Dataset Name:

kaggle>> Hotel Booking Demand

Overview:

This dataset contains booking information for a city hotel and a resort hotel. It includes various details about the reservations, such as booking and arrival dates, length of stay, number of adults, children, and babies, the type of meal booked, country of origin, market segment, distribution channel, whether the booking was canceled, and more.

Business Problem

Business Problem In recent years, City Hotel and Resort Hotel have seen high cancellation rates. Each hotel is now dealing with a number of issues as a result, including fewer revenues and less than ideal hotel room use. Consequently, lowering cancellation rates is both hotels' primary goal in order to increase their efficiency in generating revenue, and for us to offer thorough business advice to address this problem. The analysis of hotel booking cancellations as well as other factors that have no bearing on their business and yearly revenue generation are the main topics of this report.

Assumptions

1. No unusual occurrences between 2015 and 2017 will have a substantial impact on the data used.
2. The information is still current and can be used to analyze a hotel's possible plans in an efficient manner.
3. There are no unanticipated negatives to the hotel employing any advised technique.
4. The hotels are not currently using any of the suggested solution

Hypothesis

1. More cancellations occur when prices are higher.
2. When there is a longer waiting list, customers tend to cancel more frequently.
3. The majority of clients are coming from offline travel agents to make their
4. The biggest factor affecting the effectiveness of earning income is booking cancellations.
5. Cancellations result in vacant rooms for the booked length of time.
6. Clients make hotel reservations the same year they make cancellations.

Research Question

1. What are the variables that affect hotel reservation cancellations?
2. How can we make hotel reservations cancellations better?
3. How will hotels be assisted in making pricing and promotional decisions?**

{1}Importing Libraries

Generate 10 random numbers using numpy Close

Suggested code may be subject to a license | medium.com/@nidhinchandrasekhar/time-series-forecasting-using-various-methods-a-real-life-case-study-58875fc71a06

```
#importing libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
warnings.filterwarnings('ignore')
```

{2} Loading The Dataset

```
df = pd.read_csv('/content/hotel_booking.csv')
```

{3}Exploratory Data Analysis & Data Cleaning

```
df.head(3)
```

	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 rows × 36 columns

```
df.tail(3)
```

	hotel	is_canceled	lead_time	arrival_date_year	arrival_date_mo
119387	City Hotel	0	34	2017	Aug
119388	City Hotel	0	109	2017	Aug
119389	City Hotel	0	205	2017	Aug

3 rows × 36 columns

```
df.shape
```

```
(119390, 36)
```

```
df.columns
```

```
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', 'name', 'email',
       'phone-number', 'credit_card'],
      dtype='object')
```

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 119390 entries, 0 to 119389
Data columns (total 36 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 
 32  name                            119390 non-null  object 
 33  email                           119390 non-null  object 
 34  phone-number                    119390 non-null  object 
 35  credit_card                     119390 non-null  object 
dtypes: float64(4), int64(16), object(16)
memory usage: 32.8+ MB
```

```
df['reservation_status_date'] = pd.to_datetime(df['reservation_status_date'])
df.describe(include='object')
```

	hotel	arrival_date_month	meal	country	market_segment	distr
count	119390	119390	119390	118902	119390	
unique	2	12	5	177	8	
top	City Hotel	August	BB	PRT	Online TA	
freq	79330	13877	92310	48590	56477	

```
for col in df.describe(include='object').columns:
    print(col)
    print(df[col].unique())
    print('-'*50)
```

```
hotel
['Resort Hotel' 'City Hotel']
--------------------------------------------------
arrival_date_month
['July' 'August' 'September' 'October' 'November' 'December' 'January'
 'February' 'March' 'April' 'May' 'June']
--------------------------------------------------
meal
['BB' 'FB' 'HB' 'SC' 'Undefined']
--------------------------------------------------
country
['PRT' 'GBR' 'USA' 'ESP' 'IRL' 'FRA' nan 'ROU' 'NOR' 'OMN' 'ARG' 'POL'
 'DEU' 'BEL' 'CHE' 'CN' 'GRC' 'ITA' 'NLD' 'DNK' 'RUS' 'SWE' 'AUS' 'EST'
 'CZE' 'BRA' 'FIN' 'MOZ' 'BWA' 'LUX' 'SVN' 'ALB' 'IND' 'CHN' 'MEX' 'MAR'
 'UKR' 'SMR' 'LVA' 'PRI' 'SRB' 'CHL' 'AUT' 'BLR' 'LTU' 'TUR' 'ZAF' 'AGO'
```

```
 'ISR' 'CYM' 'ZMB' 'CPV' 'ZWE' 'DZA' 'KOR' 'CRI' 'HUN' 'ARE' 'TUN' 'JAM'
 'HRV' 'HKG' 'IRN' 'GEO' 'AND' 'GIB' 'URY' 'JEY' 'CAF' 'CYP' 'COL' 'GGY'
 'KWT' 'NGA' 'MDV' 'VEN' 'SVK' 'FJI' 'KAZ' 'PAK' 'IDN' 'LBN' 'PHL' 'SEN'
 'SYC' 'AZE' 'BHR' 'NZL' 'THA' 'DOM' 'MKD' 'MYS' 'ARM' 'JPN' 'LKA' 'CUB'
 'CMR' 'BIH' 'MUS' 'COM' 'SUR' 'UGA' 'BGR' 'CIV' 'JOR' 'SYR' 'SGP' 'BDI'
 'SAU' 'VNM' 'PLW' 'QAT' 'EGY' 'PER' 'MLT' 'MWI' 'ECU' 'MDG' 'ISL' 'UZB'
 'NPL' 'BHS' 'MAC' 'TGO' 'TWN' 'DJI' 'STP' 'KNA' 'ETH' 'IRQ' 'HND' 'RWA'
 'KHM' 'MCO' 'BGD' 'IMN' 'TJK' 'NIC' 'BEN' 'VGB' 'TZA' 'GAB' 'GHA' 'TMP'
 'GLP' 'KEN' 'LIE' 'GNB' 'MNE' 'UMI' 'MYT' 'FRO' 'MMR' 'PAN' 'BFA' 'LBY'
 'MLI' 'NAM' 'BOL' 'PRY' 'BRB' 'ABW' 'AIA' 'SLV' 'DMA' 'PYF' 'GUY' 'LCA'
 'ATA' 'GTM' 'ASM' 'MRT' 'NCL' 'KIR' 'SDN' 'ATF' 'SLE' 'LAO']
--------------------------------------------------
market_segment
['Direct' 'Corporate' 'Online TA' 'Offline TA/TO' 'Complementary' 'Groups'
 'Undefined' 'Aviation']
--------------------------------------------------
distribution_channel
['Direct' 'Corporate' 'TA/TO' 'Undefined' 'GDS']
--------------------------------------------------
reserved_room_type
['C' 'A' 'D' 'E' 'G' 'F' 'H' 'L' 'P' 'B']
--------------------------------------------------
assigned_room_type
['C' 'A' 'D' 'E' 'G' 'F' 'I' 'B' 'H' 'P' 'L' 'K']
--------------------------------------------------
deposit_type
['No Deposit' 'Refundable' 'Non Refund']
--------------------------------------------------
customer_type
['Transient' 'Contract' 'Transient-Party' 'Group']
--------------------------------------------------
reservation_status
['Check-Out' 'Canceled' 'No-Show']
--------------------------------------------------
name
['Ernest Barnes' 'Andrea Baker' 'Rebecca Parker' ... 'Wesley Aguilar'
 'Caroline Conley MD' 'Ariana Michael']
--------------------------------------------------
email
['Ernest.Barnes31@outlook.com' 'Andrea_Baker94@aol.com'
 'Rebecca_Parker@comcast.net' ... 'Mary_Morales@hotmail.com'
 'MD_Caroline@comcast.net' 'Ariana_M@xfinity.com']
```

```
df.isnull().sum()
```

```
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
name                                  0
email                                 0
phone-number                          0
credit_card                           0
dtype: int64
```

To handle agent and company is very deficult so we remove this

```
df.dropna(inplace=True) #This will drop rows with any missing values.
```

```
df.isnull().sum()
```

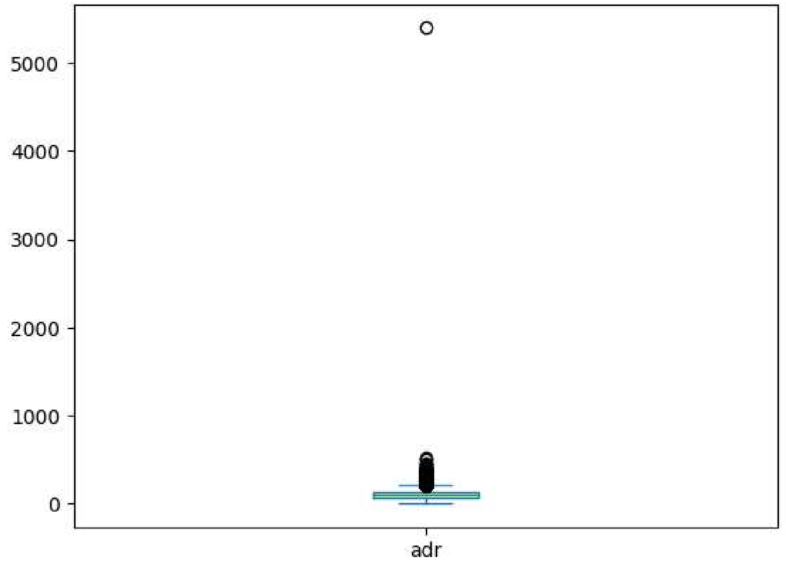
```
hotel                             0
is_canceled                       0
lead_time                         0
arrival_date_year                 0
arrival_date_month                0
arrival_date_week_number          0
arrival_date_day_of_month         0
stays_in_weekend_nights           0
stays_in_week_nights              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
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
name                              0
email                             0
phone-number                      0
credit_card                       0
dtype: int64
```

```
df.describe()
```

Analysis performed on data after outlier removal

```
df['adr'].plot(kind='box')
```

```
<Axes: >
```

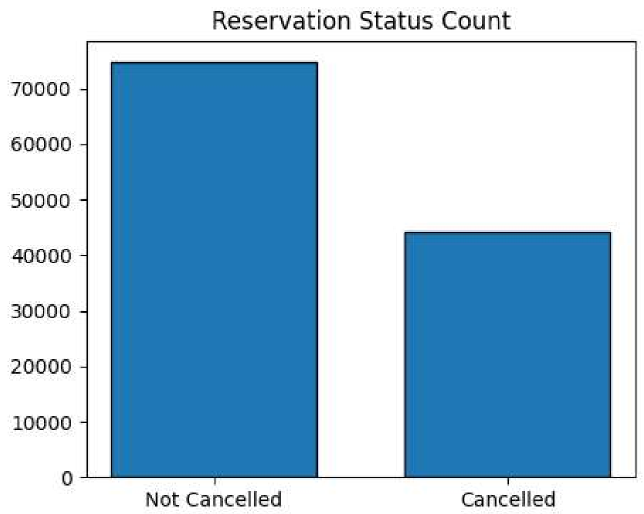



```
df= df[df['adr']<5000]
```

{4} Data Analysis & Visualization

```
cancelled_perc= df['is_canceled'].value_counts(normalize=True)
print(cancelled_perc)
plt.figure(figsize=(5,4))
plt.title('Reservation Status Count')
plt.bar(['Not Cancelled','Cancelled'],df['is_canceled'].value_counts(),edgecolor='k',width=0.7)
plt.show()
```

```
is_canceled
0    0.628653
1    0.371347
Name: proportion, dtype: float64
```



The accompanying bar graph shows the percentage of reservations that are canceled and those that are not. It is obvious that there are still a significant number of reservations that have not been canceled. There are still 37% of clients who canceled their reservation, which has a significant impact on the hotels' earnings.

Generate randomly select 5 items from a list Close

Generate is available for a limited time for unsubscribed users. Upgrade to Colab Pro

```
plt.figure(figsize=(8,4))
ax1=sns.countplot(x='hotel',hue='is_canceled',data=df,palette='Blues')
legend_labels,_=ax1.get_legend_handles_labels()
ax1.legend(bbox_to_anchor=(1,1))
plt.title('Reservation status in different hotels',size=20)
plt.xlabel('Hotel')
plt.ylabel('Number of reservations')
plt.legend(['Not Cancelled','Cancelled'])
plt.show()
```

In comparison to resort hotels, city hotels have more bookings. It's possible that resort hotels are more expensive than those in cities.

in

```
resort_hotel=df[df['hotel']=='Resort Hotel']
resort_hotel['is_canceled'].value_counts(normalize=True)
```

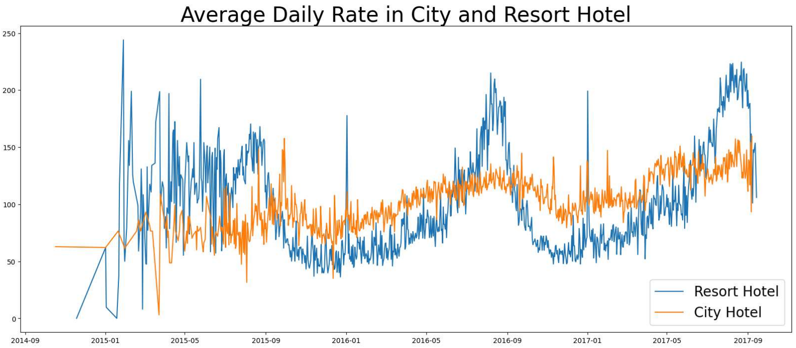
```
is_canceled
0    0.72025
1    0.27975
Name: proportion, dtype: float64
```

```
city_hotel=df[df['hotel']=='City Hotel']
city_hotel['is_canceled'].value_counts(normalize=True)
```

```
is_canceled
0    0.582918
1    0.417082
Name: proportion, dtype: float64
```

```
resort_hotel=resort_hotel.groupby('reservation_status_date')[['adr']].mean()
city_hotel=city_hotel.groupby('reservation_status_date')[['adr']].mean()
```

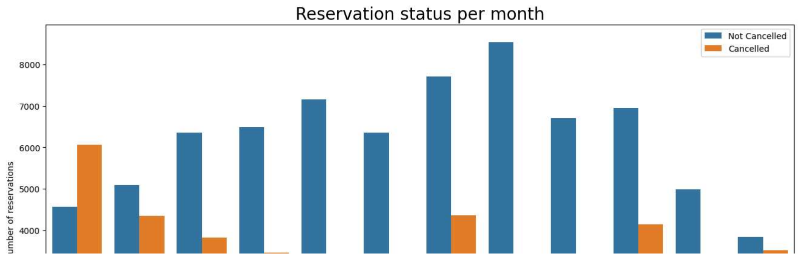
```
plt.figure(figsize=(20,8))
plt.title('Average Daily Rate in City and Resort Hotel',fontsize=30)
plt.plot(resort_hotel.index,resort_hotel['adr'], label='Resort Hotel')
plt.plot(city_hotel.index,city_hotel['adr'], label='City Hotel')
plt.legend(fontsize=20)
plt.show()
```



The line graph above shows that, on certain days, the average daily rate for a city hotel is less than that of a resort hotel, and on other days, it is even less. It goes without saying that weekends and holidays may see a rise in resort hotel rates.

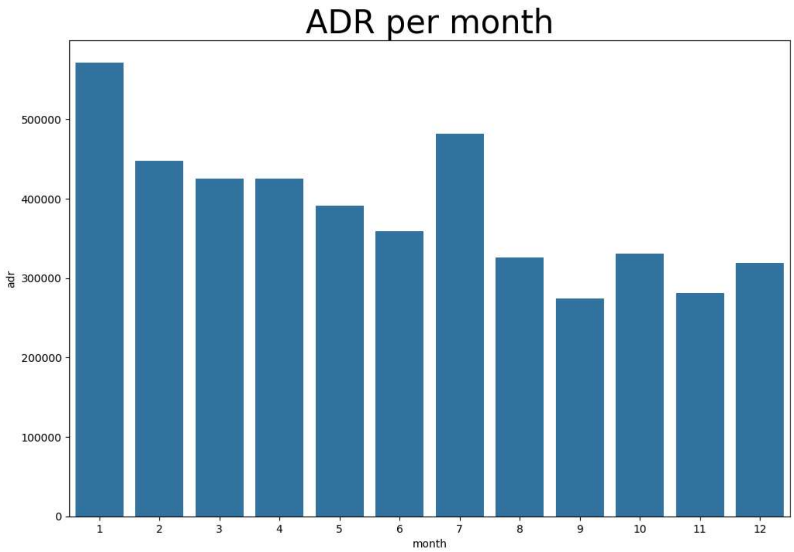
Generate a slider using jupyter widgets Close

```
df['month'] = df['reservation_status_date'].dt.month
plt.figure(figsize=(16, 8))
ax1=sns.countplot(x='month',hue='is_canceled',data=df)
plt.title('Reservation status per month',size=20)
plt.xlabel('Month')
plt.ylabel('Number of reservations')
plt.legend(['Not Cancelled','Cancelled'])
plt.show()
```



We have developed the grouped bar graph to analyze the months with the highest and lowest reservation levels according to reservation status. As can be seen, both the number of confirmed reservations and the number of canceled reservations are largest in the month of August. whereas January is the month with the most canceled reservations.

```
plt.figure(figsize=(12,8))
plt.title('ADR per month',size=30)
sns.barplot(x='month',y='adr',data=df[df['is_canceled']==1].groupby('month')[['adr']].sum().reset_index())
plt.show()
```



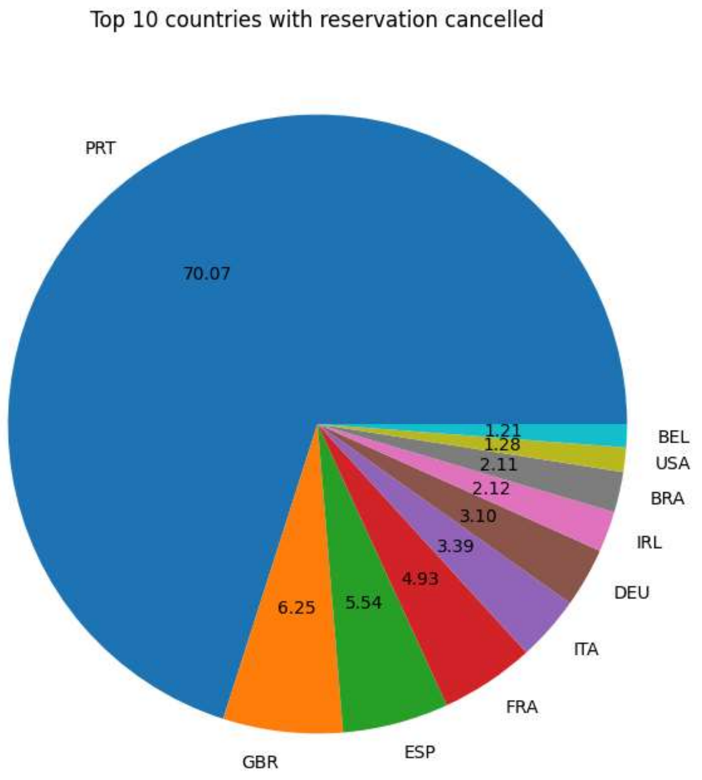
This bar graph demonstrates that cancellations are most common when prices are greatest and are least common when they are lowest. Therefore, the cost of the accommodation is solely responsible for the cancellation.

ASUMPTION: **The Higher the Crisis, the More Cancellations**

This chart shows a clear correlation: as uncertainty and crisis increase (we can assume this from external factors), hotel cancellations rise as well. People become more cautious with their spending and travel plans when faced with instability

Double-click (or enter) to edit

```
cancelled_data= df[df['is_canceled']==1]
top_10_country=cancelled_data['country'].value_counts()[:10]
plt.figure(figsize=(8,8))
plt.title('Top 10 countries with reservation cancelled')
plt.pie(top_10_country,autopct='%.2f',labels=top_10_country.index)
plt.show()
```



This pie chart shows the top 10 countries with the most canceled hotel reservations. Portugal leads, followed by the UK and then Spain. This information can help hotels understand which markets are more likely to cancel bookings.

Let's check the area from where guests are visiting the hotels and making reservations. Is it coming from Direct or Groups, Online or Offline Travel Agents? Around 46% of the clients come from online travel agencies, whereas 27% come from groups. Only 4% of clients book hotels directly by visiting them and making reservations.

```
df['market_segment'].value_counts()
```

```
market_segment
Online TA        56402
Offline TA/TO    24159
Groups           19806
Direct           12448
Corporate         5111
Complementary      734
Aviation           237
Name: count, dtype: int64
```

Generate create a dataframe with 2 columns and 10 rows Close

Generate is available for a limited time for unsubscribed users. Upgrade to Colab Pro

```
df['market_segment'].value_counts(normalize=True)
```

```
market_segment
Online TA        0.474377
Offline TA/TO    0.203193
Groups           0.166581
Direct           0.104696
```

```
Corporate        0.042987
Complementary    0.006173
Aviation         0.001993
Name: proportion, dtype: float64
```

Double-click (or enter) to edit

Generate 10 random numbers using numpy Close

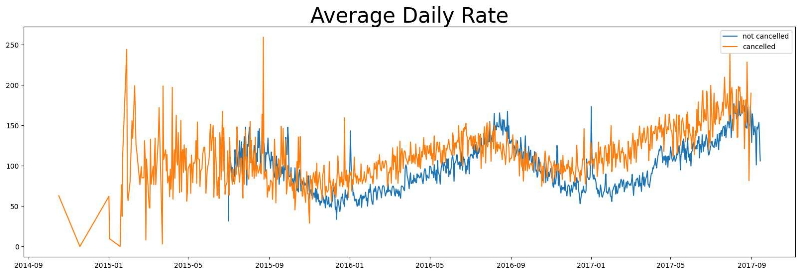
Generate is available for a limited time for unsubscribed users. Upgrade to Colab Pro

```
cancelled_data['market_segment'].value_counts(normalize=True)
```

```
market_segment
Online TA        0.469696
Groups           0.273985
Offline TA/TO    0.187466
Direct           0.043486
Corporate        0.022151
Complementary    0.002038
Aviation         0.001178
Name: proportion, dtype: float64
```

```
plt.figure(figsize=(20,6))
plt.title('Average Daily Rate' ,fontsize=30)

plt.plot(not_cancelled_df_adr.index, not_cancelled_df_adr['adr'], label='not cancelled')
plt.plot(cancelled_df_adr['date'], cancelled_df_adr['average_daily_rate'], label='cancelled')
plt.legend()
plt.show()
```



As seen in the graph, reservations are canceled when the average daily rate is higher than when it is not canceled. It clearly proves all the above analysis, that the higher price leads to higher cancellation.

Suggestions