Demand Forecasting: A Case Study of Hotel Booking Cancellations

```
by Siddharth Dixit
```

Context

Have you ever wondered when the best time of year to book a hotel room is? Or the optimal length of stay in order to get the best daily rate? What if you wanted to predict whether or not a hotel was likely to receive a disproportionately high number of special requests?

This hotel booking dataset can help you explore those questions!

Content

This data set contains booking information for a city hotel and a resort hotel, and includes information such as when the booking was made, length of stay, the number of adults, children, and/or babies, and the number of available parking spaces, among other things.

All personally identifying information has been removed from the data.

Acknowledgements

The data is originally from the article Hotel Booking Demand Datasets, written by Nuno Antonio, Ana Almeida, and Luis Nunes for Data in Brief, Volume 22, February 2019. The data was downloaded and cleaned by Thomas Mock and Antoine Bichat for #TidyTuesday during the week of February 11th, 2020.

Research Paper Link: [https://www.sciencedirect.com/science/article/pii/S2352340918315191 (https://www.sciencedirect.com/science/article/pii/S2352340918315191)](https://www.sciencedirect.com/science/article/pii/S2352340918315191)

In [1]:

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
```

Load Data

In [2]:

```
hotel_1 = pd.read_csv('H1.csv',parse_dates=True,index_col='ReservationStatusDate')
hotel_2 = pd.read_csv('H2.csv',parse_dates=True,index_col='ReservationStatusDate')
hotel_1.head(10)
```

Out[2]:

	IsCanceled	LeadTime	ArrivalDateYear	ArrivalDateMonth	ArrivalDateWee
ReservationStatusDate					
2015-07-01	0	342	2015	July	
2015-07-01	0	737	2015	July	
2015-07-02	0	7	2015	July	
2015-07-02	0	13	2015	July	
2015-07-03	0	14	2015	July	
2015-07-03	0	14	2015	July	
2015-07-03	0	0	2015	July	
2015-07-03	0	9	2015	July	
2015-05-06	1	85	2015	July	
2015-04-22	1	75	2015	July	

10 rows × 30 columns

Exploratory Data Analysis

- Before starting this step you must have a good understanding of all the features present in your data
- Goal is to find hidden trends and patterns within your data.
- Every plot should convey a story which relates it to the real world.
- This step depends entirely upon your imagination!

1. Data Cleaning

In [3]:

```
# Find out missing entries
print(hotel_1.isna().sum())
print(hotel_2.isna().sum())
```

```
IsCanceled                       0
LeadTime                         0
ArrivalDateYear                  0
ArrivalDateMonth                 0
ArrivalDateWeekNumber            0
ArrivalDateDayOfMonth            0
StaysInWeekendNights             0
StaysInWeekNights                0
Adults                           0
Children                         0
Babies                           0
Meal                             0
Country                        464
MarketSegment                    0
DistributionChannel              0
IsRepeatedGuest                  0
PreviousCancellations            0
PreviousBookingsNotCanceled      0
ReservedRoomType                 0
AssignedRoomType                 0
BookingChanges                   0
DepositType                      0
Agent                            0
Company                          0
DaysInWaitingList                0
CustomerType                     0
ADR                              0
RequiredCarParkingSpaces         0
TotalOfSpecialRequests           0
ReservationStatus                0
dtype: int64
IsCanceled                      0
LeadTime                        0
ArrivalDateYear                 0
ArrivalDateMonth                0
ArrivalDateWeekNumber           0
ArrivalDateDayOfMonth           0
StaysInWeekendNights            0
StaysInWeekNights               0
Adults                          0
Children                        4
Babies                          0
Meal                            0
Country                        24
MarketSegment                   0
DistributionChannel             0
IsRepeatedGuest                 0
PreviousCancellations           0
PreviousBookingsNotCanceled     0
ReservedRoomType                0
AssignedRoomType                0
BookingChanges                  0
DepositType                     0
Agent                           0
Company                         0
```

```
DaysInWaitingList           0
CustomerType                0
ADR                         0
RequiredCarParkingSpaces    0
TotalOfSpecialRequests      0
ReservationStatus           0
dtype: int64
```

In [4]:

```
# Representing all null values in the same way so that they can be treated later on


hotel_1 = hotel_1.replace(to_replace = '       NULL',
                  value =np.NAN)
print(hotel_1.isna().sum())
hotel_2 = hotel_2.replace(to_replace = '       NULL',
                  value =np.NAN)
print(hotel_2.isna().sum())
#hotel_1['Country'].value_counts()
```

```
IsCanceled                       0
LeadTime                         0
ArrivalDateYear                  0
ArrivalDateMonth                 0
ArrivalDateWeekNumber            0
ArrivalDateDayOfMonth            0
StaysInWeekendNights             0
StaysInWeekNights                0
Adults                           0
Children                         0
Babies                           0
Meal                             0
Country                        464
MarketSegment                    0
DistributionChannel              0
IsRepeatedGuest                  0
PreviousCancellations            0
PreviousBookingsNotCanceled      0
ReservedRoomType                 0
AssignedRoomType                 0
BookingChanges                   0
DepositType                      0
Agent                         8209
Company                      36952
DaysInWaitingList                0
CustomerType                     0
ADR                              0
RequiredCarParkingSpaces         0
TotalOfSpecialRequests           0
ReservationStatus                0
dtype: int64
IsCanceled                       0
LeadTime                         0
ArrivalDateYear                  0
ArrivalDateMonth                 0
ArrivalDateWeekNumber            0
ArrivalDateDayOfMonth            0
StaysInWeekendNights             0
StaysInWeekNights                0
Adults                           0
Children                         4
Babies                           0
Meal                             0
Country                         24
MarketSegment                    0
DistributionChannel              0
IsRepeatedGuest                  0
PreviousCancellations            0
```

```
PreviousBookingsNotCanceled        0
ReservedRoomType                   0
AssignedRoomType                   0
BookingChanges                     0
DepositType                        0
Agent                           8131
Company                        75641
DaysInWaitingList                  0
CustomerType                       0
ADR                                0
RequiredCarParkingSpaces           0
TotalOfSpecialRequests             0
ReservationStatus                  0
dtype: int64
```

In [5]:

```
# Drop Company from both hotel_1 & hotel_2 datasets
hotel_1 = hotel_1.drop(['Company'],axis=1)
hotel_2 = hotel_2.drop(['Company'],axis=1)

# Fill NA values using Most frequently occuring value in that column
hotel_1['Country'] = hotel_1['Country'].fillna(hotel_1['Country'].mode()[0])
hotel_1['Agent'] = hotel_1['Agent'].fillna(hotel_1['Agent'].mode()[0])

hotel_2['Country'] = hotel_2['Country'].fillna(hotel_2['Country'].mode()[0])
hotel_2['Agent'] = hotel_2['Agent'].fillna(hotel_2['Agent'].mode()[0])
hotel_2['Children'] = hotel_2['Children'].fillna(hotel_2['Children'].mode()[0])
```

In [6]:

```
print(hotel_1.isna().sum())
```

```
IsCanceled                     0
LeadTime                       0
ArrivalDateYear                0
ArrivalDateMonth               0
ArrivalDateWeekNumber          0
ArrivalDateDayOfMonth          0
StaysInWeekendNights           0
StaysInWeekNights              0
Adults                         0
Children                       0
Babies                         0
Meal                           0
Country                        0
MarketSegment                  0
DistributionChannel            0
IsRepeatedGuest                0
PreviousCancellations          0
PreviousBookingsNotCanceled    0
ReservedRoomType               0
AssignedRoomType               0
BookingChanges                 0
DepositType                    0
Agent                          0
DaysInWaitingList              0
CustomerType                   0
ADR                            0
RequiredCarParkingSpaces       0
TotalOfSpecialRequests         0
ReservationStatus              0
dtype: int64
```

2) Data Exploration

In [7]:

```
hotel_1.columns
```

Out[7]:

```
Index(['IsCanceled', 'LeadTime', 'ArrivalDateYear', 'ArrivalDateMont
h',
       'ArrivalDateWeekNumber', 'ArrivalDateDayOfMonth',
       'StaysInWeekendNights', 'StaysInWeekNights', 'Adults', 'Childre
n',
       'Babies', 'Meal', 'Country', 'MarketSegment', 'DistributionChan
nel',
       'IsRepeatedGuest', 'PreviousCancellations',
       'PreviousBookingsNotCanceled', 'ReservedRoomType', 'AssignedRoo
mType',
       'BookingChanges', 'DepositType', 'Agent', 'DaysInWaitingList',
       'CustomerType', 'ADR', 'RequiredCarParkingSpaces',
       'TotalOfSpecialRequests', 'ReservationStatus'],
      dtype='object')
```

In [8]:

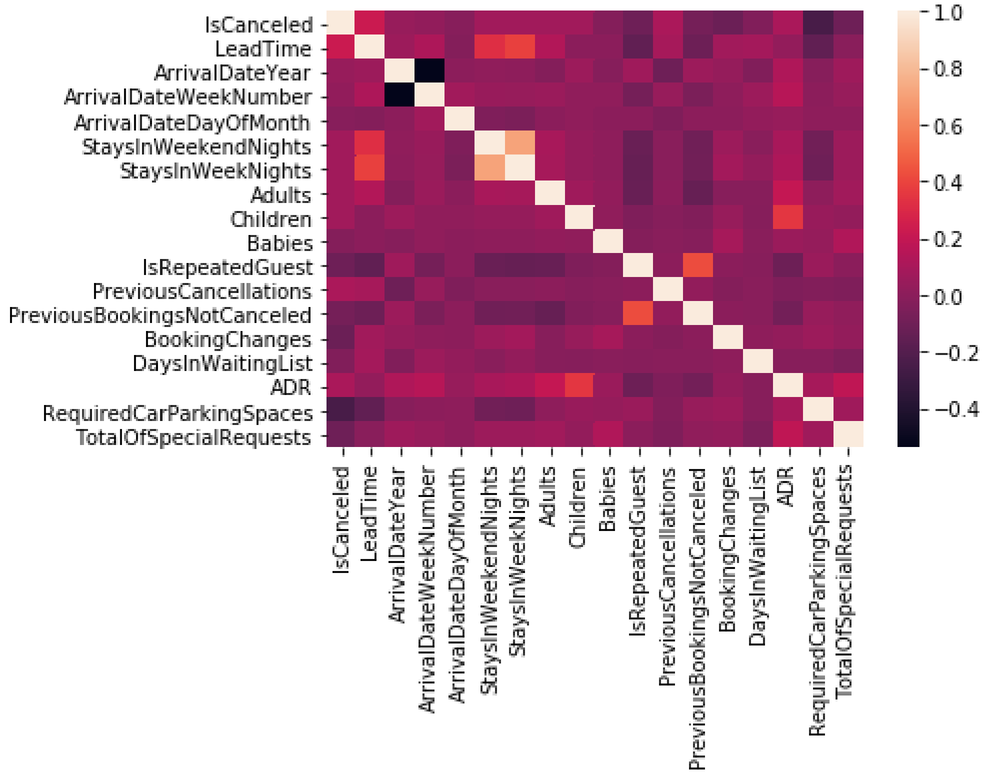
```
# Separate out your Numerical & Categorical Features
categorical_features = []
numerical_features = []

for col in hotel_1.columns:
    if(hotel_1[col].dtype!='object'):
        numerical_features.append(col)
    else:
        categorical_features.append(col)
print(categorical_features)
import seaborn as sns
sns.heatmap(hotel_1[numerical_features].corr())
```

```
['ArrivalDateMonth', 'Meal', 'Country', 'MarketSegment', 'Distribution
Channel', 'ReservedRoomType', 'AssignedRoomType', 'DepositType', 'Agen
t', 'CustomerType', 'ReservationStatus']
```

Out[8]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f74d2760f50>
```



Start asking questions pertaining to your problem and answer them using your Data

- **Q1. Are booking cancellations affected by the time of the year?**

  Ans: *Plot a Bargraph to see the total number of cancellations in each month for each hotel.*

In [9]:

```
hotel_1['IsCanceled'].sample(10)
```

Out[9]:

```
ReservationStatusDate
2016-11-03    0
2016-03-10    0
2017-04-10    1
2017-02-25    0
2015-10-25    0
2017-02-01    1
2015-06-17    1
2016-06-30    0
2016-12-18    0
2016-10-20    1
Name: IsCanceled, dtype: int64
```

In [10]:

```
# Create a new Dataframe which contains only the cancelled entries from Hotel_1
h1_canc = hotel_1[hotel_1['IsCanceled']==1]

# Similarly create a new Dataframe which contains only the NON-cancelled entries fr
h1_not_canc = hotel_1[hotel_1['IsCanceled']==0]

# Total number of monthly Cancellations of Hotel-1 by month
h1_canc_by_month = h1_canc.groupby(['ArrivalDateMonth']).count()
h1_not_canc_by_month = h1_not_canc.groupby(['ArrivalDateMonth']).count()
h1_canc_by_month.head(12)
```

Out[10]:

	IsCanceled	LeadTime	ArrivalDateYear	ArrivalDateWeekNumber	ArrivalDateDa
ArrivalDateMonth					
April	1059	1059	1059	1059	
August	1637	1637	1637	1637	
December	631	631	631	631	
February	795	795	795	795	
January	325	325	325	325	
July	1436	1436	1436	1436	
June	1007	1007	1007	1007	
March	763	763	763	763	
May	1024	1024	1024	1024	
November	461	461	461	461	
October	978	978	978	978	
September	1006	1006	1006	1006	

12 rows × 28 columns

Similarly repeat the process for Hotel-2

In [11]:

```
# Create a new Dataframe which contains only the cancelled entries from Hotel_2
h2_canc = hotel_2[hotel_2['IsCanceled']==1]

# Similarly create a new Dataframe which contains only the NON-cancelled entries fr
h2_not_canc = hotel_2[hotel_2['IsCanceled']==0]

# Group by a feature of your choice and then apply a summary statistic

# Total number of monthly Cancellations of Hotel-1 by month
h2_canc_by_month = h2_canc.groupby(['ArrivalDateMonth']).count()
h2_not_canc_by_month = h2_not_canc.groupby(['ArrivalDateMonth']).count()
h2_canc_by_month.head(12)
```

Out[11]:

	IsCanceled	LeadTime	ArrivalDateYear	ArrivalDateWeekNumber	ArrivalDateDa
ArrivalDateMonth					
April	3465	3465	3465	3465	
August	3602	3602	3602	3602	
December	1740	1740	1740	1740	
February	1901	1901	1901	1901	
January	1482	1482	1482	1482	
July	3306	3306	3306	3306	
June	3528	3528	3528	3528	
March	2386	2386	2386	2386	
May	3653	3653	3653	3653	
November	1661	1661	1661	1661	
October	3268	3268	3268	3268	
September	3110	3110	3110	3110	

12 rows × 28 columns

In [12]:

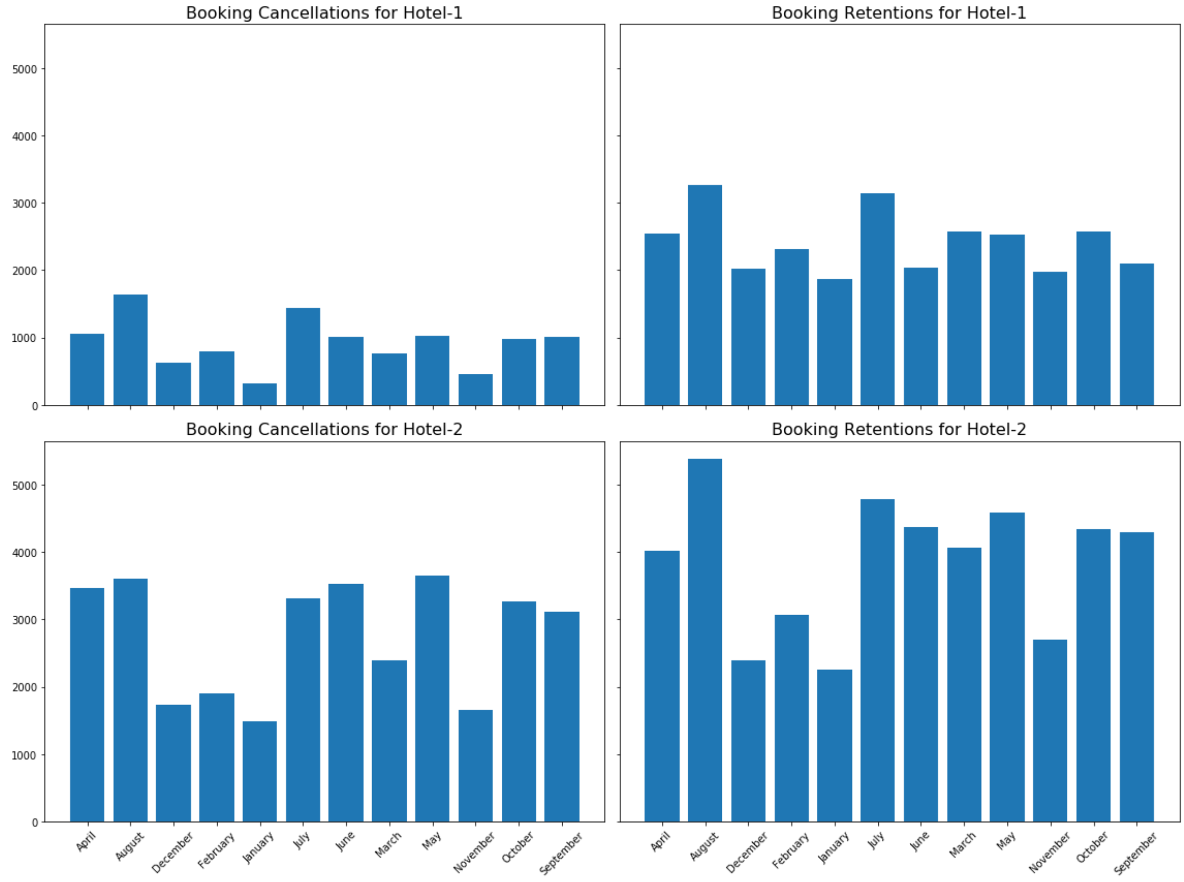
```
import matplotlib.pyplot as plt
import seaborn as sns
fig, ax = plt.subplots(nrows=2,ncols=2,sharex=True,sharey=True,figsize=(16,12))
ax[0,0].bar(x=h1_canc_by_month.index,height='IsCanceled',data=h1_canc_by_month)
ax[0, 0].set_title('Booking Cancellations for Hotel-1', fontsize=16)

ax[0,1].bar(x=h1_not_canc_by_month.index,height='IsCanceled',data=h1_not_canc_by_mo
ax[0, 1].set_title('Booking Retentions for Hotel-1', fontsize=16)

ax[1,0].bar(x=h2_canc_by_month.index,height='IsCanceled',data=h2_canc_by_month)
ax[1, 0].set_title('Booking Cancellations for Hotel-2', fontsize=16)
plt.sca(ax[1, 0])
plt.xticks(rotation=45)

ax[1,1].bar(x=h2_not_canc_by_month.index,height='IsCanceled',data=h2_not_canc_by_mo
ax[1, 1].set_title('Booking Retentions for Hotel-2', fontsize=16)
plt.sca(ax[1, 1])
plt.xticks(rotation=45)

fig.tight_layout()
plt.show()
```



So do Booking cancelations depend on the month of booking?

Ans: _____

Feature Engineering

- Process of creating new features and meaningful features from exisiting ones to replace them.
- Moslty used before building models but extremely helpful while EDA as well.
- Works best when combined with domain knowledge.

Ex- In our case, perhaps it makes more sense to consider the percentage of cancelations rather than the total number of cancelations as total number of cancelations is a misleading term to answer our question!

In [14]:

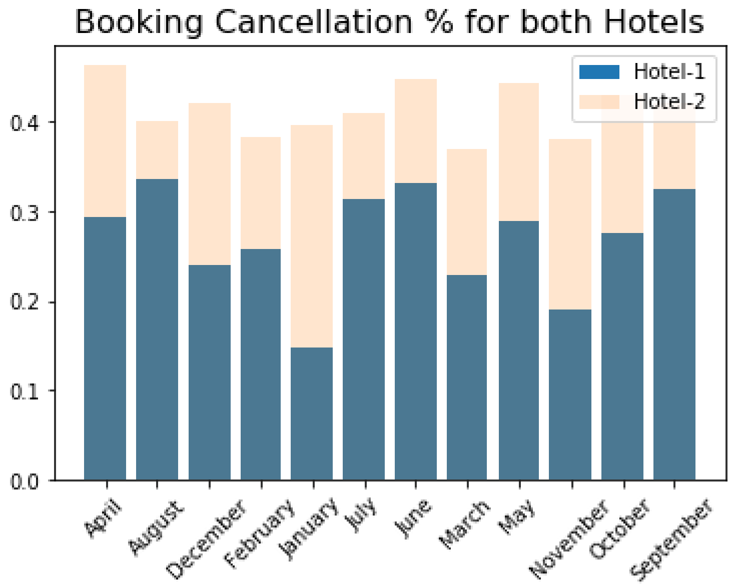
```
canc_h1_list = h1_canc_by_month['IsCanceled']
total_bookings_h1_by_month = h1_canc_by_month['IsCanceled'] + h1_not_canc_by_month[
percent_canc_h1 = canc_h1_list/total_bookings_h1_by_month
```

In [15]:

```
canc_h2_list = h2_canc_by_month['IsCanceled']
total_bookings_h2_by_month = h2_canc_by_month['IsCanceled'] + h2_not_canc_by_month[
percent_canc_h2 = canc_h2_list/total_bookings_h2_by_month
```

In [16]:

```
plt.bar(x=percent_canc_h1.index,height=percent_canc_h1.values,label= 'Hotel-1')
plt.bar(x=percent_canc_h2.index,height=percent_canc_h2.values,label= 'Hotel-2',alph
plt.legend()
plt.title('Booking Cancellation % for both Hotels', fontsize=16)
plt.xticks(rotation=45)
plt.show()
```



Notice the subtle difference in the month receiving highest cancellations for Hotel-2 Using simply the total number of cancellations we were getting August as the worst month for Hotel-2, whereas now we get April. Many more interesting things come up from this plot Ex- The highest difference b/w cancellations for the two hotels is during January.

Conclusion

We conclude that month of booking definitely plays a role in determining whether a person would *cancel* the Booking or not. In addition we observe that **August** is more or less the best month for both the Hotels as they recieve the highest numbers of customers during that time. Thus the hotel staff or the booking website should offer people more incentives to prevent cancellations during this month!

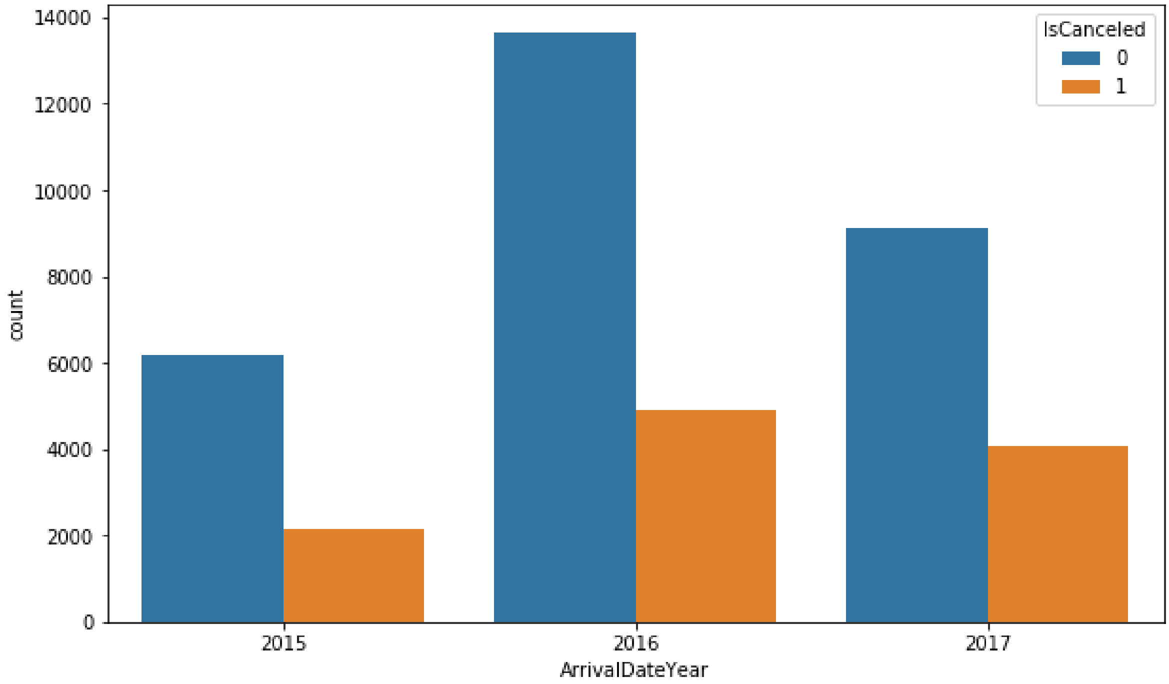
Further Questions?

A follow up question would be:- Now that we know that month of booking is important, Do Booking Cancellations also depend upon the week of the year? Or were these trend of Bookings same for all 3 years?

This was just the analysis for a single feature (Month of Booking). You can try to formulate questions and conduct similar analysis for almost all the features!!

In [17]:

```
# Cancellations for Hotel-1 across different years
plt.figure(figsize=(10,6))
sns.countplot(data=hotel_1,x='ArrivalDateYear',hue='IsCanceled')
plt.show()
```



Data Preparation for Modelling

In [18]:

```
#hotel_bookings_df['arrival_date_month'] = hotel_1['ArrivalDateMonth'].map({'Januar
                                                            # 'August':8, 'September
#hotel_1['hotel'] = hotel_1['hotel'].map({'Resort Hotel':0, 'City Hotel':1})
#hotel_1["total_members"] = hotel_1["adults"] + hotel_bookings_df["children"] + hot
#hotel_1["total_stay"] = hotel_1["stays_in_weekend_nights"]+ hotel_bookings_df["sta
#hotel_1.drop(columns = ['adults', 'babies', 'children', 'stays_in_weekend_nights',
```

In [19]:

```
hotel_1.dtypes
```

Out[19]:

```
IsCanceled                        int64
LeadTime                          int64
ArrivalDateYear                   int64
ArrivalDateMonth                 object
ArrivalDateWeekNumber             int64
ArrivalDateDayOfMonth             int64
StaysInWeekendNights              int64
StaysInWeekNights                 int64
Adults                            int64
Children                          int64
Babies                            int64
Meal                             object
Country                          object
MarketSegment                    object
DistributionChannel              object
IsRepeatedGuest                   int64
PreviousCancellations             int64
PreviousBookingsNotCanceled       int64
ReservedRoomType                 object
AssignedRoomType                 object
BookingChanges                    int64
DepositType                      object
Agent                            object
DaysInWaitingList                 int64
CustomerType                     object
ADR                             float64
RequiredCarParkingSpaces          int64
TotalOfSpecialRequests            int64
ReservationStatus                object
dtype: object
```

Select Features which you want to include in your model.

In [20]:

```
hotel_1['Agent'].value_counts()# Too many categories
# ReservationStatus can cause data leakage as it is very related to Booking Cancell
h1_df_modelling = hotel_1.drop(['ArrivalDateYear','ArrivalDateDayOfMonth','Agent','
h1_df_modelling.head()
```

Out[20]:

	IsCanceled	LeadTime	ArrivalDateMonth	ArrivalDateWeekNumber	Sta
ReservationStatusDate					
2015-07-01	0	342	July	27	
2015-07-01	0	737	July	27	
2015-07-02	0	7	July	27	
2015-07-02	0	13	July	27	
2015-07-03	0	14	July	27	

5 rows × 25 columns

In [21]:

```
df_encoded = pd.get_dummies(h1_df_modelling)
print("Dimensions of Encoded dataset are:-", df_encoded.shape)
df_encoded.sample(20)
```

```
Dimensions of Encoded dataset are:- (40060, 196)
```

Out[21]:

	IsCanceled	LeadTime	ArrivalDateWeekNumber	StaysInWeekendNights
ReservationStatusDate				
2017-01-30	0	0	5	1
2017-05-22	0	251	19	4
2015-12-27	0	1	52	0
2016-07-30	0	150	30	2
2015-08-10	1	181	35	1
2015-10-23	0	0	43	0
2016-12-26	0	1	52	1
2016-04-19	0	8	16	2
2017-08-12	0	204	32	0
2016-11-06	0	37	45	0
2015-10-12	0	36	41	1
2016-02-17	0	0	8	1
2016-06-08	0	129	24	2
2016-10-09	0	383	41	0
2016-09-14	0	301	37	2
2016-06-30	1	75	38	2
2017-07-24	0	47	29	1
2016-02-11	0	0	7	0
2017-06-18	0	25	24	0
2016-10-14	1	123	7	1

20 rows × 196 columns

In [22]:

```
df_encoded = pd.get_dummies(h1_df_modelling)
print("Dimensions of Encoded dataset are:-", df_encoded.shape)
df_encoded.sample(20)
```

```
Dimensions of Encoded dataset are:- (40060, 196)
```

Out[22]:

	IsCanceled	LeadTime	ArrivalDateWeekNumber	StaysInWeekendNights
ReservationStatusDate				
2015-10-01	0	115	39	2
2015-11-20	0	0	47	0
2017-06-08	0	0	23	0
2016-04-06	0	171	15	1
2015-09-02	1	247	41	1
2017-07-30	0	165	29	2
2016-08-08	0	194	32	2
2017-03-19	0	3	11	0
2015-11-01	0	4	44	0
2017-01-06	0	5	1	1
2016-01-21	0	5	4	0
2016-12-18	0	1	51	0
2016-04-23	0	37	17	0
2015-08-04	0	2	32	2
2017-05-30	1	129	32	0
2016-03-31	0	17	14	2
2015-08-07	0	82	32	2
2016-11-08	0	0	46	1
2016-03-23	0	28	12	2
2015-10-24	0	47	43	1

20 rows × 196 columns

Split into training and test set

In [23]:

```
y = df_encoded.iloc[:,0]
X = df_encoded.drop(['IsCanceled'],axis=1)# Dropping response variable
X.head()# Confirm to see that response is no longer in X
```

Out[23]:

	LeadTime	ArrivalDateWeekNumber	StaysInWeekendNights	StaysInWeekN
ReservationStatusDate				
2015-07-01	342	27	0	
2015-07-01	737	27	0	
2015-07-02	7	27	0	
2015-07-02	13	27	0	
2015-07-03	14	27	0	

5 rows × 195 columns

In [24]:

```
# Convert response from int to categorical(object type)
#y = y.astype("int64")
#y.sample(5)
```

In [25]:

```
from sklearn.model_selection import train_test_split
X_train,X_test,y_train,y_test = train_test_split(X,y,test_size=0.25,random_state=26
```

In [26]:

```
# Defining a function to train models
def training(model,X_train, y_train):
    return model.fit(X_train, y_train)
```

In [27]:

```
# Defining a function to test models
def evaluation_stats(model,X_train, X_test, y_train, y_test,algo):
    print('Train Accuracy')
    if algo=='NN':
        print(confusion_matrix(y_train,model.predict_classes(X_train)))
        y_pred = model.predict_classes(X_test)
    else:
        print(confusion_matrix(y_train,model.predict(X_train)))
        y_pred = model.predict(X_test)
    print('Validation Accuracy')

    print(confusion_matrix(y_test,y_pred))
    print('Classification_report')
    print(classification_report(y_test,y_pred))
```

In [28]:

```
from sklearn.ensemble import RandomForestClassifier
from xgboost import XGBClassifier
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import GridSearchCV
from sklearn.metrics import confusion_matrix,classification_report
#from imblearn.over_sampling import SMOTE
```

Random Forest Classifier

In [29]:

```
rf_model = training(RandomForestClassifier(n_estimators=1000,max_depth=10),X_train,
evaluation_stats(rf_model,X_train, X_test, y_train, y_test,'RANDOM FOREST')
```

```
Train Accuracy
[[21449   317]
 [ 4641  3638]]
Validation Accuracy
[[7065  107]
 [1617 1226]]
Classification_report
              precision    recall  f1-score   support

           0       0.81      0.99      0.89      7172
           1       0.92      0.43      0.59      2843

    accuracy                           0.83     10015
   macro avg       0.87      0.71      0.74     10015
weighted avg       0.84      0.83      0.80     10015
```

XGBoost Classifier

In [30]:

```
xbg_model = training(XGBClassifier(n_estimators=1000,max_depth=10),X_train,y_train)
evaluation_stats(xbg_model,X_train, X_test, y_train, y_test,'XGBoost')
```

```
Train Accuracy
[[21748    18]
 [   49  8230]]
Validation Accuracy
[[6708  464]
 [ 598 2245]]
Classification_report
              precision    recall  f1-score   support

           0       0.92      0.94      0.93      7172
           1       0.83      0.79      0.81      2843

    accuracy                           0.89     10015
   macro avg       0.87      0.86      0.87     10015
weighted avg       0.89      0.89      0.89     10015
```

Artificial Neural Network

In [31]:

```
from keras.models import Sequential
from keras.layers import Dense
```

```
Using TensorFlow backend.
```

ANN with 1 hidden layer, 12 Neurons and Sigmoid Activation

In [32]:

```
model = Sequential()
model.add(Dense(12, input_dim=195, activation='sigmoid'))
model.add(Dense(1, activation='sigmoid'))
model.compile(loss='binary_crossentropy', optimizer='adam', metrics=['accuracy'])
model.summary()
model.fit(X, y, epochs=20, batch_size= 100)# Dataset would be divided into n/100 pa
#The model weights will be updated after each batch of 100 samples.
#This also means that one epoch will involve n/100 batches or n/100 weight updates
```

```
Model: "sequential_1"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
dense_1 (Dense)              (None, 12)                2352
_________________________________________________________________
dense_2 (Dense)              (None, 1)                 13
=================================================================
Total params: 2,365
Trainable params: 2,365
Non-trainable params: 0
_________________________________________________________________
Epoch 1/20
40060/40060 [==============================] - 1s 20us/step - loss: 0.
6025 - accuracy: 0.6753
Epoch 2/20
40060/40060 [==============================] - 1s 14us/step - loss: 0.
4978 - accuracy: 0.7299
Epoch 3/20
40060/40060 [==============================] - 1s 13us/step - loss: 0.
4239 - accuracy: 0.8125
Epoch 4/20
40060/40060 [==============================] - 1s 13us/step - loss: 0.
3752 - accuracy: 0.8448
Epoch 5/20
40060/40060 [==============================] - 1s 14us/step - loss: 0.
3517 - accuracy: 0.8529
Epoch 6/20
40060/40060 [==============================] - 1s 13us/step - loss: 0.
3373 - accuracy: 0.8569
Epoch 7/20
40060/40060 [==============================] - 1s 14us/step - loss: 0.
3274 - accuracy: 0.8600
Epoch 8/20
40060/40060 [==============================] - 1s 14us/step - loss: 0.
3207 - accuracy: 0.8611
Epoch 9/20
40060/40060 [==============================] - 1s 14us/step - loss: 0.
3147 - accuracy: 0.8635
Epoch 10/20
40060/40060 [==============================] - 1s 13us/step - loss: 0.
3094 - accuracy: 0.8646
Epoch 11/20
40060/40060 [==============================] - 1s 13us/step - loss: 0.
3052 - accuracy: 0.8654
Epoch 12/20
40060/40060 [==============================] - 1s 13us/step - loss: 0.
3020 - accuracy: 0.8666
Epoch 13/20
40060/40060 [==============================] - 1s 13us/step - loss: 0.
```

```
2988 - accuracy: 0.8669
Epoch 14/20
40060/40060 [==============================] - 1s 13us/step - loss: 0.
2968 - accuracy: 0.8672
Epoch 15/20
40060/40060 [==============================] - 1s 13us/step - loss: 0.
2947 - accuracy: 0.8679
Epoch 16/20
40060/40060 [==============================] - 1s 13us/step - loss: 0.
2926 - accuracy: 0.8683
Epoch 17/20
40060/40060 [==============================] - 1s 13us/step - loss: 0.
2903 - accuracy: 0.8691
Epoch 18/20
40060/40060 [==============================] - 1s 13us/step - loss: 0.
2882 - accuracy: 0.8707
Epoch 19/20
40060/40060 [==============================] - 1s 13us/step - loss: 0.
2870 - accuracy: 0.8712
Epoch 20/20
40060/40060 [==============================] - 1s 13us/step - loss: 0.
2854 - accuracy: 0.8710
```

Out[32]:

```
<keras.callbacks.callbacks.History at 0x7f745ad17250>
```

In [33]:

```
evaluation_stats(model,X_train, X_test, y_train, y_test,'NN')
```

```
Train Accuracy
[[20257  1509]
 [ 2310  5969]]
Validation Accuracy
[[6694  478]
 [ 806 2037]]
Classification_report
              precision    recall  f1-score   support

           0       0.89      0.93      0.91      7172
           1       0.81      0.72      0.76      2843

    accuracy                           0.87     10015
   macro avg       0.85      0.82      0.84     10015
weighted avg       0.87      0.87      0.87     10015
```

In [34]:

```
model2 = Sequential()
model2.add(Dense(1000, input_dim=195, activation='sigmoid'))
model2.add(Dense(1, activation='sigmoid'))
model2.compile(loss='binary_crossentropy', optimizer='adam', metrics=['accuracy'])
model2.fit(X, y, epochs=20, batch_size= 100)
```

```
Epoch 1/20
40060/40060 [==============================] - 2s 42us/step - loss: 0.
4141 - accuracy: 0.8082
Epoch 2/20
40060/40060 [==============================] - 2s 45us/step - loss: 0.
3262 - accuracy: 0.8570
Epoch 3/20
40060/40060 [==============================] - 2s 46us/step - loss: 0.
3147 - accuracy: 0.8612
Epoch 4/20
40060/40060 [==============================] - 2s 46us/step - loss: 0.
3053 - accuracy: 0.8648
Epoch 5/20
40060/40060 [==============================] - 2s 45us/step - loss: 0.
3013 - accuracy: 0.8665
Epoch 6/20
40060/40060 [==============================] - 2s 45us/step - loss: 0.
2976 - accuracy: 0.8681
Epoch 7/20
40060/40060 [==============================] - 2s 46us/step - loss: 0.
2910 - accuracy: 0.8725
Epoch 8/20
40060/40060 [==============================] - 2s 45us/step - loss: 0.
2878 - accuracy: 0.8730
Epoch 9/20
40060/40060 [==============================] - 2s 53us/step - loss: 0.
2876 - accuracy: 0.8697
Epoch 10/20
40060/40060 [==============================] - 2s 54us/step - loss: 0.
2790 - accuracy: 0.8765
Epoch 11/20
40060/40060 [==============================] - 2s 51us/step - loss: 0.
2761 - accuracy: 0.8783
Epoch 12/20
40060/40060 [==============================] - 2s 49us/step - loss: 0.
2732 - accuracy: 0.8783
Epoch 13/20
40060/40060 [==============================] - 2s 55us/step - loss: 0.
2713 - accuracy: 0.8793
Epoch 14/20
40060/40060 [==============================] - 2s 53us/step - loss: 0.
2684 - accuracy: 0.8818
Epoch 15/20
40060/40060 [==============================] - 2s 52us/step - loss: 0.
2672 - accuracy: 0.8810
Epoch 16/20
40060/40060 [==============================] - 2s 48us/step - loss: 0.
2653 - accuracy: 0.8808
Epoch 17/20
40060/40060 [==============================] - 2s 49us/step - loss: 0.
2620 - accuracy: 0.8833
Epoch 18/20
40060/40060 [==============================] - 2s 48us/step - loss: 0.
```

```
2617 - accuracy: 0.8834
Epoch 19/20
40060/40060 [==============================] - 2s 48us/step - loss: 0.
2576 - accuracy: 0.8857
Epoch 20/20
40060/40060 [==============================] - 2s 48us/step - loss: 0.
2588 - accuracy: 0.8848
```

Out[34]:

```
<keras.callbacks.callbacks.History at 0x7f74581ac6d0>
```

In [35]:

```
evaluation_stats(model2,X_train, X_test, y_train, y_test,'NN')
```

```
Train Accuracy
[[21009   757]
 [ 2671  5608]]
Validation Accuracy
[[6923  249]
 [ 957 1886]]
Classification_report
              precision    recall  f1-score   support

           0       0.88      0.97      0.92      7172
           1       0.88      0.66      0.76      2843

    accuracy                           0.88     10015
   macro avg       0.88      0.81      0.84     10015
weighted avg       0.88      0.88      0.87     10015
```

Tasks before next lab

- Scale the data and try building the NN once again.
- Conduct more Exploratory Data Analysis and come up with interesting insights!
- Using Feature Engineering construct reduce the number of features to be used while building these Classification Models.
- Perform a Regression Problem by trying to predict ADR prices.

In [ ]:

```

```