In [24]:
```
plt.figure(figsize = (10, 6))
ax = sns.countplot(data = df, x = "arrival_date_month", palette = 'Set1')
plt.xticks(rotation = 90)
plt.show()
```

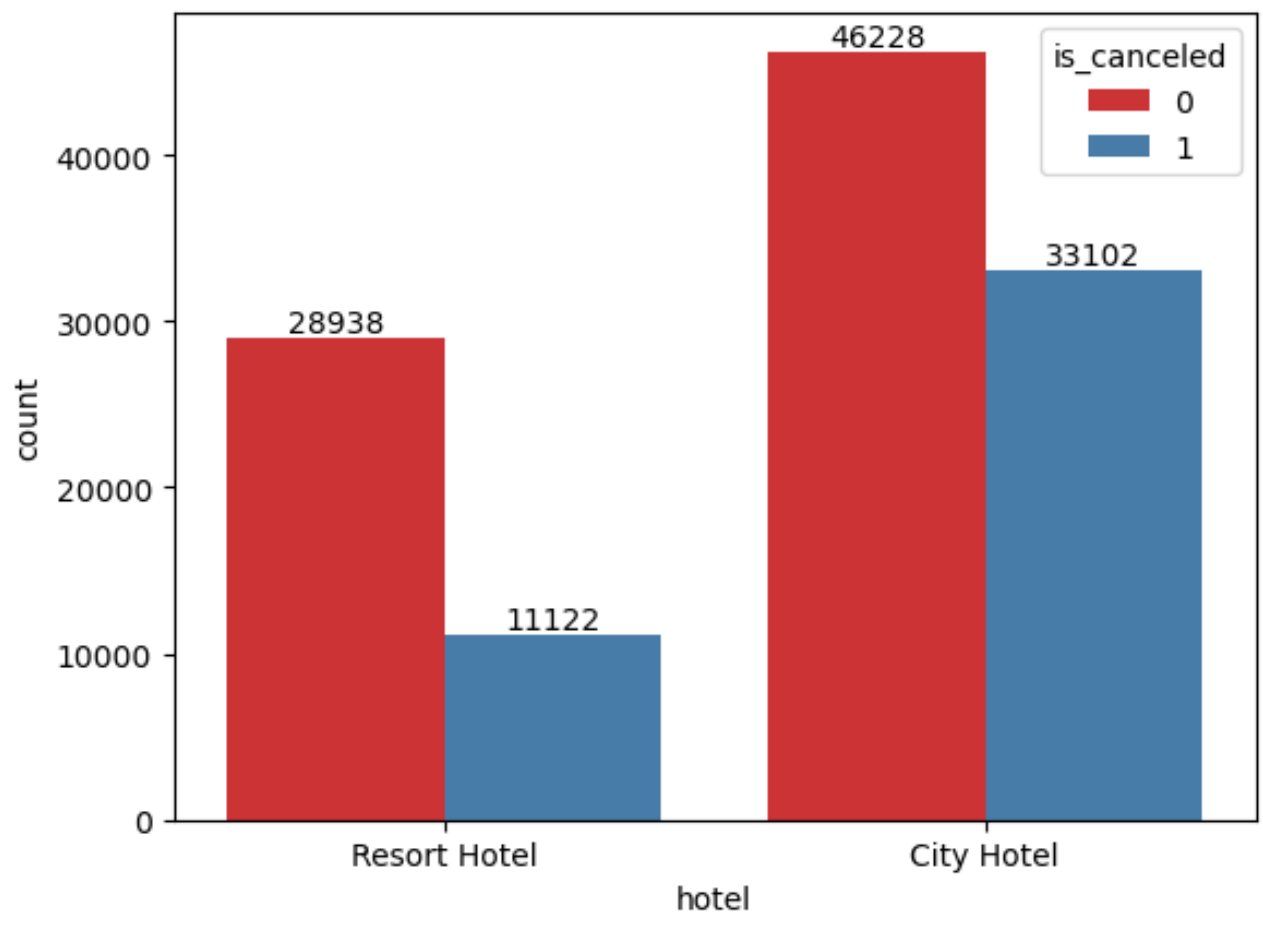


In [25]:
```
# Maximum bookings have been done in the months of August, followed by the months from April to July.
```

Bivariate analysis

Booking cancellation as per Hotel type

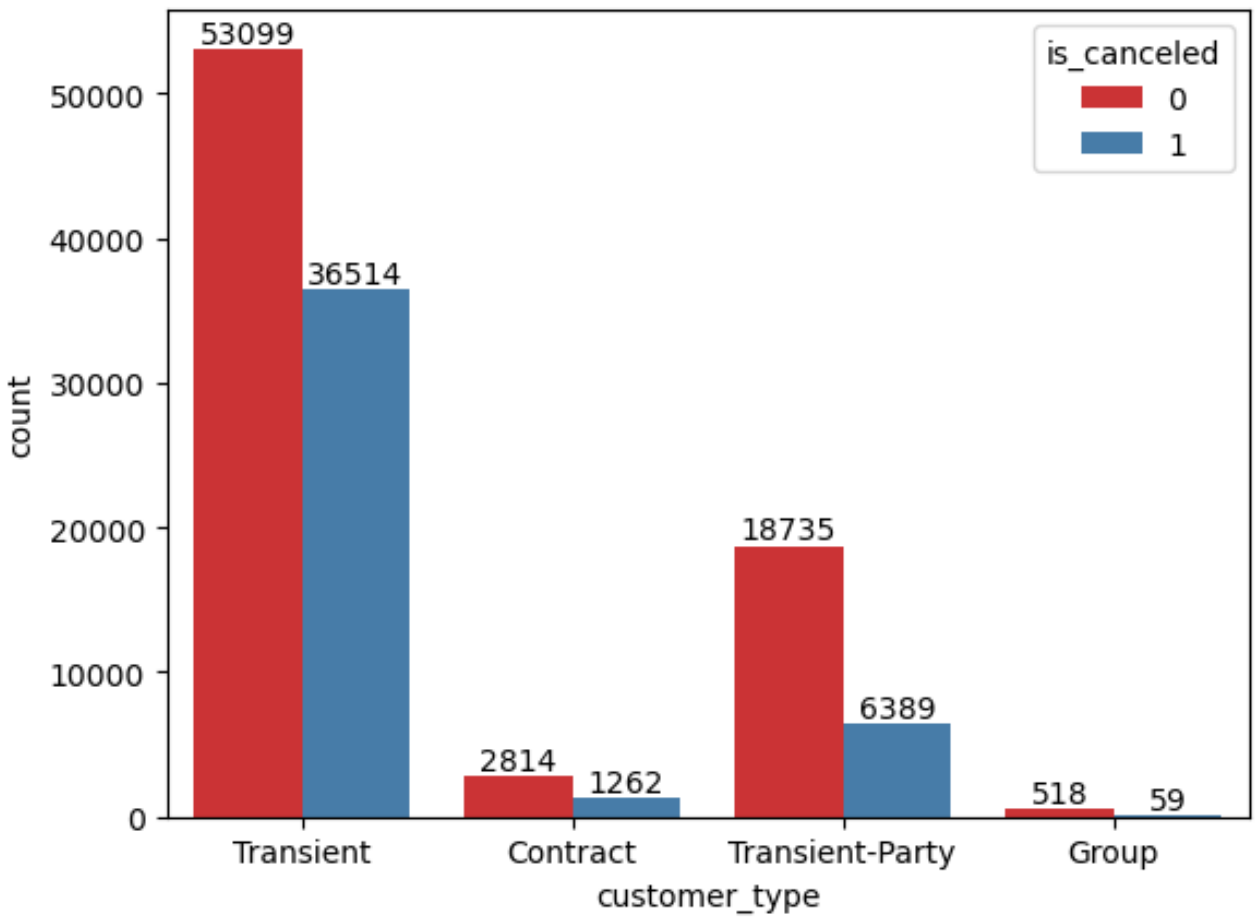
In [26]:
```
ax = sns.countplot(x = 'hotel', hue = 'is_canceled', data = df, palette = 'Set1')
for i in ax.containers:
    ax.bar_label(i)
plt.show()
```



In [27]:
```
# As more number of bookings have been don in City Hotel, more number of cancellations have also been d
```

Booking cancellation as per customer_type

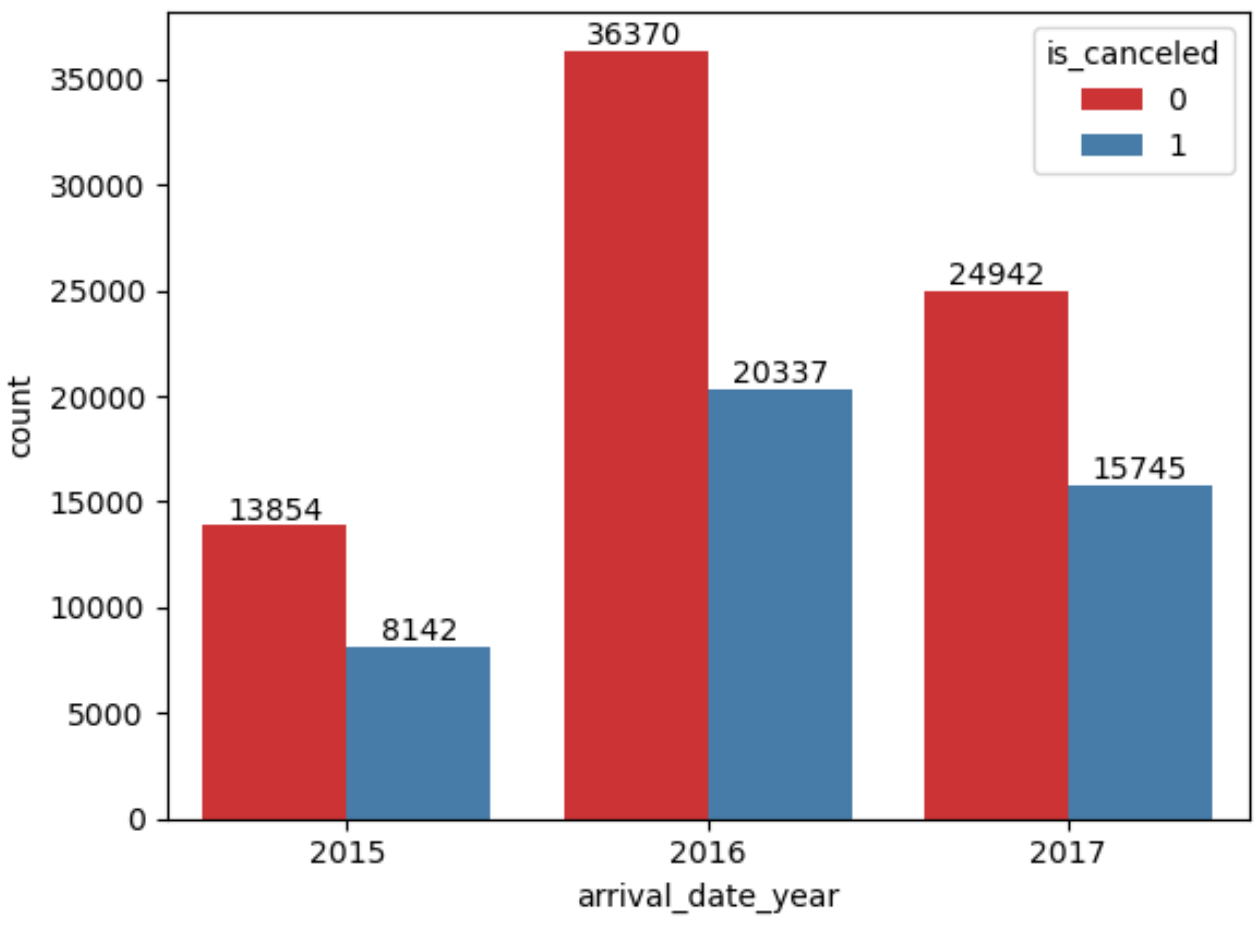
In [28]:
```
ax = sns.countplot(x = 'customer_type', hue = 'is_canceled', data = df,palette = 'Set1')
for i in ax.containers:
    ax.bar_label(i)
plt.show()
```



In [29]:
```
# Maximum cancellations have been done by Transient, followed by Transient party type.
```

Booking cancellation as per arrival_date_year

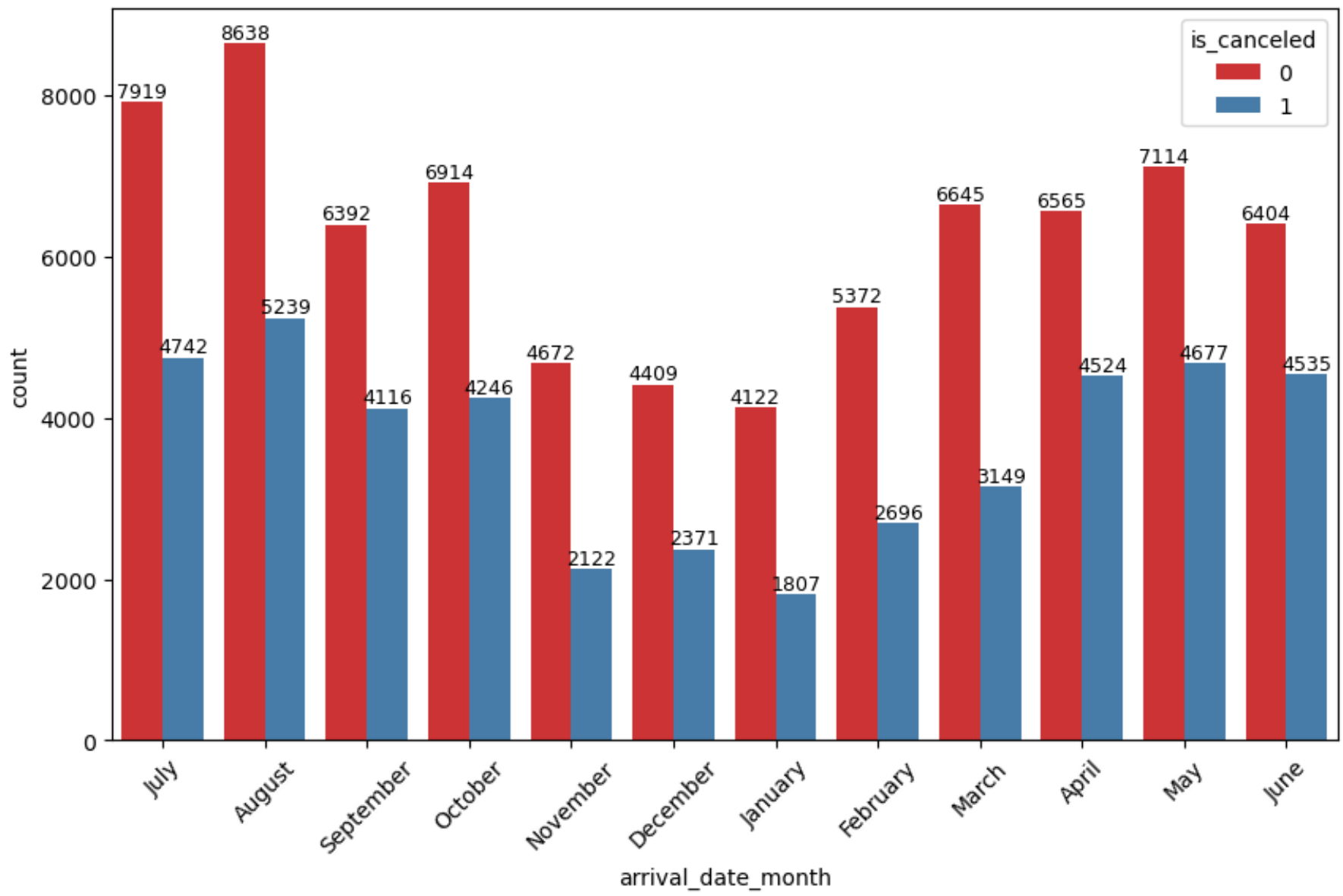
In [30]:
```
ax = sns.countplot(x = 'arrival_date_year', hue = 'is_canceled', data = df, palette = 'Set1')
for i in ax.containers:
    ax.bar_label(i)
plt.show()
```



In [31]:
```
# Maximum cancellations have been done in 2016, followed by 2017.
```

Booking cancellation as per arrival_date_month

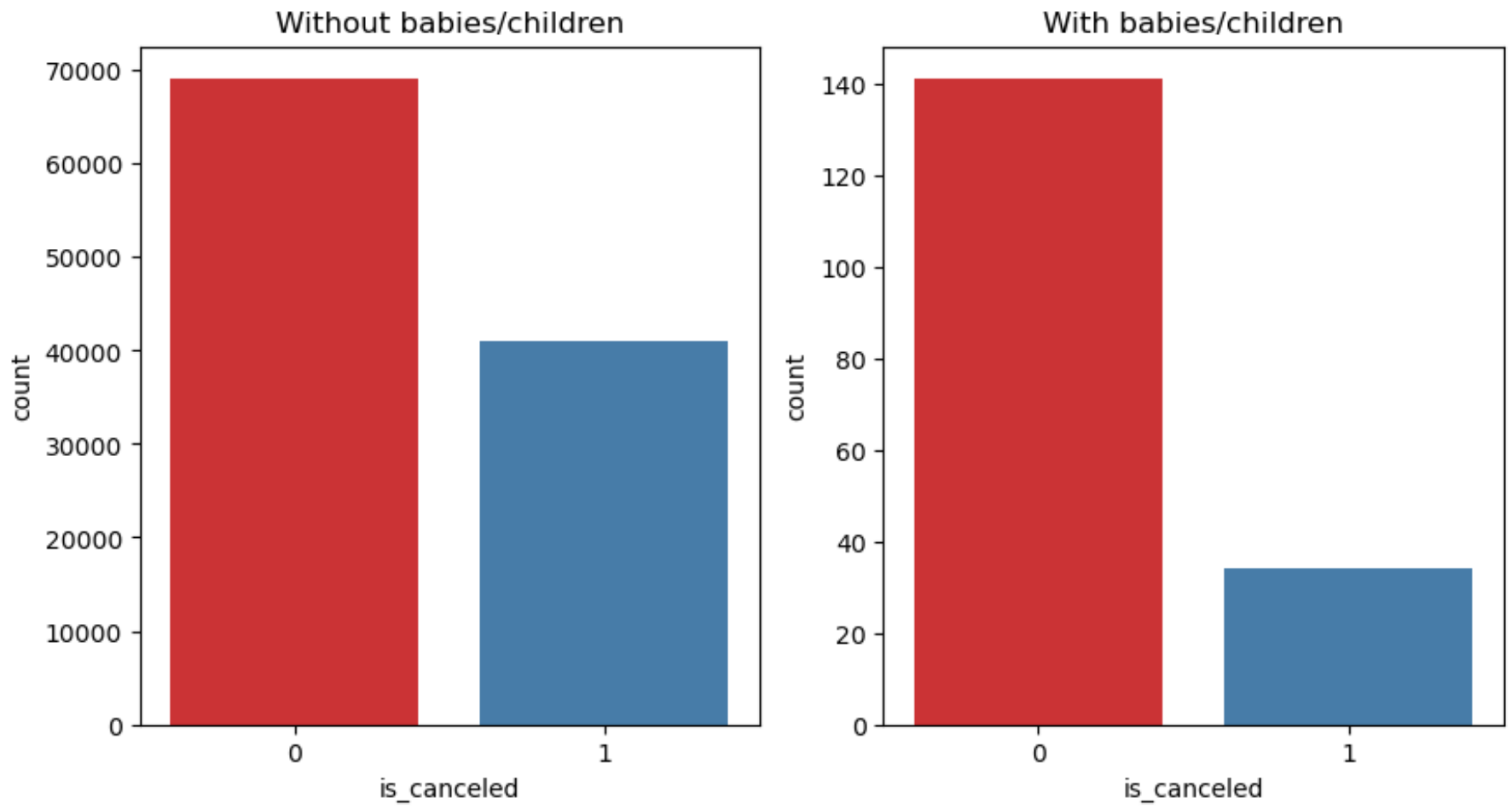
In [32]:
```
plt.figure(figsize=(10,6),dpi=100)
ax = sns.countplot(x = 'arrival_date_month', hue = 'is_canceled', data = df, palette = 'Set1')
for i in ax.containers:
    ax.bar_label(i, size = 9)
plt.xticks(rotation = 45)
plt.show()
```



In [33]:
```
# Maximum cancellations have been done in August, followed by months from April to July.
```

Booking cancellation as per guests_type

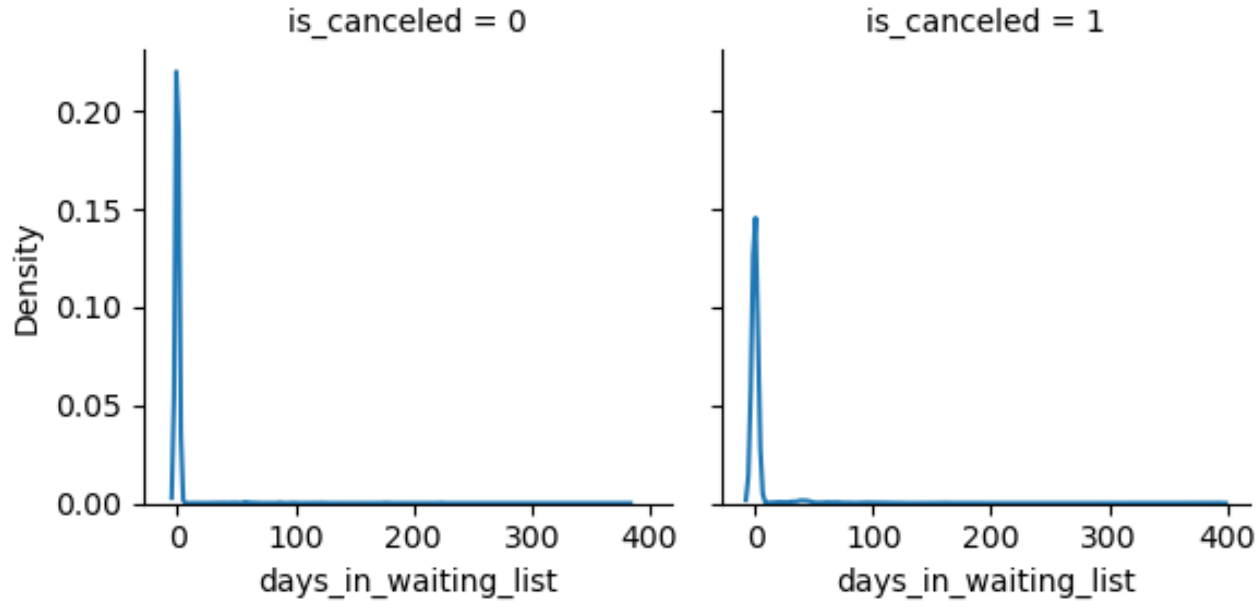
In [34]:
```
no_family = df.loc[(df['children'] == 0) & (df['babies'] == 0)]

fig,axes =  plt.subplots(1, 2, figsize =(10,5))
sns.countplot(ax=axes[0], data = no_family, x = "is_canceled", palette = 'Set1')
axes[0].set_title("Without babies/children")



family = df.loc[(df['children'] != 0) & (df['babies'] != 0)]

sns.countplot(ax=axes[1], data = family, x = "is_canceled", palette = 'Set1')
axes[1].set_title("With babies/children")
plt.show()
```



In [35]:
```
# People who do not have any child have canceled the bookings more number of times.
```

Booking cancellation according to waiting_period

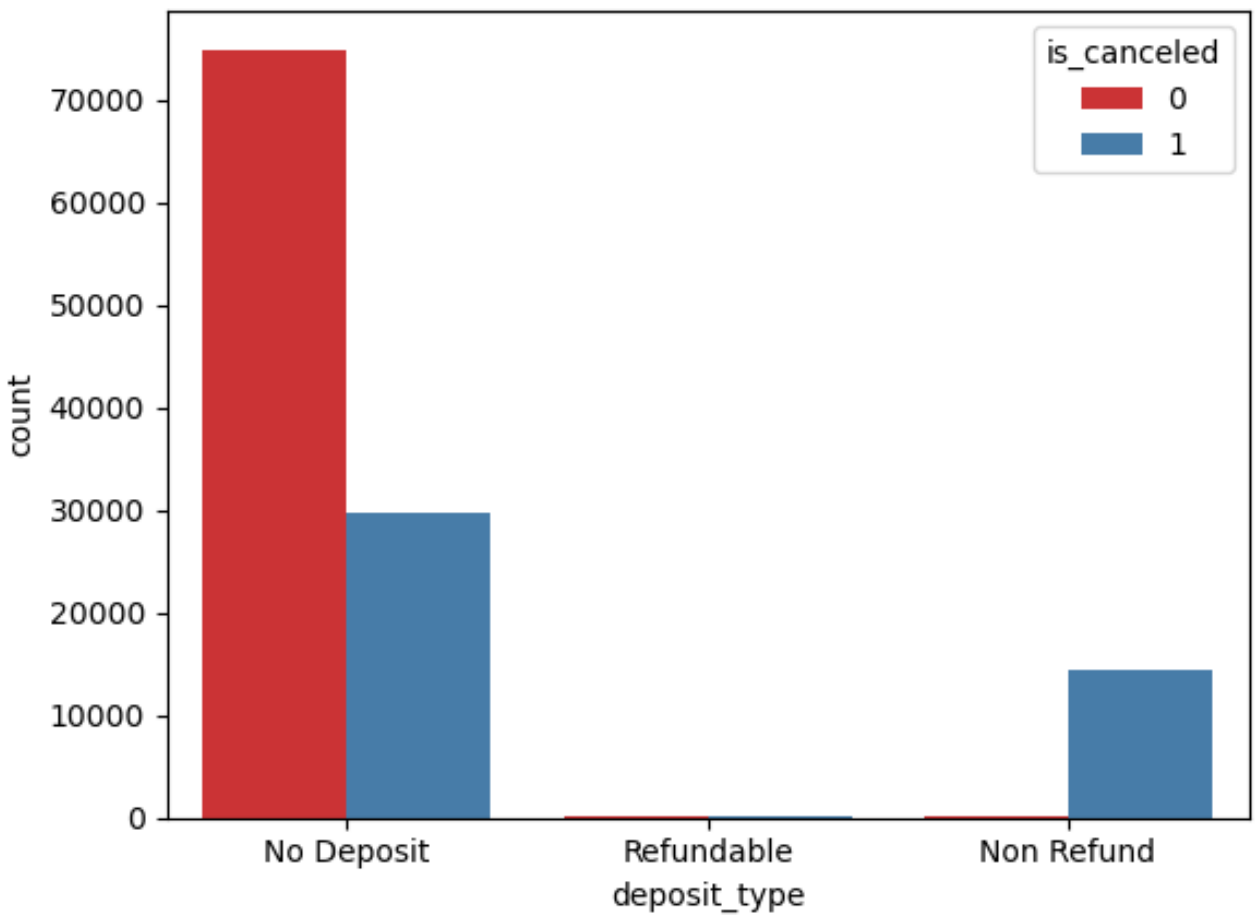
In [36]:
```
days = sns.FacetGrid(df, col="is_canceled")
days.map(sns.kdeplot, "days_in_waiting_list")
plt.show()

```



In [37]:
```
# There is no impact of waiting period on booking cancellation.
```

Booking cancellation according to deposit_type

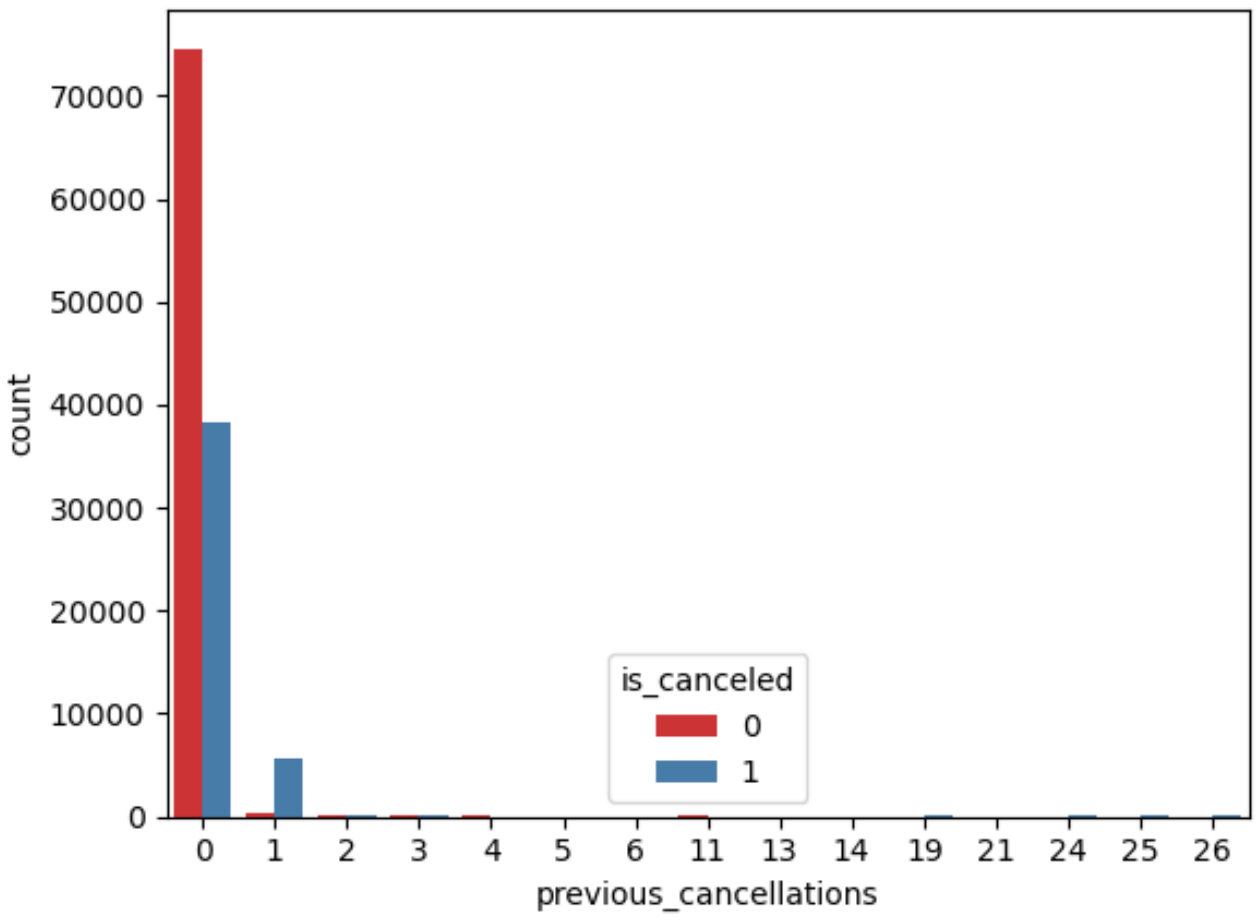
In [38]:
```
sns.countplot(data = df, x ="deposit_type", hue = "is_canceled", palette = 'Set1')
plt.show()
```



In [39]:
```
# Maximum number of bookings have been cancelled by people with no deposit.
```

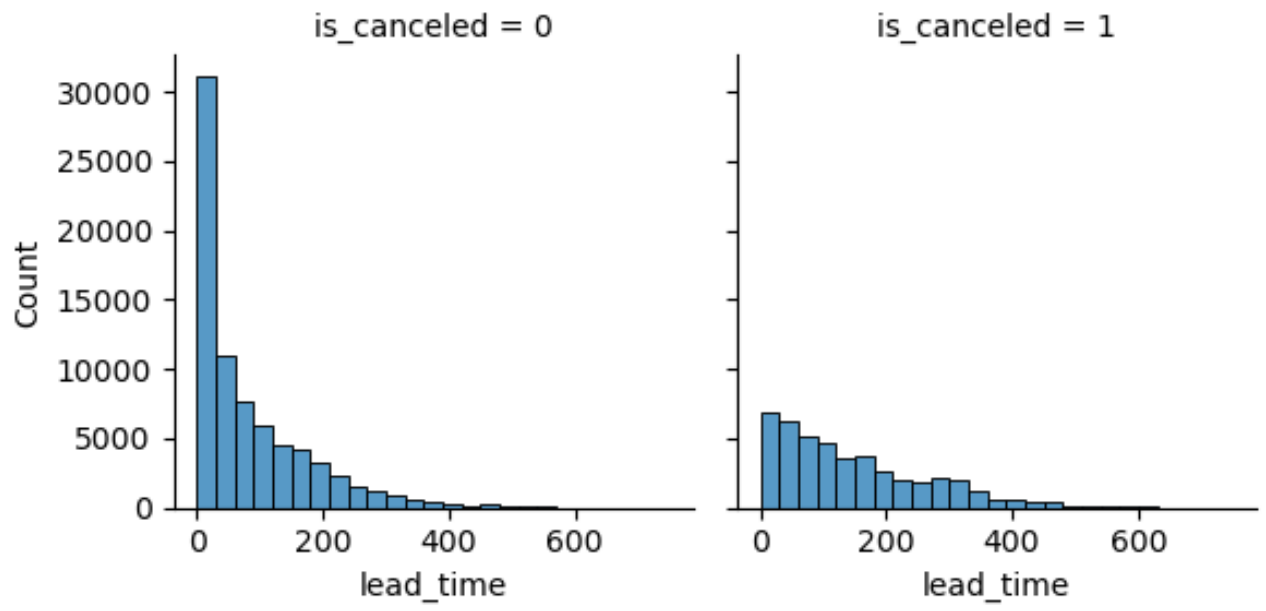
Booking cancellation as per previous_cancellations

In [40]:
```
sns.countplot(data = df, x ="previous_cancellations", hue = "is_canceled", palette = 'Set1')
plt.show()
```



Booking cancellation as per lead_time

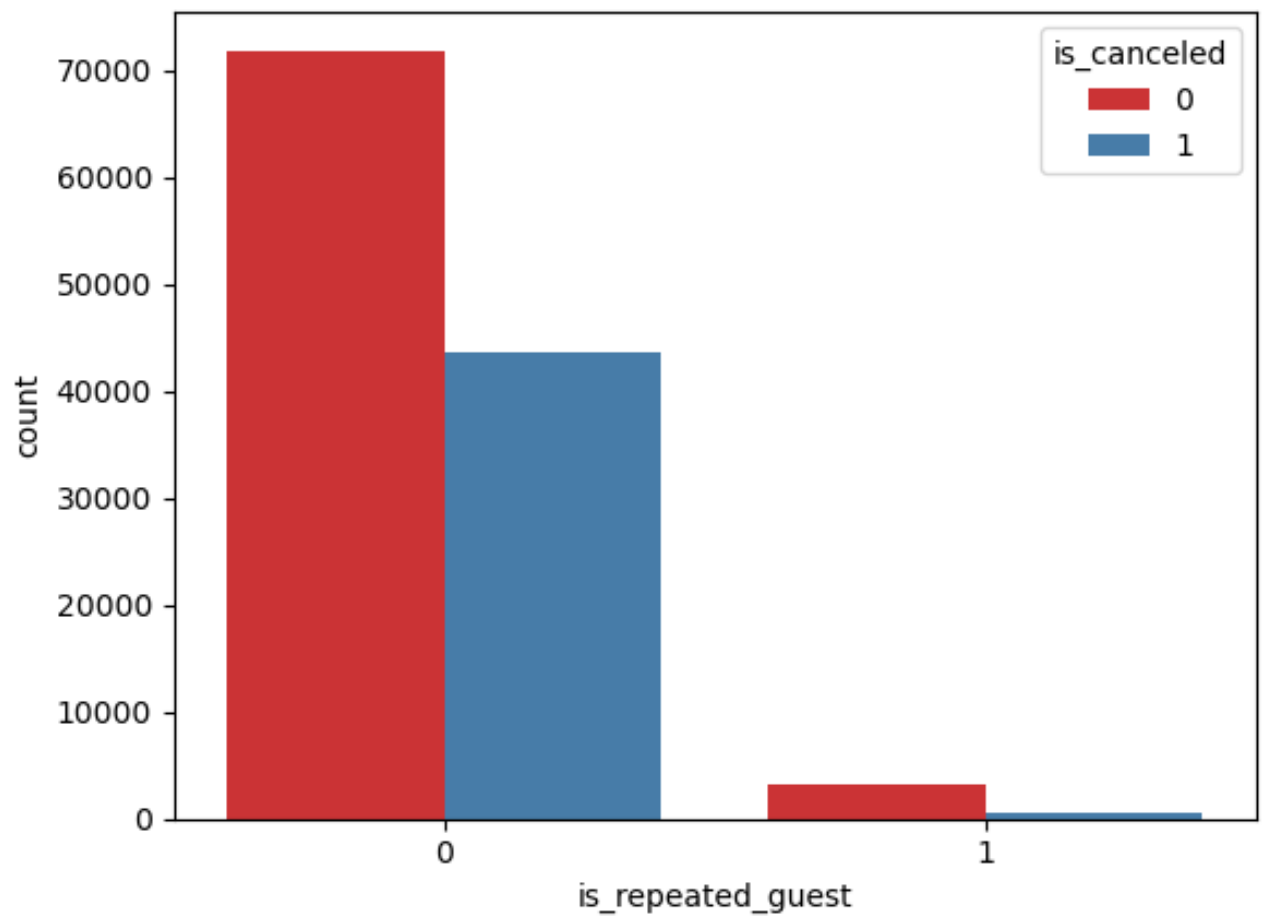
In [41]:
```
g = sns.FacetGrid(df, col="is_canceled")
g.map(sns.histplot, "lead_time", binwidth = 30)
plt.show()
```



In [42]:
```
# Longer the lead_time, lower is the cancelation rate.
```

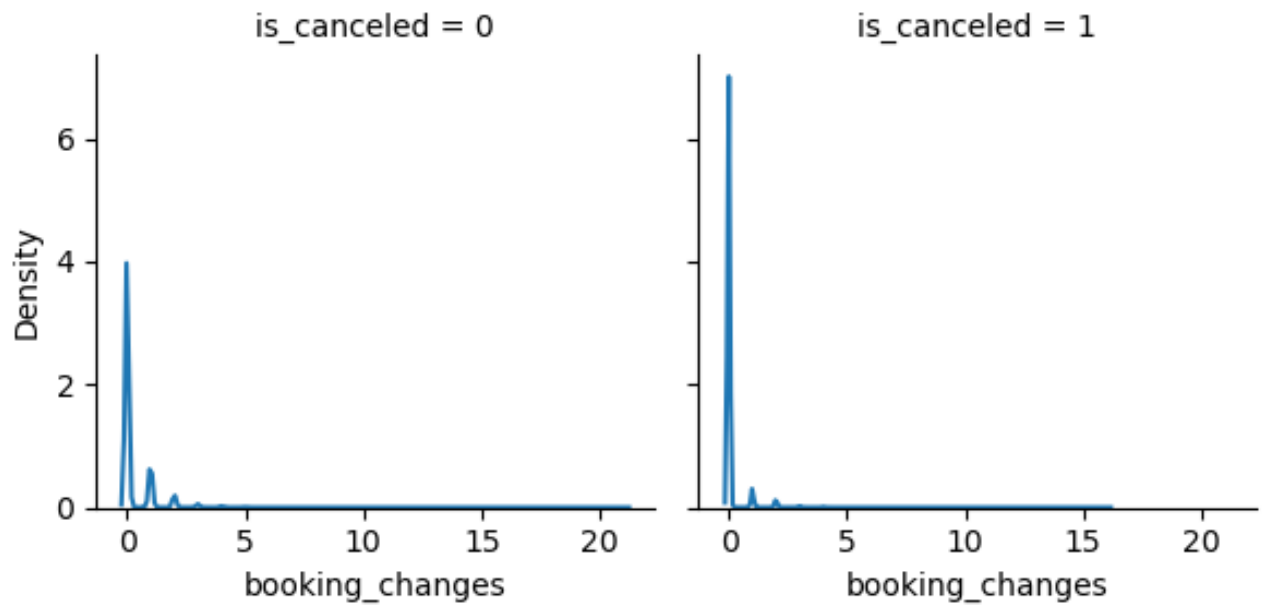
Booking cancellation as per is_repeated_guest

In [43]:
```
sns.countplot(data = df, x ="is_repeated_guest", hue = "is_canceled", palette = 'Set1')
plt.show()
```



Booking cancellation as per booking_changes

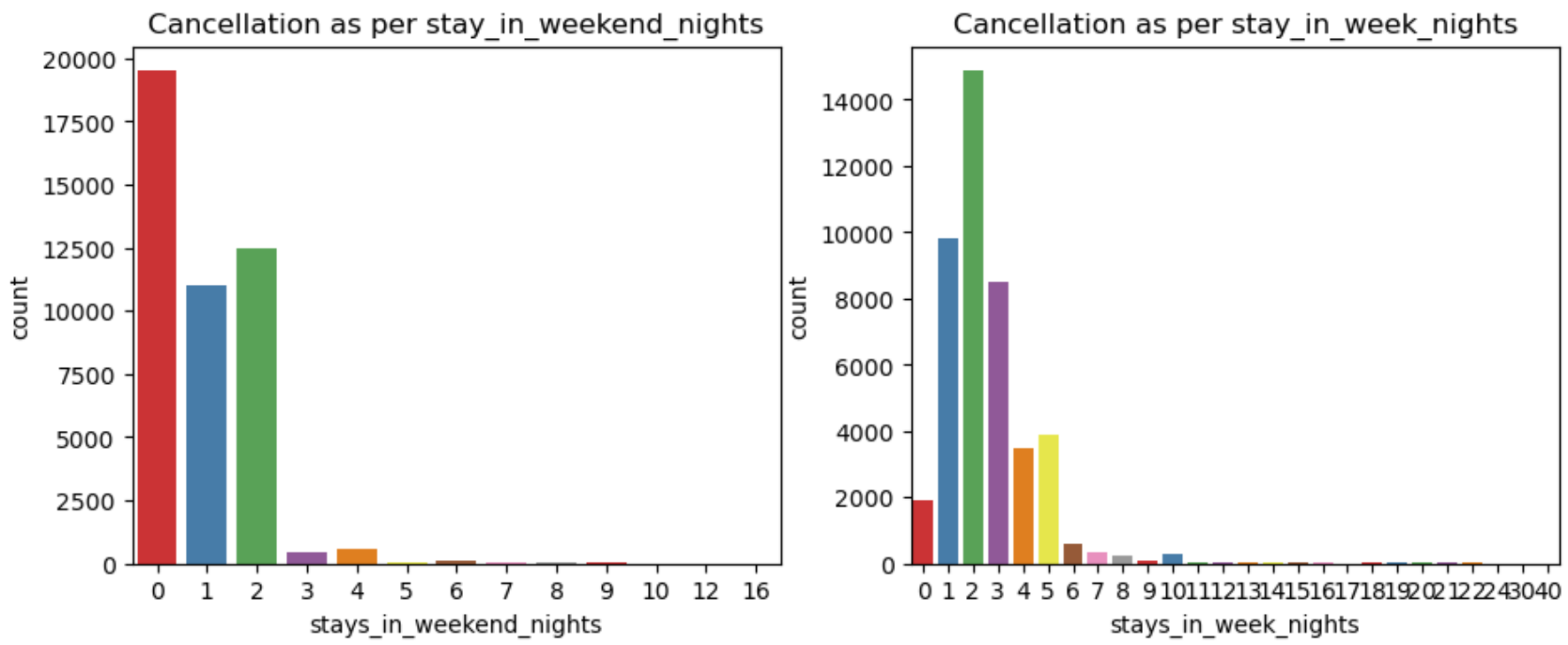
In [44]:
```
g = sns.FacetGrid(df, col="is_canceled")
g.map(sns.kdeplot, "booking_changes")
plt.show()
```



In [45]:
```
# No relation between booking changes and its cancellation rate.
```

Booking cancellation as per stay in weekend or week nights

In [46]:
```
canceled = df[df.is_canceled == 1]
fig,axes =  plt.subplots(1, 2, figsize =(11,4))

# weekend nights
sns.countplot(ax=axes[0], data = canceled, x ="stays_in_weekend_nights", palette = 'Set1')
axes[0].set_title("Cancellation as per stay_in_weekend_nights")

# week nights
sns.countplot(ax=axes[1], data = canceled, x ="stays_in_week_nights", palette = 'Set1')
axes[1].set_title("Cancellation as per stay_in_week_nights")

plt.show()
```



In [47]:
```
#Maximum cancellations have been done for the bookings for week nights.
```

Booking cancellation as per country

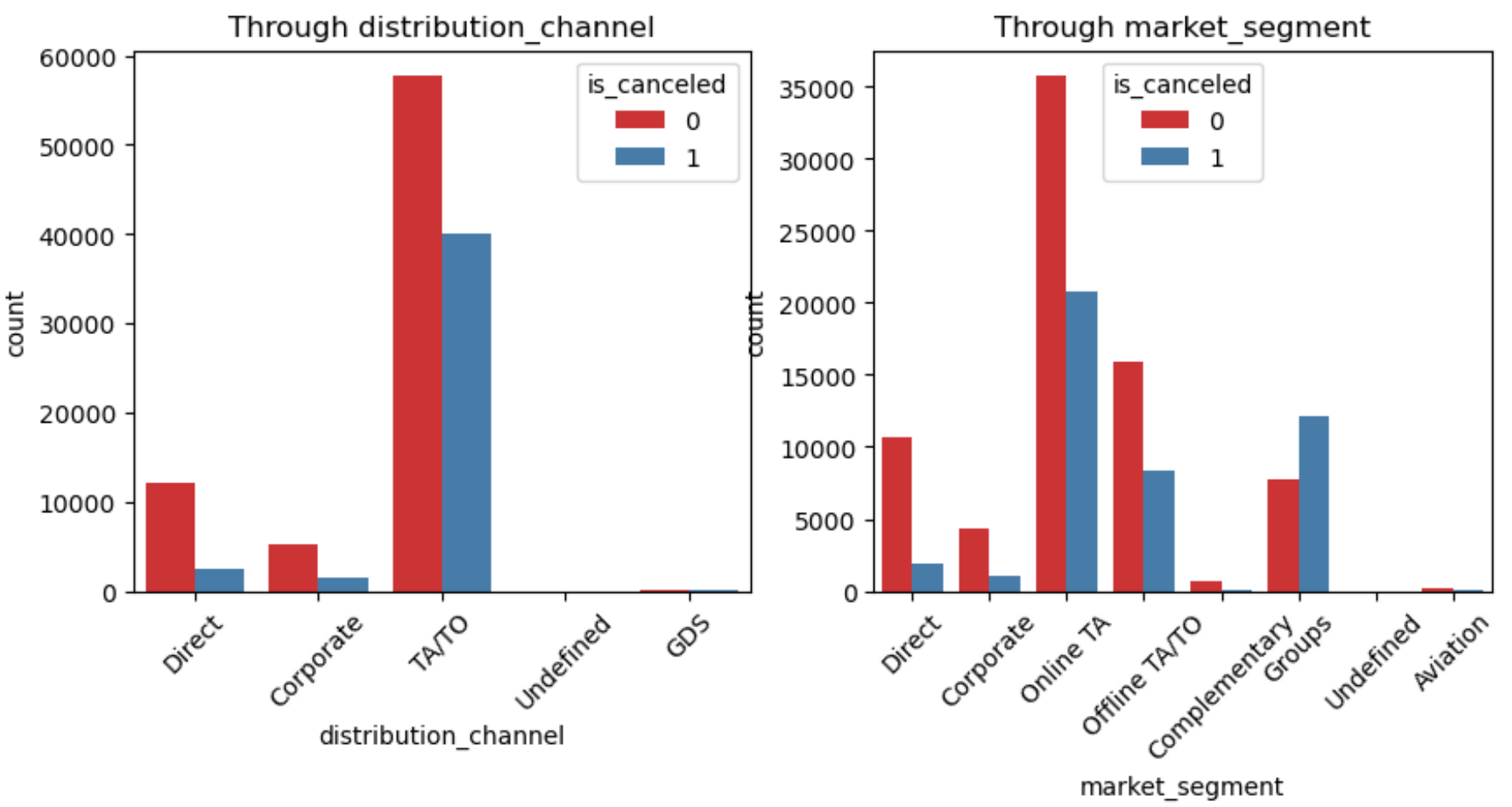
In [48]:
```
top_10 = df[df["is_canceled"] == 1]["country"].value_counts().head(10)
top_10
```

Out[48]:
```
PRT    27519
GBR     2453
ESP     2177
FRA     1934
ITA     1333
DEU     1218
IRL      832
BRA      830
USA      501
BEL      474
Name: country, dtype: int64
```

In [49]:
```
# Maximum cancellations have done by guests from country with code 'PRT'.
```

Booking cancellation as per distribution_channel and market_segment

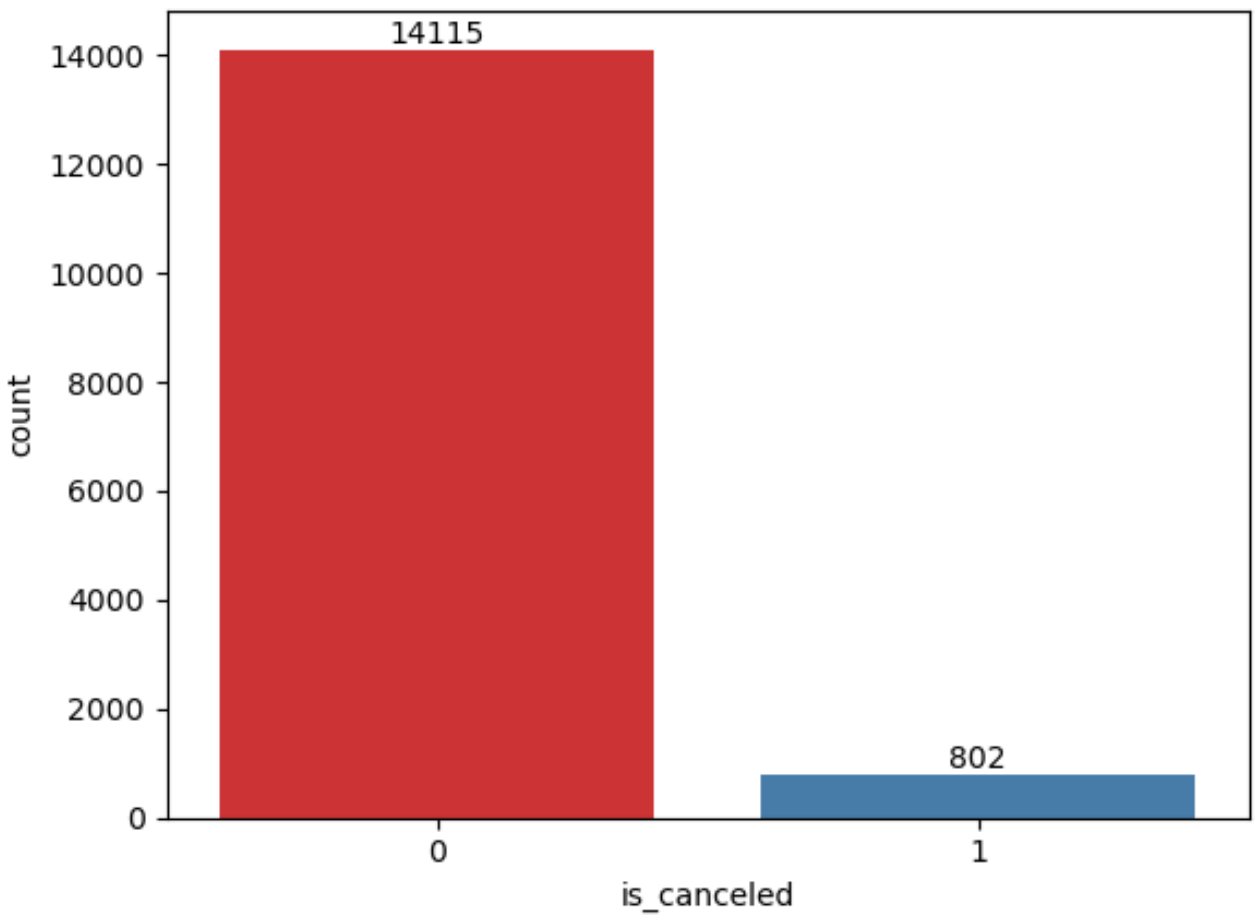
In [50]:
```
fig,axes =  plt.subplots(1, 2, figsize =(10,4))

sns.countplot(ax=axes[0], data = df, x ="distribution_channel", hue = "is_canceled", palette = 'Set1')
axes[0].set_title("Through distribution_channel")
axes[0].tick_params(axis='x', rotation=45)


sns.countplot(ax=axes[1], data = df, x ="market_segment", hue = "is_canceled", palette = 'Set1')
axes[1].set_title("Through market_segment")
axes[1].tick_params(axis='x', rotation=45)

plt.show()
```



In [51]:
```
# Maximum cancellations have been done through TA/TO and that too through Online TA.
```

Booking cancellation as per change_in_room (reserved vs assigned)

In [52]:
```
room_change = df.loc[df['reserved_room_type'] != df['assigned_room_type']]
ax = sns.countplot(data = room_change, x = "is_canceled", palette = 'Set1')

for i in ax.containers:
    ax.bar_label(i)
plt.show()
```



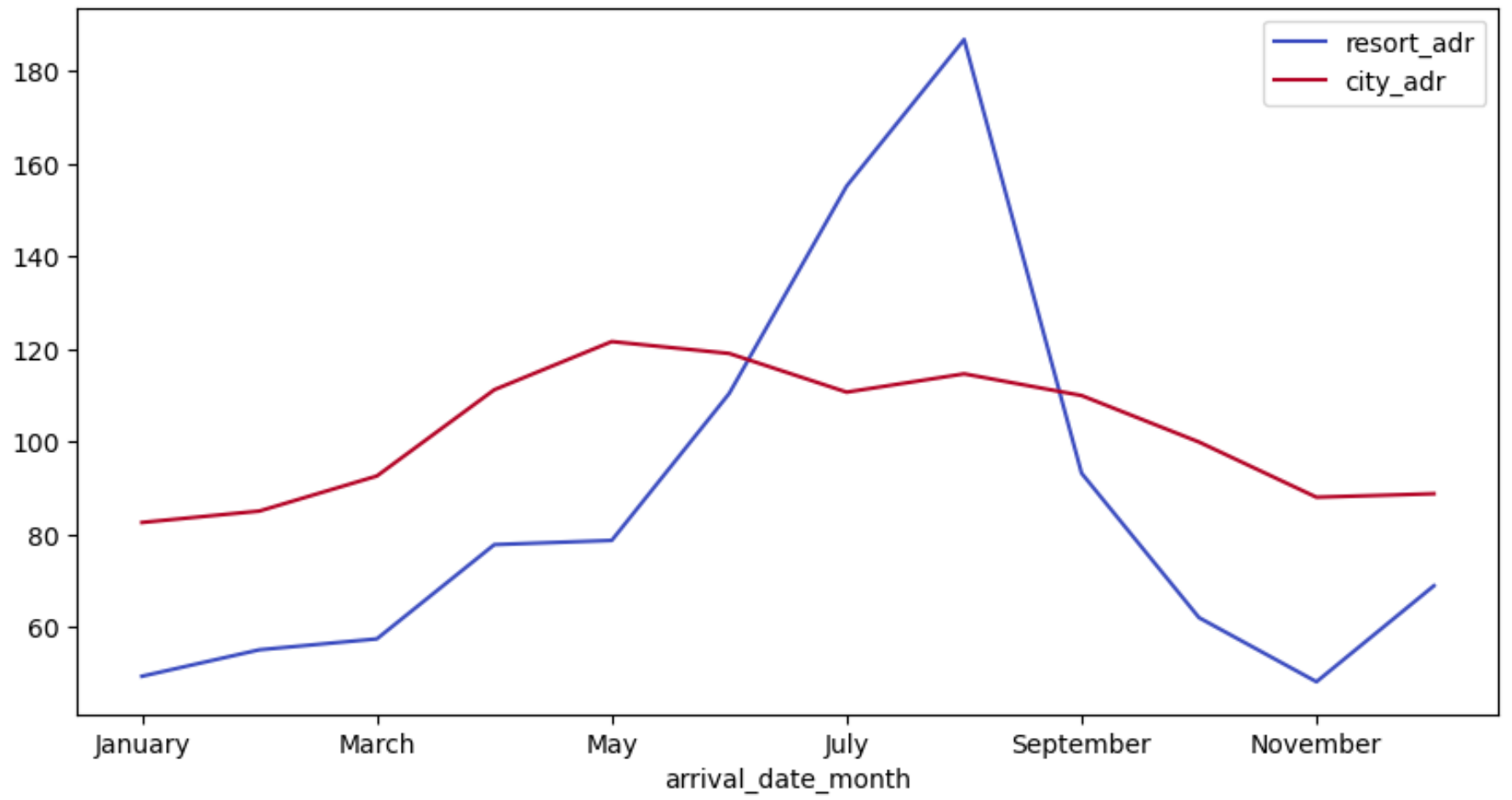
In [53]:
```
# There are very cancellations by guests who have not been assigned room type as reserved by them.
```

Multivariate Analysis

Monthly analysis of 'average adr' as per hotel_type

In [54]:
```
month_dict = {'January':1,'February':2,'March':3, 'April':4, 'May':5, 'June':6, 'July':7, 'August':8, '
              'October':10, 'November':11, 'December':12}

resort = df[df.hotel == "Resort Hotel"]
resort_adr = resort.groupby(["arrival_date_month"])["adr"].mean().reset_index()
resort_adr = resort_adr.sort_values("arrival_date_month", key = lambda x : x.apply (lambda x : month_di
resort_adr.set_index("arrival_date_month", inplace = True)

city = df[df.hotel == "City Hotel"]
city_adr = city.groupby(["arrival_date_month"])["adr"].mean().reset_index()
city_adr = city_adr.sort_values("arrival_date_month", key = lambda x : x.apply (lambda x : month_dict[x
city_adr.set_index("arrival_date_month", inplace = True)

```

In [55]:
```
result = pd.concat([resort_adr, city_adr], axis=1)
result.set_axis(['resort_adr', 'city_adr'], axis='columns', inplace=True)
result.reset_index(level=0, inplace=True)

result.plot(x='arrival_date_month', figsize=(10, 5), colormap = 'coolwarm')
plt.show()

```



In [56]:
```
# On average, adr has been highest in Resort hotel in the month of August, and higher than the adr of C
# On the other hand, City hotel has highest adr in the month of May.
```

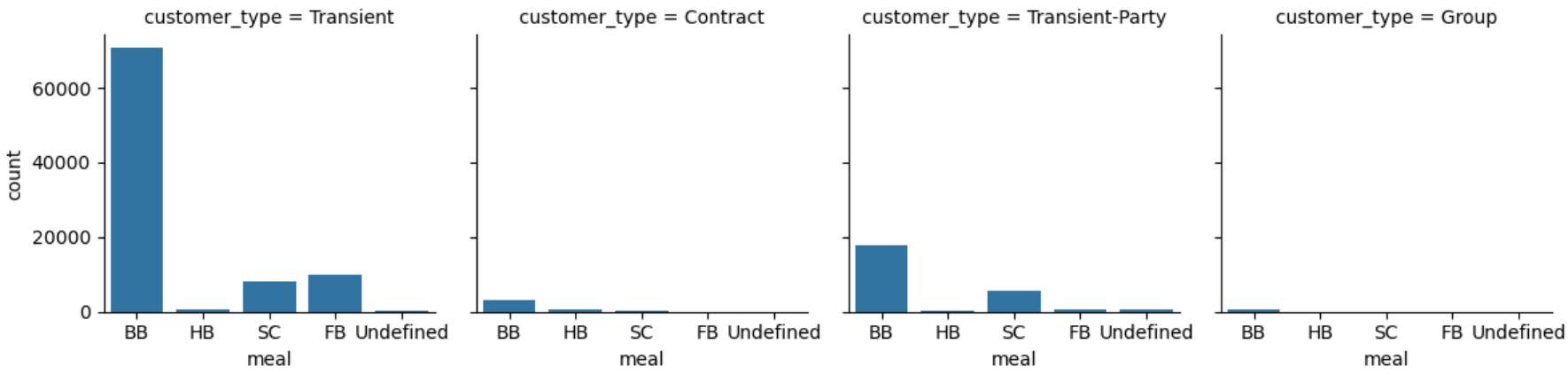
Bookings as per customer_type and their special_requests.

In [57]:
```
df.groupby(['customer_type',"total_of_special_requests"]).size()
```

Out[57]:
```
customer_type    total_of_special_requests
Contract         0                           2106
                 1                           1121
                 2                            711
                 3                            128
                 4                              6
                 5                              4
Group            0                            314
                 1                            177
                 2                             68
                 3                             14
                 4                              3
                 5                              1
Transient        0                          49331
                 1                          26777
                 2                          11052
                 3                           2124
                 4                            300
                 5                             29
Transient-Party  0                          18567
                 1                           5151
                 2                           1138
                 3                            231
                 4                             31
                 5                              6
dtype: int64
```

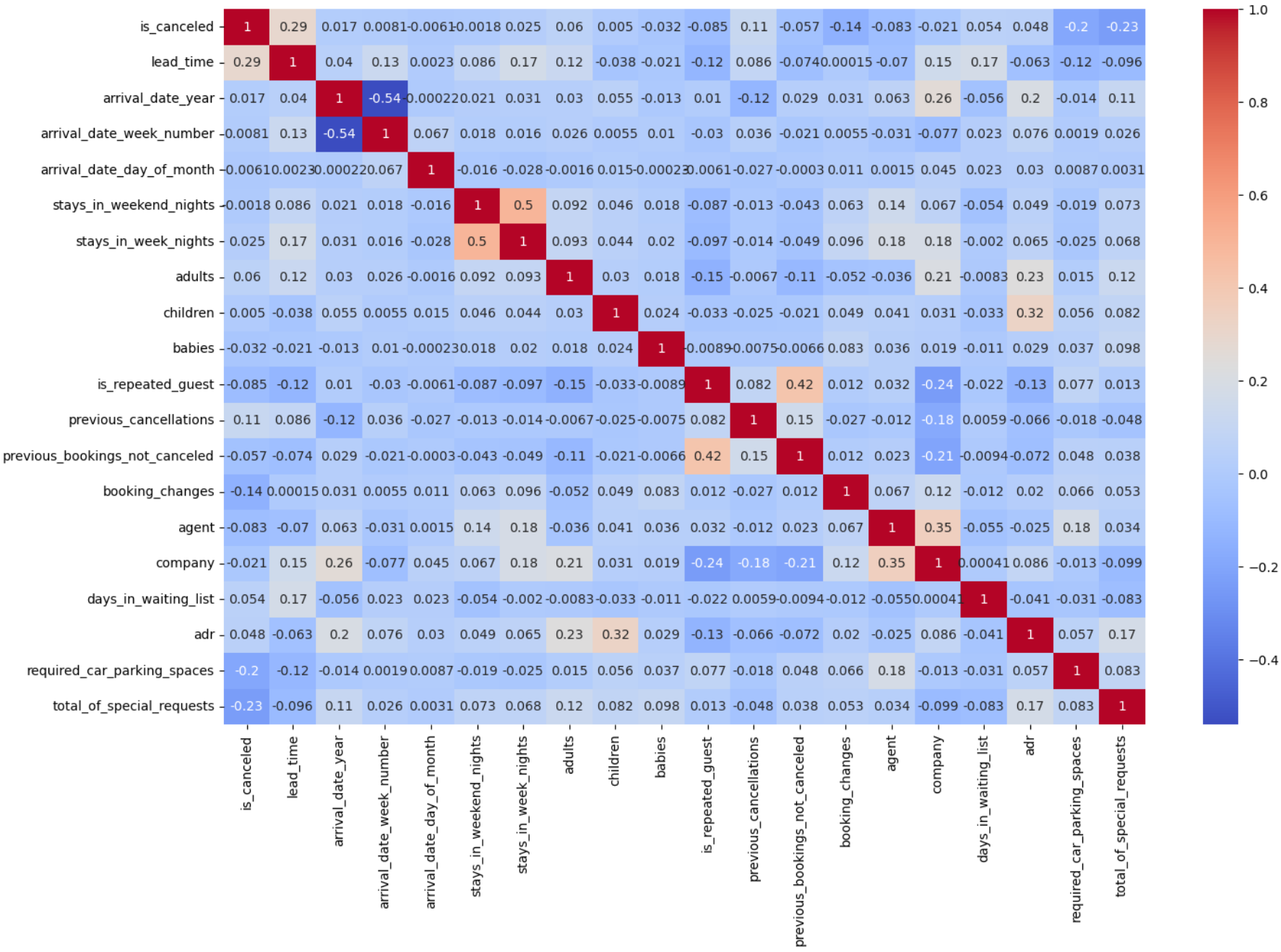
Meal preferred by customer type

In [58]:
```
grid = sns.FacetGrid(df, col='customer_type')
grid.map(sns.countplot, 'meal')
plt.show()
```



Correlation among features

In [59]:
```
plt.figure(figsize=(16,10),dpi=100)
sns.heatmap(df.corr(), annot=True, cmap = 'coolwarm' )
plt.show()
```



Correlation between features and booking cancellation

In [60]:
```
1 df.corr()["is_canceled"][:]
```

Out[60]:
```
is_canceled                      1.000000
lead_time                        0.293123
arrival_date_year                0.016660
arrival_date_week_number         0.008148
arrival_date_day_of_month       -0.006130
stays_in_weekend_nights         -0.001791
stays_in_week_nights             0.024765
adults                           0.060017
children                         0.005048
babies                          -0.032491
is_repeated_guest               -0.084793
previous_cancellations           0.110133
previous_bookings_not_canceled  -0.057358
booking_changes                 -0.144381
agent                           -0.083114
company                         -0.020642
days_in_waiting_list             0.054186
adr                              0.047557
required_car_parking_spaces     -0.195498
total_of_special_requests       -0.234658
Name: is_canceled, dtype: float64
```

In [61]:
```
1 # positive = lead_time, previous_cancellations
2
3 # negative = special_requests, parking spaces, booking changes
```

Data Pre-processing

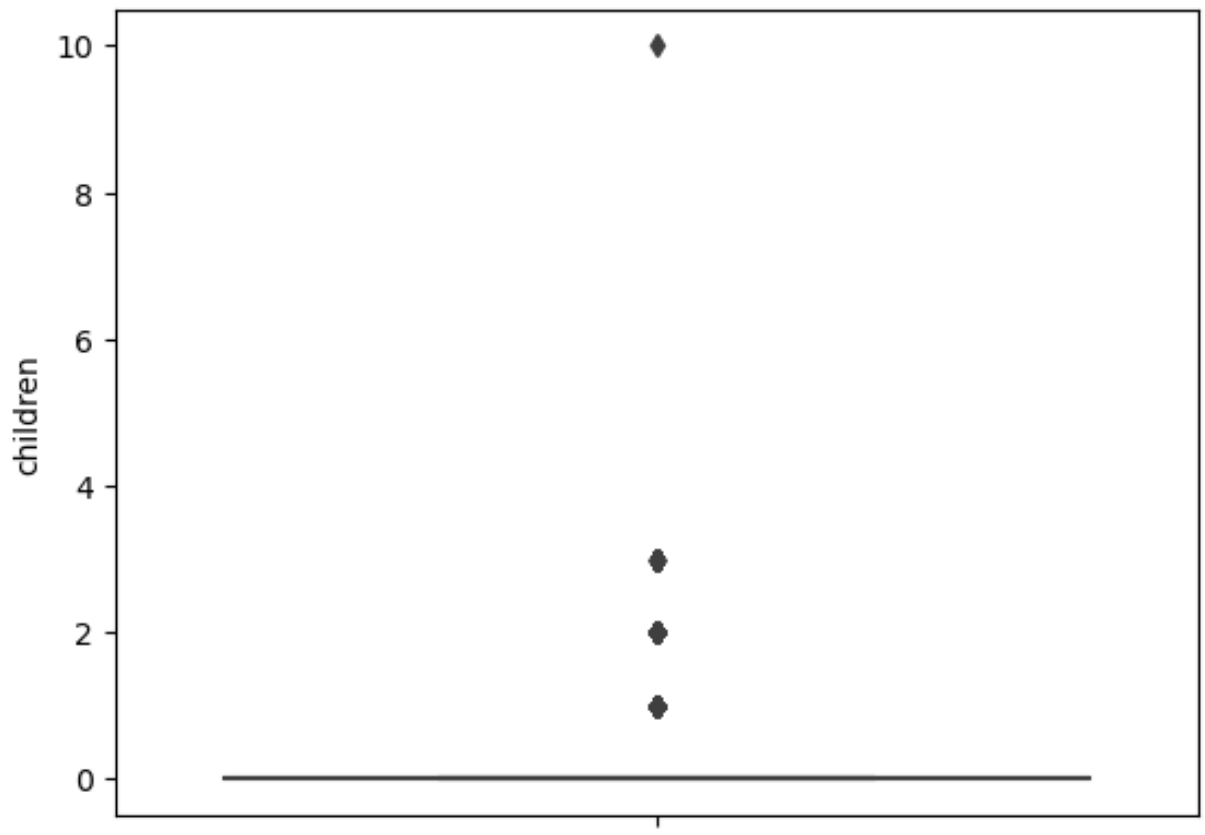
Treating Null values

In [62]:
```
1 df.isna().sum()
```

Out[62]:
```
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
```

1. Children column

In [63]:
```
sns.boxplot(data = df, y = "children")
plt.show()
```



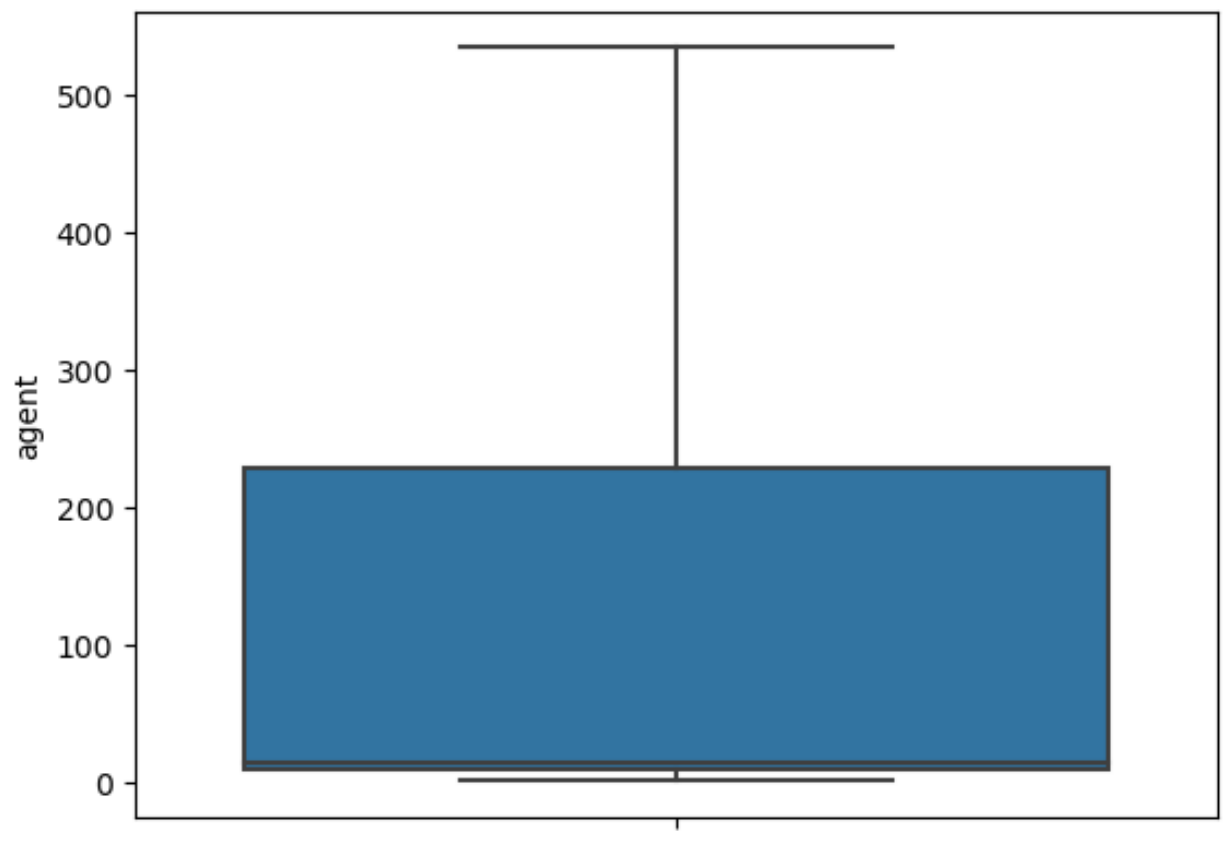
In [64]:
```
## As ouliers are present in this column, therefore, we can impute missing values with the median of th

df["children"].fillna(df["children"].median(), inplace=True)
```

2. Country column

In [65]:
```
## As country column is categorical in nature, therefore, we can impute missing values with the mode of

df["country"].fillna(df["country"].mode()[0], inplace=True)
```

3. Agent column

In [66]:
```
sns.boxplot(data = df, y = "agent")
plt.show()
```



In [67]:
```
## As no ouliers are present in this column, therefore, we can impute missing values with the mean of t

df["agent"].fillna(df["agent"].mean(), inplace=True)
```

4. Company column

In [68]:
```
## As 94% of the values in company column are missing. Therefore, it is better to drop that column.

df.drop("company", axis=1, inplace = True)
```

All the null values have been successfully treated

In [69]:
```
df.isna().sum()
```

Out[69]:
```
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                        0
babies                          0
meal                            0
country                         0
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                           0
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
```

Handling Duplicate records

In [70]:
```
## Duplicate records will only confuse the model. Therefore, it is advisable to remove them.

df.drop_duplicates(inplace = True)
```

In [71]:
```
df.duplicated().sum()
```

Out[71]:
```
0
```

Dropping unnecessary records

1. Undefined rows

In [72]:
```
undefined_rows = df[(df["market_segment"] == "Undefined") | (df["distribution_channel"] == "Undefined")
df.drop(undefined_rows, axis = 0, inplace = True)
```

2. No_stay rows

In [73]:
```
## Includes bookings neither at week nights nor at the weekedn nights ---> Not possible

no_stays = df[(df["stays_in_weekend_nights"]==0) & (df["stays_in_week_nights"]==0)].index
df.drop(no_stays, axis = 0, inplace = True)
```

3. Zero guests

In [74]:
```
# Includes bookings by neither adults nor family ----> Not possible

zeros = df[(df["adults"]==0) & (df["babies"]==0) & (df["children"]==0)].index
df.drop(zeros, axis = 0, inplace = True)
```

Feature Engineering

1. Total children

In [75]:
```
df["total_guests"] = df["children"].astype(int) + df["babies"] + df["adults"]
```

2. Change in room

In [76]:
```
# Checking whether there is difference bewtween the reserved and assigned room type.

def room_change(row):
    if row['assigned_room_type'] == row['reserved_room_type']:
        return False
    else:
        return True

df['change_in_room'] = df.apply(room_change, axis=1)
```

3. Total stay

In [77]:
```
df["total_stay"] = df["stays_in_weekend_nights"] + df["stays_in_week_nights"]
```

Converting categorical columns

1. arrival_date_month

In [78]:
```
month_dict = {'January':1,'February':2,'March':3, 'April':4, 'May':5, 'June':6, 'July':7, 'August':8, '
df.arrival_date_month = df.arrival_date_month.map(month_dict).astype(int)
```

2. arrival_date_year

In [79]:
```
year_dict = {2015 : 0, 2016 : 1, 2017 : 2}
df.arrival_date_year = df.arrival_date_year.map(year_dict).astype(int)
```

3. is_previously_cancelled

In [80]:
```
is_cancel = df[(df["previous_cancellations"] > 0)]["previous_cancellations"].index
df.loc[is_cancel, 'previous_cancellations'] = 1
df.previous_cancellations.value_counts()
```

Out[80]:
```
0    84931
1     1677
Name: previous_cancellations, dtype: int64
```

4. is_booking_changes

In [81]:
```
b_changes = df[(df["booking_changes"] > 0)]["booking_changes"].index
df.loc[b_changes, 'booking_changes'] = 1
df.booking_changes.value_counts()
```

Out[81]:
```
0    70925
1    15683
Name: booking_changes, dtype: int64
```

5. is_required_parking_space

In [82]:
```
is_space = df[(df["required_car_parking_spaces"] > 0)]["required_car_parking_spaces"].index
df.loc[is_space, 'required_car_parking_spaces'] = 1
df.required_car_parking_spaces.value_counts()
```

Out[82]:
```
0    79319
1     7289
Name: required_car_parking_spaces, dtype: int64
```

6. is_special_request

In [83]:
```
is_request = df[(df["total_of_special_requests"] > 0)]["total_of_special_requests"].index
df.loc[is_request, 'total_of_special_requests'] = 1
df.total_of_special_requests.value_counts()
```

Out[83]:
```
0    43415
1    43193
Name: total_of_special_requests, dtype: int64
```

In [84]:
```
df.rename(columns={"total_of_special_requests": "is_special_request", "required_car_parking_spaces": "i
```

7. Country

In [85]:
```
df.replace({'country' : { 'PRT' : 1, 'GBR' : 2}}, inplace = True)
other_countries = df[(df["country"] != 1) & (df["country"] != 2)]["country"].index
df.loc[other_countries, 'country'] = 0
df.country.value_counts()
```

Out[85]:
```
0    48930
1    27278
2    10400
Name: country, dtype: int64
```

Encoding

In [86]:
```
df = pd.get_dummies(data = df, columns = ['hotel', "arrival_date_year", "country", "deposit_type", "cus
                                          "market_segment", "change_in_room" ],drop_first=True)
```

In [87]:
```
df.head()
```

Out[87]:

	is_canceled	lead_time	arrival_date_month	arrival_date_week_number	arrival_date_day_of_month	stays_in_weekend_nights	stays_i
2	0	7	7	27	1	0	
3	0	13	7	27	1	0	
4	0	14	7	27	1	0	
6	0	0	7	27	1	0	
7	0	9	7	27	1	0	

Dropping unwanted columns

In [88]:
```
df = df.drop(columns = ["arrival_date_week_number", "arrival_date_day_of_month","stays_in_weekend_night
                        "stays_in_week_nights", "adults", "children", "babies","meal","distribution_cha
                        "previous_bookings_not_canceled", "reserved_room_type", "assigned_room_type",
                        "days_in_waiting_list", "reservation_status", "reservation_status_date"], axis
```

Final Dataset for Model Training

In [89]:
```
1 df.head()
```

Out[89]:

	is_canceled	lead_time	arrival_date_month	is_repeated_guest	is_previously_cancelled	is_booking_changes	agent	adr	is_
2	0	7	7	0	0	0	86.693382	75.0	
3	0	13	7	0	0	0	304.000000	75.0	
4	0	14	7	0	0	0	240.000000	98.0	
6	0	0	7	0	0	0	86.693382	107.0	
7	0	9	7	0	0	0	303.000000	103.0	

In [90]:
```
1 df.shape
```

Out[90]: (86608, 29)

In [91]:
```
1 df1 = df.copy()
```

In [92]:
```
1 df1.head()
```

Out[92]:

	is_canceled	lead_time	arrival_date_month	is_repeated_guest	is_previously_cancelled	is_booking_changes	agent	adr	is_
2	0	7	7	0	0	0	86.693382	75.0	
3	0	13	7	0	0	0	304.000000	75.0	
4	0	14	7	0	0	0	240.000000	98.0	
6	0	0	7	0	0	0	86.693382	107.0	
7	0	9	7	0	0	0	303.000000	103.0	

In [93]:
```
1 df1.shape
```

Out[93]: (86608, 29)

Separating Independent features and Target

In [94]:
```
1 x = df1.drop("is_canceled", axis = 1)
2 y = df1.is_canceled
```

Scaling

In [95]:
```
1 from sklearn.preprocessing import StandardScaler
2 scaler = StandardScaler()
3 scaled_x = scaler.fit_transform(x)
4 x = pd.DataFrame(scaled_x,columns=x.columns)
```

In [96]:
```
1 x
```

Out[96]:

	lead_time	arrival_date_month	is_repeated_guest	is_previously_cancelled	is_booking_changes	agent	adr	is_require
0	-0.851750	0.170641	-0.194117	-0.140518	-0.470235	-0.059306	-0.593481	
1	-0.782046	0.170641	-0.194117	-0.140518	-0.470235	2.008937	-0.593481	
2	-0.770428	0.170641	-0.194117	-0.140518	-0.470235	1.399809	-0.170331	
3	-0.933071	0.170641	-0.194117	-0.140518	-0.470235	-0.059306	-0.004750	
4	-0.828515	0.170641	-0.194117	-0.140518	-0.470235	1.999419	-0.078342	
...	...	...	...	...	...	...	...	
86603	-0.665872	0.494037	-0.194117	-0.140518	-0.470235	2.865523	-0.204551	
86604	0.251899	0.494037	-0.194117	-0.140518	-0.470235	-0.798762	2.174104	
86605	-0.538081	0.494037	-0.194117	-0.140518	-0.470235	-0.798762	0.928204	
86606	0.333220	0.494037	-0.194117	-0.140518	-0.470235	-0.037352	-0.052585	
86607	1.448486	0.494037	-0.194117	-0.140518	-0.470235	-0.798762	0.808434	

86608 rows × 28 columns

Splitting

In [97]:
```
from sklearn.model_selection import train_test_split
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size = 0.30, random_state = 11)
```

Model Training

In [98]:
```
from sklearn.metrics import classification_report
from sklearn.metrics import confusion_matrix
from sklearn.metrics import accuracy_score
```

1. Logistic Regression

In [99]:
```
from sklearn.linear_model import LogisticRegression
# fitting
logreg = LogisticRegression()
logreg.fit(x_train, y_train)

# predicting
y_pred = logreg.predict(x_test)
y_pred_train=logreg.predict(x_train)

# results
print('For test data')
print(classification_report(y_test,y_pred))
print('For train data')
print(classification_report(y_train,y_pred_train))
```

```
For test data
              precision    recall  f1-score   support

           0       0.82      0.91      0.87     18867
           1       0.68      0.48      0.56      7116

    accuracy                           0.79     25983
   macro avg       0.75      0.70      0.71     25983
weighted avg       0.78      0.79      0.78     25983

For train data
              precision    recall  f1-score   support

           0       0.82      0.91      0.87     43760
           1       0.69      0.49      0.57     16865

    accuracy                           0.80     60625
   macro avg       0.76      0.70      0.72     60625
weighted avg       0.79      0.80      0.78     60625
```

2. Decision Tree

In [100]:
```
from sklearn.tree import DecisionTreeClassifier

dt = DecisionTreeClassifier()
dt.fit(x_train,y_train)

y_predd = dt.predict(x_test)
y_predd_train=dt.predict(x_train)


print('For test data')
print(classification_report(y_test,y_predd))
print('For train data')
print(classification_report(y_train,y_predd_train))

```

```
For test data
              precision    recall  f1-score   support

           0       0.86      0.86      0.86     18867
           1       0.63      0.64      0.63      7116

    accuracy                           0.80     25983
   macro avg       0.75      0.75      0.75     25983
weighted avg       0.80      0.80      0.80     25983

For train data
              precision    recall  f1-score   support

           0       0.99      1.00      1.00     43760
           1       1.00      0.98      0.99     16865

    accuracy                           1.00     60625
   macro avg       1.00      0.99      0.99     60625
weighted avg       1.00      1.00      1.00     60625
```

3. KNN

In [101]:
```
from sklearn.neighbors import KNeighborsClassifier

knn = KNeighborsClassifier()
knn.fit(x_train, y_train)

y_pred = knn.predict(x_test)
y_pred_train=knn.predict(x_train)


print('For test data')
print(classification_report(y_test,y_pred))
print('For train data')
print(classification_report(y_train,y_pred_train))

```

```
For test data
              precision    recall  f1-score   support

           0       0.86      0.89      0.87     18867
           1       0.68      0.61      0.64      7116

    accuracy                           0.81     25983
   macro avg       0.77      0.75      0.76     25983
weighted avg       0.81      0.81      0.81     25983

For train data
              precision    recall  f1-score   support

           0       0.90      0.92      0.91     43760
           1       0.79      0.73      0.76     16865

    accuracy                           0.87     60625
   macro avg       0.84      0.83      0.83     60625
weighted avg       0.87      0.87      0.87     60625
```

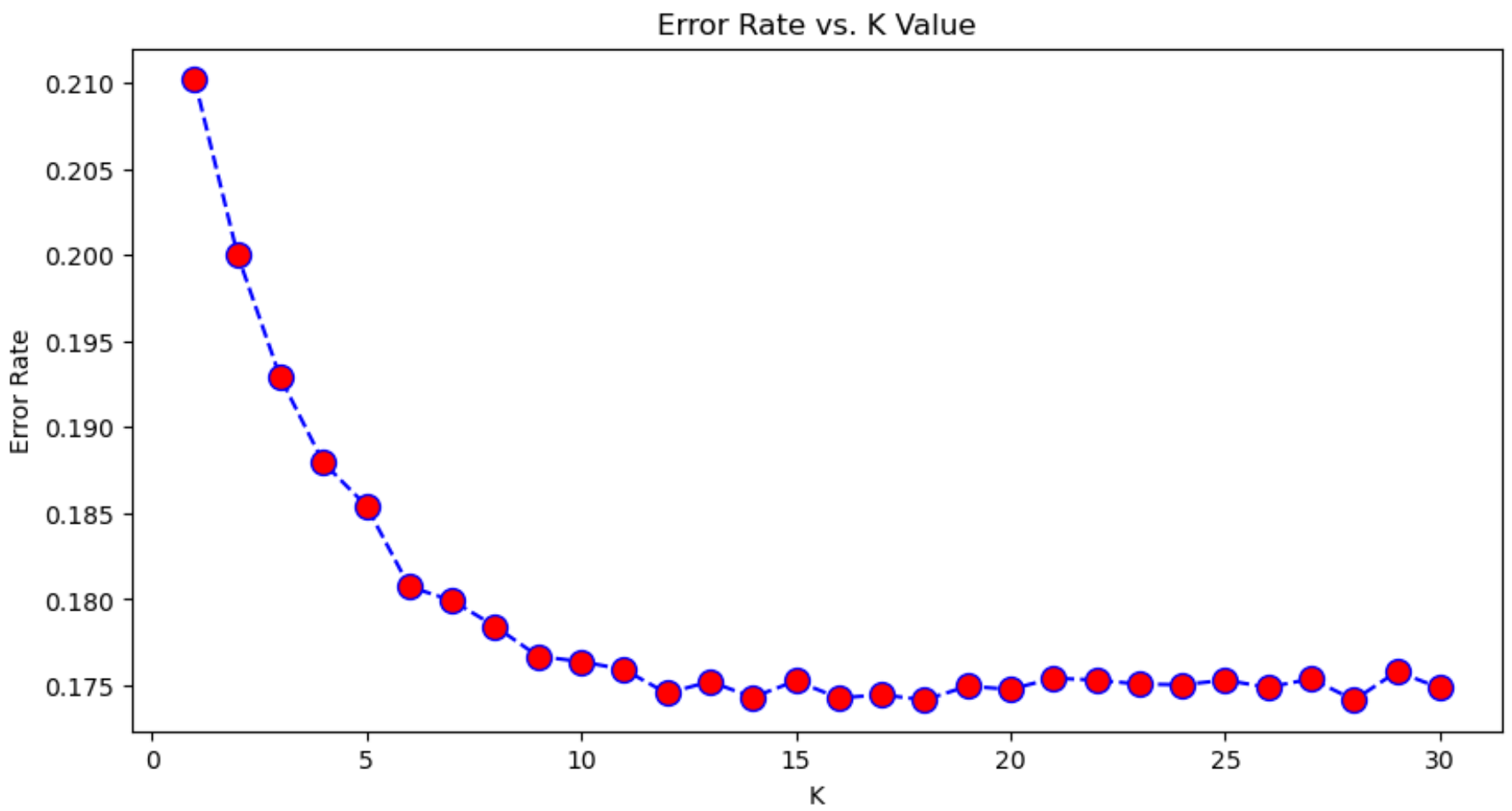
Finding optimal value of k

In [102]:
```
error_rate = []

# Will take some time
for i in range(1,31):
    knn = KNeighborsClassifier(n_neighbors=i)
    knn.fit(x_train,y_train)
    pred_i = knn.predict(x_test)
    error_rate.append(np.mean(pred_i != y_test))

print(error_rate)
```

```
[0.21017588423199784, 0.20001539468113766, 0.19285686795212253, 0.18793056998806912, 0.18542893430319823,
0.18073355655620982, 0.17992533579648232, 0.17842435438555979, 0.17669245275757225, 0.17638455913481893,
0.1759227187006889, 0.1745371973982989, 0.1752299580494939, 0.17430627718123387, 0.17526844475233808, 0.17
426779047838972, 0.17446022399261055, 0.17415233036985722, 0.17496055112958472, 0.1747681176153639, 0.1754
2239156371472, 0.17530693145518222, 0.17507601123811722, 0.17503752453527308, 0.17530693145518222, 0.17488
35777238964, 0.17538390486087058, 0.17415233036985722, 0.1758072585921564, 0.17484509102105222]
```

In [103]:
```
plt.figure(figsize=(10,5))
plt.plot(range(1,31),error_rate,color='blue', linestyle='dashed', marker='o',
         markerfacecolor='red', markersize=10)
plt.title('Error Rate vs. K Value')
plt.xlabel('K')
plt.ylabel('Error Rate')
```

Out[103]: Text(0, 0.5, 'Error Rate')



In [104]:
```
# With Optimal value of K

knn = KNeighborsClassifier(n_neighbors = 12)
knn.fit(x_train, y_train)

y_pred = knn.predict(x_test)
y_pred_train=knn.predict(x_train)


print('For test data')
print(classification_report(y_test,y_pred))
print('For train data')
print(classification_report(y_train,y_pred_train))
```

```
For test data
              precision    recall  f1-score   support

           0       0.85      0.92      0.88     18867
           1       0.73      0.57      0.64      7116

    accuracy                           0.83     25983
   macro avg       0.79      0.75      0.76     25983
weighted avg       0.82      0.83      0.82     25983

For train data
              precision    recall  f1-score   support

           0       0.86      0.93      0.90     43760
           1       0.78      0.62      0.69     16865

    accuracy                           0.85     60625
   macro avg       0.82      0.78      0.79     60625
weighted avg       0.84      0.85      0.84     60625
```

4. Random Forest

In [105]:
```
from sklearn.ensemble import RandomForestClassifier

rfc = RandomForestClassifier(random_state=77)
rfc.fit(x_train,y_train)

y_pred = rfc.predict(x_test)
y_pred_train = rfc.predict(x_train)


print('For test data')
print(classification_report(y_test,y_pred))
print('For train data')
print(classification_report(y_train,y_pred_train))
```

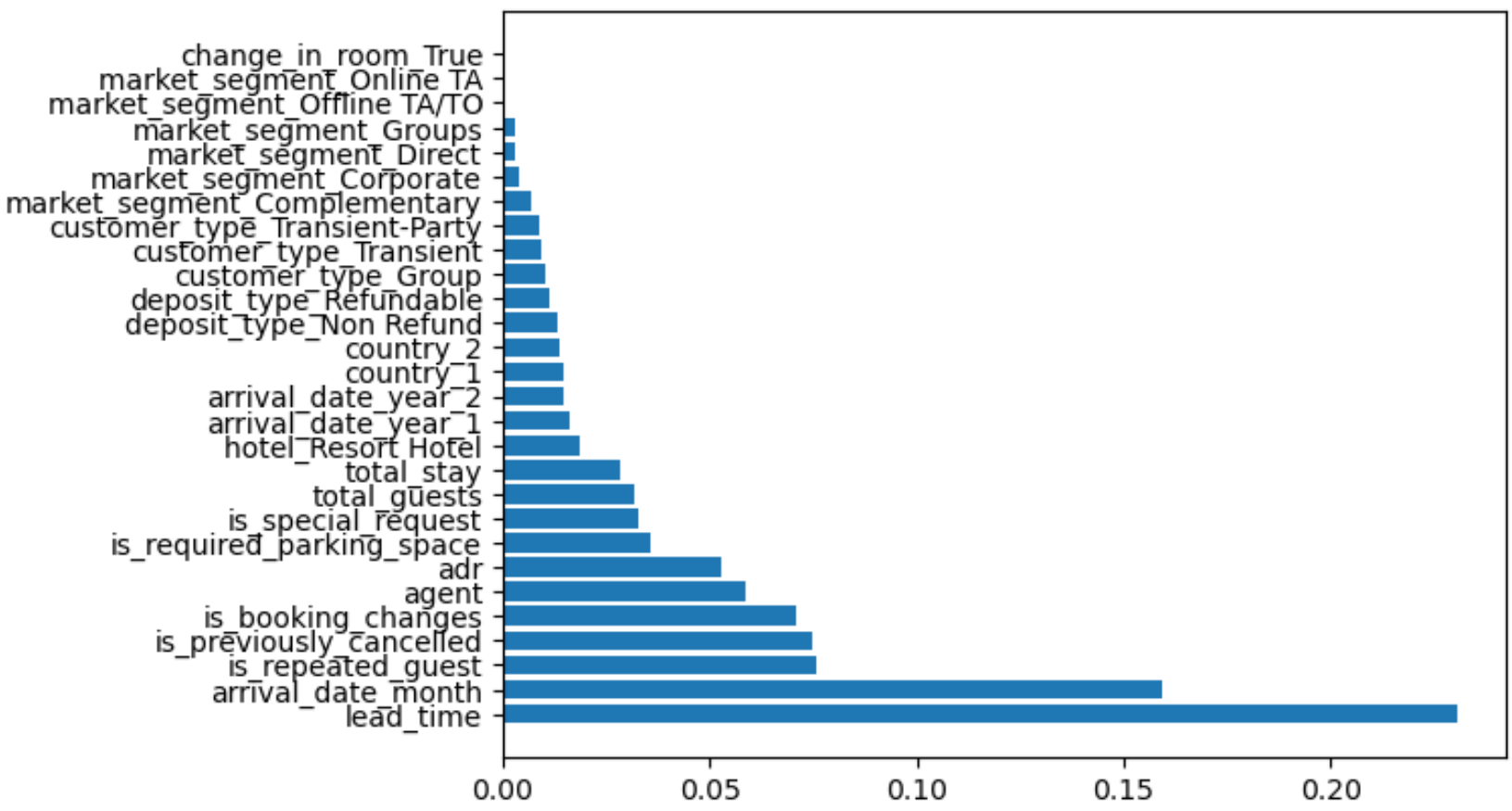
```
For test data
              precision    recall  f1-score   support

           0       0.88      0.91      0.89     18867
           1       0.74      0.66      0.70      7116

    accuracy                           0.84     25983
   macro avg       0.81      0.79      0.80     25983
weighted avg       0.84      0.84      0.84     25983

For train data
              precision    recall  f1-score   support

           0       1.00      1.00      1.00     43760
           1       0.99      0.99      0.99     16865

    accuracy                           1.00     60625
   macro avg       0.99      0.99      0.99     60625
weighted avg       1.00      1.00      1.00     60625
```

Important features

In [106]:
```
feature_scores = pd.Series(rfc.feature_importances_, index=x_train.columns).sort_values(ascending=False

feature_scores
```

Out[106]:
```
lead_time                       0.230795
adr                             0.159242
total_stay                      0.075585
arrival_date_month              0.074768
agent                           0.070682
country_1                       0.058611
is_special_request              0.052705
change_in_room_True             0.035565
is_required_parking_space       0.033002
market_segment_Online TA        0.031879
total_guests                    0.028413
deposit_type_Non Refund         0.018470
is_booking_changes              0.015984
is_previously_cancelled         0.014662
arrival_date_year_1             0.014578
customer_type_Transient         0.013964
arrival_date_year_2             0.013137
market_segment_Offline TA/TO    0.011176
hotel_Resort Hotel              0.010316
country_2                       0.009486
customer_type_Transient-Party   0.008631
market_segment_Direct           0.007155
is_repeated_guest               0.004052
market_segment_Groups           0.002880
market_segment_Corporate        0.002856
market_segment_Complementary    0.000619
customer_type_Group             0.000462
deposit_type_Refundable         0.000327
dtype: float64
```

In [107]:
```
plt.barh(x_train.columns, feature_scores)
plt.show()
```



5. SVM

In [108]:
```
from sklearn.svm import SVC

svc = SVC(random_state=77)
svc.fit(x_train,y_train)

y_pred = svc.predict(x_test)
y_pred_train = svc.predict(x_train)


print('For test data')
print(classification_report(y_test,y_pred))
print('For train data')
print(classification_report(y_train,y_pred_train))
```

```
For test data
              precision    recall  f1-score   support

           0       0.85      0.92      0.88     18867
           1       0.73      0.58      0.65      7116

    accuracy                           0.83     25983
   macro avg       0.79      0.75      0.77     25983
weighted avg       0.82      0.83      0.82     25983

For train data
              precision    recall  f1-score   support

           0       0.86      0.92      0.89     43760
           1       0.74      0.60      0.66     16865

    accuracy                           0.83     60625
   macro avg       0.80      0.76      0.77     60625
weighted avg       0.82      0.83      0.82     60625
```

6. Naive Bayes

In [109]:
```
from sklearn.naive_bayes import GaussianNB
nb = GaussianNB()
nb.fit(x_train,y_train)

y_pred = nb.predict(x_test)
y_pred_train = nb.predict(x_train)


print('For test data')
print(classification_report(y_test,y_pred))
print('For train data')
print(classification_report(y_train,y_pred_train))
```

```
For test data
              precision    recall  f1-score   support

           0       0.95      0.35      0.51     18867
           1       0.36      0.95      0.52      7116

    accuracy                           0.52     25983
   macro avg       0.65      0.65      0.52     25983
weighted avg       0.79      0.52      0.51     25983

For train data
              precision    recall  f1-score   support

           0       0.95      0.35      0.51     43760
           1       0.36      0.95      0.52     16865

    accuracy                           0.52     60625
   macro avg       0.66      0.65      0.52     60625
weighted avg       0.79      0.52      0.51     60625
```

7. Gradient Boosting

In [110]:
```
from sklearn.ensemble import GradientBoostingClassifier

gdb = GradientBoostingClassifier()
gdb.fit(x_train,y_train)

y_pred = gdb.predict(x_test)
y_pred_train = gdb.predict(x_train)


print('For test data')
print(classification_report(y_test,y_pred))
print('For train data')
print(classification_report(y_train,y_pred_train))
```

```
For test data
              precision    recall  f1-score   support

           0       0.86      0.92      0.89     18867
           1       0.74      0.59      0.66      7116

    accuracy                           0.83     25983
   macro avg       0.80      0.76      0.77     25983
weighted avg       0.83      0.83      0.83     25983

For train data
              precision    recall  f1-score   support

           0       0.86      0.92      0.89     43760
           1       0.75      0.61      0.67     16865

    accuracy                           0.83     60625
   macro avg       0.80      0.76      0.78     60625
weighted avg       0.83      0.83      0.83     60625
```

8. AdaBoost

In [111]:
```
from sklearn.ensemble import AdaBoostClassifier
adb = AdaBoostClassifier()
adb.fit(x_train,y_train)

y_pred = adb.predict(x_test)
y_pred_train = adb.predict(x_train)


print('For test data')
print(classification_report(y_test,y_pred))
print('For train data')
print(classification_report(y_train,y_pred_train))

```

```
For test data
              precision    recall  f1-score   support

           0       0.84      0.91      0.88     18867
           1       0.70      0.54      0.61      7116

    accuracy                           0.81     25983
   macro avg       0.77      0.73      0.74     25983
weighted avg       0.80      0.81      0.80     25983

For train data
              precision    recall  f1-score   support

           0       0.84      0.91      0.88     43760
           1       0.71      0.55      0.62     16865

    accuracy                           0.81     60625
   macro avg       0.78      0.73      0.75     60625
weighted avg       0.81      0.81      0.81     60625
```

9. Ridge Classifier

In [112]:

```
from sklearn.linear_model import RidgeClassifier

rc = RidgeClassifier()
rc.fit(x_train,y_train)

y_pred = rc.predict(x_test)
y_pred_train = rc.predict(x_train)


print('For test data')
print(classification_report(y_test,y_pred))
print('For train data')
print(classification_report(y_train,y_pred_train))

```

```
For test data
              precision    recall  f1-score   support

           0       0.80      0.94      0.87     18867
           1       0.71      0.38      0.49      7116

    accuracy                           0.79     25983
   macro avg       0.76      0.66      0.68     25983
weighted avg       0.78      0.79      0.76     25983

For train data
              precision    recall  f1-score   support

           0       0.80      0.94      0.86     43760
           1       0.72      0.39      0.51     16865

    accuracy                           0.79     60625
   macro avg       0.76      0.67      0.69     60625
weighted avg       0.78      0.79      0.76     60625
```

10. XGBoost

In [113]:

```
from xgboost import XGBClassifier

xgb= XGBClassifier()
xgb.fit(x_train,y_train)

y_pred = xgb.predict(x_test)
y_pred_train = xgb.predict(x_train)


print('For test data')
print(classification_report(y_test,y_pred))
print('For train data')
print(classification_report(y_train,y_pred_train))

```

```
For test data
              precision    recall  f1-score   support

           0       0.88      0.91      0.90     18867
           1       0.75      0.67      0.71      7116

    accuracy                           0.85     25983
   macro avg       0.81      0.79      0.80     25983
weighted avg       0.84      0.85      0.85     25983

For train data
              precision    recall  f1-score   support

           0       0.90      0.93      0.91     43760
           1       0.80      0.72      0.76     16865

    accuracy                           0.87     60625
   macro avg       0.85      0.83      0.83     60625
weighted avg       0.87      0.87      0.87     60625
```

Cross - Validation on each model

In [114]:
```
from sklearn.model_selection import cross_val_score, GridSearchCV
```

In [115]:
```
# Function to find out mean of cross-validation scores

def cv(model):
    scores = cross_val_score(model, x_train, y_train, cv=10)

    return scores.mean()
```

In [116]:
```
# 1. Logistic Regression

logreg = LogisticRegression(random_state = 11).fit(x_train, y_train)
cv(logreg)
```

Out[116]: 0.7958927821168177

In [117]:
```
# 2. Decision Tree

dt = DecisionTreeClassifier(random_state = 11).fit(x_train, y_train)
cv(dt)
```

Out[117]: 0.7965358811115205

In [118]:
```
# 3. KNN

knn = KNeighborsClassifier().fit(x_train, y_train)
cv(knn)
```

Out[118]: 0.8130142603074623

In [119]:
```
# KNN with optimal value of K

knn = KNeighborsClassifier(n_neighbors = 12).fit(x_train, y_train)
cv(knn)
```

Out[119]: 0.8201401532669751

In [120]:
```
# 4. Random Forest

rfc = RandomForestClassifier().fit(x_train, y_train)
cv(rfc)
```

Out[120]: 0.8422266765333729

In [121]:
```
# 5. SVM

svc = SVC().fit(x_train, y_train)
cv(svc)
```

Out[121]: 0.8243464436133673

In [122]:
```
# 6. Naive Bayes

nb = GaussianNB().fit(x_train, y_train)
cv(nb)
```

Out[122]: 0.517459551101861

In [123]:
```
# 7. Gradient boosting

gdb = GradientBoostingClassifier().fit(x_train, y_train)
cv(gdb)
```

Out[123]: 0.8330062470095015

In [124]:
```
# 8. AdaBoost

adb = AdaBoostClassifier().fit(x_train, y_train)
cv(adb)
```

Out[124]: 0.813344363997666

In [125]:
```
# 9. Ridge Classifier

rc = RidgeClassifier().fit(x_train, y_train)
cv(rc)
```

Out[125]: 0.7874804082047768

In [126]:
```
# 10. XGBoost

xgb = XGBClassifier().fit(x_train, y_train)
cv(xgb)
```

Out[126]: 0.8474887213348155

In [127]:
```
### Best-Performing Models = Random Forest, Gradient Boosting, XG Boost
```

Hyper-Parameter tuning on best performing models

In [128]:
```
# Function to find out best parameters using Grid Search CV

def classifier(model, param_grid):
    grid_search = GridSearchCV(model, param_grid, cv=10, scoring = "accuracy")
    grid_search.fit(x_train, y_train)
    print("Best parameters:", grid_search.best_params_)
    print("Best score:", grid_search.best_score_)

```

1. Random Forest

In [129]:
```
# Testing hyper parameters

param_grid = {'max_depth':[30, 50, 80], 'criterion':['entropy', 'gini'],
              'max_leaf_nodes':[500, 1000, 1200],'min_samples_split':[8,10,12,14,16]}
rf = RandomForestClassifier()
classifier(rf, param_grid)
```

```
Best parameters: {'criterion': 'gini', 'max_depth': 70, 'max_leaf_nodes': 1400, 'min_samples_split': 14}
Best score: 0.8479341216141763
```

In [131]:
```
from sklearn.metrics import precision_score, recall_score
```

In [132]:
```
rfc = RandomForestClassifier(max_depth = 50, max_leaf_nodes= 1200, criterion = 'entropy', min_samples_s
                             random_state=77)
# fitting
rfc.fit(x_train,y_train)

# predicting
y_pred = rfc.predict(x_test)
y_pred_train = rfc.predict(x_train)

# results
print('For test data:')
print(classification_report(y_test,y_pred))
print('For train data:')
print(classification_report(y_train,y_pred_train))

# Training accuracy
print(f'Training accuracy = {accuracy_score(y_train, y_pred_train)}')
# Testing accuracy
print(f'Testing accuracy = {accuracy_score(y_test, y_pred)}')
# Testing precision
print(f'Testing precision = {precision_score(y_test, y_pred)}')
# Testing recall
print(f'Testing recall = {recall_score(y_test, y_pred)}')
```

```
For test data:
              precision    recall  f1-score   support

           0       0.87      0.93      0.90     18867
           1       0.77      0.63      0.69      7116

    accuracy                           0.85     25983
   macro avg       0.82      0.78      0.79     25983
weighted avg       0.84      0.85      0.84     25983

For train data:
              precision    recall  f1-score   support

           0       0.89      0.94      0.91     43760
           1       0.82      0.68      0.75     16865

    accuracy                           0.87     60625
   macro avg       0.85      0.81      0.83     60625
weighted avg       0.87      0.87      0.87     60625

Training accuracy = 0.8702020618556701
Testing accuracy = 0.845899241811954
Testing precision = 0.7676298589611283
Testing recall = 0.6271781899943789
```

2. XGBoost

In [133]:
```
# Testing hyper parameters

param_grid = {'gamma':[i/10.0 for i in range(10,20,1)],
 'min_child_weight': [7],
              'max_depth' : [11]}

xgb = XGBClassifier()
classifier(xgb, param_grid)
```

```
Best parameters: {'gamma': 1.9, 'max_depth': 11, 'min_child_weight': 7}
Best score: 0.847703109432777
```

In [134]:
```
from xgboost import XGBClassifier

xgb= XGBClassifier(max_depth = 11, min_child_weight = 7, gamma = 1.9, random_state = 11)
xgb.fit(x_train,y_train)

y_pred = xgb.predict(x_test)
y_pred_train = xgb.predict(x_train)


print('For test data:')
print(classification_report(y_test,y_pred))
print('For train data:')
print(classification_report(y_train,y_pred_train))


# Training accuracy
print(f'Training accuracy = {accuracy_score(y_train, y_pred_train)}')
# Testing accuracy
print(f'Testing accuracy = {accuracy_score(y_test, y_pred)}')
# Testing precision
print(f'Testing precision = {precision_score(y_test, y_pred)}')
# Testing recall
print(f'Testing recall = {recall_score(y_test, y_pred)}')
```

```
For test data:
              precision    recall  f1-score   support

           0       0.89      0.91      0.90     18867
           1       0.74      0.69      0.71      7116

    accuracy                           0.85     25983
   macro avg       0.81      0.80      0.81     25983
weighted avg       0.85      0.85      0.85     25983

For train data:
              precision    recall  f1-score   support

           0       0.92      0.94      0.93     43760
           1       0.84      0.78      0.81     16865

    accuracy                           0.90     60625
   macro avg       0.88      0.86      0.87     60625
weighted avg       0.90      0.90      0.90     60625

Training accuracy = 0.8966268041237113
Testing accuracy = 0.8493245583650849
Testing precision = 0.7437185929648241
Testing recall = 0.6863406408094435
```

In [135]:
```
xgb= XGBClassifier(max_depth = 15, min_child_weight = 7, gamma = 1.9, learning_rate =0.1, subsample= 0.
                   random_state = 11)
xgb.fit(x_train,y_train)

y_pred = xgb.predict(x_test)
y_pred_train = xgb.predict(x_train)


print('For test data:')
print(classification_report(y_test,y_pred))
print('For train data:')
print(classification_report(y_train,y_pred_train))


# Training accuracy
print(f'Training accuracy = {accuracy_score(y_train, y_pred_train)}')
# Testing accuracy
print(f'Testing accuracy = {accuracy_score(y_test, y_pred)}')
# Testing precision
print(f'Testing precision = {precision_score(y_test, y_pred)}')
# Testing recall
print(f'Testing recall = {recall_score(y_test, y_pred)}')
```

```
For test data:
              precision    recall  f1-score   support

           0       0.88      0.91      0.90     18867
           1       0.75      0.68      0.71      7116

    accuracy                           0.85     25983
   macro avg       0.82      0.80      0.81     25983
weighted avg       0.85      0.85      0.85     25983

For train data:
              precision    recall  f1-score   support

           0       0.91      0.94      0.92     43760
           1       0.83      0.76      0.79     16865

    accuracy                           0.89     60625
   macro avg       0.87      0.85      0.86     60625
weighted avg       0.89      0.89      0.89     60625

Training accuracy = 0.8890886597938145
Testing accuracy = 0.8497094253935266
Testing precision = 0.7479536679536679
Testing recall = 0.6805789769533446
```

3. Gradient Boosting

In [136]:
```
param_grid = {'n_estimators' : range(140,151,10)}

gdb = GradientBoostingClassifier()
classifier(gdb, param_grid)
```

```
Best parameters: {'n_estimators': 150}
Best score: 0.8373773987450477
```

In [137]:
```
param_grid = {'n_estimators' : [150],'max_depth':range(9,10,1)}

gdb = GradientBoostingClassifier()
classifier(gdb, param_grid)
```

```
Best parameters: {'max_depth': 9, 'n_estimators': 150}
Best score: 0.8477360964029238
```

In [138]:
```
param_grid = {'n_estimators' : [150],'max_depth':[9], 'min_samples_split' : [80,100,120,140]}

gdb = GradientBoostingClassifier()
classifier(gdb, param_grid)
```

```
Best parameters: {'max_depth': 9, 'min_samples_split': 100, 'n_estimators': 150}
Best score: 0.8498639545957374
```

In [139]:
```
from sklearn.ensemble import GradientBoostingClassifier

gdb = GradientBoostingClassifier(max_depth= 9, min_samples_split= 100, n_estimators= 200)
gdb.fit(x_train,y_train)

y_pred = gdb.predict(x_test)
y_pred_train = gdb.predict(x_train)


print('For test data:')
print(classification_report(y_test,y_pred))
print('For train data:')
print(classification_report(y_train,y_pred_train))


# Training accuracy
print(f'Training accuracy = {accuracy_score(y_train, y_pred_train)}')
# Testing accuracy
print(f'Testing accuracy = {accuracy_score(y_test, y_pred)}')
# Testing precision
print(f'Testing precision = {precision_score(y_test, y_pred)}')
# Testing recall
print(f'Testing recall = {recall_score(y_test, y_pred)}')
```

```
For test data:
              precision    recall  f1-score   support

           0       0.88      0.91      0.90     18867
           1       0.75      0.68      0.71      7116

    accuracy                           0.85     25983
   macro avg       0.81      0.80      0.80     25983
weighted avg       0.85      0.85      0.85     25983

For train data:
              precision    recall  f1-score   support

           0       0.91      0.94      0.93     43760
           1       0.84      0.77      0.80     16865

    accuracy                           0.89     60625
   macro avg       0.87      0.85      0.86     60625
weighted avg       0.89      0.89      0.89     60625

Training accuracy = 0.8928659793814433
Testing accuracy = 0.8488242312281107
Testing precision = 0.7469786179113728
Testing recall = 0.677487352445194
```

In [140]:
```
from sklearn.ensemble import GradientBoostingClassifier

gdb = GradientBoostingClassifier(max_depth= 9, min_samples_split= 100, n_estimators= 150, max_features=
                                 random_state = 11)
gdb.fit(x_train,y_train)

y_pred = gdb.predict(x_test)
y_pred_train = gdb.predict(x_train)


print('For test data:')
print(classification_report(y_test,y_pred))
print('For train data:')
print(classification_report(y_train,y_pred_train))


# Training accuracy
print(f'Training accuracy = {accuracy_score(y_train, y_pred_train)}')
# Testing accuracy
print(f'Testing accuracy = {accuracy_score(y_test, y_pred)}')
# Testing precision
print(f'Testing precision = {precision_score(y_test, y_pred)}')
# Testing recall
print(f'Testing recall = {recall_score(y_test, y_pred)}')
```

```
For test data:
              precision    recall  f1-score   support

           0       0.88      0.92      0.90     18867
           1       0.75      0.68      0.71      7116

    accuracy                           0.85     25983
   macro avg       0.82      0.80      0.80     25983
weighted avg       0.85      0.85      0.85     25983

For train data:
              precision    recall  f1-score   support

           0       0.91      0.94      0.92     43760
           1       0.82      0.75      0.78     16865

    accuracy                           0.88     60625
   macro avg       0.86      0.84      0.85     60625
weighted avg       0.88      0.88      0.88     60625

Training accuracy = 0.8842721649484536
Testing accuracy = 0.8495554785821499
Testing precision = 0.7501950382274926
Testing recall = 0.6756604834176504
```

Performance Comparison:

In [141]:
```
from tabulate import tabulate
```

In [142]:
```
table = [['Model_Name', 'Training_accuracy', 'Testing_accuracy', 'Testing_Precision', 'Testing_Recall']
         ['Random Forest', 0.870, 0.845, 0.767, 0.627],
         ['XGBoost', 0.896, 0.849, 0.743, 0.686],
         ['Gradient Boosting', 0.884, 0.849, 0.750, 0.675]]

print(tabulate(table, headers = 'firstrow', tablefmt = "fancy_grid"))
```

Model_Name	Training_accuracy	Testing_accuracy	Testing_Precision	Testing_Recall
Random Forest	0.87	0.845	0.767	0.627
XGBoost	0.896	0.849	0.743	0.686
Gradient Boosting	0.884	0.849	0.75	0.675

In [143]:
```
## With 85% accuracy, algorithms are able to classify data points correctly.
```