Telecom Churn Case Study

With 21 predictor variables we need to predict whether a particular customer will switch to another telecom provider or not. In telecom terminology, this is referred to as churning and not churning, respectively.

Step 1: Importing and Merging Data

In [1]:
```
# Suppressing Warnings
import warnings
warnings.filterwarnings('ignore')
```

In [2]:
```
# Importing Pandas and NumPy
import pandas as pd, numpy as np
```

In [110]:
```
# Importing all datasets
churn_data = pd.read_csv("churn_data.csv")
churn_data.head()
```

Out[110]:

	customerID	tenure	PhoneService	Contract	PaperlessBilling	PaymentMethod	MonthlyCharges	TotalChar
0	7590-VHVEG	1	No	Month-to-month	Yes	Electronic check	29.85	2
1	5575-GNVDE	34	Yes	One year	No	Mailed check	56.95	18
2	3668-QPYBK	2	Yes	Month-to-month	Yes	Mailed check	53.85	10
3	7795-CFOCW	45	No	One year	No	Bank transfer (automatic)	42.30	184
4	9237-HQITU	2	Yes	Month-to-month	Yes	Electronic check	70.70	15

In [111]:
```
customer_data = pd.read_csv("customer_data.csv")
customer_data.head()
```

Out[111]:

	customerID	gender	SeniorCitizen	Partner	Dependents
0	7590-VHVEG	Female	0	Yes	No
1	5575-GNVDE	Male	0	No	No
2	3668-QPYBK	Male	0	No	No
3	7795-CFOCW	Male	0	No	No
4	9237-HQITU	Female	0	No	No

In [112]:
```
internet_data = pd.read_csv("internet_data.csv")
internet_data.head()
```

Out[112]:

	customerID	MultipleLines	InternetService	OnlineSecurity	OnlineBackup	DeviceProtection	TechSupport
0	7590-VHVEG	No phone service	DSL	No	Yes	No	No
1	5575-GNVDE	No	DSL	Yes	No	Yes	No
2	3668-QPYBK	No	DSL	Yes	Yes	No	No
3	7795-CFOCW	No phone service	DSL	Yes	No	Yes	Yes
4	9237-HQITU	No	Fiber optic	No	No	No	No

Combining all data files into one consolidated dataframe

In [113]:
```
# Merging on 'customerID'
df_1 = pd.merge(churn_data, customer_data, how='inner', on='customerID')
```

In [114]:
```
# Final dataframe with all predictor variables
telecom = pd.merge(df_1, internet_data, how='inner', on='customerID')
```

In [62]:
```
jm_telecom = telecom
```

In [67]:
```
jm_telecom['OnlineBackup'].astype('category').value_counts()
```

Out[67]:
```
No                     3088
Yes                    2429
No internet service    1526
Name: OnlineBackup, dtype: int64
```

In [68]:
```
jm_telecom['OnlineSecurity'].astype('category').value_counts()
```

Out[68]:
```
No                     3498
Yes                    2019
No internet service    1526
Name: OnlineSecurity, dtype: int64
```

In [69]:
```
jm_telecom['DeviceProtection'].astype('category').value_counts()
```

Out[69]:
```
No                     3095
Yes                    2422
No internet service    1526
Name: DeviceProtection, dtype: int64
```

In [70]:
```
jm_telecom['InternetService'].astype('category').value_counts()
```

Out[70]:
```
Fiber optic    3096
DSL            2421
No             1526
Name: InternetService, dtype: int64
```

Step 2: Inspecting the Dataframe

In [71]:
```
# Let's see the head of our master dataset
telecom.head()
```

Out[71]:

	customerID	tenure	PhoneService	Contract	PaperlessBilling	PaymentMethod	MonthlyCharges	TotalChar
0	7590-VHVEG	1	No	Month-to-month	Yes	Electronic check	29.85	2
1	5575-GNVDE	34	Yes	One year	No	Mailed check	56.95	18
2	3668-QPYBK	2	Yes	Month-to-month	Yes	Mailed check	53.85	10
3	7795-CFOCW	45	No	One year	No	Bank transfer (automatic)	42.30	184
4	9237-HQITU	2	Yes	Month-to-month	Yes	Electronic check	70.70	15

5 rows × 21 columns

In [48]:
```
# Let's check the dimensions of the dataframe
telecom.shape
```

Out[48]:
```
(7043, 21)
```

In [49]:
```
# let's look at the statistical aspects of the dataframe
telecom.describe()
```

Out[49]:

	tenure	MonthlyCharges	SeniorCitizen
count	7043.000000	7043.000000	7043.000000
mean	32.371149	64.761692	0.162147
std	24.559481	30.090047	0.368612
min	0.000000	18.250000	0.000000
25%	9.000000	35.500000	0.000000
50%	29.000000	70.350000	0.000000
75%	55.000000	89.850000	0.000000
max	72.000000	118.750000	1.000000

In [72]:
```
# Let's see the type of each column
telecom.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 7043 entries, 0 to 7042
Data columns (total 21 columns):
customerID          7043 non-null object
tenure              7043 non-null int64
PhoneService        7043 non-null object
Contract            7043 non-null object
PaperlessBilling    7043 non-null object
PaymentMethod       7043 non-null object
MonthlyCharges      7043 non-null float64
TotalCharges        7043 non-null object
Churn               7043 non-null object
gender              7043 non-null object
SeniorCitizen       7043 non-null int64
Partner             7043 non-null object
Dependents          7043 non-null object
MultipleLines       7043 non-null object
InternetService     7043 non-null object
OnlineSecurity      7043 non-null object
OnlineBackup        7043 non-null object
DeviceProtection    7043 non-null object
TechSupport         7043 non-null object
StreamingTV         7043 non-null object
StreamingMovies     7043 non-null object
dtypes: float64(1), int64(2), object(18)
memory usage: 1.2+ MB
```

Step 3: Data Preparation

In [73]:
```
telecom['MultipleLines'].astype('category').value_counts()
```

Out[73]:
```
No                  3390
Yes                 2971
No phone service     682
Name: MultipleLines, dtype: int64
```

for the column ‘MultipleLines’, you dropped the level ‘MultipleLines_No phone service’ manually instead of simply using ‘drop_first = True’ which would’ve dropped the first level present in the ‘MultipleLines’ column. The reason we did this is that if you check the variables ‘MultipleLines’ using the following command, you can see that it has the three levels above.

To simply put it, the variable ‘PhoneService’ already tells you whether the phone services are availed or not by a particular customer. In fact, if you check the value counts of the variable 'PhoneService', following is the output that you get:

In [31]:
```
telecom['PhoneService'].astype('category').value_counts()
```

Out[31]:
```
Yes    6361
No      682
Name: PhoneService, dtype: int64
```

You can see that the level 'No' appears 682 times which is exactly equal to the count of the level 'No phone service' in 'MultipleLines'. Hence 'No phone service' in 'MultipleLines' column is clearly redundant. So, while creating dummies we can get rid off this column later.

Converting some binary variables (Yes/No) to 0/1

In [115]:
```
# List of variables to map

varlist =  ['PhoneService', 'PaperlessBilling', 'Churn', 'Partner', 'Depend
ents']

# Defining the map function
def binary_map(x):
    return x.map({'Yes': 1, "No": 0})

# Applying the function to the housing list
telecom[varlist] = telecom[varlist].apply(binary_map)
```

In [33]:
```
telecom.head()
```

Out[33]:

	customerID	tenure	PhoneService	Contract	PaperlessBilling	PaymentMethod	MonthlyCharges	TotalChar
0	7590-VHVEG	1	0	Month-to-month	1	Electronic check	29.85	2!
1	5575-GNVDE	34	1	One year	0	Mailed check	56.95	18!
2	3668-QPYBK	2	1	Month-to-month	1	Mailed check	53.85	10!
3	7795-CFOCW	45	0	One year	0	Bank transfer (automatic)	42.30	184(
4	9237-HQITU	2	1	Month-to-month	1	Electronic check	70.70	15:

5 rows × 21 columns

For categorical variables with multiple levels, create dummy features (one-hot encoded)

In [116]:
```
# Creating a dummy variable for some of the categorical variables and dropp
ing the first one.
dummy1 = pd.get_dummies(telecom[['Contract', 'PaymentMethod', 'gender', 'In
ternetService']], drop_first=True)

# Adding the results to the master dataframe
telecom = pd.concat([telecom, dummy1], axis=1)
```

In [35]:
```
telecom.head()
```

Out[35]:

	customerID	tenure	PhoneService	Contract	PaperlessBilling	PaymentMethod	MonthlyCharges	TotalChar
0	7590-VHVEG	1	0	Month-to-month	1	Electronic check	29.85	2!
1	5575-GNVDE	34	1	One year	0	Mailed check	56.95	18!
2	3668-QPYBK	2	1	Month-to-month	1	Mailed check	53.85	10!
3	7795-CFOCW	45	0	One year	0	Bank transfer (automatic)	42.30	184(
4	9237-HQITU	2	1	Month-to-month	1	Electronic check	70.70	15:

5 rows × 29 columns

In [117]:
```
# Creating dummy variables for the remaining categorical variables and drop
ping the level with big names.

# Creating dummy variables for the variable 'MultipleLines'
ml = pd.get_dummies(telecom['MultipleLines'], prefix='MultipleLines')
# Dropping MultipleLines_No phone service column
ml1 = ml.drop(['MultipleLines_No phone service'], 1)
#Adding the results to the master dataframe
telecom = pd.concat([telecom,ml1], axis=1)

# Creating dummy variables for the variable 'OnlineSecurity'.
os = pd.get_dummies(telecom['OnlineSecurity'], prefix='OnlineSecurity')
os1 = os.drop(['OnlineSecurity_No internet service'], 1)
# Adding the results to the master dataframe
telecom = pd.concat([telecom,os1], axis=1)

# Creating dummy variables for the variable 'OnlineBackup'.
ob = pd.get_dummies(telecom['OnlineBackup'], prefix='OnlineBackup')
ob1 = ob.drop(['OnlineBackup_No internet service'], 1)
# Adding the results to the master dataframe
telecom = pd.concat([telecom,ob1], axis=1)

# Creating dummy variables for the variable 'DeviceProtection'.
dp = pd.get_dummies(telecom['DeviceProtection'], prefix='DeviceProtection')
dp1 = dp.drop(['DeviceProtection_No internet service'], 1)
# Adding the results to the master dataframe
telecom = pd.concat([telecom,dp1], axis=1)

# Creating dummy variables for the variable 'TechSupport'.
ts = pd.get_dummies(telecom['TechSupport'], prefix='TechSupport')
ts1 = ts.drop(['TechSupport_No internet service'], 1)
# Adding the results to the master dataframe
telecom = pd.concat([telecom,ts1], axis=1)

# Creating dummy variables for the variable 'StreamingTV'.
st =pd.get_dummies(telecom['StreamingTV'], prefix='StreamingTV')
st1 = st.drop(['StreamingTV_No internet service'], 1)
# Adding the results to the master dataframe
telecom = pd.concat([telecom,st1], axis=1)

# Creating dummy variables for the variable 'StreamingMovies'.
sm = pd.get_dummies(telecom['StreamingMovies'], prefix='StreamingMovies')
sm1 = sm.drop(['StreamingMovies_No internet service'], 1)
# Adding the results to the master dataframe
telecom = pd.concat([telecom,sm1], axis=1)
```

In [38]:
```
telecom.head()
```

Out[38]:

	customerID	tenure	PhoneService	Contract	PaperlessBilling	PaymentMethod	MonthlyCharges	TotalChar
0	7590-VHVEG	1	0	Month-to-month	1	Electronic check	29.85	2!
1	5575-GNVDE	34	1	One year	0	Mailed check	56.95	18!
2	3668-QPYBK	2	1	Month-to-month	1	Mailed check	53.85	10!
3	7795-CFOCW	45	0	One year	0	Bank transfer (automatic)	42.30	184(
4	9237-HQITU	2	1	Month-to-month	1	Electronic check	70.70	15:

5 rows × 43 columns

Dropping the repeated variables

In [118]:
```
# We have created dummies for the below variables, so we can drop them
telecom = telecom.drop(['Contract','PaymentMethod','gender','MultipleLines'
,'InternetService', 'OnlineSecurity', 'OnlineBackup', 'DeviceProtection',
       'TechSupport', 'StreamingTV', 'StreamingMovies'], 1)
```

In [78]:
```
telecom.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 7043 entries, 0 to 7042
Data columns (total 32 columns):
customerID                               7043 non-null object
tenure                                   7043 non-null int64
PhoneService                             7043 non-null int64
PaperlessBilling                         7043 non-null int64
MonthlyCharges                           7043 non-null float64
TotalCharges                             7043 non-null object
Churn                                    7043 non-null int64
SeniorCitizen                            7043 non-null int64
Partner                                  7043 non-null int64
Dependents                               7043 non-null int64
Contract_One year                        7043 non-null uint8
Contract_Two year                        7043 non-null uint8
PaymentMethod_Credit card (automatic)    7043 non-null uint8
PaymentMethod_Electronic check           7043 non-null uint8
PaymentMethod_Mailed check               7043 non-null uint8
gender_Male                              7043 non-null uint8
InternetService_Fiber optic              7043 non-null uint8
InternetService_No                       7043 non-null uint8
MultipleLines_No                         7043 non-null uint8
MultipleLines_Yes                        7043 non-null uint8
OnlineSecurity_No                        7043 non-null uint8
OnlineSecurity_Yes                       7043 non-null uint8
OnlineBackup_No                          7043 non-null uint8
OnlineBackup_Yes                         7043 non-null uint8
DeviceProtection_No                      7043 non-null uint8
DeviceProtection_Yes                     7043 non-null uint8
TechSupport_No                           7043 non-null uint8
TechSupport_Yes                          7043 non-null uint8
StreamingTV_No                           7043 non-null uint8
StreamingTV_Yes                          7043 non-null uint8
StreamingMovies_No                       7043 non-null uint8
StreamingMovies_Yes                      7043 non-null uint8
dtypes: float64(1), int64(7), object(2), uint8(22)
memory usage: 756.6+ KB
```

In [119]:
```
#The varaible was imported as a string we need to convert it to float
#telecom['TotalCharges'] = telecom['TotalCharges'].convert_objects(convert_
numeric=True)
telecom['TotalCharges'] = pd.to_numeric(telecom['TotalCharges'], errors='co
erce')
#telecom['TotalCharges'] = telecom['TotalCharges'].astype(np.float64)
```

Now you can see that you have all variables as numeric.

Checking for Outliers

In [120]:
```
# Checking for outliers in the continuous variables
num_telecom = telecom[['tenure','MonthlyCharges','SeniorCitizen','TotalChar
ges']]
```

In [121]:
```
# Checking outliers at 25%, 50%, 75%, 90%, 95% and 99%
num_telecom.describe(percentiles=[.25, .5, .75, .90, .95, .99])
```

Out[121]:

	tenure	MonthlyCharges	SeniorCitizen	TotalCharges
count	7043.000000	7043.000000	7043.000000	7032.000000
mean	32.371149	64.761692	0.162147	2283.300441
std	24.559481	30.090047	0.368612	2266.771362
min	0.000000	18.250000	0.000000	18.800000
25%	9.000000	35.500000	0.000000	401.450000
50%	29.000000	70.350000	0.000000	1397.475000
75%	55.000000	89.850000	0.000000	3794.737500
90%	69.000000	102.600000	1.000000	5976.640000
95%	72.000000	107.400000	1.000000	6923.590000
99%	72.000000	114.729000	1.000000	8039.883000
max	72.000000	118.750000	1.000000	8684.800000

From the distribution shown above, you can see that there no outliers in your data. The numbers are gradually increasing.

Checking for Missing Values and Inputing Them

In [23]:
```
# Adding up the missing values (column-wise)
telecom.isnull().sum()
```

Out[23]:
```
customerID                               0
tenure                                   0
PhoneService                             0
PaperlessBilling                         0
MonthlyCharges                           0
TotalCharges                            11
Churn                                    0
SeniorCitizen                            0
Partner                                  0
Dependents                               0
Contract_One year                        0
Contract_Two year                        0
PaymentMethod_Credit card (automatic)    0
PaymentMethod_Electronic check           0
PaymentMethod_Mailed check               0
gender_Male                              0
InternetService_Fiber optic              0
InternetService_No                       0
MultipleLines_No                         0
MultipleLines_Yes                        0
OnlineSecurity_No                        0
OnlineSecurity_Yes                       0
OnlineBackup_No                          0
OnlineBackup_Yes                         0
DeviceProtection_No                      0
DeviceProtection_Yes                     0
TechSupport_No                           0
TechSupport_Yes                          0
StreamingTV_No                           0
StreamingTV_Yes                          0
StreamingMovies_No                       0
StreamingMovies_Yes                      0
dtype: int64
```

You saw that one of the columns, i.e. 'TotalCharges' had 11 missing values. Since this isn't a big number compared to the number of rows present in a dataset, we decided to drop them since we won't lose much data.

It means that 11/7043 = 0.001561834 i.e 0.1%, best is to remove these observations from the analysis

In [24]:
```
# Checking the percentage of missing values
round(100*(telecom.isnull().sum()/len(telecom.index)), 2)
```

Out[24]:
```
customerID                                0.00
tenure                                    0.00
PhoneService                              0.00
PaperlessBilling                          0.00
MonthlyCharges                            0.00
TotalCharges                              0.16
Churn                                     0.00
SeniorCitizen                             0.00
Partner                                   0.00
Dependents                                0.00
Contract_One year                         0.00
Contract_Two year                         0.00
PaymentMethod_Credit card (automatic)     0.00
PaymentMethod_Electronic check            0.00
PaymentMethod_Mailed check                0.00
gender_Male                               0.00
InternetService_Fiber optic               0.00
InternetService_No                        0.00
MultipleLines_No                          0.00
MultipleLines_Yes                         0.00
OnlineSecurity_No                         0.00
OnlineSecurity_Yes                        0.00
OnlineBackup_No                           0.00
OnlineBackup_Yes                          0.00
DeviceProtection_No                       0.00
DeviceProtection_Yes                      0.00
TechSupport_No                            0.00
TechSupport_Yes                           0.00
StreamingTV_No                            0.00
StreamingTV_Yes                           0.00
StreamingMovies_No                        0.00
StreamingMovies_Yes                       0.00
dtype: float64
```

In [122]:
```
# Removing NaN TotalCharges rows
telecom = telecom[~np.isnan(telecom['TotalCharges'])]
```

In [26]:
```
# Checking percentage of missing values after removing the missing values
round(100*(telecom.isnull().sum()/len(telecom.index)), 2)
```

Out[26]:
```
customerID                               0.0
tenure                                   0.0
PhoneService                             0.0
PaperlessBilling                         0.0
MonthlyCharges                           0.0
TotalCharges                             0.0
Churn                                    0.0
SeniorCitizen                            0.0
Partner                                  0.0
Dependents                               0.0
Contract_One year                        0.0
Contract_Two year                        0.0
PaymentMethod_Credit card (automatic)    0.0
PaymentMethod_Electronic check           0.0
PaymentMethod_Mailed check               0.0
gender_Male                              0.0
InternetService_Fiber optic              0.0
InternetService_No                       0.0
MultipleLines_No                         0.0
MultipleLines_Yes                        0.0
OnlineSecurity_No                        0.0
OnlineSecurity_Yes                       0.0
OnlineBackup_No                          0.0
OnlineBackup_Yes                         0.0
DeviceProtection_No                      0.0
DeviceProtection_Yes                     0.0
TechSupport_No                           0.0
TechSupport_Yes                          0.0
StreamingTV_No                           0.0
StreamingTV_Yes                          0.0
StreamingMovies_No                       0.0
StreamingMovies_Yes                      0.0
dtype: float64
```

Now we don't have any missing values

Now that you have completely prepared your data, you can start with the preprocessing steps. As you might remember from the previous module, you first need to split the data into train and test sets and then rescale the features

Step 4: Test-Train Split

In [123]:
```
from sklearn.model_selection import train_test_split
```

In [124]:
```
# Putting feature variable to X
X = telecom.drop(['Churn','customerID'], axis=1)

X.head()
```

Out[124]:

	tenure	PhoneService	PaperlessBilling	MonthlyCharges	TotalCharges	SeniorCitizen	Partner	Dependents
0	1	0	1	29.85	29.85	0	1	0
1	34	1	0	56.95	1889.50	0	0	0
2	2	1	1	53.85	108.15	0	0	0
3	45	0	0	42.30	1840.75	0	0	0
4	2	1	1	70.70	151.65	0	0	0

5 rows × 30 columns

In [125]:
```
# Putting response variable to y
y = telecom['Churn']

y.head()
```

Out[125]:
```
0    0
1    0
2    1
3    0
4    1
Name: Churn, dtype: int64
```

In [126]:
```
# Splitting the data into train and test
X_train, X_test, y_train, y_test = train_test_split(X, y, train_size=0.7, t
est_size=0.3, random_state=100)
```

Step 5: Feature Scaling

In [90]:
```
from sklearn.preprocessing import StandardScaler
```

In [127]:
```
scaler = StandardScaler()
# standard scaler is => X-mu/sigma, thats what this scaler doe sto each of the variable

X_train[['tenure','MonthlyCharges','TotalCharges']] = scaler.fit_transform(X_train[['tenure','MonthlyCharges','TotalCharges']])

X_train.head()
```

Out[127]:

	tenure	PhoneService	PaperlessBilling	MonthlyCharges	TotalCharges	SeniorCitizen	Partner	Depe
879	0.019693	1	1	-0.338074	-0.276449	0	0	
5790	0.305384	0	1	-0.464443	-0.112702	0	1	
6498	-1.286319	1	1	0.581425	-0.974430	0	0	
880	-0.919003	1	1	1.505913	-0.550676	0	0	
2784	-1.163880	1	1	1.106854	-0.835971	0	0	

5 rows × 30 columns

The 'fit_transform' command first fits the data to have a mean of 0 and a standard deviation of 1, i.e. it scales all the variables using:

$$Xscaled=X-\mu/\sigma$$

Now, once this is done, all the variables are transformed using this formula. Now, when you go ahead to the test set, you want the variables to not learn anything new. You want to use the old centralisation that you had when you used fit on the train dataset. And this is why you don't apply 'fit' on the test data, just the 'transform'.

In [128]:
```
### Checking the Churn Rate
churn = (sum(telecom['Churn'])/len(telecom['Churn'].index))*100
churn
```

Out[128]: 26.578498293515356

We have almost 27% churn rate

Data Imbalance can cause a major problem while building an ML model. ML Model works well when the data is properly balanced. Let's say if it's a Binomial Logistic Regression, and if one of the data is dominating, in case of Churn, if Person Leaving the Firm is very very less compared to Person staying, it's will mislead the whole ML Model Building.

Why you might be thinking, as you have rightly asked above "Churn is already a Dependent variable then how can it cause an imbalance?", now you have to remember how a Model Performace is being tuned, i.e. the Accuracy is improved, by minimizing the Cost Functions, in that case, we take help of Dependent Variable only. If the Data is imbalanced, then the ML model can be fooled easily.

Let's say if we train the model with only Churn rate as True (as the data is imbalanced) obviously model will be trained on True, and there will be a high probability that the model will always predict True.

How to handle this data imbalance, there are certain ways of handling it. You can find further information on [https://towardsdatascience.com/methods-for-dealing-with-imbalanced-data-5b761be45a18 (https://towardsdatascience.com/methods-for-dealing-with-imbalanced-data-5b761be45a18)](https://towardsdatascience.com/methods-for-dealing-with-imbalanced-data-5b761be45a18)

Recall that, for continuous variables, Rahim scaled the variables to standardise the three continuous variables — tenure, monthly charges and total charges. Recall that scaling basically reduces the values in a column to within a certain range — in this case, we have converted the values to the Z-scores.

For example, let’s say that, for a particular customer, tenure = 72. After standardising, the value of scaled tenure becomes:

```
72-32.4/24.6=1.61
```

because for the variable tenure, mean(μ) = 32.4 and standard deviation(σ) = 24.6.

The variables had these ranges before standardisation:

Tenure = 1 to 72 Monthly charges = 18.25 to 118.80 Total charges = 18.8 to 8685

After standardisation, the ranges of the variables changed to:

Tenure = -1.28 to +1.61 Monthly charges = -1.55 to +1.79 Total charges = -0.99 to 2.83 Clearly, none of the variables will have a disproportionate effect on the model’s results now.

Churn Rate and Class Imbalance

Another thing to note here was the Churn Rate which Rahim talked about at the end of the video. You saw that the data has almost 27% churn rate. Checking the churn rate is important since you usually want your data to have a balance between the 0s and 1s (in this case churn and not-churn).

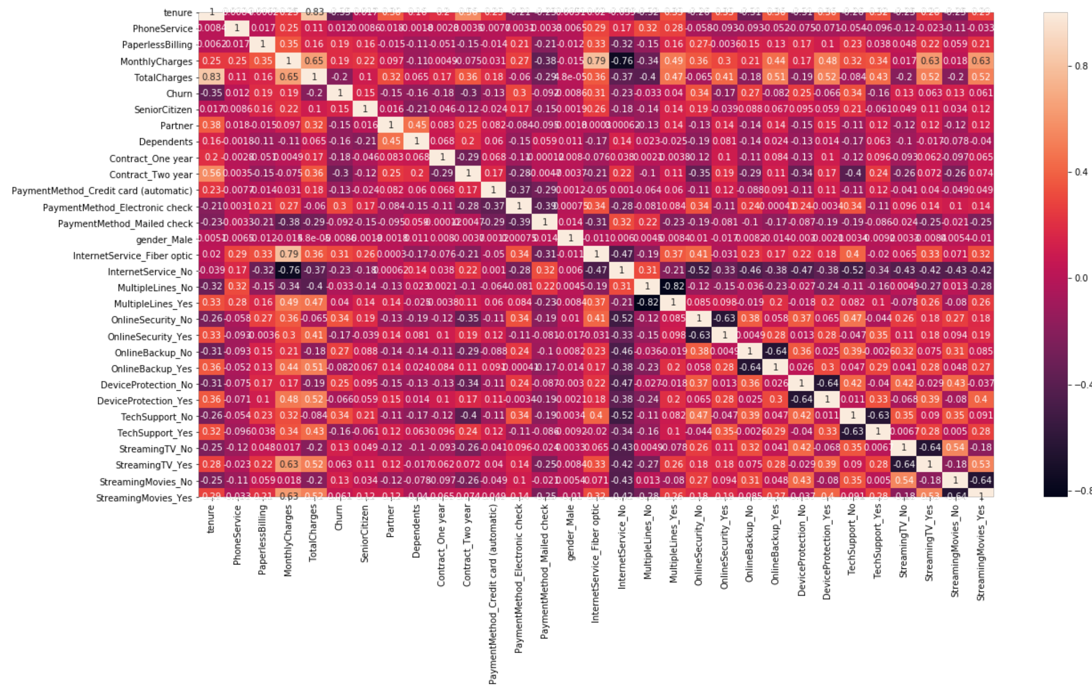
The reason for having a balance is simple. Let’s do a simple thought experiment - if you had a data with, say, 95% not-churn (0) and just 5% churn (1), then even if you predict everything as 0, you would still get a model which is 95% accurate (though it is, of course, a bad model). This problem is called class-imbalance and you'll learn to solve such cases later.

Fortunately, in this case, we have about 27% churn rate. This is neither exactly 'balanced' (which a 50-50 ratio would be called) nor heavily imbalanced. So we'll not have to do any special treatment for this dataset.

Step 6: Looking at Correlations

In [98]:
```
# Importing matplotlib and seaborn
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
```

In [99]:
```
# Let's see the correlation matrix
plt.figure(figsize = (20,10))        # Size of the figure
sns.heatmap(telecom.corr(),annot = True)
plt.show()
```

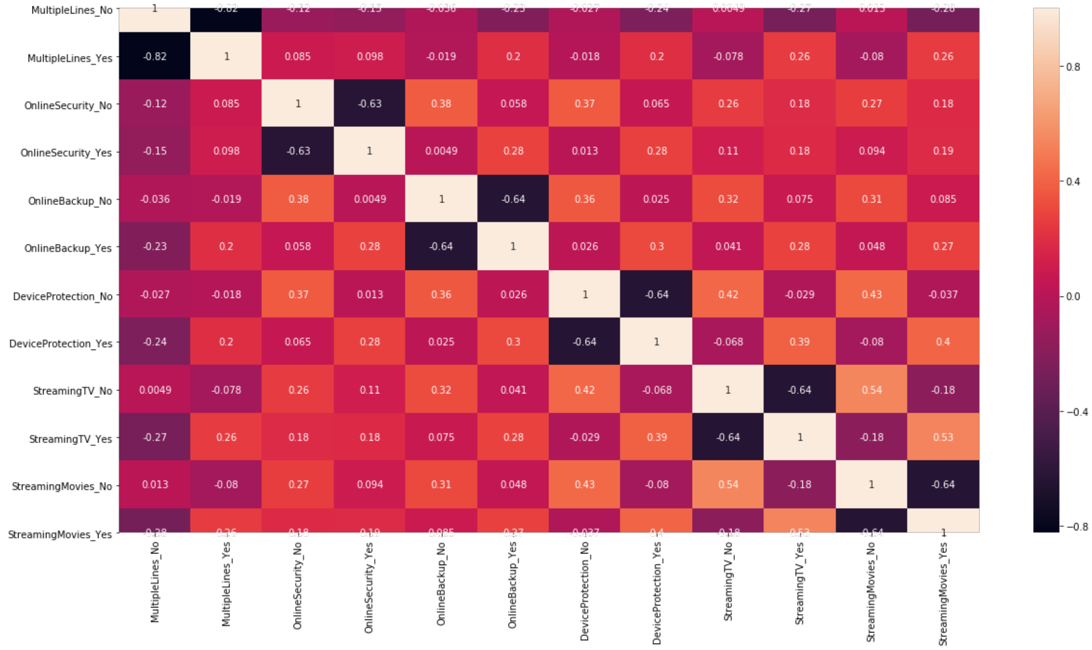


Looking at the correlations certainly did help, as you identified a lot of features beforehand which wouldn't have been useful for model building. Recall that Rahim dropped the following features after looking at the correlations from the heatmap:

- MultipleLines_No
- OnlineSecurity_No
- OnlineBackup_No
- DeviceProtection_No
- TechSupport_No
- StreamingTV_No
- StreamingMovies_No

If you look at the correlations between these dummy variables with their complimentary dummy variables, i.e. 'MultipleLines_No' with 'MultipleLines_Yes' or 'OnlineSecurity_No' with 'OnlineSecurity_Yes', you'll find out they're highly correlated.

In [102]:
```
plt.figure(figsize=(20,10))
sns.heatmap(telecom[['MultipleLines_No','MultipleLines_Yes','OnlineSecurity_No','OnlineSecurity_Yes',
                     'OnlineBackup_No','OnlineBackup_Yes','DeviceProtection_No','DeviceProtection_Yes',
                     'StreamingTV_No','StreamingTV_Yes','StreamingMovies_No',
                     'StreamingMovies_Yes']].corr(), annot=True)
plt.show()
```



you'll see that there are high correlations among the pairs of dummy variables which were created for the same column. For example, 'StreamingTV_No' has a correlation of -0.64 with 'StreamingTV_Yes'. So it is better than we drop one of these variables from each pair as they won't add much value to the model. The choice of which of these pair of variables you desire to drop is completely up to you; we've chosen to drop all the 'Nos' because the 'Yeses' are generally more interpretable and easy-to-work-with variables.

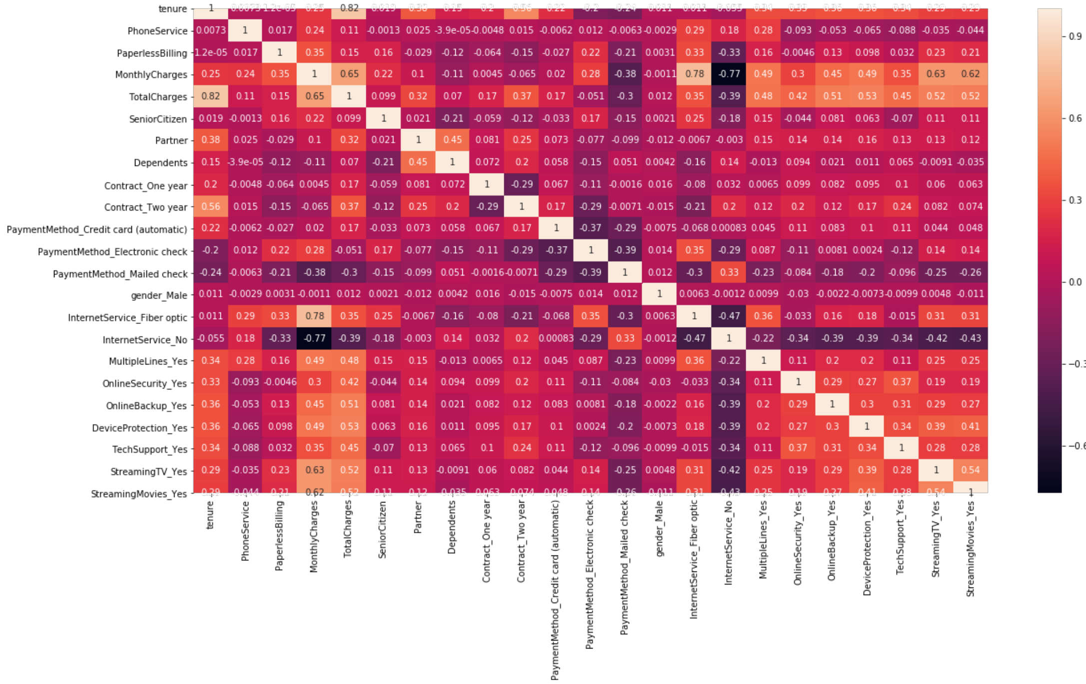
Dropping highly correlated dummy variables

In [129]:
```
X_test = X_test.drop(['MultipleLines_No','OnlineSecurity_No','OnlineBackup_No','DeviceProtection_No','TechSupport_No',
                      'StreamingTV_No','StreamingMovies_No'], 1)
X_train = X_train.drop(['MultipleLines_No','OnlineSecurity_No','OnlineBackup_No','DeviceProtection_No','TechSupport_No',
                        'StreamingTV_No','StreamingMovies_No'], 1)
```

Checking the Correlation Matrix

After dropping highly correlated variables now let's check the correlation matrix again.

In [104]:
```
plt.figure(figsize = (20,10))
sns.heatmap(X_train.corr(),annot = True)
plt.show()
```



Step 7: Model Building

Let's start by splitting our data into a training set and a test set.

Running Your First Training Model

In [131]:
```
import statsmodels.api as sm
```

Here, you use the GLM (Generalized Linear Models) method of the library statsmodels. 'Binomial()' in the 'family' argument tells statsmodels that it needs to fit a logit curve to a binomial data (i.e. in which the target will have just two classes, here 'Churn' and 'Non-Churn').

In [132]:
```
# Logistic regression model
# GLM stands for Generalized Linear Model which is used for logistics regre
ssion.
logm1 = sm.GLM(y_train,(sm.add_constant(X_train)), family = sm.families.Bin
omial())
logm1.fit().summary()
```

Out[132]:

Generalized Linear Model Regression Results

Dep. Variable:	Churn	**No. Observations:**	4922
Model:	GLM	**Df Residuals:**	4898
Model Family:	Binomial	**Df Model:**	23
Link Function:	logit	**Scale:**	1.0000
Method:	IRLS	**Log-Likelihood:**	-2004.7
Date:	Sat, 26 Oct 2019	**Deviance:**	4009.4
Time:	07:35:15	**Pearson chi2:**	6.07e+03
No. Iterations:	7		
Covariance Type:	nonrobust		

	coef	std err	z	P>|z|	[0.025	0.975]
const	-3.9382	1.546	-2.547	0.011	-6.969	-0.908
tenure	-1.5172	0.189	-8.015	0.000	-1.888	-1.146
PhoneService	0.9507	0.789	1.205	0.228	-0.595	2.497
PaperlessBilling	0.3254	0.090	3.614	0.000	0.149	0.502
MonthlyCharges	-2.1806	1.160	-1.880	0.060	-4.454	0.092
TotalCharges	0.7332	0.198	3.705	0.000	0.345	1.121
SeniorCitizen	0.3984	0.102	3.924	0.000	0.199	0.597
Partner	0.0374	0.094	0.399	0.690	-0.146	0.221
Dependents	-0.1430	0.107	-1.332	0.183	-0.353	0.067
Contract_One year	-0.6578	0.129	-5.106	0.000	-0.910	-0.405
Contract_Two year	-1.2455	0.212	-5.874	0.000	-1.661	-0.830
PaymentMethod_Credit card (automatic)	-0.2577	0.137	-1.883	0.060	-0.526	0.011
PaymentMethod_Electronic check	0.1615	0.113	1.434	0.152	-0.059	0.382
PaymentMethod_Mailed check	-0.2536	0.137	-1.845	0.065	-0.523	0.016
gender_Male	-0.0346	0.078	-0.442	0.658	-0.188	0.119
InternetService_Fiber optic	2.5124	0.967	2.599	0.009	0.618	4.407
InternetService_No	-2.7792	0.982	-2.831	0.005	-4.703	-0.855
MultipleLines_Yes	0.5623	0.214	2.628	0.009	0.143	0.982
OnlineSecurity_Yes	-0.0245	0.216	-0.113	0.910	-0.448	0.399
OnlineBackup_Yes	0.1740	0.212	0.822	0.411	-0.241	0.589
DeviceProtection_Yes	0.3229	0.215	1.501	0.133	-0.099	0.744
TechSupport_Yes	-0.0305	0.216	-0.141	0.888	-0.455	0.394
StreamingTV_Yes	0.9598	0.396	2.423	0.015	0.183	1.736
StreamingMovies_Yes	0.8484	0.396	2.143	0.032	0.072	1.624

We have the feature, we have the coefficient, we have the standard error of the coefficient and p-values for those coefficients as well. Essencially this is the significance which tests the hypothesis. Null hypothesis is that the coefficiant should be '0'. The lower the p-value the higher the significance of that particular relationship, coefficient in this case.

- The null hypothesis is that the coefficient is 0. If the p-value is small, you can say that the coefficient is significant and hence the null hypothesis is can be rejected.

  βi=0

And if the p-value is small, you can say that the coefficient is significant, and hence, you can reject the null hypothesis that βi=0

Step 8: Feature Selection Using RFE (Recursive Feature Elimination)

You built your first model in the previous segment. Based on the summary statistics, you inferred that many of the variables might be insignificant and hence, you need to do some feature elimination. Since the number of features is huge, let's first start off with an automated feature selection technique (RFE) and then move to manual feature elimination (using p-values and VIFs) - this is exactly the same process that you did in linear regression.

In [133]:
```
from sklearn.linear_model import LogisticRegression
logreg = LogisticRegression()
```

In [134]:
```
from sklearn.feature_selection import RFE
rfe = RFE(logreg, 15)             # running RFE with 15 variables as output
rfe = rfe.fit(X_train, y_train)
```

In [42]:
```
rfe.support_
```

Out[42]:
```
array([ True,  True,  True, False,  True,  True, False, False,  True,
        True,  True, False,  True, False,  True,  True,  True,  True,
       False, False,  True,  True, False])
```

In [43]:
```
list(zip(X_train.columns, rfe.support_, rfe.ranking_))
```

Out[43]:
```
[('tenure', True, 1),
 ('PhoneService', True, 1),
 ('PaperlessBilling', True, 1),
 ('MonthlyCharges', False, 6),
 ('TotalCharges', True, 1),
 ('SeniorCitizen', True, 1),
 ('Partner', False, 8),
 ('Dependents', False, 4),
 ('Contract_One year', True, 1),
 ('Contract_Two year', True, 1),
 ('PaymentMethod_Credit card (automatic)', True, 1),
 ('PaymentMethod_Electronic check', False, 3),
 ('PaymentMethod_Mailed check', True, 1),
 ('gender_Male', False, 9),
 ('InternetService_Fiber optic', True, 1),
 ('InternetService_No', True, 1),
 ('MultipleLines_Yes', True, 1),
 ('OnlineSecurity_Yes', True, 1),
 ('OnlineBackup_Yes', False, 2),
 ('DeviceProtection_Yes', False, 7),
 ('TechSupport_Yes', True, 1),
 ('StreamingTV_Yes', True, 1),
 ('StreamingMovies_Yes', False, 5)]
```

RFE assigns ranks to the different variables based on their significance. While 1 means that the variable should be selected, a rank > 1 tells you that the variable is insignificant. The ranking given to 'gender_Male' by RFE is 9 which is the highest and hence, it is the most insignificant variable present in the RFE output.

In [138]:
```
col = X_train.columns[rfe.support_]
```

In [45]:
```
X_train.columns[~rfe.support_]
```

Out[45]:
```
Index(['MonthlyCharges', 'Partner', 'Dependents',
       'PaymentMethod_Electronic check', 'gender_Male', 'OnlineBackup_Yes',
       'DeviceProtection_Yes', 'StreamingMovies_Yes'],
      dtype='object')
```

Assessing the model with StatsModels

In [139]:
```
X_train_sm = sm.add_constant(X_train[col])
logm2 = sm.GLM(y_train,X_train_sm, family = sm.families.Binomial())
res = logm2.fit()
res.summary()
```

Out[139]:

Generalized Linear Model Regression Results

Dep. Variable:	Churn	**No. Observations:**	4922
Model:	GLM	**Df Residuals:**	4906
Model Family:	Binomial	**Df Model:**	15
Link Function:	logit	**Scale:**	1.0000
Method:	IRLS	**Log-Likelihood:**	-2011.8
Date:	Sat, 26 Oct 2019	**Deviance:**	4023.5
Time:	07:54:42	**Pearson chi2:**	6.22e+03
No. Iterations:	7		
Covariance Type:	nonrobust		

	coef	std err	z	P>|z|	[0.025	0.975]
const	-1.0343	0.171	-6.053	0.000	-1.369	-0.699
tenure	-1.5386	0.184	-8.381	0.000	-1.898	-1.179
PhoneService	-0.5231	0.161	-3.256	0.001	-0.838	-0.208
PaperlessBilling	0.3397	0.090	3.789	0.000	0.164	0.515
TotalCharges	0.7116	0.188	3.794	0.000	0.344	1.079
SeniorCitizen	0.4294	0.100	4.312	0.000	0.234	0.625
Contract_One year	-0.6813	0.128	-5.334	0.000	-0.932	-0.431
Contract_Two year	-1.2680	0.211	-6.011	0.000	-1.681	-0.855
PaymentMethod_Credit card (automatic)	-0.3775	0.113	-3.352	0.001	-0.598	-0.157
PaymentMethod_Mailed check	-0.3760	0.111	-3.389	0.001	-0.594	-0.159
InternetService_Fiber optic	0.7421	0.117	6.317	0.000	0.512	0.972
InternetService_No	-0.9385	0.166	-5.650	0.000	-1.264	-0.613
MultipleLines_Yes	0.2086	0.096	2.181	0.029	0.021	0.396
OnlineSecurity_Yes	-0.4049	0.102	-3.968	0.000	-0.605	-0.205
TechSupport_Yes	-0.3967	0.102	-3.902	0.000	-0.596	-0.197
StreamingTV_Yes	0.2747	0.094	2.911	0.004	0.090	0.460

In [140]:
```
# Getting the predicted values on the train set
y_train_pred = res.predict(X_train_sm)
y_train_pred[:10]
```

Out[140]:
```
879     0.225111
5790    0.274893
6498    0.692126
880     0.504909
2784    0.645261
3874    0.417544
5387    0.420131
6623    0.809427
4465    0.223211
5364    0.512246
dtype: float64
```

Now, recall that the logistic regression curve gives you the probabilities of churning and not churning. You can get these probabilities by simply using the 'predict' function as shown in the notebook.

In [141]:
```
y_train_pred = y_train_pred.values.reshape(-1)
y_train_pred[:10]
```

Out[141]:
```
array([0.22511138, 0.27489289, 0.69212611, 0.50490896, 0.6452606 ,
       0.41754449, 0.42013086, 0.80942651, 0.2232105 , 0.51224637])
```

Creating a dataframe with the actual churn flag and the predicted probabilities

In [142]:
```
y_train_pred_final = pd.DataFrame({'Churn':y_train.values, 'Churn_Prob':y_t
rain_pred})
y_train_pred_final['CustID'] = y_train.index
y_train_pred_final.head()
```

Out[142]:

	Churn	Churn_Prob	CustID
0	0	0.225111	879
1	0	0.274893	5790
2	1	0.692126	6498
3	1	0.504909	880
4	1	0.645261	2784

Creating new column 'predicted' with 1 if Churn_Prob > 0.5 else 0

In [143]:
```
y_train_pred_final['predicted'] = y_train_pred_final.Churn_Prob.map(lambda
x: 1 if x > 0.5 else 0)

# Let's see the head
y_train_pred_final.head()
```

Out[143]:

	Churn	Churn_Prob	CustID	predicted
0	0	0.225111	879	0
1	0	0.274893	5790	0
2	1	0.692126	6498	1
3	1	0.504909	880	1
4	1	0.645261	2784	1

Since the logistic curve gives you just the probabilities and not the actual classification of 'Churn' and 'Non-Churn', you need to find a threshold probability to classify customers as 'churn' and 'non-churn'. Here, we choose 0.5 as an arbitrary cutoff wherein if the probability of a particular customer churning is less than 0.5, you'd classify it as 'Non-Churn' and if it's greater than 0.5, you'd classify it as 'Churn'. The choice of 0.5 is completely arbitrary at this stage and you'll learn how to find the optimal cutoff in 'Model Evaluation', but for now, we'll move forward with 0.5 as the cutoff.

Confusion Matrix and Accuracy

In [51]:
```
from sklearn import metrics
```

In [52]:
```
# Confusion matrix
confusion = metrics.confusion_matrix(y_train_pred_final.Churn, y_train_pred
_final.predicted )
print(confusion)
```

```
[[3270  365]
 [ 579  708]]
```

In [145]:
```
# confusion matrix, vertically it will have the true/actual value
# and horizontally it will have the predicted value

# Predicted     not_churn    churn
# Actual
# not_churn        3270      365
# churn            579       708
```

In [54]:
```
# Let's check the overall accuracy.
print(metrics.accuracy_score(y_train_pred_final.Churn, y_train_pred_final.p
redicted))
```

```
0.8082080455099553
```

Checking VIFs (Variance Inflation Factor)

In [55]:
```
# Check for the VIF values of the feature variables.
from statsmodels.stats.outliers_influence import variance_inflation_factor
```

In [56]:
```
# Create a dataframe that will contain the names of all the feature variabl
es and their respective VIFs
vif = pd.DataFrame()
vif['Features'] = X_train[col].columns
vif['VIF'] = [variance_inflation_factor(X_train[col].values, i) for i in ra
nge(X_train[col].shape[1])]
vif['VIF'] = round(vif['VIF'], 2)
vif = vif.sort_values(by = "VIF", ascending = False)
vif
```

Out[56]:

	Features	VIF
1	PhoneService	8.86
3	TotalCharges	7.37
0	tenure	6.88
9	InternetService_Fiber optic	3.97
6	Contract_Two year	3.28
10	InternetService_No	3.25
2	PaperlessBilling	2.68
11	MultipleLines_Yes	2.53
14	StreamingTV_Yes	2.34
13	TechSupport_Yes	2.08
5	Contract_One year	1.93
12	OnlineSecurity_Yes	1.90
8	PaymentMethod_Mailed check	1.72
7	PaymentMethod_Credit card (automatic)	1.46
4	SeniorCitizen	1.31

There are a few variables with high VIF. It's best to drop these variables as they aren't helping much with prediction and unnecessarily making the model complex. The variable 'PhoneService' has the highest VIF. So let's start by dropping that.

In [57]:
```
col = col.drop('PhoneService', 1)
col
```

Out[57]:
```
Index(['tenure', 'PaperlessBilling', 'TotalCharges', 'SeniorCitizen',
       'Contract_One year', 'Contract_Two year',
       'PaymentMethod_Credit card (automatic)', 'PaymentMethod_Mailed check
',
       'InternetService_Fiber optic', 'InternetService_No',
       'MultipleLines_Yes', 'OnlineSecurity_Yes', 'TechSupport_Yes',
       'StreamingTV_Yes'],
      dtype='object')
```

In [58]:
```
# Let's re-run the model using the selected variables
X_train_sm = sm.add_constant(X_train[col])
logm3 = sm.GLM(y_train,X_train_sm, family = sm.families.Binomial())
res = logm3.fit()
res.summary()
```

Out[58]:

Generalized Linear Model Regression Results

Dep. Variable:	Churn	**No. Observations:**	4922
Model:	GLM	**Df Residuals:**	4907
Model Family:	Binomial	**Df Model:**	14
Link Function:	logit	**Scale:**	1.0000
Method:	IRLS	**Log-Likelihood:**	-2017.0
Date:	Thu, 29 Nov 2018	**Deviance:**	4034.0
Time:	11:23:05	**Pearson chi2:**	5.94e+03
No. Iterations:	7	**Covariance Type:**	nonrobust

	coef	std err	z	P>|z|	[0.025	0.975]
const	-1.3885	0.133	-10.437	0.000	-1.649	-1.128
tenure	-1.4138	0.179	-7.884	0.000	-1.765	-1.062
PaperlessBilling	0.3425	0.089	3.829	0.000	0.167	0.518
TotalCharges	0.5936	0.184	3.225	0.001	0.233	0.954
SeniorCitizen	0.4457	0.099	4.486	0.000	0.251	0.640
Contract_One year	-0.6905	0.128	-5.411	0.000	-0.941	-0.440
Contract_Two year	-1.2646	0.211	-6.002	0.000	-1.678	-0.852
PaymentMethod_Credit card (automatic)	-0.3785	0.113	-3.363	0.001	-0.599	-0.158
PaymentMethod_Mailed check	-0.3769	0.111	-3.407	0.001	-0.594	-0.160
InternetService_Fiber optic	0.6241	0.111	5.645	0.000	0.407	0.841
InternetService_No	-1.0940	0.158	-6.919	0.000	-1.404	-0.784
MultipleLines_Yes	0.1607	0.094	1.712	0.087	-0.023	0.345
OnlineSecurity_Yes	-0.4094	0.102	-4.016	0.000	-0.609	-0.210
TechSupport_Yes	-0.4085	0.101	-4.025	0.000	-0.607	-0.210
StreamingTV_Yes	0.3077	0.094	3.277	0.001	0.124	0.492

In [59]:
```
y_train_pred = res.predict(X_train_sm).values.reshape(-1)
```

In [60]:
```
y_train_pred[:10]
```

Out[60]:
```
array([0.25403236, 0.22497676, 0.69386521, 0.51008735, 0.65172434,
       0.45441958, 0.3272777 , 0.80583357, 0.17618503, 0.50403034])
```

In [61]:
```
y_train_pred_final['Churn_Prob'] = y_train_pred
```

In [62]:
```
# Creating new column 'predicted' with 1 if Churn_Prob > 0.5 else 0
y_train_pred_final['predicted'] = y_train_pred_final.Churn_Prob.map(lambda
x: 1 if x > 0.5 else 0)
y_train_pred_final.head()
```

Out[62]:

	Churn	Churn_Prob	CustID	predicted
0	0	0.254032	879	0
1	0	0.224977	5790	0
2	1	0.693865	6498	1
3	1	0.510087	880	1
4	1	0.651724	2784	1

In [63]:
```
# Let's check the overall accuracy.
print(metrics.accuracy_score(y_train_pred_final.Churn, y_train_pred_final.p
redicted))
```

```
0.8051605038602194
```

So overall the accuracy hasn't dropped much.

Let's check the VIFs again

In [64]:
```
vif = pd.DataFrame()
vif['Features'] = X_train[col].columns
vif['VIF'] = [variance_inflation_factor(X_train[col].values, i) for i in ra
nge(X_train[col].shape[1])]
vif['VIF'] = round(vif['VIF'], 2)
vif = vif.sort_values(by = "VIF", ascending = False)
vif
```

Out[64]:

	Features	VIF
2	TotalCharges	7.30
0	tenure	6.79
5	Contract_Two year	3.16
8	InternetService_Fiber optic	2.94
9	InternetService_No	2.53
1	PaperlessBilling	2.52
13	StreamingTV_Yes	2.31
10	MultipleLines_Yes	2.27
12	TechSupport_Yes	2.00
4	Contract_One year	1.83
11	OnlineSecurity_Yes	1.80
7	PaymentMethod_Mailed check	1.66
6	PaymentMethod_Credit card (automatic)	1.44
3	SeniorCitizen	1.31

In [65]:
```
# Let's drop TotalCharges since it has a high VIF
col = col.drop('TotalCharges')
col
```

Out[65]:
```
Index(['tenure', 'PaperlessBilling', 'SeniorCitizen', 'Contract_One year',
       'Contract_Two year', 'PaymentMethod_Credit card (automatic)',
       'PaymentMethod_Mailed check', 'InternetService_Fiber optic',
       'InternetService_No', 'MultipleLines_Yes', 'OnlineSecurity_Yes',
       'TechSupport_Yes', 'StreamingTV_Yes'],
      dtype='object')
```

In [66]:
```
# Let's re-run the model using the selected variables
X_train_sm = sm.add_constant(X_train[col])
logm4 = sm.GLM(y_train,X_train_sm, family = sm.families.Binomial())
res = logm4.fit()
res.summary()
```

Out[66]:

Generalized Linear Model Regression Results

Dep. Variable:	Churn	**No. Observations:**	4922
Model:	GLM	**Df Residuals:**	4908
Model Family:	Binomial	**Df Model:**	13
Link Function:	logit	**Scale:**	1.0000
Method:	IRLS	**Log-Likelihood:**	-2022.5
Date:	Thu, 29 Nov 2018	**Deviance:**	4044.9
Time:	11:23:06	**Pearson chi2:**	5.22e+03
No. Iterations:	7	**Covariance Type:**	nonrobust

	coef	std err	z	P>|z|	[0.025	0.975]
const	-1.4695	0.130	-11.336	0.000	-1.724	-1.215
tenure	-0.8857	0.065	-13.553	0.000	-1.014	-0.758
PaperlessBilling	0.3367	0.089	3.770	0.000	0.162	0.512
SeniorCitizen	0.4517	0.100	4.527	0.000	0.256	0.647
Contract_One year	-0.6792	0.127	-5.360	0.000	-0.927	-0.431
Contract_Two year	-1.2308	0.208	-5.903	0.000	-1.639	-0.822
PaymentMethod_Credit card (automatic)	-0.3827	0.113	-3.399	0.001	-0.603	-0.162
PaymentMethod_Mailed check	-0.3393	0.110	-3.094	0.002	-0.554	-0.124
InternetService_Fiber optic	0.7914	0.098	8.109	0.000	0.600	0.983
InternetService_No	-1.1205	0.157	-7.127	0.000	-1.429	-0.812
MultipleLines_Yes	0.2166	0.092	2.355	0.019	0.036	0.397
OnlineSecurity_Yes	-0.3739	0.101	-3.684	0.000	-0.573	-0.175
TechSupport_Yes	-0.3611	0.101	-3.591	0.000	-0.558	-0.164
StreamingTV_Yes	0.3995	0.089	4.465	0.000	0.224	0.575

In [67]:
```
y_train_pred = res.predict(X_train_sm).values.reshape(-1)
```

In [68]:
```
y_train_pred[:10]
```

Out[68]:
```
array([0.28219274, 0.2681923 , 0.68953115, 0.53421409, 0.67433213,
       0.42980951, 0.31009304, 0.81248467, 0.20462744, 0.50431479])
```

In [69]:
```
y_train_pred_final['Churn_Prob'] = y_train_pred
```

In [70]:
```
# Creating new column 'predicted' with 1 if Churn_Prob > 0.5 else 0
y_train_pred_final['predicted'] = y_train_pred_final.Churn_Prob.map(lambda
x: 1 if x > 0.5 else 0)
y_train_pred_final.head()
```

Out[70]:

	Churn	Churn_Prob	CustID	predicted
0	0	0.282193	879	0
1	0	0.268192	5790	0
2	1	0.689531	6498	1
3	1	0.534214	880	1
4	1	0.674332	2784	1

In [71]:
```
# Let's check the overall accuracy.
print(metrics.accuracy_score(y_train_pred_final.Churn, y_train_pred_final.p
redicted))
```

```
0.804754164973588
```

The accuracy is still practically the same.

Let's now check the VIFs again

In [72]:
```
vif = pd.DataFrame()
vif['Features'] = X_train[col].columns
vif['VIF'] = [variance_inflation_factor(X_train[col].values, i) for i in ra
nge(X_train[col].shape[1])]
vif['VIF'] = round(vif['VIF'], 2)
vif = vif.sort_values(by = "VIF", ascending = False)
vif
```

Out[72]:

	Features	VIF
4	Contract_Two year	3.07
7	InternetService_Fiber optic	2.60
1	PaperlessBilling	2.44
9	MultipleLines_Yes	2.24
12	StreamingTV_Yes	2.17
8	InternetService_No	2.12
0	tenure	2.04
11	TechSupport_Yes	1.98
3	Contract_One year	1.82
10	OnlineSecurity_Yes	1.78
6	PaymentMethod_Mailed check	1.66
5	PaymentMethod_Credit card (automatic)	1.44
2	SeniorCitizen	1.31

All variables have a good value of VIF. So we need not drop any more variables and we can proceed with making predictions using this model only

In [73]:
```
# Let's take a look at the confusion matrix again
confusion = metrics.confusion_matrix(y_train_pred_final.Churn, y_train_pred
_final.predicted )
confusion
```

Out[73]:
```
array([[3269,  366],
       [ 595,  692]], dtype=int64)
```

In [74]:
```
# Actual/Predicted     not_churn    churn
        # not_churn        3269      366
        # churn            595       692
```

In [75]:
```
# Let's check the overall accuracy.
metrics.accuracy_score(y_train_pred_final.Churn, y_train_pred_final.predict
ed)
```

Out[75]:
```
0.804754164973588
```

Metrics beyond simply accuracy

In [76]:
```
TP = confusion[1,1] # true positive - 692
TN = confusion[0,0] # true negatives - 3269
FP = confusion[0,1] # false positives - 366
FN = confusion[1,0] # false negatives - 595
```

In [77]:
```
# Let's see the sensitivity of our logistic regression model
TP / float(TP+FN)
```

Out[77]:
```
0.5376845376845377
```

In [78]:
```
# Let us calculate specificity
TN / float(TN+FP)
```

Out[78]:
```
0.8993122420907841
```

In [79]:
```
# Calculate false postive rate - predicting churn when customer does not ha
ve churned
print(FP/ float(TN+FP))
```

```
0.10068775790921596
```

In [80]:
```
# positive predictive value
print (TP / float(TP+FP))
```

```
0.6540642722117203
```

In [81]:
```
# Negative predictive value
print (TN / float(TN+ FN))
```

```
0.8460144927536232
```

Step 9: Plotting the ROC Curve

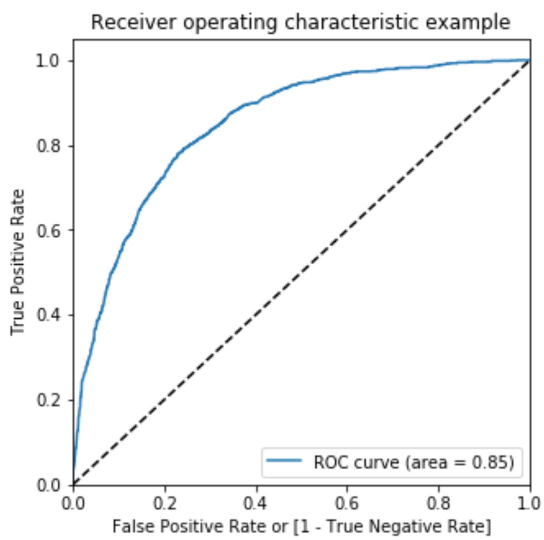
An ROC curve demonstrates several things:

- It shows the tradeoff between sensitivity and specificity (any increase in sensitivity will be accompanied by a decrease in specificity).
- The closer the curve follows the left-hand border and then the top border of the ROC space, the more accurate the test.
- The closer the curve comes to the 45-degree diagonal of the ROC space, the less accurate the test.

In [82]:
```
def draw_roc( actual, probs ):
    fpr, tpr, thresholds = metrics.roc_curve( actual, probs,
                                              drop_intermediate = False )
    auc_score = metrics.roc_auc_score( actual, probs )
    plt.figure(figsize=(5, 5))
    plt.plot( fpr, tpr, label='ROC curve (area = %0.2f)' % auc_score )
    plt.plot([0, 1], [0, 1], 'k--')
    plt.xlim([0.0, 1.0])
    plt.ylim([0.0, 1.05])
    plt.xlabel('False Positive Rate or [1 - True Negative Rate]')
    plt.ylabel('True Positive Rate')
    plt.title('Receiver operating characteristic example')
    plt.legend(loc="lower right")
    plt.show()

    return None
```

In [83]:
```
fpr, tpr, thresholds = metrics.roc_curve( y_train_pred_final.Churn, y_train
_pred_final.Churn_Prob, drop_intermediate = False )
```

In [84]:
```
draw_roc(y_train_pred_final.Churn, y_train_pred_final.Churn_Prob)
```



Step 10: Finding Optimal Cutoff Point

Optimal cutoff probability is that prob where we get balanced sensitivity and specificity

In [85]:
```
# Let's create columns with different probability cutoffs
numbers = [float(x)/10 for x in range(10)]
for i in numbers:
    y_train_pred_final[i]= y_train_pred_final.Churn_Prob.map(lambda x: 1 if
x > i else 0)
y_train_pred_final.head()
```

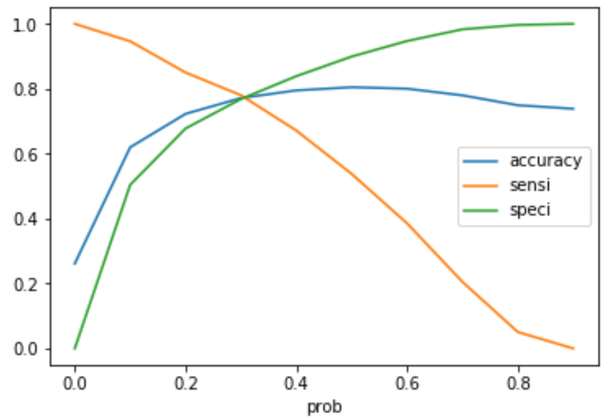
Out[85]:

	Churn	Churn_Prob	CustID	predicted	0.0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
0	0	0.282193	879	0	1	1	1	0	0	0	0	0	0	0
1	0	0.268192	5790	0	1	1	1	0	0	0	0	0	0	0
2	1	0.689531	6498	1	1	1	1	1	1	1	1	0	0	0
3	1	0.534214	880	1	1	1	1	1	1	1	0	0	0	0
4	1	0.674332	2784	1	1	1	1	1	1	1	1	0	0	0

In [86]:
```
# Now let's calculate accuracy sensitivity and specificity for various prob
ability cutoffs.
cutoff_df = pd.DataFrame( columns = ['prob','accuracy','sensi','speci'])
from sklearn.metrics import confusion_matrix

# TP = confusion[1,1] # true positive
# TN = confusion[0,0] # true negatives
# FP = confusion[0,1] # false positives
# FN = confusion[1,0] # false negatives

num = [0.0,0.1,0.2,0.3,0.4,0.5,0.6,0.7,0.8,0.9]
for i in num:
    cm1 = metrics.confusion_matrix(y_train_pred_final.Churn, y_train_pred_f
inal[i] )
    total1=sum(sum(cm1))
    accuracy = (cm1[0,0]+cm1[1,1])/total1

    speci = cm1[0,0]/(cm1[0,0]+cm1[0,1])
    sensi = cm1[1,1]/(cm1[1,0]+cm1[1,1])
    cutoff_df.loc[i] =[ i ,accuracy,sensi,speci]
print(cutoff_df)
```

```
     prob  accuracy     sensi     speci
0.0   0.0  0.261479  1.000000  0.000000
0.1   0.1  0.619667  0.946387  0.503989
0.2   0.2  0.722674  0.850039  0.677579
0.3   0.3  0.771434  0.780109  0.768363
0.4   0.4  0.795002  0.671329  0.838790
0.5   0.5  0.804754  0.537685  0.899312
0.6   0.6  0.800284  0.385392  0.947180
0.7   0.7  0.779764  0.205128  0.983219
0.8   0.8  0.749289  0.050505  0.996699
0.9   0.9  0.738521  0.000000  1.000000
```

In [87]:
```
# Let's plot accuracy sensitivity and specificity for various probabilities
.
cutoff_df.plot.line(x='prob', y=['accuracy','sensi','speci'])
plt.show()
```



From the curve above, 0.3 is the optimum point to take it as a cutoff probability.

In [88]:
```
y_train_pred_final['final_predicted'] = y_train_pred_final.Churn_Prob.map(
lambda x: 1 if x > 0.3 else 0)

y_train_pred_final.head()
```

Out[88]:

	Churn	Churn_Prob	CustID	predicted	0.0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	final_predicted
0	0	0.282193	879	0	1	1	1	0	0	0	0	0	0	0	0
1	0	0.268192	5790	0	1	1	1	0	0	0	0	0	0	0	0
2	1	0.689531	6498	1	1	1	1	1	1	1	1	0	0	0	1
3	1	0.534214	880	1	1	1	1	1	1	1	0	0	0	0	1
4	1	0.674332	2784	1	1	1	1	1	1	1	1	0	0	0	1

In [89]:
```
# Let's check the overall accuracy.
metrics.accuracy_score(y_train_pred_final.Churn, y_train_pred_final.final_p
redicted)
```

Out[89]:
```
0.771434376269809
```

In [90]:
```
confusion2 = metrics.confusion_matrix(y_train_pred_final.Churn, y_train_pre
d_final.final_predicted )
confusion2
```

Out[90]:
```
array([[2793,  842],
       [ 283, 1004]], dtype=int64)
```

In [91]:
```
TP = confusion2[1,1] # true positive
TN = confusion2[0,0] # true negatives
FP = confusion2[0,1] # false positives
FN = confusion2[1,0] # false negatives
```

In [92]:
```
# Let's see the sensitivity of our logistic regression model
TP / float(TP+FN)
```

Out[92]:
```
0.7801087801087802
```

In [93]:
```
# Let us calculate specificity
TN / float(TN+FP)
```

Out[93]:
```
0.768363136176066
```

In [94]:
```
# Calculate false postive rate - predicting churn when customer does not ha
ve churned
print(FP/ float(TN+FP))
```

```
0.23163686382393398
```

In [95]:
```
# Positive predictive value
print (TP / float(TP+FP))
```

```
0.5438786565547129
```

In [96]:
```
# Negative predictive value
print (TN / float(TN+ FN))
```

```
0.907997399219766
```

Precision and Recall

In [97]:
```
#Looking at the confusion matrix again
```

In [98]:
```
confusion = metrics.confusion_matrix(y_train_pred_final.Churn, y_train_pred
_final.predicted )
confusion
```

Out[98]:
```
array([[3269,  366],
       [ 595,  692]], dtype=int64)
```

Precision

TP / TP + FP

In [99]:
```
confusion[1,1]/(confusion[0,1]+confusion[1,1])
```

Out[99]:
```
0.6540642722117203
```

Recall

TP / TP + FN

In [100]:
```
confusion[1,1]/(confusion[1,0]+confusion[1,1])
```
Out[100]: 0.5376845376845377

Using sklearn utilities for the same

In [101]:
```
from sklearn.metrics import precision_score, recall_score
```

In [102]:
```
?precision_score
```

In [103]:
```
precision_score(y_train_pred_final.Churn, y_train_pred_final.predicted)
```
Out[103]: 0.6540642722117203

In [104]:
```
recall_score(y_train_pred_final.Churn, y_train_pred_final.predicted)
```
Out[104]: 0.5376845376845377

Precision and recall tradeoff

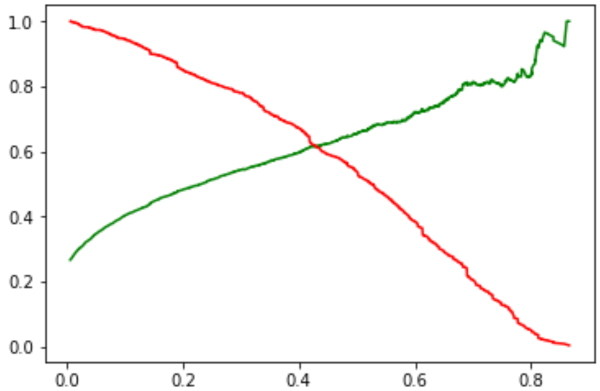
In [105]:
```
from sklearn.metrics import precision_recall_curve
```

In [106]:
```
y_train_pred_final.Churn, y_train_pred_final.predicted
```

Out[106]:
```
(0       0
 1       0
 2       1
 3       1
 4       1
 5       0
 6       0
 7       1
 8       0
 9       1
 10      0
 11      1
 12      1
 13      0
 14      0
 15      0
 16      0
 17      0
 18      0
 19      0
 20      0
 21      0
 22      0
 23      0
 24      0
 25      0
 26      0
 27      0
 28      0
 29      0
        ..
 4892    1
 4893    1
 4894    0
 4895    0
 4896    0
 4897    0
 4898    0
 4899    0
 4900    0
 4901    1
 4902    0
 4903    1
 4904    0
 4905    0
 4906    1
 4907    0
 4908    0
 4909    1
 4910    0
 4911    0
 4912    0
 4913    0
 4914    0
 4915    0
 4916    1
 4917    0
 4918    0
 4919    0
 4920    0
 4921    0
 Name: Churn, Length: 4922, dtype: int64, 0       0
 1       0
```

In [107]:
```
p, r, thresholds = precision_recall_curve(y_train_pred_final.Churn, y_train
_pred_final.Churn_Prob)
```

In [108]:
```
plt.plot(thresholds, p[:-1], "g-")
plt.plot(thresholds, r[:-1], "r-")
plt.show()
```



Step 11: Making predictions on the test set

In [146]:
```
X_test[['tenure','MonthlyCharges','TotalCharges']] = scaler.transform(X_tes
t[['tenure','MonthlyCharges','TotalCharges']])
```

In [147]:
```
X_test = X_test[col]
X_test.head()
```

Out[147]:

	tenure	PhoneService	PaperlessBilling	TotalCharges	SeniorCitizen	Contract_One year	Contract_Two year	P
942	-0.347623	1	1	-0.128378	0	0	0	
3730	0.999203	1	1	1.600302	0	0	0	
1761	1.040015	1	1	-0.343297	0	0	1	
2283	-1.286319	1	1	-0.979170	0	0	0	
1872	0.346196	1	0	-0.656086	0	0	1	

In [148]:
```
X_test_sm = sm.add_constant(X_test)
```

Making predictions on the test set

In [149]:
```
y_test_pred = res.predict(X_test_sm)
```

In [150]:
```
y_test_pred[:10]
```

Out[150]:
```
942     0.398978
3730    0.316800
1761    0.004331
2283    0.606035
1872    0.008464
1970    0.703318
2532    0.301284
1616    0.004247
2485    0.625488
5914    0.099822
dtype: float64
```

In [152]:
```
# Converting y_pred to a dataframe which is an array
y_pred_1 = pd.DataFrame(y_test_pred)
```

In [153]:
```
# Let's see the head
y_pred_1.head()
```

Out[153]:

	0
942	0.398978
3730	0.316800
1761	0.004331
2283	0.606035
1872	0.008464

In [154]:
```
# Converting y_test to dataframe
y_test_df = pd.DataFrame(y_test)
```

In [155]:
```
# Putting CustID to index
y_test_df['CustID'] = y_test_df.index
```

In [156]:
```
# Removing index for both dataframes to append them side by side
y_pred_1.reset_index(drop=True, inplace=True)
y_test_df.reset_index(drop=True, inplace=True)
```

In [157]:
```
# Appending y_test_df and y_pred_1
y_pred_final = pd.concat([y_test_df, y_pred_1],axis=1)
```

In [158]:
```
y_pred_final.head()
```

Out[158]:

	Churn	CustID	0
0	0	942	0.398978
1	1	3730	0.316800
2	0	1761	0.004331
3	1	2283	0.606035
4	0	1872	0.008464

In [159]:
```
# Renaming the column
y_pred_final= y_pred_final.rename(columns={ 0 : 'Churn_Prob'})
```

In [160]:
```
# Rearranging the columns
y_pred_final = y_pred_final.reindex_axis(['CustID','Churn','Churn_Prob'], a
xis=1)
```

```
---------------------------------------------------------------------------
AttributeError                            Traceback (most recent call last)
<ipython-input-160-b9ed2efa19f9> in <module>
      1 # Rearranging the columns
----> 2 y_pred_final = y_pred_final.reindex_axis(['CustID','Churn','Churn_P
rob'], axis=1)

~/.local/lib/python3.6/site-packages/pandas/core/generic.py in __getattr__(
self, name)
   5177             if self._info_axis._can_hold_identifiers_and_holds_name
(name):
   5178                 return self[name]
-> 5179             return object.__getattribute__(self, name)
   5180
   5181     def __setattr__(self, name, value):

AttributeError: 'DataFrame' object has no attribute 'reindex_axis'
```

In [123]:
```
# Let's see the head of y_pred_final
y_pred_final.head()
```

Out[123]:

	CustID	Churn	Churn_Prob
0	942	0	0.397413
1	3730	1	0.270295
2	1761	0	0.010238
3	2283	1	0.612692
4	1872	0	0.015869

In [124]:
```
y_pred_final['final_predicted'] = y_pred_final.Churn_Prob.map(lambda x: 1 i
f x > 0.3 else 0)
```

In [125]:
```
y_pred_final.head()
```

Out[125]:

	CustID	Churn	Churn_Prob	final_predicted
0	942	0	0.397413	0
1	3730	1	0.270295	0
2	1761	0	0.010238	0
3	2283	1	0.612692	1
4	1872	0	0.015869	0

In [126]:
```
# Let's check the overall accuracy.
metrics.accuracy_score(y_pred_final.Churn, y_pred_final.final_predicted)
```

Out[126]: 0.7834123222748816

In [127]:
```
confusion2 = metrics.confusion_matrix(y_pred_final.Churn, y_pred_final.fina
l_predicted )
confusion2
```

Out[127]:
```
array([[1294,  234],
       [ 223,  359]], dtype=int64)
```

In [128]:
```
TP = confusion2[1,1] # true positive
TN = confusion2[0,0] # true negatives
FP = confusion2[0,1] # false positives
FN = confusion2[1,0] # false negatives
```

In [129]:
```
# Let's see the sensitivity of our logistic regression model
TP / float(TP+FN)
```

Out[129]:
```
0.6168384879725086
```

In [130]:
```
# Let us calculate specificity
TN / float(TN+FP)
```

Out[130]:
```
0.8468586387434555
```