Forecasting Hotel Booking Cancellations.

The hospitality industry thrives in tourist hotspots, but one of the significant challenges it faces is booking cancellations. Last-minute or unexpected cancellations can result in substantial revenue losses for hotels. When a booking is canceled, the hotel not only loses the expected income but also misses the opportunity to rebook the room for the same period.

Accurately predicting the likelihood of a booking cancellation in advance can help hotel owners mitigate these losses.

The aim of this project is to forecast room cancellations using historical booking data with the highest possible accuracy

Importing necessary libraries

```
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
import numpy as np
import sklearn

import warnings
warnings.filterwarnings('ignore')
```

Getting the data

```
df =
pd.read_csv("/kaggle/input/hotel-booking-demand/hotel_bookings.csv")

df.head()
```

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

   arrival_date_week_number  arrival_date_day_of_month  \
0                        27                          1
1                        27                          1
2                        27                          1
```

```
3                        27                           1
4                        27                           1

   stays_in_weekend_nights  stays_in_week_nights  adults  ...
deposit_type  \
0                        0                     0       2  ...    No
Deposit
1                        0                     0       2  ...    No
Deposit
2                        0                     1       1  ...    No
Deposit
3                        0                     1       1  ...    No
Deposit
4                        0                     2       2  ...    No
Deposit

   agent company days_in_waiting_list customer_type   adr  \
0    NaN     NaN                    0     Transient   0.0
1    NaN     NaN                    0     Transient   0.0
2    NaN     NaN                    0     Transient  75.0
3  304.0     NaN                    0     Transient  75.0
4  240.0     NaN                    0     Transient  98.0

   required_car_parking_spaces  total_of_special_requests
reservation_status  \
0                            0                          0
Check-Out
1                            0                          0
Check-Out
2                            0                          0
Check-Out
3                            0                          0
Check-Out
4                            0                          1
Check-Out

  reservation_status_date
0              2015-07-01
1              2015-07-01
2              2015-07-02
3              2015-07-02
4              2015-07-03

[5 rows x 32 columns]
```

```
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
```

- There are 119390 records in total and 32 columns.
- There are missing values in a few columns

Exploratory Data Analysis and Data Pre-processing

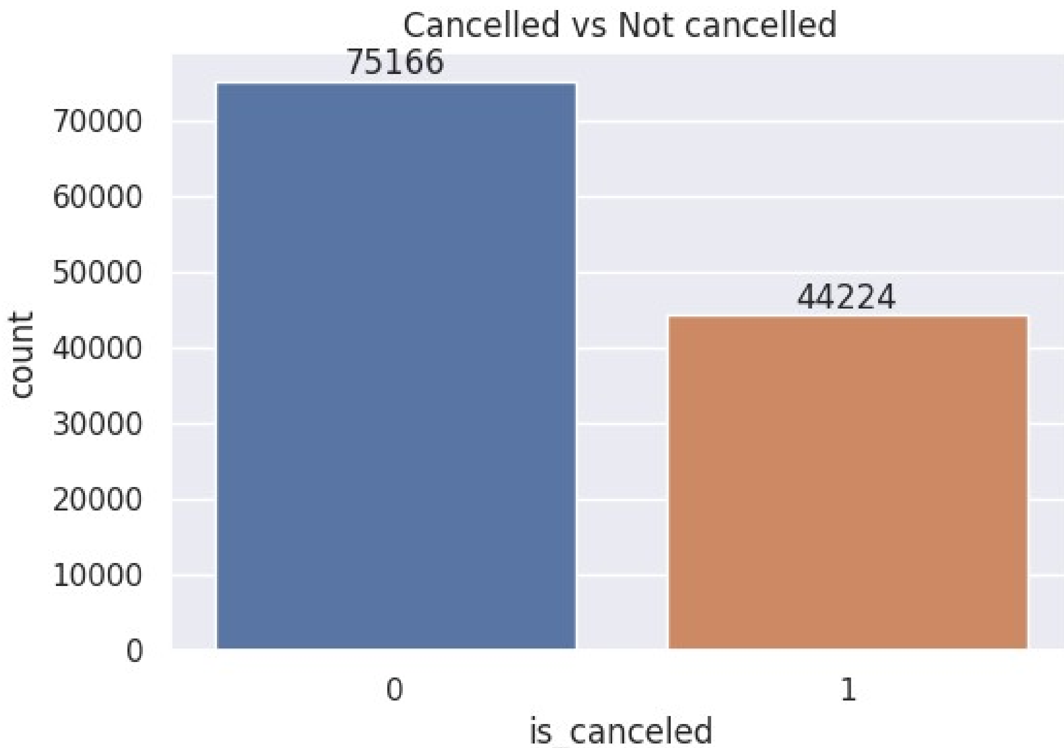
```
df.isnull().sum()/len(df) * 100
```

```
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
```

There is only one column that has more than 90% null values. This column can be dropped.

```
#Dropping column with more than 90% missing value
df = df.drop(columns = ["company"])

# Distribution of target column
plt.figure(figsize=(6,4))

ax = sns.countplot(x=df["is_canceled"])
for i in ax.containers:
    ax.bar_label(i)
ax.set(title="Cancelled vs Not cancelled")
plt.show()
```



- Out of all records, 44224 rooms have been cancelled ,i.e., 37%

In the fields present, there are children and babies. Both can be combined into a single column and the redundancy can be dropped.

```
df["kids"]=df["children"]+df["babies"]

df = df.drop(columns = ["children", "babies"])

df.describe().T

                                  count         mean         std
min  \
is_canceled                    119390.0     0.370416    0.482918
0.00
lead_time                      119390.0   104.011416  106.863097
0.00
arrival_date_year              119390.0  2016.156554    0.707476
2015.00
arrival_date_week_number       119390.0    27.165173   13.605138
1.00
arrival_date_day_of_month      119390.0    15.798241    8.780829
1.00
stays_in_weekend_nights        119390.0     0.927599    0.998613
0.00
stays_in_week_nights           119390.0     2.500302    1.908286
0.00
```

```
adults                              119390.0     1.856403    0.579261
0.00
is_repeated_guest                   119390.0     0.031912    0.175767
0.00
previous_cancellations              119390.0     0.087118    0.844336
0.00
previous_bookings_not_canceled      119390.0     0.137097    1.497437
0.00
booking_changes                     119390.0     0.221124    0.652306
0.00
agent                               103050.0    86.693382  110.774548
1.00
days_in_waiting_list                119390.0     2.321149   17.594721
0.00
adr                                 119390.0   101.831122   50.535790    -
6.38
required_car_parking_spaces         119390.0     0.062518    0.245291
0.00
total_of_special_requests           119390.0     0.571363    0.792798
0.00
kids                                119386.0     0.111839    0.412567
0.00

                                        25%        50%     75%     max
is_canceled                            0.00      0.000     1.0     1.0
lead_time                             18.00     69.000   160.0   737.0
arrival_date_year                   2016.00   2016.000  2017.0  2017.0
arrival_date_week_number              16.00     28.000    38.0    53.0
arrival_date_day_of_month              8.00     16.000    23.0    31.0
stays_in_weekend_nights                0.00      1.000     2.0    19.0
stays_in_week_nights                   1.00      2.000     3.0    50.0
adults                                 2.00      2.000     2.0    55.0
is_repeated_guest                      0.00      0.000     0.0     1.0
previous_cancellations                 0.00      0.000     0.0    26.0
previous_bookings_not_canceled         0.00      0.000     0.0    72.0
booking_changes                        0.00      0.000     0.0    21.0
agent                                  9.00     14.000   229.0   535.0
days_in_waiting_list                   0.00      0.000     0.0   391.0
adr                                   69.29     94.575   126.0  5400.0
required_car_parking_spaces            0.00      0.000     0.0     8.0
total_of_special_requests              0.00      0.000     1.0     5.0
kids                                   0.00      0.000     0.0    10.0
```

In the above cell, we can see some odd values in a few columns.

Stays in weekend nights and weeknights minimum value is 0. If both are 0 in the same row, it is unrealistic. We will check for these records and drop them

```
stays = df[(df["stays_in_weekend_nights"]==0) &
(df["stays_in_week_nights"]==0)]
```

```
stays["is_canceled"].value_counts()
```

```
is_canceled
0    680
1     35
Name: count, dtype: int64
```

Here, we see that rooms were reserved and very few cancellations are present for the records but the stays are 0.

We will drop these unrealistic records

```
#Dropping records where stays in weekend nights and also weekday
nights are 0
row_index=0

for i in df["stays_in_weekend_nights"]:
    if i==0 and df["stays_in_week_nights"][row_index]==0:
        df = df.drop(row_index)

    row_index=row_index+1

df = df.reset_index()
df = df.drop(columns=["index"])
```

Kids and Adults

There is also possibility of erroneous records where the bookings are done only with kids and no adults. We will filter out if there are any.

```
only_kids = df[(df["adults"]==0) & (df["kids"]!=0)]

only_kids
```

```
             hotel  is_canceled  lead_time  arrival_date_year  \
40598   City Hotel            0          1               2015
40661   City Hotel            0        104               2015
41058   City Hotel            0          3               2015
41564   City Hotel            0         15               2015
44762   City Hotel            1         48               2015
...            ...          ...        ...                ...
116493  City Hotel            0        296               2017
116563  City Hotel            0        276               2017
116592  City Hotel            0        291               2017
116742  City Hotel            0        159               2017
117487  City Hotel            0         10               2017

       arrival_date_month  arrival_date_week_number  \
40598              August                        33
40661              August                        33
```

```
41058             August                        34
41564             August                        35
44762            October                        43
...                  ...                       ...
116493              July                        30
116563              July                        31
116592              July                        30
116742              July                        31
117487            August                        32

        arrival_date_day_of_month  stays_in_weekend_nights  \
40598                          10                        1
40661                          11                        0
41058                          16                        2
41564                          28                        0
44762                          19                        1
...                           ...                      ...
116493                         27                        1
116563                         30                        2
116592                         29                        2
116742                         31                        1
117487                         12                        2

        stays_in_week_nights  adults  ... deposit_type agent  \
40598                      1       0  ...   No Deposit   NaN
40661                      3       0  ...   No Deposit   7.0
41058                      0       0  ...   No Deposit   NaN
41564                      1       0  ...   No Deposit   NaN
44762                      3       0  ...   No Deposit  13.0
...                      ...     ...  ...          ...   ...
116493                     3       0  ...   No Deposit   9.0
116563                     1       0  ...   No Deposit   9.0
116592                     2       0  ...   No Deposit   9.0
116742                     3       0  ...   No Deposit   9.0
117487                     2       0  ...   No Deposit   NaN

       days_in_waiting_list    customer_type     adr  \
40598                     0  Transient-Party    9.00
40661                     0  Transient-Party    6.00
41058                     0  Transient-Party    6.00
41564                     0        Transient    0.00
44762                     0  Transient-Party    6.00
...                     ...              ...     ...
116493                    0        Transient   98.85
116563                    0        Transient   93.64
116592                    0        Transient   98.85
116742                    0        Transient  121.88
117487                    0  Transient-Party    6.00

        required_car_parking_spaces  total_of_special_requests  \
```

```
40598                            0                          0
40661                            0                          2
41058                            0                          1
41564                            0                          1
44762                            0                          1
...                            ...                        ...
116493                           0                          1
116563                           0                          2
116592                           0                          1
116742                           0                          1
117487                           0                          1

       reservation_status reservation_status_date  kids
40598           Check-Out              2015-08-12   3.0
40661           Check-Out              2015-08-14   2.0
41058           Check-Out              2015-08-18   2.0
41564           Check-Out              2015-08-29   2.0
44762            Canceled              2015-09-02   2.0
...                   ...                     ...   ...
116493          Check-Out              2017-07-31   2.0
116563          Check-Out              2017-08-02   2.0
116592          Check-Out              2017-08-02   2.0
116742          Check-Out              2017-08-04   2.0
117487          Check-Out              2017-08-16   3.0

[223 rows x 30 columns]
```

- There are 223 rows with records where adults are 0 and kids are more than 0.
- All the records where the number of adults are 0 are unrealistic and will be dropped.

```
#Dropping rows where there are no adults
row_index=0
c=0
for i in df["adults"]:
    if i==0:
        df = df.drop(row_index)

    row_index=row_index+1

df = df.reset_index()
df = df.drop(columns=["index"])
```

Looking at values in all the columns

```
cols = df.columns
for i in cols:
    print(f"-----------------------{i}---------------------------")
    print(f"Values in {i} are {df[i].value_counts()}")
```

```
-----------------------hotel---------------------------
Values in hotel are hotel
City Hotel      78676
Resort Hotel    39666
Name: count, dtype: int64
-----------------------is_canceled---------------------------
Values in is_canceled are is_canceled
0    74250
1    44092
Name: count, dtype: int64
-----------------------lead_time---------------------------
Values in lead_time are lead_time
0      6001
1      3382
2      2042
3      1801
4      1697
       ... 
387       1
709       1
389       1
380       1
463       1
Name: count, Length: 478, dtype: int64
-----------------------arrival_date_year---------------------------
Values in arrival_date_year are arrival_date_year
2016    56090
2017    40447
2015    21805
Name: count, dtype: int64
-----------------------arrival_date_month---------------------------
Values in arrival_date_month are arrival_date_month
August       13780
July         12553
May          11688
October      11048
April        11024
June         10879
September    10466
March         9699
February      7980
November      6706
December      6666
January       5853
Name: count, dtype: int64
-----------------------
arrival_date_week_number---------------------------
Values in arrival_date_week_number are arrival_date_week_number
33    3556
30    3059
```

32	3024
34	3017
18	2908
28	2821
21	2805
17	2799
20	2771
29	2750
42	2720
31	2719
41	2679
15	2668
38	2653
25	2646
27	2645
23	2605
35	2572
39	2567
22	2541
24	2486
13	2392
16	2391
40	2388
19	2377
26	2374
43	2336
14	2248
44	2243
37	2213
8	2202
36	2159
10	2131
9	2083
7	2083
11	2060
12	2055
45	1921
53	1796
49	1766
47	1669
46	1550
6	1493
48	1478
50	1473
4	1469
5	1373
3	1297
2	1201
52	1166
1	1035

```
51     909
Name: count, dtype: int64
-----------------------
arrival_date_day_of_month---------------------------
Values in arrival_date_day_of_month are arrival_date_day_of_month
17    4344
5     4284
15    4158
25    4133
26    4116
9     4058
12    4055
16    4044
19    4031
2     4029
20    3995
18    3980
24    3946
28    3918
8     3879
3     3830
30    3817
6     3795
14    3780
27    3759
21    3728
4     3726
13    3717
7     3624
1     3599
23    3579
22    3574
11    3559
29    3547
10    3546
31    2192
Name: count, dtype: int64
-----------------------
stays_in_weekend_nights---------------------------
Values in stays_in_weekend_nights are stays_in_weekend_nights
0     51160
2     33185
1     30565
4      1846
3      1251
6       152
5        77
8        58
7        19
9        10
```

```
10       7
12       5
13       2
16       2
18       1
19       1
14       1
Name: count, dtype: int64
-----------------------stays_in_week_nights----------------------------
Values in stays_in_week_nights are stays_in_week_nights
2     33611
1     30242
3     22180
5     11054
4      9516
0      6921
6      1491
10     1029
7      1024
8       654
9       226
15       85
11       55
19       43
12       42
20       39
14       35
13       27
21       15
16       15
22        7
18        6
25        6
17        4
30        4
24        3
40        2
33        1
50        1
42        1
32        1
26        1
34        1
Name: count, dtype: int64
-----------------------adults---------------------------
Values in adults are adults
2     89253
1     22825
3      6186
4        62
```

```
26        5
5         2
27        2
20        2
40        1
55        1
50        1
6         1
10        1
Name: count, dtype: int64
-----------------------meal---------------------------
Values in meal are meal
BB           91505
HB           14380
SC           10500
Undefined     1160
FB             797
Name: count, dtype: int64
-----------------------country---------------------------
Values in country are country
PRT    47900
GBR    12080
FRA    10364
ESP     8530
DEU     7271
       ...
NAM        1
GUY        1
LCA        1
MRT        1
ASM        1
Name: count, Length: 177, dtype: int64
-----------------------market_segment---------------------------
Values in market_segment are market_segment
Online TA        55942
Offline TA/TO    24046
Groups           19759
Direct           12420
Corporate         5231
Complementary      711
Aviation           231
Undefined            2
Name: count, dtype: int64
-----------------------distribution_channel---------------------------
Values in distribution_channel are distribution_channel
TA/TO        97145
Direct       14418
Corporate     6584
GDS            190
Undefined        5
```

```
Name: count, dtype: int64
----------------------is_repeated_guest--------------------------
Values in is_repeated_guest are is_repeated_guest
0    114844
1      3498
Name: count, dtype: int64
----------------------
previous_cancellations--------------------------
Values in previous_cancellations are previous_cancellations
0     111869
1       6042
2        114
3         65
24        48
11        35
4         31
26        26
25        25
6         22
5         19
19        19
14        14
13        12
21         1
Name: count, dtype: int64
----------------------
previous_bookings_not_canceled--------------------------
Values in previous_bookings_not_canceled are
previous_bookings_not_canceled
0     114760
1       1519
2        576
3        331
4        226
       ...
60         1
61         1
62         1
63         1
72         1
Name: count, Length: 73, dtype: int64
----------------------reserved_room_type--------------------------
Values in reserved_room_type are reserved_room_type
A    85388
D    19095
E     6481
F     2877
G     2073
C      923
B      902
```

```
H      597
L        6
Name: count, dtype: int64
-----------------------assigned_room_type---------------------------
Values in assigned_room_type are assigned_room_type
A    73752
D    25202
E     7763
F     3728
G     2531
C     2350
B     1961
H      708
I      219
K      127
L        1
Name: count, dtype: int64
-----------------------booking_changes---------------------------
Values in booking_changes are booking_changes
0     100548
1      12529
2       3752
3        906
4        364
5        110
6         60
7         27
8         14
9          8
10         6
13         5
15         3
14         3
17         2
16         2
12         1
18         1
11         1
Name: count, dtype: int64
-----------------------deposit_type---------------------------
Values in deposit_type are deposit_type
No Deposit    103593
Non Refund     14587
Refundable       162
Name: count, dtype: int64
-----------------------agent---------------------------
Values in agent are agent
9.0      31676
240.0    13795
1.0       7185
```

```
14.0      3604
7.0       3515
         ...
59.0         1
451.0        1
358.0        1
397.0        1
433.0        1
Name: count, Length: 333, dtype: int64
-----------------------days_in_waiting_list--------------------------
Values in days_in_waiting_list are days_in_waiting_list
0      114650
39        227
58        164
44        141
31        127
        ...
109         1
37          1
193         1
73          1
36          1
Name: count, Length: 127, dtype: int64
-----------------------customer_type--------------------------
Values in customer_type are customer_type
Transient          88796
Transient-Party    24923
Contract            4055
Group                568
Name: count, dtype: int64
-----------------------adr--------------------------
Values in adr are adr
62.00     3754
75.00     2714
90.00     2472
65.00     2418
80.00     1889
          ...
199.77       1
213.81       1
90.70        1
95.12        1
173.73       1
Name: count, Length: 8859, dtype: int64
-----------------------
required_car_parking_spaces--------------------------
Values in required_car_parking_spaces are required_car_parking_spaces
0    110951
1      7358
2        28
```

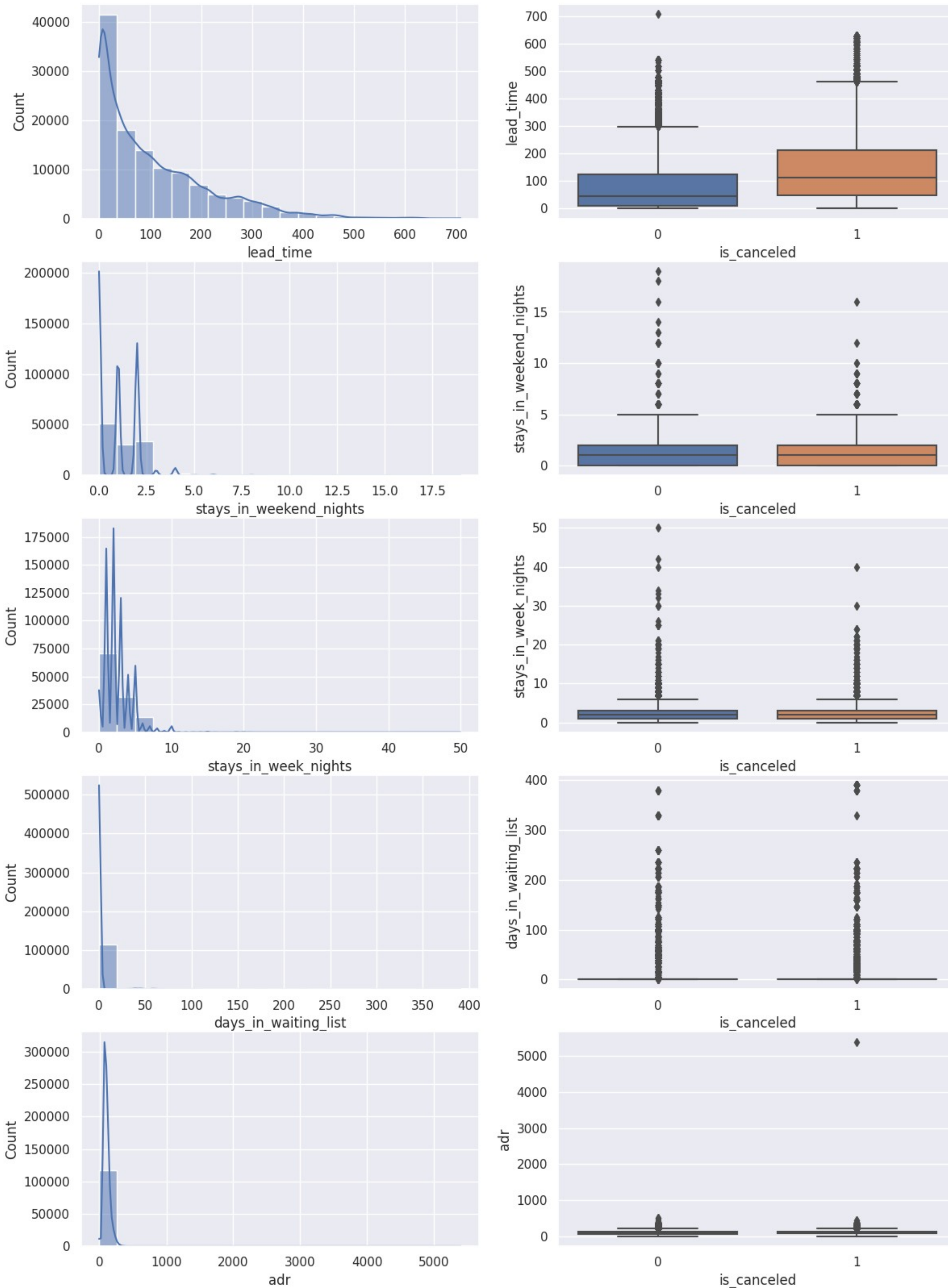
```
3         3
8         2
Name: count, dtype: int64
-----------------------
total_of_special_requests---------------------------
Values in total_of_special_requests are total_of_special_requests
0    69732
1    32907
2    12853
3     2472
4      338
5       40
Name: count, dtype: int64
-----------------------reservation_status---------------------------
Values in reservation_status are reservation_status
Check-Out    74250
Canceled     42902
No-Show       1190
Name: count, dtype: int64
-----------------------
reservation_status_date---------------------------
Values in reservation_status_date are reservation_status_date
2015-10-21    1456
2015-07-06     803
2016-11-25     787
2015-01-01     763
2016-01-18     623
              ...
2015-04-21       1
2015-03-11       1
2015-03-12       1
2015-03-18       1
2017-09-12       1
Name: count, Length: 926, dtype: int64
-----------------------kids---------------------------
Values in kids are kids
0.0     109268
1.0       5418
2.0       3552
3.0         97
10.0         2
9.0          1
Name: count, dtype: int64
```

- Lead time, stays_in_weeknights, stays_in_weekend, waiting list and adr are the only three numerical columns
- Although many other columns have numerical values, they are categorical in nature

```
#Diving columns into numerical ad categorical
num_cols = ["lead_time",'stays_in_weekend_nights',
'stays_in_week_nights','days_in_waiting_list','adr']
cat_cols = ['hotel', 'is_canceled',
'arrival_date_year','arrival_date_month',
'arrival_date_day_of_month','adults', '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',
       'customer_type','required_car_parking_spaces',
'total_of_special_requests','reservation_status',
            'reservation_status_date', 'kids']
```

Numerical columns

```
#plotting distribution of numerical columns
r = 5
c = 2
f,axes = plt.subplots(r,c,figsize=(14,20))
ctr = 0
for i in range(r):
    #for j in range(c):
    j=0
    col = num_cols[ctr]
    sns.histplot(x=df[col],bins=20,kde=True,ax=axes[i,j])
    sns.boxplot(x=df["is_canceled"],y=df[col],ax=axes[i,j+1])
    ctr = ctr + 1
plt.show()
```


Count
lead_time
0
100
200
300
400
500
600
700
10000
20000
30000
40000
is_canceled
stays_in_weekend_nights
0.0
2.5
5.0
7.5
10.0
12.5
15.0
17.5
50000
100000
150000
200000
stays_in_week_nights
25000
75000
125000
175000
10
20
30
40
50
days_in_waiting_list
150
250
350
400000
300000
500000
adr
1000
2000
3000
4000
5000
250000
1

- There are significant number of outliers in adr, days in waiting list, stays in weeknights and weekend nights.
- Outliers in waiting list column and adr need to be addressed as they are very high and may significantly impact the outcome.

Categorical columns

```
#Plotting distribution of  categorical columns
r = 8
c = 3
f,axes = plt.subplots(r,c,figsize=(20,45))
ctr = 0
for i in range(r):
    for j in range(c):
        col = cat_cols[ctr]
        sns.countplot(x=df[col],hue=df["is_canceled"],ax=axes[i,j])

        ctr = ctr + 1
plt.show()
```

is_canceled
0
1
count
Resort Hotel
City Hotel
hotel
is_canceled
arrival_date_year
2015
2016
2017
arrival_date_month
arrival_date_day_of_month
adults
meal
BB
FB
HB
SC
Undefined
country
market_segment
distribution_channel
Direct
Corporate
TA/TO
Undefined
GDS
is_repeated_guest
previous_cancellations
previous_bookings_not_canceled
reserved_room_type
assigned_room_type

- Bookings and cancellations in a city hotel is higher than resort hotel
- Bookings in year 2016 is highest because of the data distribution. We have data from July 2015 to June 2017.
- There is a significant dip in bookings in November, December and January. As summer in most inhabited continents of the world lasts from May to September, we can assume that for a tourist destination like Portugal, November to January will be a low season and May to September will be high season.
- There is no discernable pattern between day of the month and cancellation.
- The maximum number of bookings seem to be amongst 1 to 3 adults where 2 adults is the highest.
- THere are different types of meals available for the occupants. However, it can be assumed that this will not have impact on the cancellations as there are other more significant factors involved.
- There are total of 177 countries from which tourists are visiting. This needs to be examined further.
- market_segment and distribution_channel are interrelated columns. We can keep market_segment for further exploration.
- is_repeated_guest, previous_cancellations and previous_bookings_not_cancelled data is highly skewed. Needs further exploration before being dropped.
- room A has highest bookings. We must check if cancellations are high where reserved and assigned room types are not same.
- booking_changes also has highly skewed data.
- Cancellations are high for non-refundable deposit types.
- There is no particular description for agent column. It appears to be a number associated with the agent responsible for the booking. This column can be dropped.
- reservation_status and reservation_status_date can be dropped as they are redundant.

Checking data and cancellation percentages for columns with skewed data.

```
perc = df.groupby(['is_repeated_guest',
'is_canceled']).size().unstack(1)
perc["total perc"] = (perc[0] + perc[1])/len(df["is_canceled"])
perc["canc perc"] = (perc[1]/(perc[0] + perc[1]))
perc
```

is_canceled	0	1	total perc	canc perc
is_repeated_guest				
0	71301	43543	0.970442	0.379149
1	2949	549	0.029558	0.156947

More than 96% of the data is for one value only. We will drop this column as it is skewed.

```
perc = df.groupby(['previous_cancellations',
'is_canceled']).size().unstack(1)
perc["total perc"] = (perc[0] + perc[1])/len(df["is_canceled"])
perc["canc perc"] = (perc[1]/(perc[0] + perc[1]))
perc
```

```
is_canceled                       0        1  total perc  canc perc
previous_cancellations
0                           73715.0  38154.0    0.945303   0.341060
1                             332.0   5710.0    0.051055   0.945051
2                              76.0     38.0    0.000963   0.333333
3                              45.0     20.0    0.000549   0.307692
4                              24.0      7.0    0.000262   0.225806
5                              17.0      2.0    0.000161   0.105263
6                              15.0      7.0    0.000186   0.318182
11                             25.0     10.0    0.000296   0.285714
13                              1.0     11.0    0.000101   0.916667
14                              NaN     14.0         NaN        NaN
19                              NaN     19.0         NaN        NaN
21                              NaN      1.0         NaN        NaN
24                              NaN     48.0         NaN        NaN
25                              NaN     25.0         NaN        NaN
26                              NaN     26.0         NaN        NaN
```

```
perc = df.groupby(['previous_bookings_not_canceled',
'is_canceled']).size().unstack(1)
perc["total perc"] = (perc[0] + perc[1])/len(df["is_canceled"])
perc["canc perc"] = (perc[1]/(perc[0] + perc[1]))
perc
```

```
is_canceled                             0        1  total perc  canc
perc
previous_bookings_not_canceled

0                                 70867.0  43893.0    0.969732
0.382476
1                                  1441.0     78.0    0.012836
0.051350
2                                   544.0     32.0    0.004867
0.055556
3                                   314.0     17.0    0.002797
0.051360
4                                   214.0     12.0    0.001910
0.053097
...                                   ...      ...         ...        ..
.
68                                    1.0      NaN         NaN
NaN
69                                    1.0      NaN         NaN
NaN
70                                    1.0      NaN         NaN
NaN
71                                    1.0      NaN         NaN
NaN
72                                    1.0      NaN         NaN
NaN
```

```
[73 rows x 4 columns]
```

More than 96% of the data is for one value only. We will drop this column as it is skewed.

```
perc = df.groupby(['booking_changes',
'is_canceled']).size().unstack(1)
perc["total perc"] = (perc[0] + perc[1])/len(df["is_canceled"])
perc["canc perc"] = (perc[1]/(perc[0] + perc[1]))
perc
```

is_canceled	0	1	total perc	canc perc
booking_changes				
0	59268.0	41280.0	0.849639	0.410550
1	10737.0	1792.0	0.105871	0.143028
2	2991.0	761.0	0.031705	0.202825
3	763.0	143.0	0.007656	0.157837
4	297.0	67.0	0.003076	0.184066
5	90.0	20.0	0.000930	0.181818
6	42.0	18.0	0.000507	0.300000
7	24.0	3.0	0.000228	0.111111
8	10.0	4.0	0.000118	0.285714
9	7.0	1.0	0.000068	0.125000
10	5.0	1.0	0.000051	0.166667
11	1.0	NaN	NaN	NaN
12	1.0	NaN	NaN	NaN
13	5.0	NaN	NaN	NaN
14	2.0	1.0	0.000025	0.333333
15	3.0	NaN	NaN	NaN
16	1.0	1.0	0.000017	0.500000
17	2.0	NaN	NaN	NaN
18	1.0	NaN	NaN	NaN

```
perc = df.groupby(['required_car_parking_spaces',
'is_canceled']).size().unstack(1)
perc["total perc"] = (perc[0] + perc[1])/len(df["is_canceled"])
perc["canc perc"] = (perc[1]/(perc[0] + perc[1]))
perc
```

is_canceled	0	1	total perc	canc perc
required_car_parking_spaces				
0	66859.0	44092.0	0.937545	0.397401
1	7358.0	NaN	NaN	NaN
2	28.0	NaN	NaN	NaN
3	3.0	NaN	NaN	NaN
8	2.0	NaN	NaN	NaN

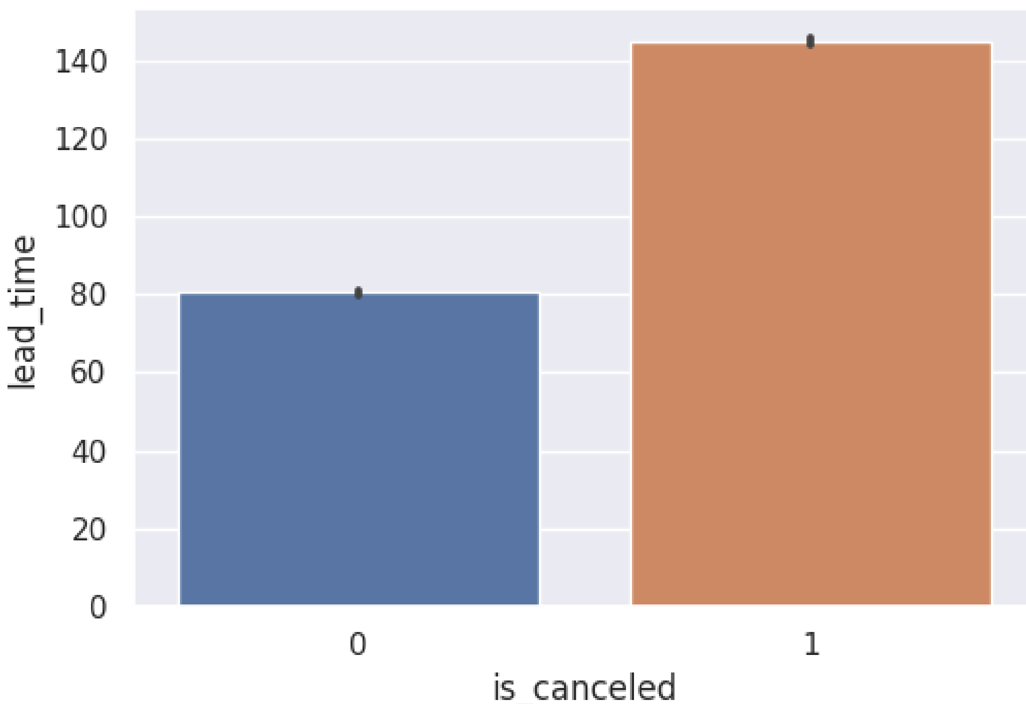
```
#Dropping columns with lesser impact
cols_to_drop = ['reservation_status',
```

```
'reservation_status_date','agent','distribution_channel','meal',
               'previous_bookings_not_canceled','is_repeated_guest']

df.drop(columns = cols_to_drop, inplace=True)
```

Lead Time and waiting list

We may assume that if there is higher lead time, there is a higher chance of cancellation as people may have longer time to change options. We will check this.

```
sns.set(rc={"figure.figsize":(6,4)})
sns.barplot(x=df["is_canceled"],y=df["lead_time"])

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

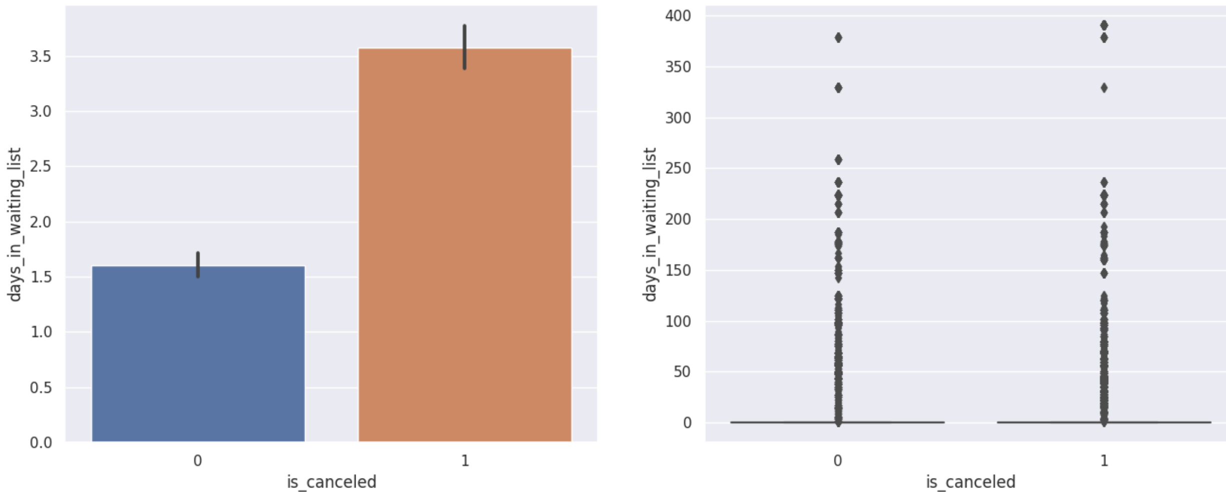


Our assumption was correct. Higher lead time is leading to higher cancellations.

Similarly, we may also assume that higher number of days in waiting list may also lead to higher cancellations.

```
sns.set(rc={"figure.figsize":(16,6)})
f, axes = plt.subplots(1, 2)

sns.barplot(x=df["is_canceled"],y=df["days_in_waiting_list"],ax=axes[0
])
sns.boxplot(x=df["is_canceled"],y=df["days_in_waiting_list"],ax=axes[1
])
```

```
plt.show()
```



- This assumption is also true. Higher days in waiting list lead to higher cancellations.
- The mean number of days in waiting list is around 3.5 but there are outliers that go up to 400 days in waiting list.

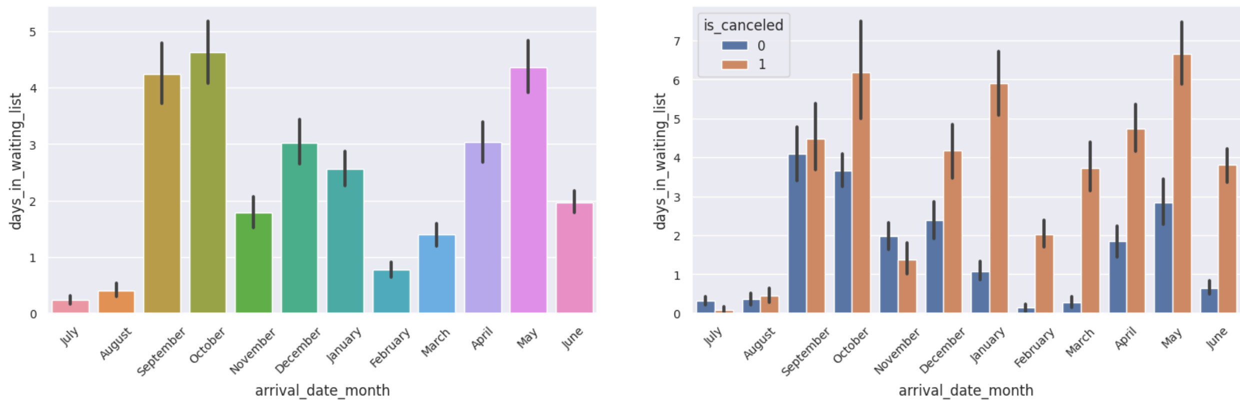
We can drop week number column as year, month and day is already given

```
df = df.drop(columns = ["arrival_date_week_number"])
```

Relationship between month and days in waiting list.

```
# Set figure size
sns.set(rc={"figure.figsize":(16,6)})
f, axes = plt.subplots(1, 2, figsize=(16, 6))

# Plotting barplots
sns.barplot(x=df["arrival_date_month"], y=df["days_in_waiting_list"],
ax=axes[0])
sns.barplot(x=df["arrival_date_month"], y=df["days_in_waiting_list"],
hue=df["is_canceled"], ax=axes[1])

# Adjust font size and rotation of labels
for ax in axes:
    ax.tick_params(axis='both', which='major', labelsize=10)  # Reduce
font size of tick labels
    ax.set_xlabel(ax.get_xlabel(), fontsize=12)  # Adjust font size of
x-axis labels
    ax.set_ylabel(ax.get_ylabel(), fontsize=12)  # Adjust font size of
y-axis labels
    ax.set_xticklabels(ax.get_xticklabels(), rotation=45)  # Rotate x-
axis labels to prevent overlap
```

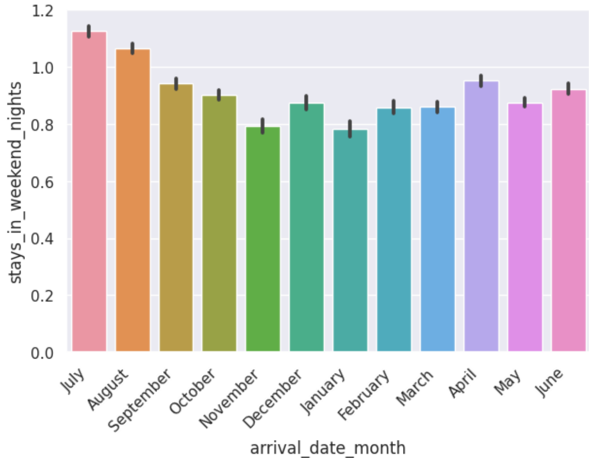
```
plt.tight_layout(pad=4.0)  # Adjust spacing between subplots
plt.show()
```

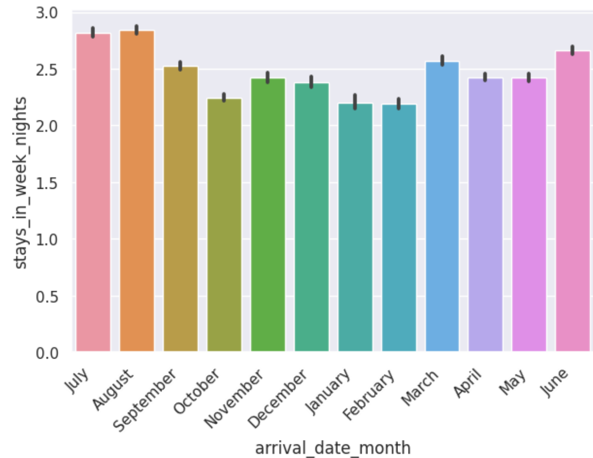


- The peak tourist season as per many travel websites is between July and September.
- We can assume that since October is the end of tourist season and May being the beginning of tourist season, the mean number of days in waiting list is high.
- We can also see that despite lesser mean number of days in waiting list in January, February, March and June, the mean days in waiting list for cancellation is very high. This can indicate that if days in waiting list crosses a certain threshold especially during off-season, there is higher tendency of cancellation.

Duration and type of stay

```
# Set a more appropriate figure size
sns.set(rc={"figure.figsize":(14,6)})  # Adjust width and height to
better fit the plots
f, axes = plt.subplots(1, 2, figsize=(14, 6))  # Adjust figure size

# Plotting barplots
sns.barplot(x=df["arrival_date_month"],
y=df["stays_in_weekend_nights"], ax=axes[0])
sns.barplot(x=df["arrival_date_month"], y=df["stays_in_week_nights"],
ax=axes[1])

# Rotate x-axis labels to prevent overlap
for ax in axes:
    ax.set_xticklabels(ax.get_xticklabels(), rotation=45, ha='right')
# Rotate labels and align them to the right

plt.tight_layout(pad=4.0)  # Adjust spacing between subplots
plt.show()
```



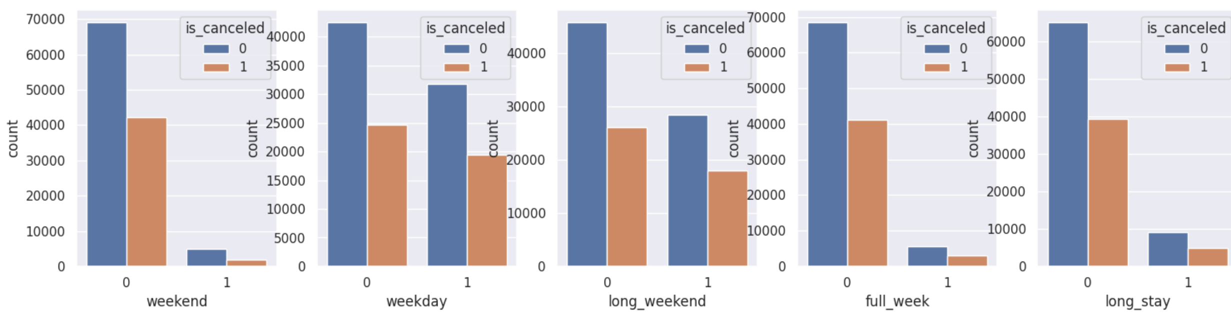


The average number of stays in weeknights is more than weekend nights. This is probably because there are more number of weeknights. However, the overall pattern of bookings look similar for both.

We want to see if there is any relation between cancellation and duration of stay during weekends or weeknights.

```
df["total_stay"] = df["stays_in_weekend_nights"] +
df["stays_in_week_nights"]

#Dividing data into different columns based on the duration of stay
df["weekend"] = 0
df["weekday"] = 0
df["full_week"] = 0
df["long_weekend"]=0
df["long_stay"] = 0

row_index = 0

for i in df["stays_in_weekend_nights"]:
    if df["total_stay"][row_index]<7:
        if i==0 and df["stays_in_week_nights"][row_index]>0:
            df["weekday"][row_index] = 1
        if i>0 and df["stays_in_week_nights"][row_index]==0:
            df["weekend"][row_index] = 1
        if i>0 and df["stays_in_week_nights"][row_index]>0:
            df["long_weekend"][row_index] = 1
    if i>0 and df["stays_in_week_nights"][row_index]>0 and
df["total_stay"][row_index]==7:
        df["full_week"][row_index] = 1

    if df["total_stay"][row_index] >= 7:
        df["long_stay"][row_index] = 1
    row_index = row_index + 1
```

```python
sns.set(rc={"figure.figsize":(18,4)})
f, axes = plt.subplots(1,5)

sns.countplot(x=df["weekend"],hue = df["is_canceled"],ax=axes[0])
sns.countplot(x=df["weekday"],hue = df["is_canceled"],ax=axes[1])
sns.countplot(x=df["long_weekend"],hue = df["is_canceled"],ax=axes[2])
sns.countplot(x=df["full_week"],hue = df["is_canceled"],ax=axes[3])
sns.countplot(x=df["long_stay"],hue = df["is_canceled"],ax=axes[4])

plt.show()
```




```python
stay_dur =
['weekend','weekday','long_weekend','full_week','long_stay']
for stay in stay_dur:
    perc = df.groupby([stay, 'is_canceled']).size().unstack(1)
    perc["total perc"] = (perc[0] + perc[1])/len(df["is_canceled"])
    perc["canc perc"] = (perc[1]/(perc[0] + perc[1]))
    print(perc)
```

```
is_canceled      0      1  total perc  canc perc
weekend
0            69205  42216    0.941517   0.378887
1             5045   1876    0.058483   0.271059
is_canceled      0      1  total perc  canc perc
weekday
0            42521  24661    0.567694   0.367077
1            31729  19431    0.432306   0.379808
is_canceled       0      1  total perc  canc perc
long_weekend
0             45795  26145    0.607899   0.363428
1             28455  17947    0.392101   0.386772
is_canceled      0      1  total perc  canc perc
full_week
0            68574  41129       0.927   0.374912
1             5676   2963       0.073   0.342980
is_canceled      0      1  total perc  canc perc
long_stay
0            65229  39254     0.88289   0.375697
1             9021   4838     0.11711   0.349087
```

- We can see that a stay of full week or more has lesser bookings but significant cancellations.
- Only weekend stay is also less common and cancellations are also less.
- But staying on weekdays or weekdays including weekends is more common and the cancellations percentages are also significant.
- We can drop the redundant columns

```
#Dropping redundant columns related to stay
df = df.drop(columns =
["stays_in_weekend_nights","stays_in_week_nights",'arrival_date_day_of_month'])
```

Country

```
cnt = dict(df['country'].value_counts(normalize=True))
cnt
```

```
{'PRT': 0.40638335779551876,
 'GBR': 0.10248665891795128,
 'FRA': 0.08792812359483834,
 'ESP': 0.0723684768683878,
 'DEU': 0.061687127234472165,
 'ITA': 0.031789529053440686,
 'IRL': 0.02858257896478294,
 'BEL': 0.01969983625889759,
 'BRA': 0.018724176840390603,
 'NLD': 0.017748517421883617,
 'USA': 0.017655193477504688,
 'CHE': 0.014550051328169408,
 'CN': 0.010842545537842859,
 'AUT': 0.010681349633915618,
 'SWE': 0.008619738862635638,
 'CHN': 0.008458542958708397,
 'POL': 0.007737403388507581,
 'ISR': 0.005667308622284061,
 'RUS': 0.005285528849824805,
 'NOR': 0.005132816940841103,
 'ROU': 0.004216545486938889,
 'FIN': 0.003766893754931322,
 'DNK': 0.003648117825721776,
 'AUS': 0.00361418184594762,
 'AGO': 0.0030627221746175838,
 'LUX': 0.00240945456396508,
 'MAR': 0.0021634187106024487,
 'TUR': 0.002095546751054136,
 'HUN': 0.0019343508471268952,
 'ARG': 0.0017986069280302708,
```

```
 'JPN': 0.0016713470038771858,
 'CZE': 0.0014507631353451714,
 'IND': 0.001272599241530852,
 'KOR': 0.0011198873325471497,
 'GRC': 0.0010859513527729937,
 'DZA': 0.0008738514791845184,
 'SRB': 0.0008568834892974404,
 'HRV': 0.0008483994943539014,
 'EST': 0.0007041715803137381,
 'MEX': 0.0007041715803137381,
 'IRN': 0.0006956875853701991,
 'LTU': 0.0006872035904266601,
 'ZAF': 0.0006702356005395821,
 'BGR': 0.000636299620765426,
 'NZL': 0.000627815625821887,
 'COL': 0.00060236364099127,
 'UKR': 0.0005769116561606529,
 'MOZ': 0.0005599436662735749,
 'SVK': 0.0005514596713300359,
 'CHL': 0.0005429756763864968,
 'THA': 0.0004920717067252628,
 'ISL': 0.0004751037168381848,
 'LVA': 0.00046661972189464577,
 'SVN': 0.00046661972189464577,
 'TWN': 0.0004326837421204897,
 'CYP': 0.0004326837421204897,
 'ARE': 0.00041571575223341167,
 'SAU': 0.00039874776234633365,
 'PHL': 0.00033935979774156054,
 'SGP': 0.0003223918078544825,
 'TUN': 0.0003223918078544825,
 'IDN': 0.0002969398230238655,
 'NGA': 0.00028845582808032644,
 'URY': 0.0002714878381932484,
 'EGY': 0.0002630038432497094,
 'LBN': 0.0002630038432497094,
 'HKG': 0.0002460358533626314,
 'PER': 0.0002460358533626314,
 'MYS': 0.0002375518584190924,
 'ECU': 0.00022906786347555338,
 'VEN': 0.00022058386853201435,
 'BLR': 0.00020361587864493633,
 'CPV': 0.00020361587864493633,
 'GEO': 0.0001866478887578583,
 'JOR': 0.00016967989887078027,
 'KAZ': 0.00016119590392724126,
 'CRI': 0.00016119590392724126,
 'GIB': 0.00015271190898370225,
 'MLT': 0.00015271190898370225,
```

```
 'AZE': 0.00014422791404016322,
 'OMN': 0.00014422791404016322,
 'MAC': 0.0001357439190966242,
 'KWT': 0.0001357439190966242,
 'QAT': 0.0001187759292095462,
 'DOM': 0.0001187759292095462,
 'IRQ': 0.0001187759292095462,
 'PAK': 0.0001187759292095462,
 'BIH': 0.00011029193426600717,
 'PRI': 0.00010180793932246817,
 'BGD': 0.00010180793932246817,
 'MDV': 0.00010180793932246817,
 'ALB': 0.00010180793932246817,
 'SEN': 9.332394437892914e-05,
 'BOL': 8.483994943539014e-05,
 'MKD': 8.483994943539014e-05,
 'CMR': 8.483994943539014e-05,
 'TJK': 7.635595449185113e-05,
 'GNB': 7.635595449185113e-05,
 'PAN': 7.635595449185113e-05,
 'ARM': 6.78719595483121e-05,
 'CUB': 6.78719595483121e-05,
 'VNM': 6.78719595483121e-05,
 'JEY': 6.78719595483121e-05,
 'LBY': 6.78719595483121e-05,
 'AND': 5.93879646047731e-05,
 'LKA': 5.93879646047731e-05,
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 'CIV': 5.090396966123408e-05,
 'JAM': 5.090396966123408e-05,
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 'FRO': 4.241997471769507e-05,
 'BHR': 4.241997471769507e-05,
 'CAF': 4.241997471769507e-05,
 'GTM': 3.393597977415605e-05,
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 'BEN': 2.545198483061704e-05,
 'TMP': 2.545198483061704e-05,
 'ETH': 2.545198483061704e-05,
 'TZA': 2.545198483061704e-05,
 'SYR': 2.545198483061704e-05,
```

```
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 'SLV': 1.6967989887078026e-05,
 'ABW': 1.6967989887078026e-05,
 'MYT': 1.6967989887078026e-05,
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 'GLP': 1.6967989887078026e-05,
 'MWI': 1.6967989887078026e-05,
 'UGA': 1.6967989887078026e-05,
 'COM': 1.6967989887078026e-05,
 'TGO': 1.6967989887078026e-05,
 'ZMB': 1.6967989887078026e-05,
 'KNA': 1.6967989887078026e-05,
 'RWA': 1.6967989887078026e-05,
 'STP': 1.6967989887078026e-05,
 'SYC': 1.6967989887078026e-05,
 'KHM': 1.6967989887078026e-05,
 'IMN': 1.6967989887078026e-05,
 'NCL': 8.483994943539013e-06,
 'KIR': 8.483994943539013e-06,
 'SDN': 8.483994943539013e-06,
 'ATF': 8.483994943539013e-06,
 'SLE': 8.483994943539013e-06,
 'AIA': 8.483994943539013e-06,
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 'MDG': 8.483994943539013e-06,
 'UMI': 8.483994943539013e-06,
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 'GUY': 8.483994943539013e-06,
 'LCA': 8.483994943539013e-06,
 'MRT': 8.483994943539013e-06,
 'ASM': 8.483994943539013e-06}
```
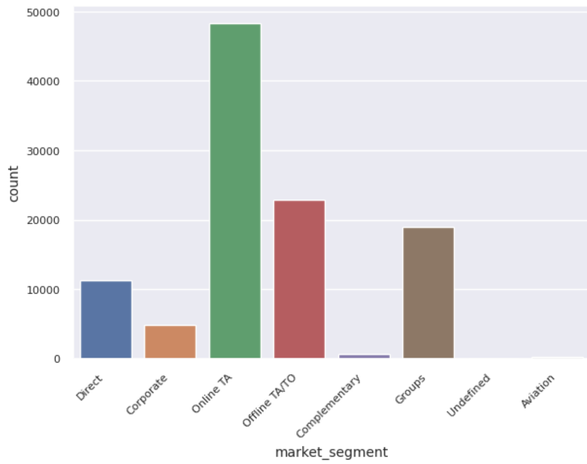
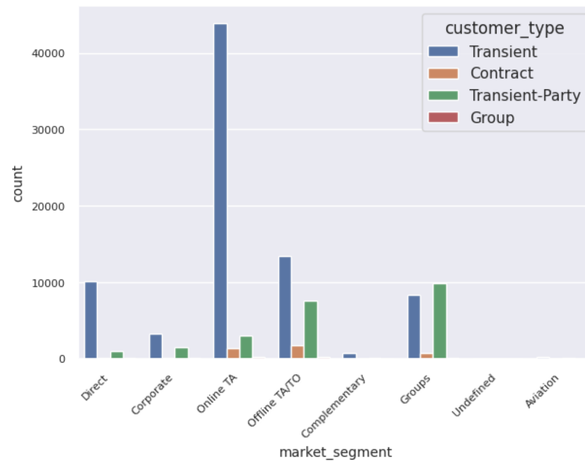

We can see that top 15 countries cover more than 80% of the data. For ease of exploration and processing, we will only keep the top 15 countries.

```
df = df[(df["country"]=="PRT") | (df["country"]=="GBR") |
(df["country"]=="FRA") |(df["country"]=="ESP") |
(df["country"]=="DEU") |
        (df["country"]=="ITA") | (df["country"]=="IRL") |
(df["country"]=="BEL") | (df["country"]=="BRA") |
        (df["country"]=="NLD") | (df["country"]=="USA") |
(df["country"]=="CHE") | (df["country"]=="CN") |
        (df["country"]=="AUT") | (df["country"]=="SWE")]
```

Market Segment and Customer type

```
# Dropping undefined values from market segment
row_index = 0
for i in df["market_segment"]:
    if i == "Undefined":
        df = df.drop(row_index)
    row_index = row_index + 1

df = df.reset_index()
df = df.drop(columns=["index"])

# Set figure size and create subplots
sns.set(rc={"figure.figsize":(14,6)})  # Adjust figure size as needed
f, axes = plt.subplots(1, 2, figsize=(14, 6))

# Plotting countplots
sns.countplot(x=df["market_segment"], ax=axes[0])
sns.countplot(x=df["market_segment"], hue=df["customer_type"],
ax=axes[1])

# Adjust font size of ticks and labels
for ax in axes:
    ax.tick_params(axis='both', which='major', labelsize=8)  # Reduce
font size of tick labels
    ax.set_xlabel(ax.get_xlabel(), fontsize=10)  # Reduce font size of
x-axis labels
    ax.set_ylabel(ax.get_ylabel(), fontsize=10)  # Reduce font size of
y-axis labels
    ax.set_xticklabels(ax.get_xticklabels(), rotation=45, ha='right')
# Rotate x-axis labels

plt.tight_layout(pad=4.0)  # Adjust spacing between subplots
plt.show()
```



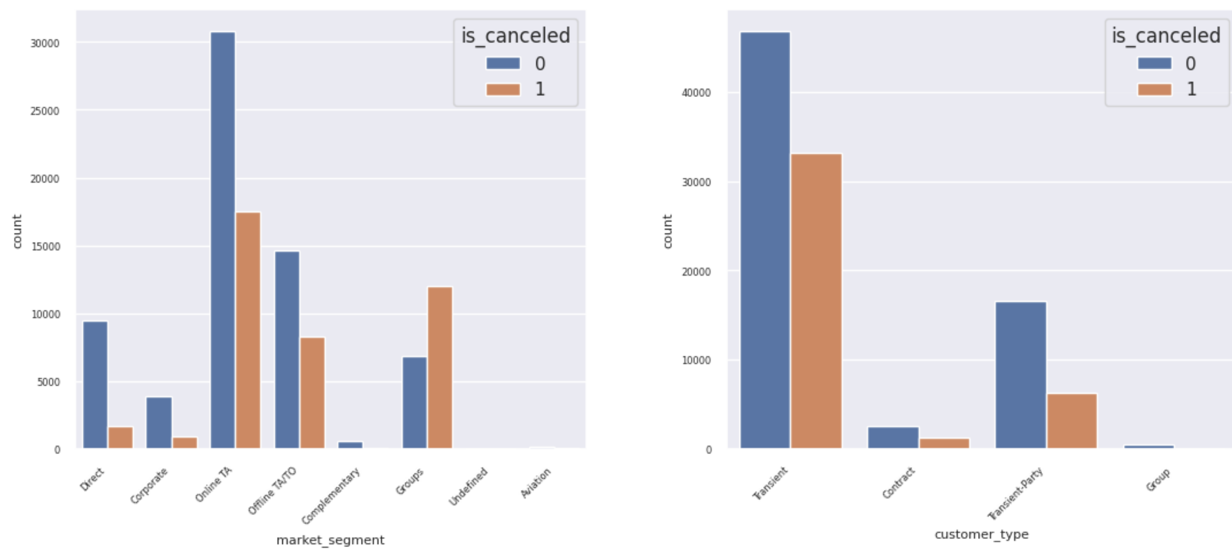



```
perc = df.groupby(['market_segment', 'is_canceled']).size().unstack(1)
perc["total perc"] = (perc[0] + perc[1])/len(df["is_canceled"])
perc["canc perc"] = (perc[1]/(perc[0] + perc[1]))
print(perc)

is_canceled            0        1  total perc  canc perc
market_segment
Aviation           152.0     50.0    0.001884   0.247525
Complementary      609.0     85.0    0.006472   0.122478
Corporate         3871.0    972.0    0.045165   0.200702
Direct            9518.0   1739.0    0.104981   0.154482
Groups            6886.0  12056.0    0.176650   0.636469
Offline TA/TO    14656.0   8267.0    0.213776   0.360642
Online TA        30831.0  17535.0    0.451053   0.362548
Undefined            NaN      2.0         NaN        NaN
```

- Under market segment, the highest booking is by Online Travel Agents. However the highest cancellation percentage is with the Groups.

```
# Adjusting figure size to prevent scrolling
sns.set(rc={"figure.figsize":(12,6)})  # Smaller figure size
f, axes = plt.subplots(1, 2, figsize=(12, 6))  # Adjust size for two
plots side by side

# Plotting countplots
sns.countplot(x=df["market_segment"], hue=df["is_canceled"],
ax=axes[0])
sns.countplot(x=df["customer_type"], hue=df["is_canceled"],
ax=axes[1])

# Adjust font size and rotate labels
for ax in axes:
    ax.tick_params(axis='both', which='major', labelsize=6)  # Reduce
font size of tick labels
    ax.set_xlabel(ax.get_xlabel(), fontsize=8)  # Reduce font size of
```

```
x-axis labels
    ax.set_ylabel(ax.get_ylabel(), fontsize=8)  # Reduce font size of
y-axis labels
    ax.set_xticklabels(ax.get_xticklabels(), rotation=45, ha='right',
fontsize=6)  # Rotate x-axis labels and reduce font size

plt.tight_layout(pad=4.0)  # Adjust spacing between subplots
plt.show()
```




```
perc = df.groupby(['customer_type', 'is_canceled']).size().unstack(1)
perc["total perc"] = (perc[0] + perc[1])/len(df["is_canceled"])
perc["canc perc"] = (perc[1]/(perc[0] + perc[1]))
print(perc)
```

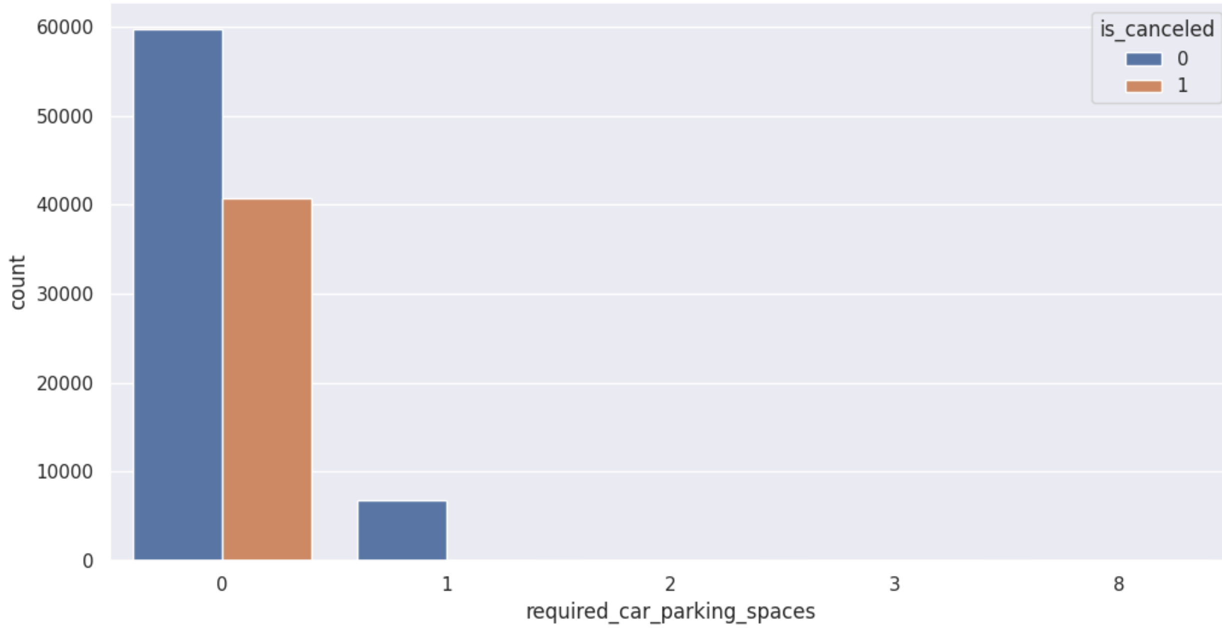
is_canceled	0	1	total perc	canc perc
customer_type				
Contract	2582	1262	0.035849	0.328304
Group	471	58	0.004933	0.109641
Transient	46833	33108	0.745517	0.414155
Transient-Party	16637	6278	0.213702	0.273969

SImilarly, transient customer has the highest cancellation among customer types.

Parking space requirement

```
sns.countplot(x=df["required_car_parking_spaces"],hue=df["is_canceled"
])
```

```
<Axes: xlabel='required_car_parking_spaces', ylabel='count'>
```




```
perc = df.groupby(['required_car_parking_spaces',
'is_canceled']).size().unstack(1)
perc["total perc"] = (perc[0] + perc[1])/len(df["is_canceled"])
perc["canc perc"] = (perc[1]/(perc[0] + perc[1]))
print(perc)
```

```
is_canceled                        0        1  total perc  canc perc
required_car_parking_spaces
0                            59732.0  40706.0    0.936668   0.405285
1                             6759.0      NaN         NaN        NaN
2                               27.0      NaN         NaN        NaN
3                                3.0      NaN         NaN        NaN
8                                2.0      NaN         NaN        NaN
```

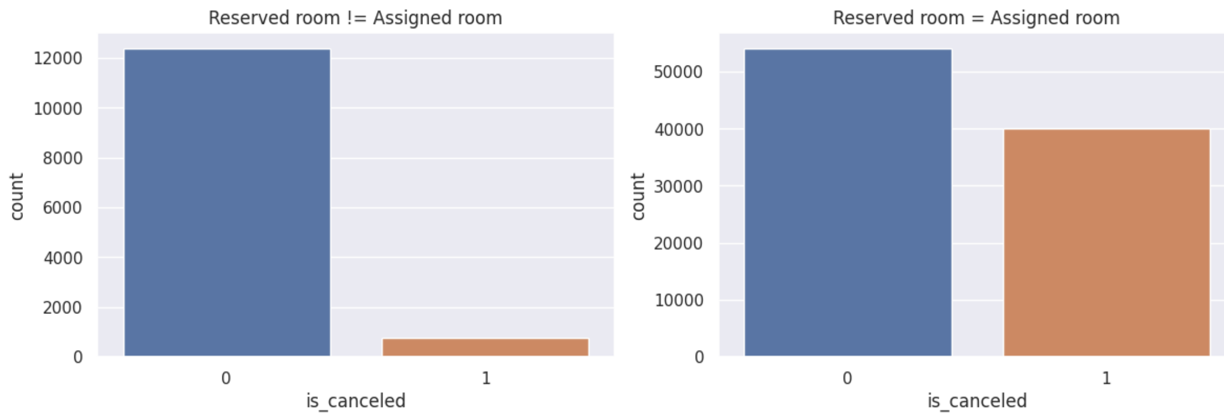
93% of data belongs to people who did not require parking spaces. All the cancellations belong to this category only.

Room reservation and allotment

We can assume that people who were not assigned the same room that was reserved for them may cancel reservations. For this, we can take a separate dataset consisting only of data where reserved room type is not same as assigned room type and check.

```
rooms = df[(df["reserved_room_type"]) != (df["assigned_room_type"])]
rooms_no_change = df[(df["reserved_room_type"]) ==
(df["assigned_room_type"])]

f,axes = plt.subplots(1,2,figsize=(14,4))
sns.countplot(x=rooms["is_canceled"],ax=axes[0]).set(title="Reserved
room != Assigned room")
```

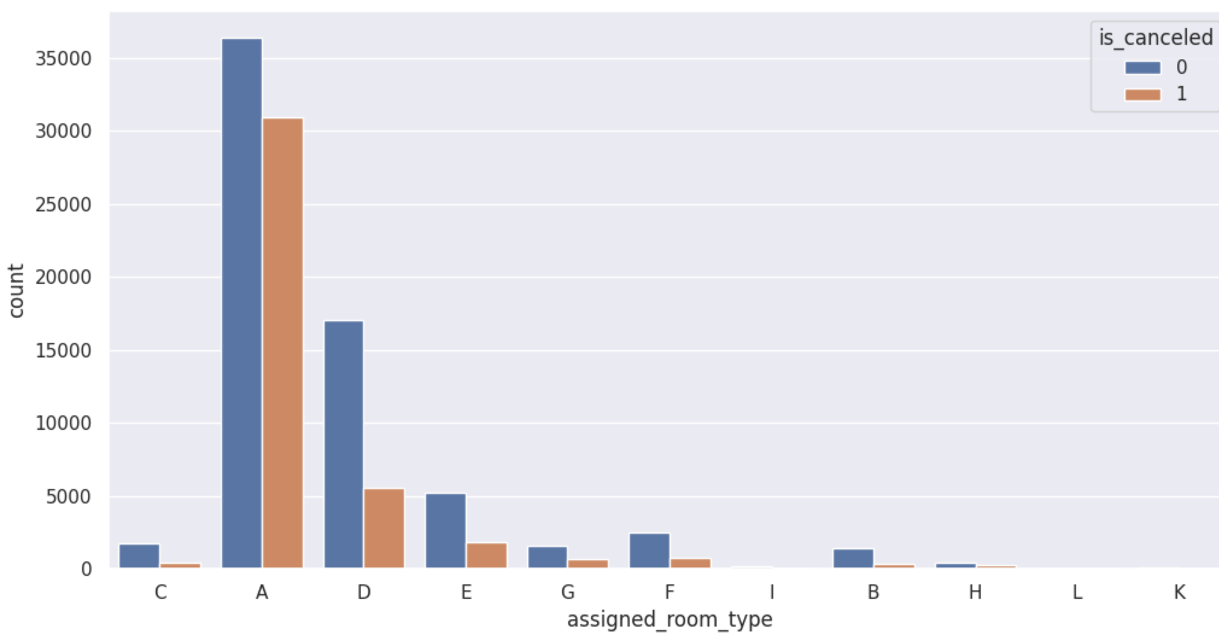
```
sns.countplot(x=rooms_no_change["is_canceled"],ax=axes[1]).set(title="
Reserved room = Assigned room")
plt.show()
```



We can see that out of the data, the impact on cancellation is marginal even if assigned room is not same as reserved room. However, to reduce redundancy, we can combine it into a single column indicating if there is a change in reserved and assigned room.

Let us also check if assigned room type has any influence on the cancellation

```
sns.countplot(x=df["assigned_room_type"],hue=df["is_canceled"])

<Axes: xlabel='assigned_room_type', ylabel='count'>
```



We see that room A and D have majority guests and cancellations are also high.

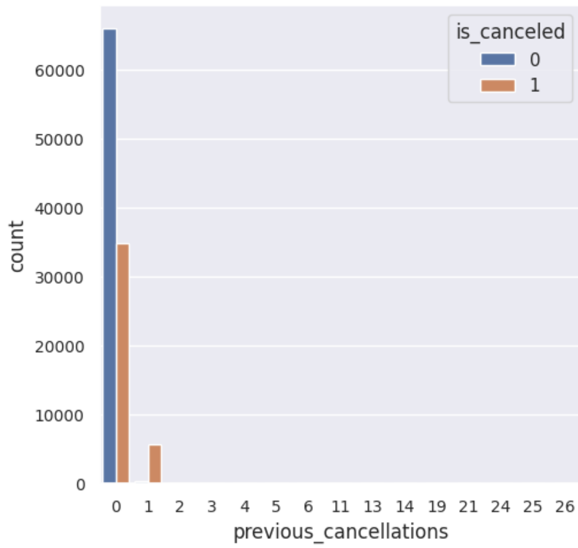
Checking if change of room has any impact on cancellation

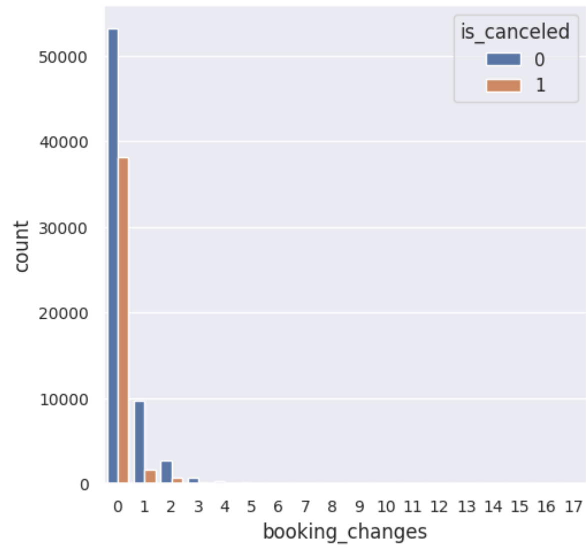
```
#Adding additional column to see if there is any change of room
df["room_change"] = 0

row_index = 0
for i in df["reserved_room_type"]:
    if i == df["assigned_room_type"][row_index]:
        df["room_change"][row_index] = 0
    else:
        df["room_change"][row_index] = 1
    row_index = row_index + 1


df.drop(columns = ["reserved_room_type","assigned_room_type"],
inplace=True)
```

Previous cancellations and booking changes

We can assume that people who have made previous cancellations have a higher likelihood to cancel this time. Similarly customers who have not canceled previous bookings will also not cancel this time.

```
sns.set(rc={"figure.figsize":(12,6)})  # Adjust figure size for better
fit
f, axes = plt.subplots(1, 2, figsize=(12, 6))  # Adjust size for two
plots side by side

# Plotting countplots
sns.countplot(x=df["previous_cancellations"], hue=df["is_canceled"],
ax=axes[0])
sns.countplot(x=df["booking_changes"], hue=df["is_canceled"],
ax=axes[1])

# Adjust font size of ticks and labels
for ax in axes:
    ax.tick_params(axis='both', which='major', labelsize=10)  # Adjust
font size of tick labels
    ax.set_xlabel(ax.get_xlabel(), fontsize=12)  # Adjust font size of
x-axis labels
    ax.set_ylabel(ax.get_ylabel(), fontsize=12)  # Adjust font size of
y-axis labels

plt.tight_layout(pad=4.0)  # Adjust spacing between subplots
plt.show()
```






```
perc = df.groupby(['previous_cancellations',
'is_canceled']).size().unstack(1)
perc["total perc"] = (perc[0] + perc[1])/len(df["is_canceled"])
perc["canc perc"] = (perc[1]/(perc[0] + perc[1]))
print(perc)
```

```
is_canceled                    0        1  total perc  canc perc
previous_cancellations
0                        66005.0  34796.0    0.940054   0.345195
1                          320.0   5683.0    0.055983   0.946693
2                           74.0     37.0    0.001035   0.333333
3                           45.0     20.0    0.000606   0.307692
4                           24.0      7.0    0.000289   0.225806
5                           17.0      2.0    0.000177   0.105263
6                           15.0      7.0    0.000205   0.318182
11                          22.0     10.0    0.000298   0.312500
13                           1.0     11.0    0.000112   0.916667
14                           NaN     14.0         NaN        NaN
19                           NaN     19.0         NaN        NaN
21                           NaN      1.0         NaN        NaN
24                           NaN     48.0         NaN        NaN
25                           NaN     25.0         NaN        NaN
26                           NaN     26.0         NaN        NaN
```

```
perc = df.groupby(['booking_changes',
'is_canceled']).size().unstack(1)
perc["total perc"] = (perc[0] + perc[1])/len(df["is_canceled"])
perc["canc perc"] = (perc[1]/(perc[0] + perc[1]))
print(perc)
```

```
is_canceled             0        1  total perc  canc perc
booking_changes
0                 53159.0  38195.0    0.851952   0.418099
```

```
1                   9649.0   1640.0    0.105279   0.145274
2                   2636.0    650.0    0.030645   0.197809
3                    660.0    123.0    0.007302   0.157088
4                    251.0     57.0    0.002872   0.185065
5                     79.0     14.0    0.000867   0.150538
6                     34.0     16.0    0.000466   0.320000
7                     21.0      3.0    0.000224   0.125000
8                     10.0      4.0    0.000131   0.285714
9                      7.0      1.0    0.000075   0.125000
10                     5.0      1.0    0.000056   0.166667
11                     1.0      NaN         NaN        NaN
12                     1.0      NaN         NaN        NaN
13                     5.0      NaN         NaN        NaN
14                     1.0      1.0    0.000019   0.500000
15                     2.0      NaN         NaN        NaN
16                     NaN      1.0         NaN        NaN
17                     2.0      NaN         NaN        NaN
```

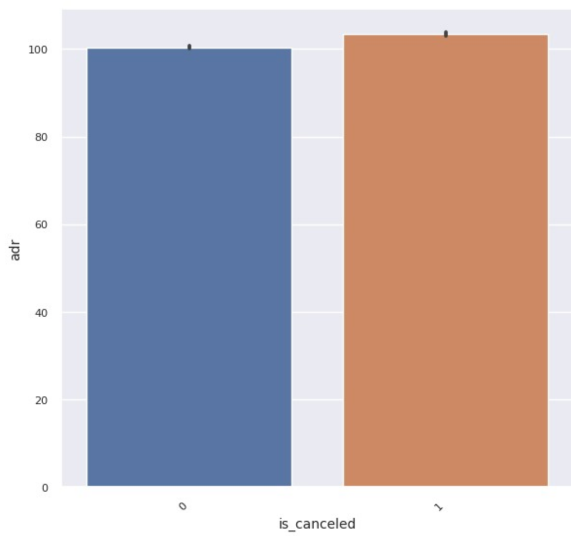
- Here, we can see that cancellation percentage is high where previous cancellation is 1. Hence our first assumption is true.
- However, second assumption has failed. But that is because of the count of data. The column has maximum number of the same value.

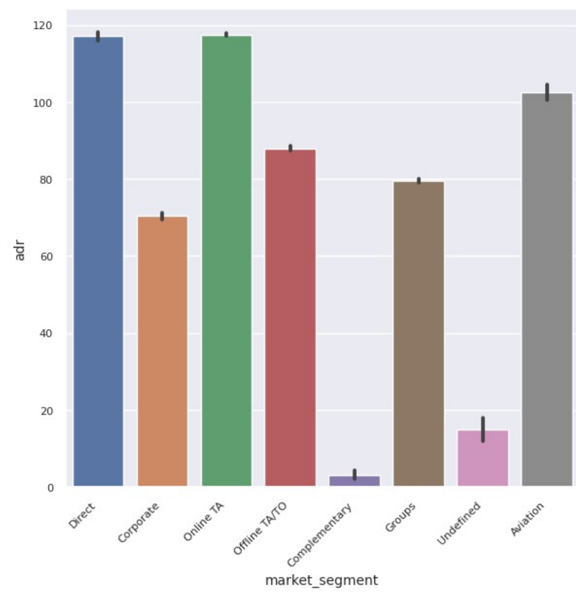
Relationship with adr

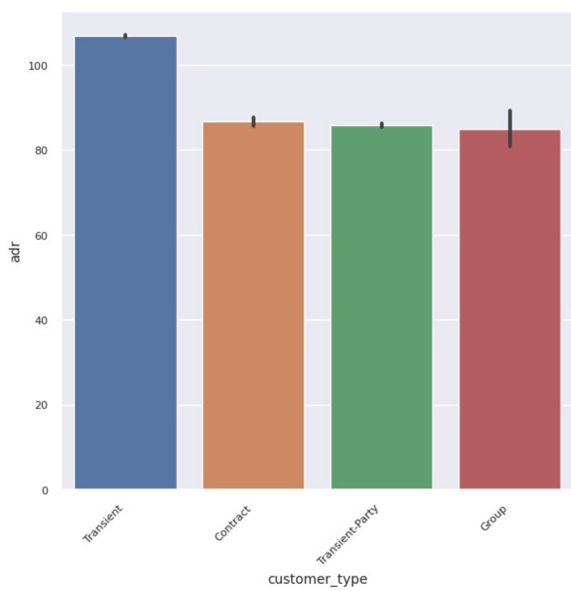
adr - Average Daily Rate - It can be assumed that rooms with higher adr may be costlier. Hence, the chances of cancellation needs to be examined. As we do not have a feature for room price, we should check the relationship of adr with other factors also.

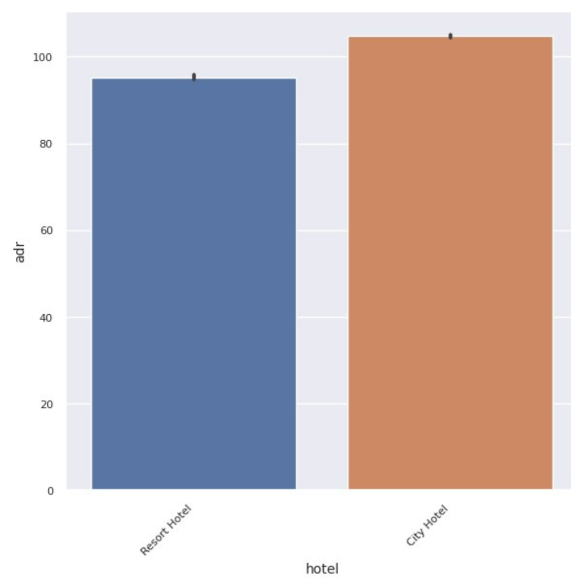
```
f, axes = plt.subplots(3, 2, figsize=(14, 20))

# Plotting barplots and scatterplots
sns.barplot(x=df["is_canceled"], y=df["adr"], ax=axes[0, 0])
sns.barplot(x=df["market_segment"], y=df["adr"], ax=axes[0, 1])
sns.barplot(x=df["customer_type"], y=df["adr"], ax=axes[1, 0])
sns.barplot(x=df["hotel"], y=df["adr"], ax=axes[1, 1])
sns.scatterplot(x=df["lead_time"], y=df["adr"], ax=axes[2, 0])
sns.scatterplot(x=df["days_in_waiting_list"], y=df["adr"], ax=axes[2, 
1])

# Adjust font size and rotate labels for barplots
for ax in axes.flat:
    if ax in [axes[0, 0], axes[0, 1], axes[1, 0], axes[1, 1]]:
        ax.tick_params(axis='both', which='major', labelsize=8)  # 
Reduce font size of tick labels
        ax.set_xlabel(ax.get_xlabel(), fontsize=10)  # Reduce font 
size of x-axis labels
        ax.set_ylabel(ax.get_ylabel(), fontsize=10)  # Reduce font 
```

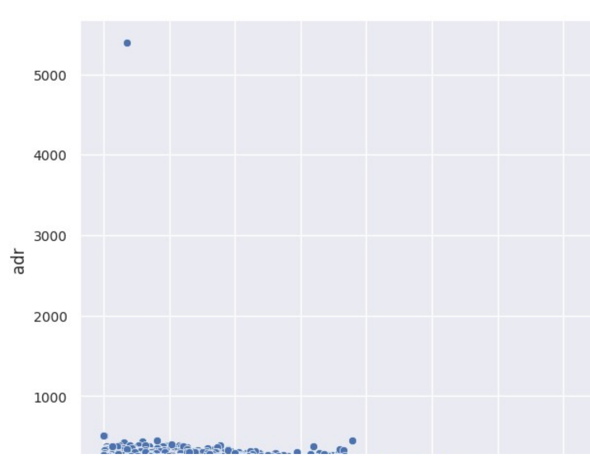
```
size of y-axis labels
        ax.set_xticklabels(ax.get_xticklabels(), rotation=45,
ha='right', fontsize=8)  # Rotate and reduce font size of x-axis
labels
    else:
        ax.tick_params(axis='both', which='major', labelsize=10)  #
Adjust font size of tick labels for scatterplots
        ax.set_xlabel(ax.get_xlabel(), fontsize=12)  # Adjust font
size of x-axis labels for scatterplots
        ax.set_ylabel(ax.get_ylabel(), fontsize=12)  # Adjust font
size of y-axis labels for scatterplots

plt.tight_layout(pad=4.0)  # Adjust spacing between subplots
plt.show()
```

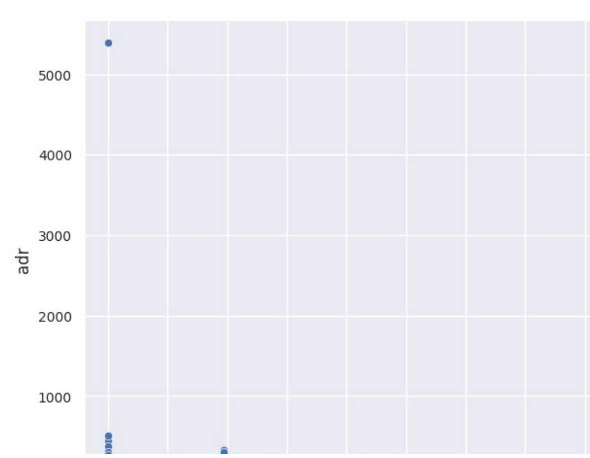

adr
is_canceled
0
1


adr
market_segment
Direct
Corporate
Online TA
Offline TA/TO
Complementary
Groups
Undefined
Aviation


adr
customer_type
Transient
Contract
Transient-Party
Group

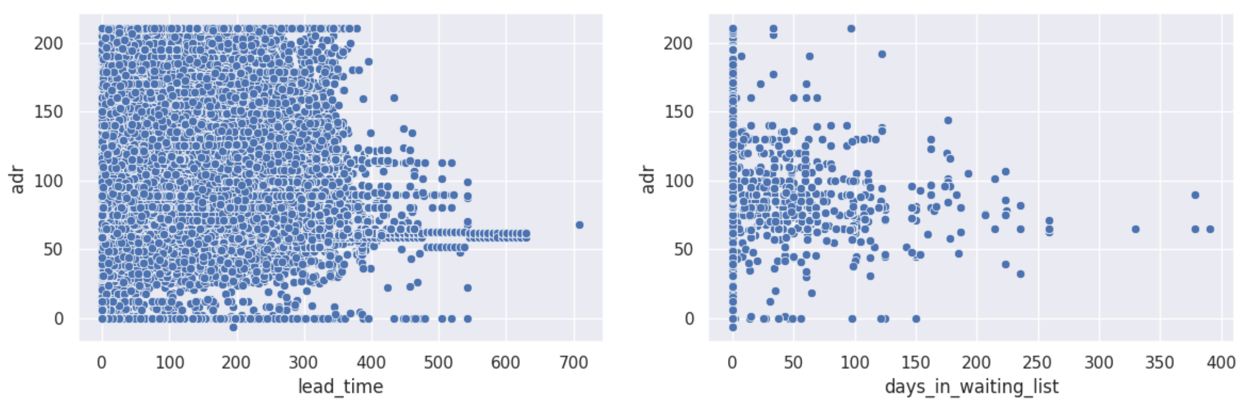

adr
hotel
Resort Hotel
City Hotel


adr


adr

- The mean adr for cancellation is slightly higher than non-cancellations.
- Direct and Online TA market segment have higher mean adr. The bookings in these categories are frequent and the likelihood of concessions is low.
- Transient customer type has higher mean adr. As transient customers are more frequent and seek shorter stays, they bring higher revenue.
- City hotels have higher adr.
- It appears that adr decreases as lead time and waiting list duration increases. But because of outliers, the pattern is unclear.

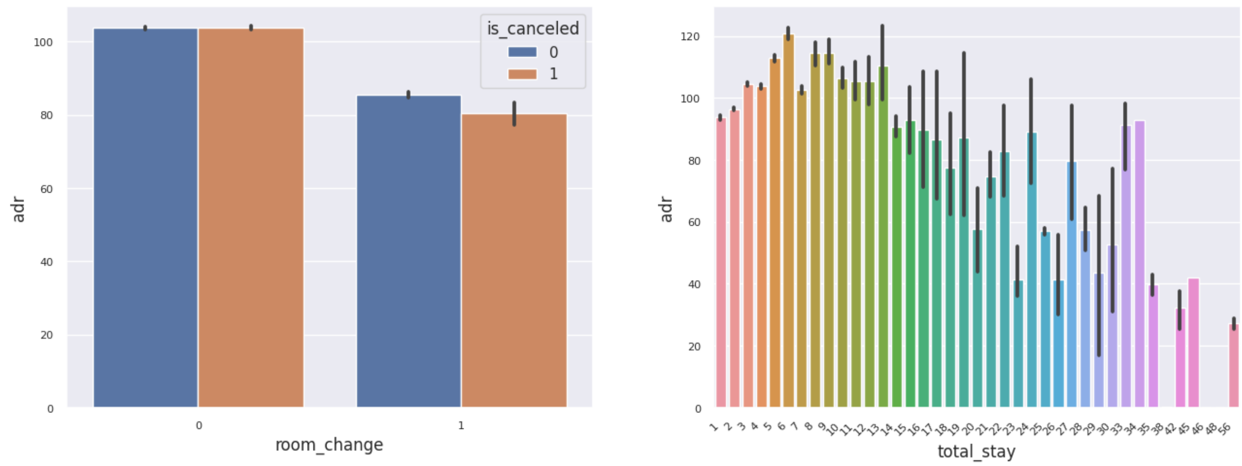
```
#Outlier treatment for waiting list and lead time columns
df1 = df.copy()
def outlier(data):
    Q1 = data.quantile(0.25)
    Q3 = data.quantile(0.75)
    IQR = Q3-Q1
    upper_bound = Q3 + 1.5*IQR
    lower_bound = Q1 - 1.5*IQR
    return data.clip(upper_bound, lower_bound)
for col in ['adr']:
    df1[col] = outlier(df1[col])

f,axes = plt.subplots(1,2,figsize=(14,4))
sns.scatterplot(x=df1["lead_time"],y=df1["adr"],ax=axes[0])
sns.scatterplot(x=df1["days_in_waiting_list"],y=df1["adr"],ax=axes[1])
plt.show()
```



There seems to be no relationship between lead time and adr or waiting list and adr after treating outliers.

```
# Set figure size and create subplots
f, axes = plt.subplots(1, 2, figsize=(14, 6))

# Plotting the first barplot
sns.barplot(x=df["room_change"], y=df["adr"], hue=df["is_canceled"],
ax=axes[0])
axes[0].tick_params(axis='both', which='major', labelsize=8)  #
Further reduce font size of tick labels
```

```
# Plotting the second barplot
sns.barplot(x=df["total_stay"], y=df["adr"], ax=axes[1])
axes[1].tick_params(axis='both', which='major', labelsize=8)  # 
Further reduce font size of tick labels
axes[1].set_xticklabels(axes[1].get_xticklabels(), rotation=45, 
ha='right', fontsize=8)  # Rotate and reduce font size of x-axis 
labels

plt.tight_layout(pad=4.0)  # Adjust spacing between subplots
plt.show()
```



- Room changes have lower mean adr than no room changes. And cancellation after room changes have even lesser adr. This can indicate that hotels incur a loss due to room changes and further cancellation.

- As the total stay duration increases, the mean adr increases and then drops with further increase in duration of stay.

```
#Dropping the remaining records with missing values
df = df.dropna(subset = ["kids"])

df = df.reset_index()
df = df.drop(columns=["index"])
```

Checking the imbalance in data after preliminary preprocessing

```
plt.figure(figsize=(6,4))

ax = sns.countplot(x=df["is_canceled"])
for i in ax.containers:
    ax.bar_label(i)
ax.set(title="Cancelled vs Not cancelled")
plt.show()
```

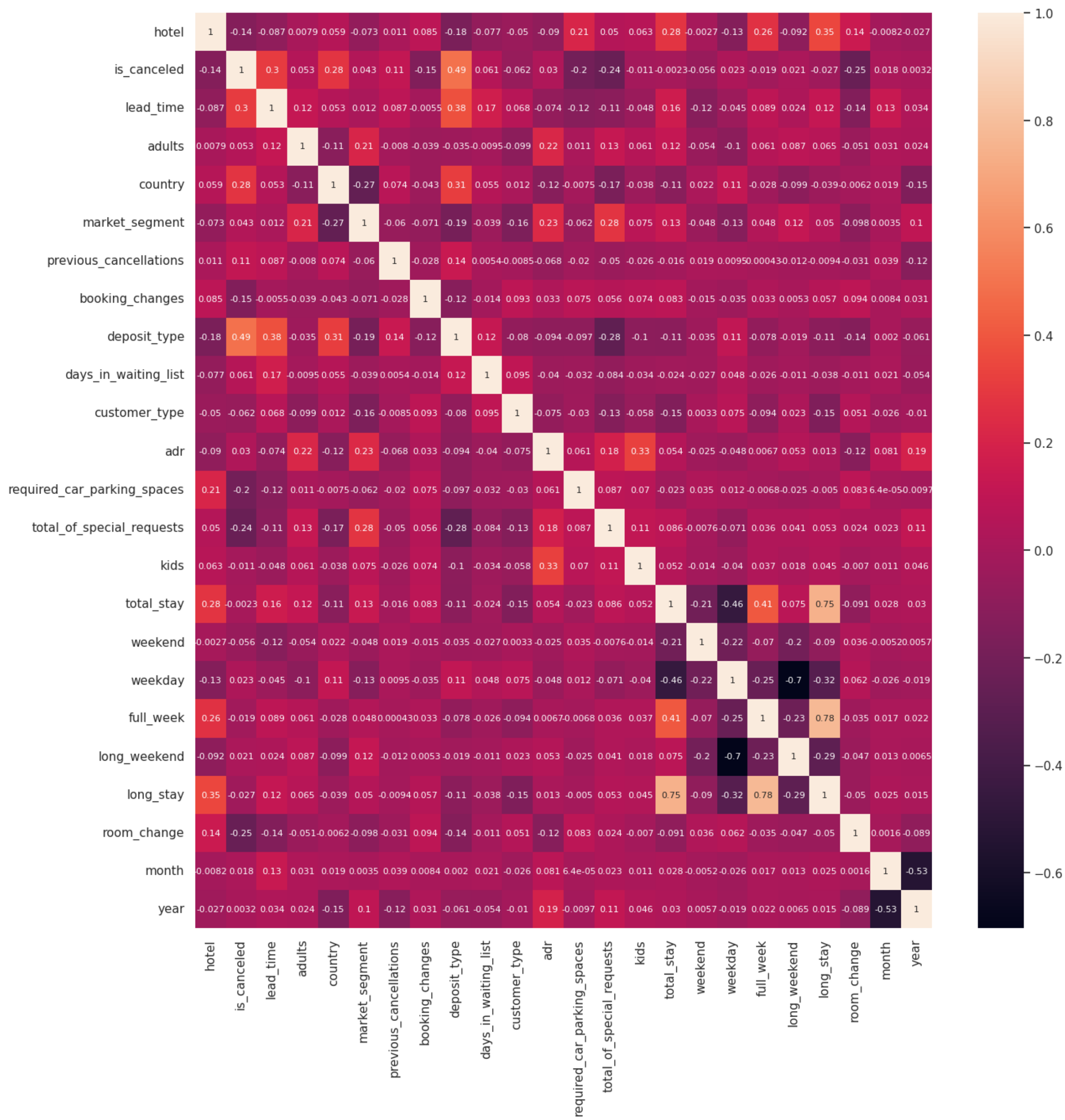
The distribution remains similar after all the eliminations. We will not consider the data as imbalanced because there is a significant amount of positive class.

Correlations

First we encode categorical columns to check correlation and we do this by creating a separate dataset so as not to disturb our original dataset

```
corr_df = df.copy()

corr_df["month"] =
corr_df["arrival_date_month"].map({"January":1,"February":2,"March":3,
"April":4,"May":5,"June":6,"July":7,"August":8,

"September":9,"October":10,"November":11,"December":12})
corr_df["year"] = corr_df["arrival_date_year"].astype(str)

corr_df["year"] = corr_df["year"].map({"2015":1,"2016":2,"2017":3})

corr_df = corr_df.drop(columns =
["arrival_date_month","arrival_date_year"])

cat_cols = corr_df.select_dtypes(include='object').columns

#Encoding all categorical columns
from sklearn.preprocessing import LabelEncoder
obj = LabelEncoder()
```

```
for i in cat_cols:
    corr_df[i] = obj.fit_transform(corr_df[i])

plt.figure(figsize=(15, 15))
sns.heatmap(corr_df.corr(), annot=True, annot_kws={"size": 8})
plt.show()
```



Two columns have a moderate to high correlation which are total stay, full week and long stay. We will drop the redundant column.

Dropping correlated columns from original dataset

```
df = df.drop(columns = ["long_stay"])
```

Converting categorical columns

Now we need to convert categorical columns into numerical

There are ordinal columns: Month and year

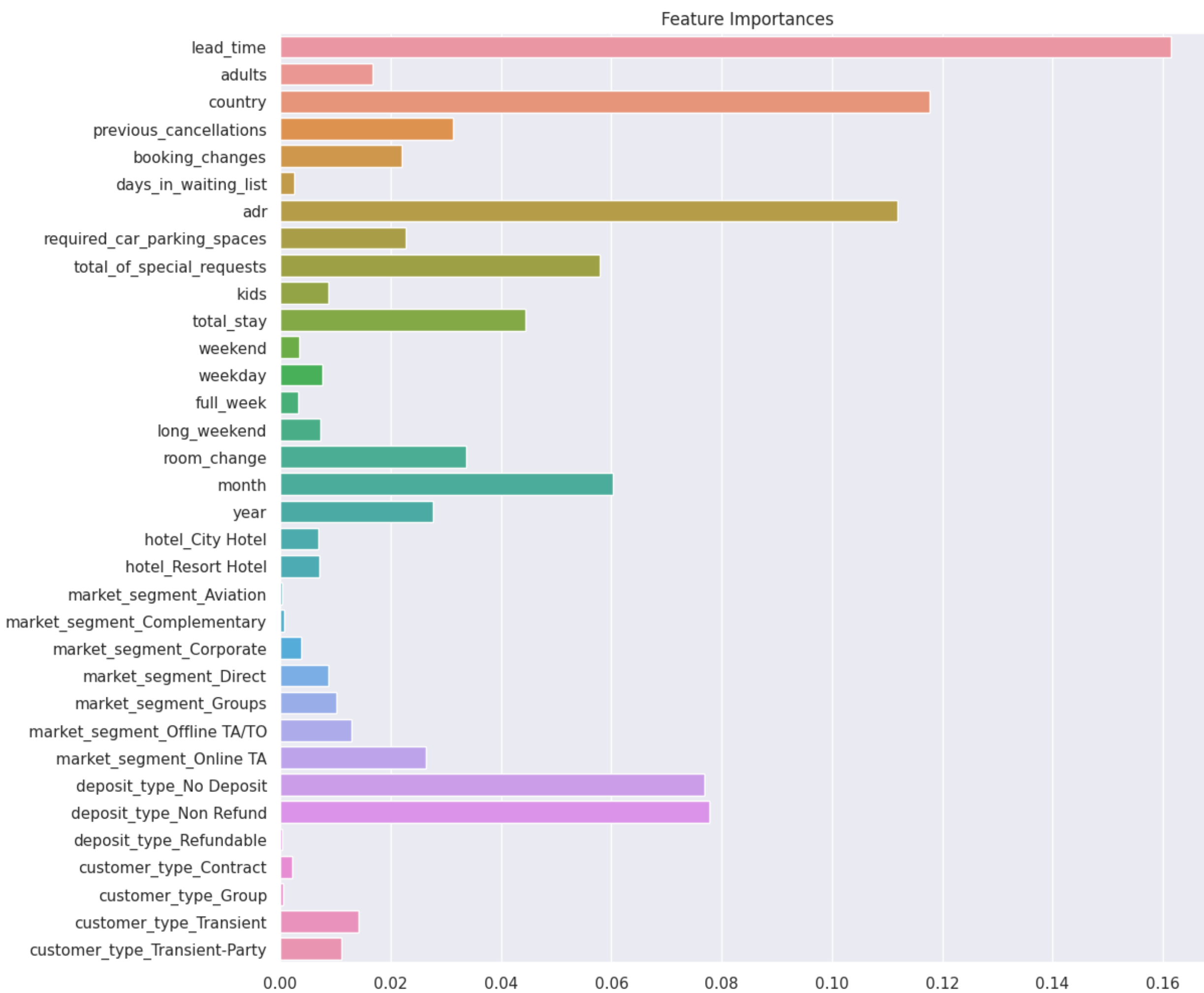
The rest can be kept as nominal.

```
from sklearn.preprocessing import LabelEncoder

obj = LabelEncoder()
df["country"] = obj.fit_transform(df["country"])
#df["assigned_room_type"] =
obj.fit_transform(df["assigned_room_type"])

#Manual encoding of ordinal column
df["month"] =
df["arrival_date_month"].map({"January":1,"February":2,"March":3,"Apri
l":4,"May":5,"June":6,"July":7,"August":8,

"September":9,"October":10,"November":11,"December":12})

df["year"] = df["arrival_date_year"].astype(str)

df["year"] = df["year"].map({"2015":1,"2016":2,"2017":3})

df = df.drop(columns = ["arrival_date_month","arrival_date_year"])

dummy_cols = ["hotel","market_segment","deposit_type","customer_type"]

#One-hot encoding
df = pd.get_dummies(df, columns = dummy_cols)
```

Standardization and Feature importances

```
X = df.drop(columns = ["is_canceled"])
y = df["is_canceled"]

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,
random_state=23, stratify=y)

#Calculating feature importances
from sklearn.ensemble import RandomForestClassifier
rfc = RandomForestClassifier()
rfc.fit(X_train,y_train)

RandomForestClassifier()
```

```
fi=rfc.feature_importances_
xc = X_train.columns

sns.set(rc={"figure.figsize":(12,12)})
sns.barplot(y=xc,x=fi).set(title="Feature Importances")

[Text(0.5, 1.0, 'Feature Importances')]
```




```
#Dropping less important features after finding Feature Importances
X = X.drop(columns =
["market_segment_Aviation","market_segment_Complementary","weekend","f
ull_week","days_in_waiting_list",

"deposit_type_Refundable","customer_type_Group","customer_type_Contrac
t"
                         ])

#Re-splitting data into train and test sets after dropping less
important features
```

```
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,
random_state=41, stratify=y)
```

Normalizing Training Data

```
from sklearn.preprocessing import MinMaxScaler
scaler = MinMaxScaler()
sc = scaler.fit_transform(X_train)

cols = X_train.columns
X_train = pd.DataFrame(sc, columns = cols)
```

Training different models one by one and testing their metrics

```
from sklearn.ensemble import RandomForestClassifier
rfc = RandomForestClassifier()


from sklearn.linear_model import LogisticRegression
lr = LogisticRegression(solver='liblinear')

from sklearn.naive_bayes import BernoulliNB
nb = BernoulliNB()

from sklearn.ensemble import GradientBoostingClassifier
gbc = GradientBoostingClassifier()

model_rfc = rfc.fit(X_train,y_train)
model_lr = lr.fit(X_train,y_train)
model_nb = nb.fit(X_train,y_train)
model_gbc = gbc.fit(X_train,y_train)
```

Normalizing Test Data

```
sc = scaler.transform(X_test)
cols = X_test.columns
X_test = pd.DataFrame(sc, columns = cols)
```

RandomForestClassifier

```
y_pred_test_rfc = model_rfc.predict(X_test)
y_pred_train_rfc = model_rfc.predict(X_train)

from sklearn.metrics import classification_report, confusion_matrix,
accuracy_score
print(f"Metrics for test set")
result_cm = confusion_matrix(y_test, y_pred_test_rfc)
print(f"Confusion matrix {model_rfc}: \n", result_cm)
result_cr = classification_report(y_test, y_pred_test_rfc)
print(f"Classification Report {model_rfc}: \n", result_cr)
```

```python
acc_score_rfc = accuracy_score(y_test,y_pred_test_rfc)
print(f"Accuracy Score: for {model_rfc} \n", acc_score_rfc)

print(f"Metrics for training set")
result_cm = confusion_matrix(y_train, y_pred_train_rfc)
print(f"Confusion matrix {model_rfc}: \n", result_cm)
result_cr = classification_report(y_train, y_pred_train_rfc)
print(f"Classification Report {model_rfc}: \n", result_cr)
acc_score = accuracy_score(y_train,y_pred_train_rfc)
print(f"Accuracy Score: for {model_rfc} \n", acc_score)
```

```
Metrics for test set
Confusion matrix RandomForestClassifier():
 [[18526  1431]
 [ 2163 10048]]
Classification Report RandomForestClassifier():
               precision    recall  f1-score   support

           0       0.90      0.93      0.91     19957
           1       0.88      0.82      0.85     12211

    accuracy                           0.89     32168
   macro avg       0.89      0.88      0.88     32168
weighted avg       0.89      0.89      0.89     32168

Accuracy Score: for RandomForestClassifier()
 0.8882740611788112
Metrics for training set
Confusion matrix RandomForestClassifier():
 [[46434   132]
 [  211 28280]]
Classification Report RandomForestClassifier():
               precision    recall  f1-score   support

           0       1.00      1.00      1.00     46566
           1       1.00      0.99      0.99     28491

    accuracy                           1.00     75057
   macro avg       1.00      0.99      1.00     75057
weighted avg       1.00      1.00      1.00     75057

Accuracy Score: for RandomForestClassifier()
 0.9954301397604487
```

```python
from sklearn.metrics import roc_auc_score
auc_rfc = np.round(roc_auc_score(y_test,y_pred_test_rfc),3)
auc_rfc
```

```
0.876
```

- For Random Forest Classifier we can see that the test set has an accuracy score of around 88% while the training set has an accuracy score of around 99%. The difference in accuracy score between training and testing set is around 11% which indicates overfitting.
- The ROC-AUC score is around 87% which is close to the accuracy score of the test set. This means that the model has the ability to classify 87% of the data correctly.

Logistic Regression

```
y_pred_test_lr = model_lr.predict(X_test)
y_pred_train_lr = model_lr.predict(X_train)

from sklearn.metrics import classification_report, confusion_matrix,
accuracy_score
print(f"Metrics for test set")
result_cm = confusion_matrix(y_test, y_pred_test_lr)
print(f"Confusion matrix {model_lr}: \n", result_cm)
result_cr = classification_report(y_test, y_pred_test_lr)
print(f"Classification Report {model_lr}: \n", result_cr)
acc_score_lr = accuracy_score(y_test,y_pred_test_lr)
print(f"Accuracy Score: for {model_lr} \n", acc_score_lr)

print(f"Metrics for training set")
result_cm = confusion_matrix(y_train, y_pred_train_lr)
print(f"Confusion matrix {model_lr}: \n", result_cm)
result_cr = classification_report(y_train, y_pred_train_lr)
print(f"Classification Report {model_lr}: \n", result_cr)
acc_score = accuracy_score(y_train,y_pred_train_lr)
print(f"Accuracy Score: for {model_lr} \n", acc_score)

Metrics for test set
Confusion matrix LogisticRegression(solver='liblinear'):
 [[18148  1809]
 [ 4627  7584]]
Classification Report LogisticRegression(solver='liblinear'):
               precision    recall  f1-score   support

           0       0.80      0.91      0.85     19957
           1       0.81      0.62      0.70     12211

    accuracy                           0.80     32168
   macro avg       0.80      0.77      0.78     32168
weighted avg       0.80      0.80      0.79     32168

Accuracy Score: for LogisticRegression(solver='liblinear')
 0.7999253916936085
Metrics for training set
Confusion matrix LogisticRegression(solver='liblinear'):
 [[42394  4172]
 [10679 17812]]
Classification Report LogisticRegression(solver='liblinear'):
```

```
              precision    recall  f1-score   support

           0       0.80      0.91      0.85     46566
           1       0.81      0.63      0.71     28491

    accuracy                           0.80     75057
   macro avg       0.80      0.77      0.78     75057
weighted avg       0.80      0.80      0.80     75057

Accuracy Score: for LogisticRegression(solver='liblinear')
 0.8021370425143558
```

```
from sklearn.metrics import roc_auc_score
auc_lr = np.round(roc_auc_score(y_test,y_pred_test_lr),3)
auc_lr
```

```
0.765
```

For Logistic Regression

- Test Accuracy: 80%
- Train Accuracy : 80%
- AUC score : 0.765

BernoulliNB

```
y_pred_test_bnb = model_nb.predict(X_test)
y_pred_train_bnb = model_nb.predict(X_train)

from sklearn.metrics import classification_report, confusion_matrix,
accuracy_score
print(f"Metrics for test set")
result_cm = confusion_matrix(y_test, y_pred_test_bnb)
print(f"Confusion matrix {model_nb}: \n", result_cm)
result_cr = classification_report(y_test, y_pred_test_bnb)
print(f"Classification Report {model_nb}: \n", result_cr)
acc_score_bnb = accuracy_score(y_test,y_pred_test_bnb)
print(f"Accuracy Score: for {model_nb} \n", acc_score_bnb)

print(f"Metrics for training set")
result_cm = confusion_matrix(y_train, y_pred_train_bnb)
print(f"Confusion matrix {model_nb}: \n", result_cm)
result_cr = classification_report(y_train, y_pred_train_bnb)
print(f"Classification Report {model_nb}: \n", result_cr)
acc_score = accuracy_score(y_train,y_pred_train_bnb)
print(f"Accuracy Score: for {model_nb} \n", acc_score)
```

```
Metrics for test set
Confusion matrix BernoulliNB():
 [[18400  1557]
 [ 5598  6613]]
```

```
Classification Report BernoulliNB():
              precision    recall  f1-score   support

           0       0.77      0.92      0.84     19957
           1       0.81      0.54      0.65     12211

    accuracy                           0.78     32168
   macro avg       0.79      0.73      0.74     32168
weighted avg       0.78      0.78      0.77     32168

Accuracy Score: for BernoulliNB()
 0.7775739865705048
Metrics for training set
Confusion matrix BernoulliNB():
 [[42862  3704]
 [13009 15482]]
Classification Report BernoulliNB():
              precision    recall  f1-score   support

           0       0.77      0.92      0.84     46566
           1       0.81      0.54      0.65     28491

    accuracy                           0.78     75057
   macro avg       0.79      0.73      0.74     75057
weighted avg       0.78      0.78      0.77     75057

Accuracy Score: for BernoulliNB()
 0.7773292297853631

from sklearn.metrics import roc_auc_score
auc_bnb = np.round(roc_auc_score(y_test,y_pred_test_bnb),3)
auc_bnb

0.732
```

For Bernoulli Naive Bayes model,

- Test Accuracy: 77%
- Train Accuracy : 77%
- AUC score : 0.732

Gradient Boosting Classifier

```
y_pred_test_gbc = model_gbc.predict(X_test)
y_pred_train_gbc = model_gbc.predict(X_train)

from sklearn.metrics import classification_report, confusion_matrix,
accuracy_score
print(f"Metrics for test set")
result_cm = confusion_matrix(y_test, y_pred_test_gbc)
print(f"Confusion matrix {model_gbc}: \n", result_cm)
```

```
result_cr = classification_report(y_test, y_pred_test_gbc)
print(f"Classification Report {model_gbc}: \n", result_cr)
acc_score_gbc = accuracy_score(y_test,y_pred_test_gbc)
print(f"Accuracy Score: for {model_gbc} \n", acc_score_gbc)

print(f"Metrics for training set")
result_cm = confusion_matrix(y_train, y_pred_train_gbc)
print(f"Confusion matrix {model_gbc}: \n", result_cm)
result_cr = classification_report(y_train, y_pred_train_gbc)
print(f"Classification Report {model_gbc}: \n", result_cr)
acc_score = accuracy_score(y_train,y_pred_train_gbc)
print(f"Accuracy Score: for {model_gbc} \n", acc_score)
```

```
Metrics for test set
Confusion matrix GradientBoostingClassifier():
 [[18041  1916]
 [ 2888  9323]]
Classification Report GradientBoostingClassifier():
               precision    recall  f1-score   support

           0       0.86      0.90      0.88     19957
           1       0.83      0.76      0.80     12211

    accuracy                           0.85     32168
   macro avg       0.85      0.83      0.84     32168
weighted avg       0.85      0.85      0.85     32168

Accuracy Score: for GradientBoostingClassifier()
 0.8506590400397911
Metrics for training set
Confusion matrix GradientBoostingClassifier():
 [[42174  4392]
 [ 6945 21546]]
Classification Report GradientBoostingClassifier():
               precision    recall  f1-score   support

           0       0.86      0.91      0.88     46566
           1       0.83      0.76      0.79     28491

    accuracy                           0.85     75057
   macro avg       0.84      0.83      0.84     75057
weighted avg       0.85      0.85      0.85     75057

Accuracy Score: for GradientBoostingClassifier()
 0.8489547943562892
```

```
from sklearn.metrics import roc_auc_score
auc_gbc = np.round(roc_auc_score(y_test,y_pred_test_gbc),3)
auc_gbc
```

```
0.834
```

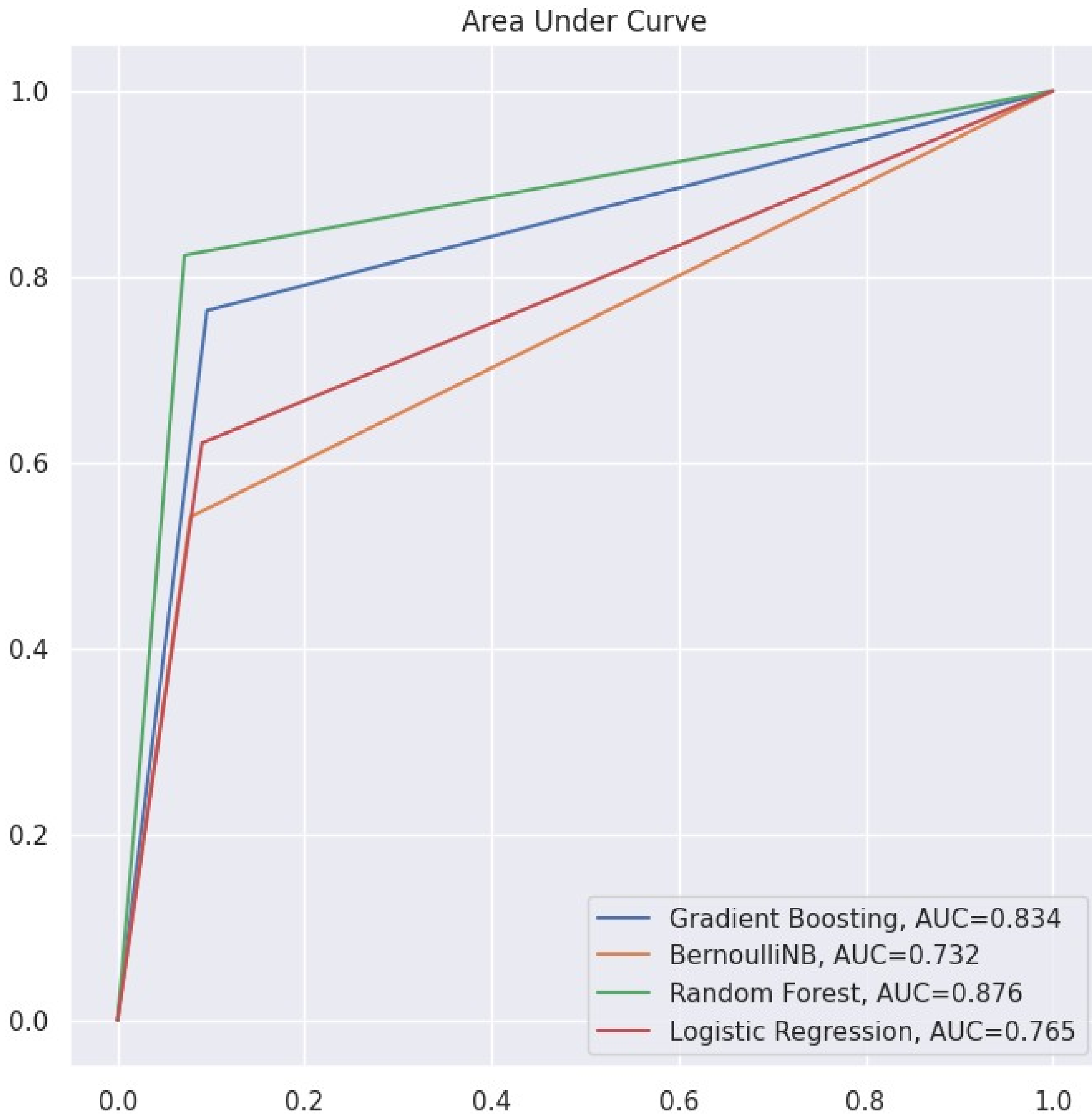
For Gradient Boosting Classifier,

- Test Accuracy: 85%
- Train Accuracy : 85%
- AUC score : 0.834

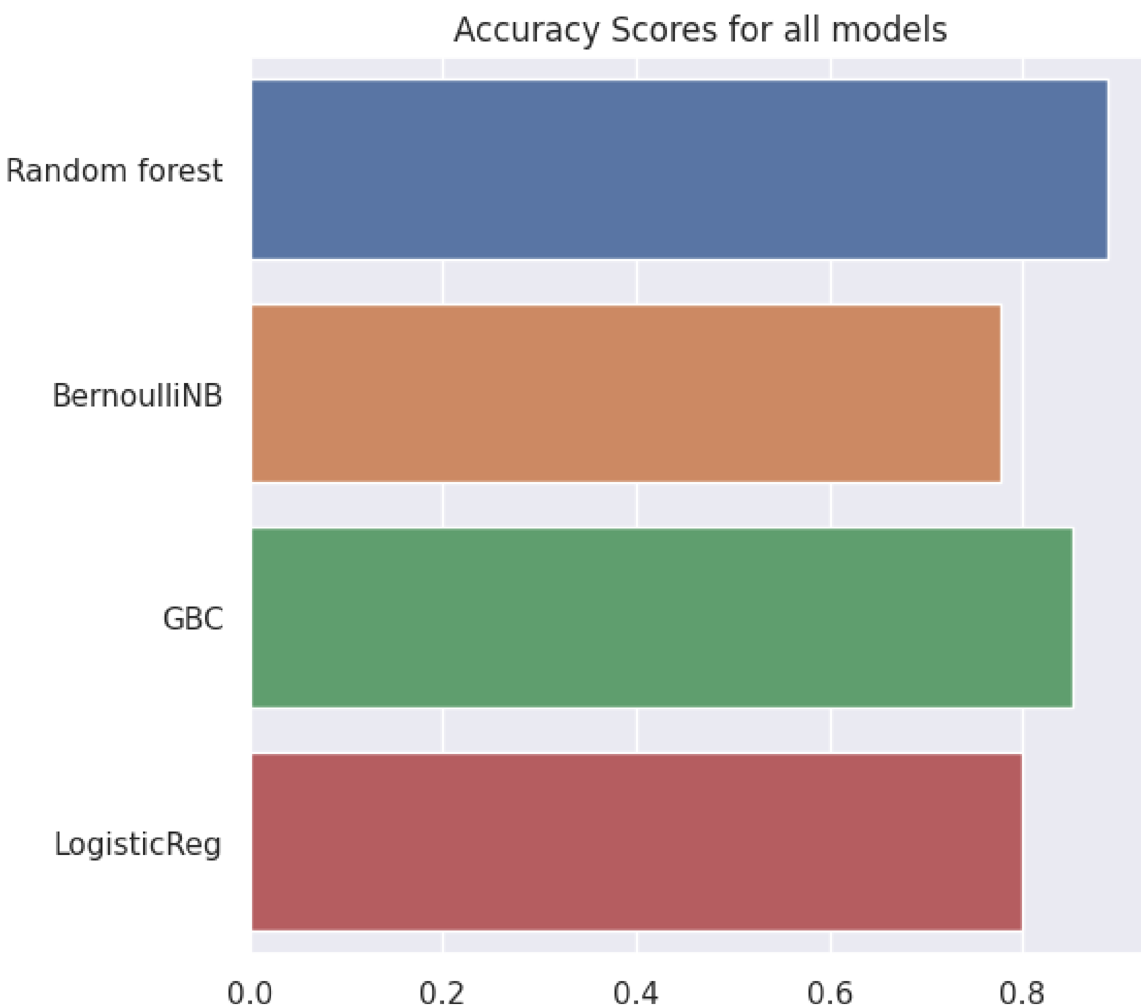
Visualizing performance of all models

```
acc = [acc_score_rfc,acc_score_bnb,acc_score_gbc, acc_score_lr]
m = ["Random forest","BernoulliNB","GBC","LogisticReg"]

from sklearn import metrics
plt.figure(figsize=(8,8))
fpr, tpr, _ = metrics.roc_curve(y_test, y_pred_test_gbc)
plt.plot(fpr,tpr,label="Gradient Boosting, AUC="+str(auc_gbc))
fpr, tpr, _ = metrics.roc_curve(y_test, y_pred_test_bnb)
plt.plot(fpr,tpr,label="BernoulliNB, AUC="+str(auc_bnb))
fpr, tpr, _ = metrics.roc_curve(y_test, y_pred_test_rfc)
plt.plot(fpr,tpr,label="Random Forest, AUC="+str(auc_rfc))
fpr, tpr, _ = metrics.roc_curve(y_test, y_pred_test_lr)
plt.plot(fpr,tpr,label="Logistic Regression, AUC="+str(auc_lr))
plt.legend()
plt.title("Area Under Curve")
```

```
Text(0.5, 1.0, 'Area Under Curve')
```




```
plt.figure(figsize=(6,6))
sns.barplot(x=acc,y=m)
plt.title("Accuracy Scores for all models")
plt.show()
```



Random Forest Classifier model has highest testing and training accuracies and also AUC score of 0.876. However, there is 11% difference between training and testing accuracy scores.

We choose Random Forest Classifier as it has highest accuracy and AUC score. We will perform K-Fold Cross-validation on training set to get the average training accuracy.

K-Fold Cross-validation of model

```
from sklearn.model_selection import cross_val_score

train_scores =
cross_val_score(model_rfc,X_train,y_train,cv=10,scoring='accuracy')
test_scores =
cross_val_score(model_rfc,X_test,y_test,cv=10,scoring='accuracy')

train_avg = train_scores.mean()
test_avg = test_scores.mean()

print(f"Training Average : {train_avg}")
print(f"Training scores : {train_scores}")
```

```
print("-"*100)
print(f"Test Average : {test_avg}")
print(f"Test scores : {test_scores}")
```

```
Training Average : 0.8856202819223636
Training scores : [0.88462563 0.88915534 0.88169464 0.89155342
0.88569145 0.88489209
 0.88022915 0.88367755 0.8898068  0.88487675]
----------------------------------------------------------------------
------------------------------
Test Average : 0.8747510504672782
Test scores : [0.87410631 0.87410631 0.88343177 0.86167237 0.87410631
0.87876904
 0.87783649 0.88218837 0.86629353 0.875     ]
```

Average performance of Random Forest Classifier model is quite good and it has average accuracy of 87% for test set and 88% for training set.

Conclusion

In summary, the Random Forest Classifier yielded the best results for our training, testing, and cross-validation datasets. With an accuracy of 87%, it is likely that the model will classify new, unseen data with an accuracy between 75% and 85%.