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.

Importing and Merging Data

In [108]:
```
# Importing Pandas and NumPy
import pandas as pd
import numpy as np
```

In [109]:
```
# Importing all datasets
churn_data = pd.read_csv("churn_data.csv")
customer_data = pd.read_csv("customer_data.csv")
internet_data = pd.read_csv("internet_data.csv")
```

In [110]:
```
#Merging on 'customerID'
df_1 = pd.merge(churn_data, customer_data, how='inner', on='customerID')
```

In [111]:
```
#Final dataframe with all predictor variables
telecom = pd.merge(df_1, internet_data, how='inner', on='customerID')
```

Let's understand the structure of our dataframe

In [112]:
```
# Let's see the head of our master dataset
telecom.head()
```

Out[112]:

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

5 rows × 21 columns

In [113]:
```
telecom.describe()
```

Out[113]:

	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 [114]:
```
# 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
```

Data Preparation

In [115]:
```
# Converting Yes to 1 and No to 0
telecom['PhoneService'] = telecom['PhoneService'].map({'Yes': 1, 'No': 0})
telecom['PaperlessBilling'] = telecom['PaperlessBilling'].map({'Yes': 1, 'No':
0})
telecom['Churn'] = telecom['Churn'].map({'Yes': 1, 'No': 0})
telecom['Partner'] = telecom['Partner'].map({'Yes': 1, 'No': 0})
telecom['Dependents'] = telecom['Dependents'].map({'Yes': 1, 'No': 0})
```

Dummy Variable Creation

In [116]:
```
# Creating a dummy variable for the variable 'Contract' and dropping the first one.
cont = pd.get_dummies(telecom['Contract'],prefix='Contract',drop_first=True)
#Adding the results to the master dataframe
telecom = pd.concat([telecom,cont],axis=1)

# Creating a dummy variable for the variable 'PaymentMethod' and dropping the first one.
pm = pd.get_dummies(telecom['PaymentMethod'],prefix='PaymentMethod',drop_first=True)
#Adding the results to the master dataframe
telecom = pd.concat([telecom,pm],axis=1)

# Creating a dummy variable for the variable 'gender' and dropping the first one.
gen = pd.get_dummies(telecom['gender'],prefix='gender',drop_first=True)
#Adding the results to the master dataframe
telecom = pd.concat([telecom,gen],axis=1)

# Creating a dummy variable for the variable 'MultipleLines' and dropping the first one.
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 a dummy variable for the variable 'InternetService' and dropping the first one.
iser = pd.get_dummies(telecom['InternetService'],prefix='InternetService',drop_first=True)
#Adding the results to the master dataframe
telecom = pd.concat([telecom,iser],axis=1)

# Creating a dummy variable 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 a dummy variable 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 a dummy variable 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 a dummy variable 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 a dummy variable 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 a dummy variable 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 [117]:
```
#telecom['MultipleLines'].value_counts()
```

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','I
nternetService', 'OnlineSecurity', 'OnlineBackup', 'DeviceProtection',
       'TechSupport', 'StreamingTV', 'StreamingMovies'], 1)
```

In [119]:
```
#The varaible was imported as a string we need to convert it to float
telecom['TotalCharges'] =telecom['TotalCharges'].convert_objects(convert_numer
ic=True)
#telecom['tenure'] = telecom['tenure'].astype(int).astype(float)
```

```
C:\Users\Sumit\Anaconda3\lib\site-packages\ipykernel_launcher.py:2: FutureWar
ning: convert_objects is deprecated.  Use the data-type specific converters p
d.to_datetime, pd.to_timedelta and pd.to_numeric.
```

In [120]:
```
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                               7032 non-null float64
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
MultipleLines_No                           7043 non-null uint8
MultipleLines_Yes                          7043 non-null uint8
InternetService_Fiber optic                7043 non-null uint8
InternetService_No                         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(2), int64(7), object(1), uint8(22)
memory usage: 756.6+ KB
```

Now we can see we have all variables as integer.

Checking for Outliers

In [121]:
```
# Checking for outliers in the continuous variables
num_telecom = telecom[['tenure','MonthlyCharges','SeniorCitizen','TotalCharge
s']]
```

In [122]:
```
# Checking outliers at 25%,50%,75%,90%,95% and 99%
num_telecom.describe(percentiles=[.25,.5,.75,.90,.95,.99])
```

Out[122]:

	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 outliner in your data. The numbers are gradually increasing.

Checking for Missing Values and Inputing Them

In [123]:
```
# Adding up the missing values (column-wise)
telecom.isnull().sum()
```

Out[123]:
```
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
MultipleLines_No                          0
MultipleLines_Yes                         0
InternetService_Fiber optic               0
InternetService_No                        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
```

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

In [124]:
```
# Checking the percentage of missing values
round(100*(telecom.isnull().sum()/len(telecom.index)), 2)
```

Out[124]:
```
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
MultipleLines_No                         0.00
MultipleLines_Yes                        0.00
InternetService_Fiber optic              0.00
InternetService_No                       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 [125]:
```
# Removing NaN TotalCharges rows
telecom = telecom[~np.isnan(telecom['TotalCharges'])]
```

In [126]:
```
# Checking percentage of missing values after removing the missing values
round(100*(telecom.isnull().sum()/len(telecom.index)), 2)
```

Out[126]:
```
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
MultipleLines_No                         0.0
MultipleLines_Yes                        0.0
InternetService_Fiber optic              0.0
InternetService_No                       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

Feature Standardisation

In [127]:
```
# Normalising continuous features
df = telecom[['tenure','MonthlyCharges','TotalCharges']]
```

In [128]:
```
normalized_df=(df-df.mean())/df.std()
```

In [129]:
```
telecom = telecom.drop(['tenure','MonthlyCharges','TotalCharges'], 1)
```

In [130]:
```
telecom = pd.concat([telecom,normalized_df],axis=1)
```

In [131]:
```
telecom
```

Out[131]:

	customerID	PhoneService	PaperlessBilling	Churn	SeniorCitizen	Partner	Depen
0	7590-VHVEG	0	1	0	0	1	0
1	5575-GNVDE	1	0	0	0	0	0
2	3668-QPYBK	1	1	1	0	0	0
3	7795-CFOCW	0	0	0	0	0	0
4	9237-HQITU	1	1	1	0	0	0
5	9305-CDSKC	1	1	1	0	0	0
6	1452-KIOVK	1	1	0	0	0	1
7	6713-OKOMC	0	0	0	0	0	0
8	7892-POOKP	1	1	1	0	1	0
9	6388-TABGU	1	0	0	0	0	1
10	9763-GRSKD	1	1	0	0	1	1
11	7469-LKBCI	1	0	0	0	0	0
12	8091-TTVAX	1	0	0	0	1	0
13	0280-XJGEX	1	1	1	0	0	0
14	5129-JLPIS	1	1	0	0	0	0
15	3655-SNQYZ	1	0	0	0	1	1
16	8191-XWSZG	1	0	0	0	0	0
17	9959-WOFKT	1	0	0	0	0	1
18	4190-MFLUW	1	0	1	0	1	1

	customerID	PhoneService	PaperlessBilling	Churn	SeniorCitizen	Partner	Depen
19	4183-MYFRB	1	1	0	0	0	0
20	8779-QRDMV	0	1	1	1	0	0
21	1680-VDCWW	1	0	0	0	1	0
22	1066-JKSGK	1	0	1	0	0	0
23	3638-WEABW	1	1	0	0	1	0
24	6322-HRPFA	1	0	0	0	1	1
25	6865-JZNKO	1	1	0	0	0	0
26	6467-CHFZW	1	1	1	0	1	1
27	8665-UTDHZ	0	0	1	0	1	1
28	5248-YGIJN	1	1	0	0	1	0
29	8773-HHUOZ	1	1	1	0	0	1
...	...	...	...	...	...	...	...
7013	1685-BQULA	1	1	0	0	0	0
7014	9053-EJUNL	1	1	0	0	0	0
7015	0666-UXTJO	1	1	0	1	1	0
7016	1471-GIQKQ	1	0	0	0	0	0
7017	4807-IZYOZ	1	0	0	0	0	0
7018	1122-JWTJW	1	1	1	0	1	1
7019	9710-NJERN	1	0	0	0	0	0
7020	9837-FWLCH	1	1	0	0	1	1

	customerID	PhoneService	PaperlessBilling	Churn	SeniorCitizen	Partner	Depen
7021	1699-HPSBG	1	1	1	0	0	0
7022	7203-OYKCT	1	1	0	0	0	0
7023	1035-IPQPU	1	1	0	1	1	0
7024	7398-LXGYX	1	1	0	0	1	0
7025	2823-LKABH	1	1	0	0	0	0
7026	8775-CEBBJ	1	1	1	0	0	0
7027	0550-DCXLH	1	0	0	0	0	0
7028	9281-CEDRU	1	0	0	0	1	0
7029	2235-DWLJU	0	1	0	1	0	0
7030	0871-OPBXW	1	1	0	0	0	0
7031	3605-JISKB	1	0	0	1	1	0
7032	6894-LFHLY	1	1	1	1	0	0
7033	9767-FFLEM	1	1	0	0	0	0
7034	0639-TSIQW	1	1	1	0	0	0
7035	8456-QDAVC	1	1	0	0	0	0
7036	7750-EYXWZ	0	0	0	0	0	0
7037	2569-WGERO	1	1	0	0	0	0
7038	6840-RESVB	1	1	0	0	1	1
7039	2234-XADUH	1	1	0	0	1	1

	customerID	PhoneService	PaperlessBilling	Churn	SeniorCitizen	Partner	Depen
7040	4801-JZAZL	0	1	0	0	1	1
7041	8361-LTMKD	1	1	1	1	1	0
7042	3186-AJIEK	1	1	0	0	0	0

7032 rows × 32 columns

Checking the Churn Rate

In [132]:
```
churn = (sum(telecom['Churn'])/len(telecom['Churn'].index))*100
```

In [133]:
```
churn
```

Out[133]:
```
26.578498293515356
```

We have almost 27% churn rate

Model Building

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

Splitting Data into Training and Test Sets

In [134]:
```
from sklearn.model_selection import train_test_split
```

In [135]:
```
# Putting feature variable to X
X = telecom.drop(['Churn','customerID'],axis=1)

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

In [136]:
```
y.head()
```

Out[136]:
```
0    0
1    0
2    1
3    0
4    1
Name: Churn, dtype: int64
```

In [137]:
```
# Splitting the data into train and test
X_train, X_test, y_train, y_test = train_test_split(X,y, train_size=0.7,test_size=0.3,random_state=100)
```

Running Your First Training Model

In [138]:
```
import statsmodels.api as sm
```

In [139]:
```
# Logistic regression model
logm1 = sm.GLM(y_train,(sm.add_constant(X_train)), family = sm.families.Binomi
al())
logm1.fit().summary()
```

Out[139]:

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:**	1.0
Method:	IRLS	**Log-Likelihood:**	-2004.7
Date:	Thu, 01 Mar 2018	**Deviance:**	4009.4
Time:	14:21:09	**Pearson chi2:**	6.07e+03
No. Iterations:	7		

	coef	std err	z	P>|z|	[0.025	0.975]
const	-3.2783	1.187	-2.762	0.006	-5.605	-0.952
PhoneService	0.8213	0.588	1.396	0.163	-0.332	1.974
PaperlessBilling	0.3254	0.090	3.614	0.000	0.149	0.502
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
MultipleLines_No	0.1295	0.205	0.632	0.527	-0.272	0.531
MultipleLines_Yes	0.6918	0.392	1.763	0.078	-0.077	1.461
InternetService_Fiber optic	2.5124	0.967	2.599	0.009	0.618	4.407
InternetService_No	-3.4348	1.324	-2.594	0.009	-6.030	-0.839
OnlineSecurity_No	0.0905	0.058	1.558	0.119	-0.023	0.204
OnlineSecurity_Yes	0.0660	0.174	0.380	0.704	-0.275	0.407
OnlineBackup_No	-0.0088	0.055	-0.161	0.872	-0.116	0.098
OnlineBackup_Yes	0.1653	0.172	0.960	0.337	-0.172	0.503
DeviceProtection_No	-0.0832	0.056	-1.487	0.137	-0.193	0.026
DeviceProtection_Yes	0.2397	0.174	1.379	0.168	-0.101	0.580

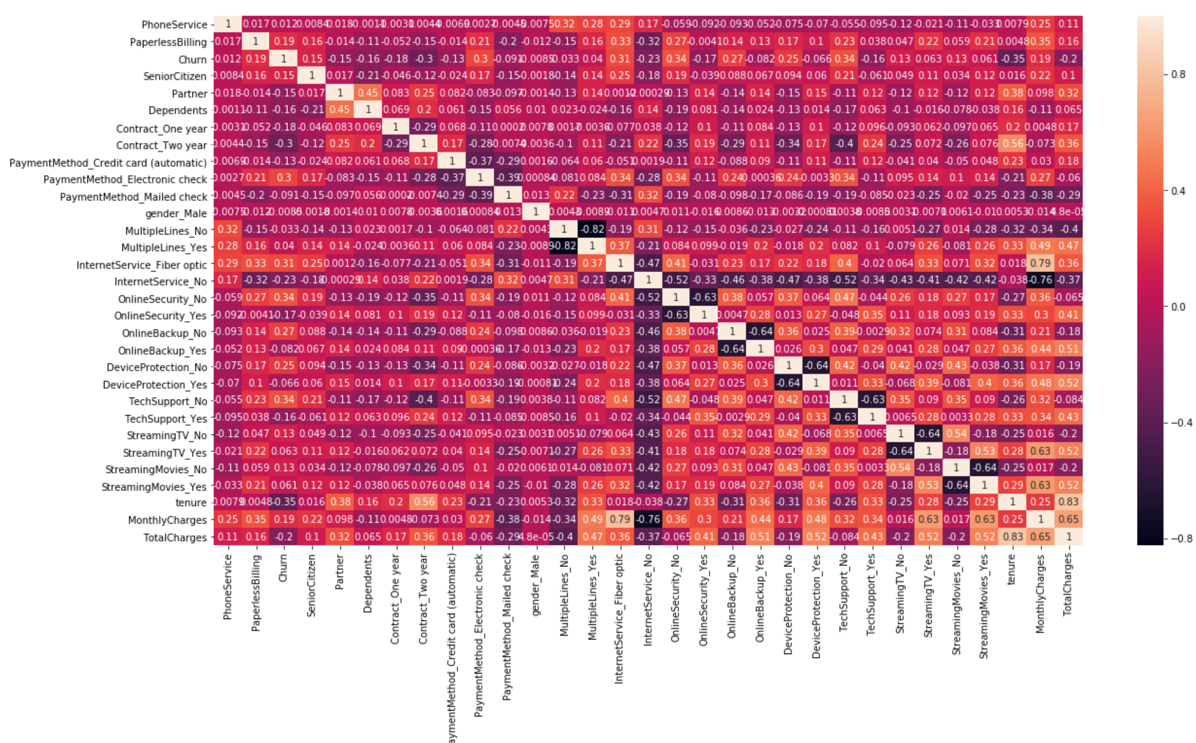
TechSupport_No	0.0935	0.058	1.604	0.109	-0.021	0.208
TechSupport_Yes	0.0630	0.174	0.362	0.717	-0.278	0.404
StreamingTV_No	-0.4016	0.133	-3.027	0.002	-0.662	-0.142
StreamingTV_Yes	0.5581	0.267	2.094	0.036	0.036	1.081
StreamingMovies_No	-0.3459	0.133	-2.609	0.009	-0.606	-0.086
StreamingMovies_Yes	0.5024	0.266	1.886	0.059	-0.020	1.025
tenure	-1.5198	0.190	-8.015	0.000	-1.891	-1.148
MonthlyCharges	-2.1817	1.160	-1.880	0.060	-4.456	0.092
TotalCharges	0.7329	0.198	3.705	0.000	0.345	1.121

Correlation Matrix

In [140]:
```
# Importing matplotlib and seaborn
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
```

In [141]:
```
# Let's see the correlation matrix
plt.figure(figsize = (20,10))        # Size of the figure
sns.heatmap(telecom.corr(),annot = True)
```

Out[141]: <matplotlib.axes._subplots.AxesSubplot at 0x1959803b7b8>



Dropping highly correlated variables.

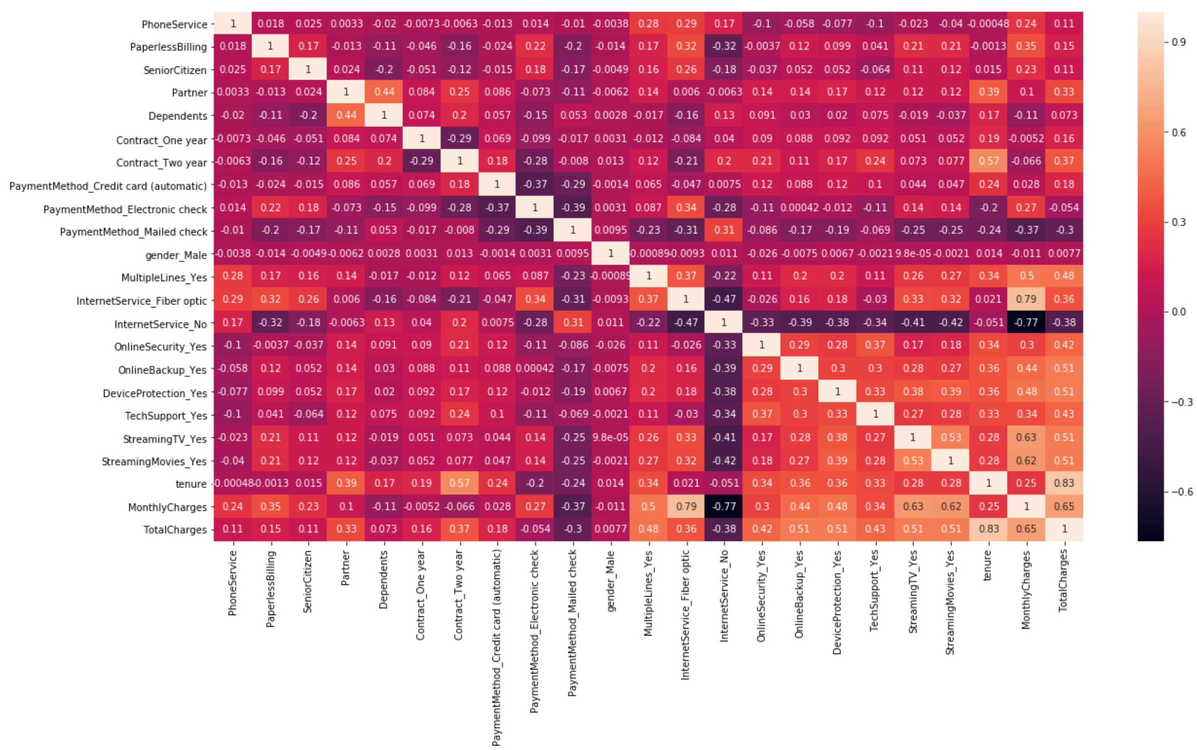
In [142]:
```
X_test2 = X_test.drop(['MultipleLines_No','OnlineSecurity_No','OnlineBackup_N
o','DeviceProtection_No','TechSupport_No','StreamingTV_No','StreamingMovies_N
o'],1)
X_train2 = X_train.drop(['MultipleLines_No','OnlineSecurity_No','OnlineBackup_
No','DeviceProtection_No','TechSupport_No','StreamingTV_No','StreamingMovies_N
o'],1)
```

Checking the Correlation Matrix

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

In [143]:
```
plt.figure(figsize = (20,10))
sns.heatmap(X_train2.corr(),annot = True)
```

Out[143]: <matplotlib.axes._subplots.AxesSubplot at 0x19595aa3dd8>



Re-Running the Model

Now let's run our model again after dropping highly correlated variables

In [144]:
```
logm2 = sm.GLM(y_train,(sm.add_constant(X_train2)), family = sm.families.Binom
ial())
logm2.fit().summary()
```

Out[144]:

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:**	1.0
Method:	IRLS	**Log-Likelihood:**	-2004.7
Date:	Thu, 01 Mar 2018	**Deviance:**	4009.4
Time:	14:21:18	**Pearson chi2:**	6.07e+03
No. Iterations:	7		

	coef	std err	z	P>|z|	[0.025	0.975]
const	-3.9338	1.545	-2.545	0.011	-6.963	-0.905
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
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
MultipleLines_Yes	0.5623	0.214	2.628	0.009	0.143	0.982
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
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
tenure	-1.5198	0.190	-8.015	0.000	-1.891	-1.148

MonthlyCharges	-2.1817	1.160	-1.880	0.060	-4.456	0.092
TotalCharges	0.7329	0.198	3.705	0.000	0.345	1.121

Feature Selection Using RFE

In [145]:

```
from sklearn.linear_model import LogisticRegression
logreg = LogisticRegression()
from sklearn.feature_selection import RFE
rfe = RFE(logreg, 13)             # running RFE with 13 variables as output
rfe = rfe.fit(X,y)
print(rfe.support_)           # Printing the boolean results
print(rfe.ranking_)           # Printing the ranking
```

```
[ True  True False False False  True  True False  True False False  True
 False  True  True False  True False False False False False  True False
 False  True False  True False  True]
[ 1  1  2 18  6  1  1 11  1 12 14  1  8  1  1  4  1 15  5 13 10  7  1  3 16
  1 17  1  9  1]
```

In [146]:

```
# Variables selected by RFE
col = ['PhoneService', 'PaperlessBilling', 'Contract_One year', 'Contract_Two
 year',
       'PaymentMethod_Electronic check','MultipleLines_No','InternetService_Fi
ber optic', 'InternetService_No',
       'OnlineSecurity_Yes','TechSupport_Yes','StreamingMovies_No','tenure','T
otalCharges']
```

In [147]:

```
# Let's run the model using the selected variables
from sklearn.linear_model import LogisticRegression
from sklearn import metrics
logsk = LogisticRegression()
logsk.fit(X_train[col], y_train)
```

Out[147]:

```
LogisticRegression(C=1.0, class_weight=None, dual=False, fit_intercept=True,
          intercept_scaling=1, max_iter=100, multi_class='ovr', n_jobs=1,
          penalty='l2', random_state=None, solver='liblinear', tol=0.0001,
          verbose=0, warm_start=False)
```

In [148]:

```
#Comparing the model with StatsModels
logm4 = sm.GLM(y_train,(sm.add_constant(X_train[col])), family = sm.families.B
inomial())
logm4.fit().summary()
```

Out[148]:

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:**	1.0
Method:	IRLS	**Log-Likelihood:**	-2024.2
Date:	Thu, 01 Mar 2018	**Deviance:**	4048.4
Time:	14:21:19	**Pearson chi2:**	6.19e+03
No. Iterations:	7		

	coef	std err	z	P>|z|	[0.025	0.975]
const	-1.0162	0.169	-6.017	0.000	-1.347	-0.685
PhoneService	-0.3090	0.173	-1.784	0.074	-0.648	0.030
PaperlessBilling	0.3595	0.089	4.029	0.000	0.185	0.534
Contract_One year	-0.7012	0.127	-5.516	0.000	-0.950	-0.452
Contract_Two year	-1.3187	0.210	-6.271	0.000	-1.731	-0.907
PaymentMethod_Electronic check	0.3668	0.083	4.446	0.000	0.205	0.529
MultipleLines_No	-0.2311	0.095	-2.435	0.015	-0.417	-0.045
InternetService_Fiber optic	0.7937	0.116	6.836	0.000	0.566	1.021
InternetService_No	-1.1832	0.182	-6.484	0.000	-1.541	-0.826
OnlineSecurity_Yes	-0.4107	0.102	-4.031	0.000	-0.610	-0.211
TechSupport_Yes	-0.4181	0.101	-4.135	0.000	-0.616	-0.220
StreamingMovies_No	-0.2024	0.094	-2.160	0.031	-0.386	-0.019
tenure	-1.4974	0.181	-8.251	0.000	-1.853	-1.142
TotalCharges	0.7373	0.186	3.965	0.000	0.373	1.102

In [149]:
```
# UDF for calculating vif value
def vif_cal(input_data, dependent_col):
    vif_df = pd.DataFrame( columns = ['Var', 'Vif'])
    x_vars=input_data.drop([dependent_col], axis=1)
    xvar_names=x_vars.columns
    for i in range(0,xvar_names.shape[0]):
        y=x_vars[xvar_names[i]]
        x=x_vars[xvar_names.drop(xvar_names[i])]
        rsq=sm.OLS(y,x).fit().rsquared
        vif=round(1/(1-rsq),2)
        vif_df.loc[i] = [xvar_names[i], vif]
    return vif_df.sort_values(by = 'Vif', axis=0, ascending=False, inplace=Fal
se)
```

In [150]:
```
telecom.columns
['PhoneService', 'PaperlessBilling', 'Contract_One year', 'Contract_Two year',
       'PaymentMethod_Electronic check','MultipleLines_No','InternetService_Fi
ber optic', 'InternetService_No',
       'OnlineSecurity_Yes','TechSupport_Yes','StreamingMovies_No','tenure','T
otalCharges']
```

Out[150]:
```
['PhoneService',
 'PaperlessBilling',
 'Contract_One year',
 'Contract_Two year',
 'PaymentMethod_Electronic check',
 'MultipleLines_No',
 'InternetService_Fiber optic',
 'InternetService_No',
 'OnlineSecurity_Yes',
 'TechSupport_Yes',
 'StreamingMovies_No',
 'tenure',
 'TotalCharges']
```

In [151]:
```
# Calculating Vif value
vif_cal(input_data=telecom.drop(['customerID','SeniorCitizen', 'Partner', 'Dep
endents',
                                 'PaymentMethod_Credit card (automatic)','Paym
entMethod_Mailed check',
                                 'gender_Male','MultipleLines_Yes','OnlineSecu
rity_No','OnlineBackup_No',
                                 'OnlineBackup_Yes', 'DeviceProtection_No', 'D
eviceProtection_Yes',
                                 'TechSupport_No','StreamingTV_No','StreamingT
V_Yes','StreamingMovies_Yes',
                                 'MonthlyCharges'], axis=1), dependent_col='Ch
urn')
```

Out[151]:

	Var	Vif
0	PhoneService	10.87
12	TotalCharges	8.58
11	tenure	6.80
1	PaperlessBilling	2.61
7	InternetService_No	0.65
3	Contract_Two year	0.28
2	Contract_One year	0.24
9	TechSupport_Yes	0.24
8	OnlineSecurity_Yes	0.21
10	StreamingMovies_No	0.19
4	PaymentMethod_Electronic check	0.05
5	MultipleLines_No	0.05
6	InternetService_Fiber optic	0.03

Dropping Variable with high VIF

In [152]:
```
col = ['PaperlessBilling', 'Contract_One year', 'Contract_Two year',
       'PaymentMethod_Electronic check','MultipleLines_No','InternetService_Fi
ber optic', 'InternetService_No',
       'OnlineSecurity_Yes','TechSupport_Yes','StreamingMovies_No','tenure','T
otalCharges']
```

In [153]:
```
logm5 = sm.GLM(y_train,(sm.add_constant(X_train[col])), family = sm.families.B
inomial())
logm5.fit().summary()
```

Out[153]:

Generalized Linear Model Regression Results

Dep. Variable:	Churn	**No. Observations:**	4922
Model:	GLM	**Df Residuals:**	4909
Model Family:	Binomial	**Df Model:**	12
Link Function:	logit	**Scale:**	1.0
Method:	IRLS	**Log-Likelihood:**	-2025.8
Date:	Thu, 01 Mar 2018	**Deviance:**	4051.5
Time:	14:21:20	**Pearson chi2:**	6.00e+03
No. Iterations:	7		

	coef	**std err**	**z**	**P>|z|**	**[0.025**	**0.975]**
const	-1.1915	0.138	-8.607	0.000	-1.463	-0.920
PaperlessBilling	0.3563	0.089	3.998	0.000	0.182	0.531
Contract_One year	-0.6965	0.127	-5.483	0.000	-0.945	-0.448
Contract_Two year	-1.3078	0.210	-6.230	0.000	-1.719	-0.896
PaymentMethod_Electronic check	0.3700	0.082	4.487	0.000	0.208	0.532
MultipleLines_No	-0.2990	0.087	-3.442	0.001	-0.469	-0.129
InternetService_Fiber optic	0.7227	0.108	6.666	0.000	0.510	0.935
InternetService_No	-1.2732	0.175	-7.276	0.000	-1.616	-0.930
OnlineSecurity_Yes	-0.4100	0.102	-4.025	0.000	-0.610	-0.210
TechSupport_Yes	-0.4202	0.101	-4.157	0.000	-0.618	-0.222
StreamingMovies_No	-0.2205	0.093	-2.366	0.018	-0.403	-0.038
tenure	-1.4276	0.177	-8.066	0.000	-1.774	-1.081
TotalCharges	0.6495	0.179	3.622	0.000	0.298	1.001

In [154]:
```
# Calculating Vif value
vif_cal(input_data=telecom.drop(['customerID','PhoneService','SeniorCitizen',
'Partner', 'Dependents',
                                 'PaymentMethod_Credit card (automatic)','Paym
entMethod_Mailed check',
                                 'gender_Male','MultipleLines_Yes','OnlineSecu
rity_No','OnlineBackup_No',
                                 'OnlineBackup_Yes', 'DeviceProtection_No', 'D
eviceProtection_Yes',
                                 'TechSupport_No','StreamingTV_No','StreamingT
V_Yes','StreamingMovies_Yes',
                                 'MonthlyCharges'], axis=1), dependent_col='Ch
urn')
```

Out[154]:

	Var	Vif
11	TotalCharges	8.24
10	tenure	6.56
0	PaperlessBilling	2.44
6	InternetService_No	0.45
2	Contract_Two year	0.26
8	TechSupport_Yes	0.24
1	Contract_One year	0.23
7	OnlineSecurity_Yes	0.21
9	StreamingMovies_No	0.17
3	PaymentMethod_Electronic check	0.05
4	MultipleLines_No	0.04
5	InternetService_Fiber optic	0.02

In [155]:
```
# Let's run the model using the selected variables
from sklearn.linear_model import LogisticRegression
from sklearn import metrics
logsk = LogisticRegression()
logsk.fit(X_train[col], y_train)
```

Out[155]:
```
LogisticRegression(C=1.0, class_weight=None, dual=False, fit_intercept=True,
          intercept_scaling=1, max_iter=100, multi_class='ovr', n_jobs=1,
          penalty='l2', random_state=None, solver='liblinear', tol=0.0001,
          verbose=0, warm_start=False)
```

Making Predictions

In [156]:
```
# Predicted probabilities
y_pred = logsk.predict_proba(X_test[col])
```

In [157]:
```
# Converting y_pred to a dataframe which is an array
y_pred_df = pd.DataFrame(y_pred)
```

In [158]:
```
# Converting to column dataframe
y_pred_1 = y_pred_df.iloc[:,[1]]
```

In [159]:
```
# Let's see the head
y_pred_1.head()
```

Out[159]:

	1
0	0.499083
1	0.372696
2	0.006738
3	0.635453
4	0.007533

In [160]:
```
# Converting y_test to dataframe
y_test_df = pd.DataFrame(y_test)
```

In [161]:
```
# Putting CustID to index
y_test_df['CustID'] = y_test_df.index
```

In [162]:
```
# 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 [163]:
```
# Appending y_test_df and y_pred_1
y_pred_final = pd.concat([y_test_df,y_pred_1],axis=1)
```

In [164]:
```
# Renaming the column
y_pred_final= y_pred_final.rename(columns={ 1 : 'Churn_Prob'})
```

In [165]:
```
# Rearranging the columns
y_pred_final = y_pred_final.reindex_axis(['CustID','Churn','Churn_Prob'], axis
=1)
```

In [166]:
```
# Let's see the head of y_pred_final
y_pred_final.head()
```

Out[166]:

	CustID	Churn	Churn_Prob
0	942	0	0.499083
1	3730	1	0.372696
2	1761	0	0.006738
3	2283	1	0.635453
4	1872	0	0.007533

In [167]:
```
# Creating new column 'predicted' with 1 if Churn_Prob>0.5 else 0
y_pred_final['predicted'] = y_pred_final.Churn_Prob.map( lambda x: 1 if x > 0.
5 else 0)
```

In [168]:
```
# Let's see the head
y_pred_final.head()
```

Out[168]:

	CustID	Churn	Churn_Prob	predicted
0	942	0	0.499083	0
1	3730	1	0.372696	0
2	1761	0	0.006738	0
3	2283	1	0.635453	1
4	1872	0	0.007533	0

Model Evaluation

In [169]:
```
from sklearn import metrics
```

In [170]:
```
help(metrics.confusion_matrix)
```

```
Help on function confusion_matrix in module sklearn.metrics.classification:

confusion_matrix(y_true, y_pred, labels=None, sample_weight=None)
    Compute confusion matrix to evaluate the accuracy of a classification

    By definition a confusion matrix :math:`C` is such that :math:`C_{i, j}`
    is equal to the number of observations known to be in group :math:`i` but
    predicted to be in group :math:`j`.

    Thus in binary classification, the count of true negatives is
    :math:`C_{0,0}`, false negatives is :math:`C_{1,0}`, true positives is
    :math:`C_{1,1}` and false positives is :math:`C_{0,1}`.

    Read more in the :ref:`User Guide <confusion_matrix>`.

    Parameters
    ----------
    y_true : array, shape = [n_samples]
        Ground truth (correct) target values.

    y_pred : array, shape = [n_samples]
        Estimated targets as returned by a classifier.

    labels : array, shape = [n_classes], optional
        List of labels to index the matrix. This may be used to reorder
        or select a subset of labels.
        If none is given, those that appear at least once
        in ``y_true`` or ``y_pred`` are used in sorted order.

    sample_weight : array-like of shape = [n_samples], optional
        Sample weights.

    Returns
    -------
    C : array, shape = [n_classes, n_classes]
        Confusion matrix

    References
    ----------
    .. [1] `Wikipedia entry for the Confusion matrix
           <https://en.wikipedia.org/wiki/Confusion_matrix>`_

    Examples
    --------
    >>> from sklearn.metrics import confusion_matrix
    >>> y_true = [2, 0, 2, 2, 0, 1]
    >>> y_pred = [0, 0, 2, 2, 0, 2]
    >>> confusion_matrix(y_true, y_pred)
    array([[2, 0, 0],
           [0, 0, 1],
           [1, 0, 2]])

    >>> y_true = ["cat", "ant", "cat", "cat", "ant", "bird"]
    >>> y_pred = ["ant", "ant", "cat", "cat", "ant", "cat"]
    >>> confusion_matrix(y_true, y_pred, labels=["ant", "bird", "cat"])
    array([[2, 0, 0],
           [0, 0, 1],
```

```
        [1, 0, 2]])

    In the binary case, we can extract true positives, etc as follows:

    >>> tn, fp, fn, tp = confusion_matrix([0, 1, 0, 1], [1, 1, 1, 0]).ravel()
    >>> (tn, fp, fn, tp)
    (0, 2, 1, 1)
```

In [171]:

```
# Confusion matrix
confusion = metrics.confusion_matrix( y_pred_final.Churn, y_pred_final.predict
ed )
confusion
```

Out[171]:

```
array([[1362,  166],
       [ 249,  333]], dtype=int64)
```

In [172]:

```
# Predicted     not_churn    churn
# Actual
# not_churn        1326      166
# churn            249       333
```

In [173]:

```
#Let's check the overall accuracy.
metrics.accuracy_score( y_pred_final.Churn, y_pred_final.predicted)
```

Out[173]:

```
0.80331753554502372
```

In [174]:

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

In [175]:

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

Out[175]:

```
0.84543761638733705
```

In [176]:

```
# Let us calculate specificity
TN / float(TN+FP)
```

Out[176]:

```
0.66733466933867736
```

In [177]:

```
# Calculate false postive rate - predicting churn when customer does not have
 churned
print(FP/ float(TN+FP))
```

```
0.332665330661
```

In [178]:

```
# positive predictive value
print (TP / float(TP+FP))
```

```
0.891361256545
```

In [179]:
```
# Negative predictive value
print (TN / float(TN+ FN))
```

```
0.572164948454
```

ROC Curve

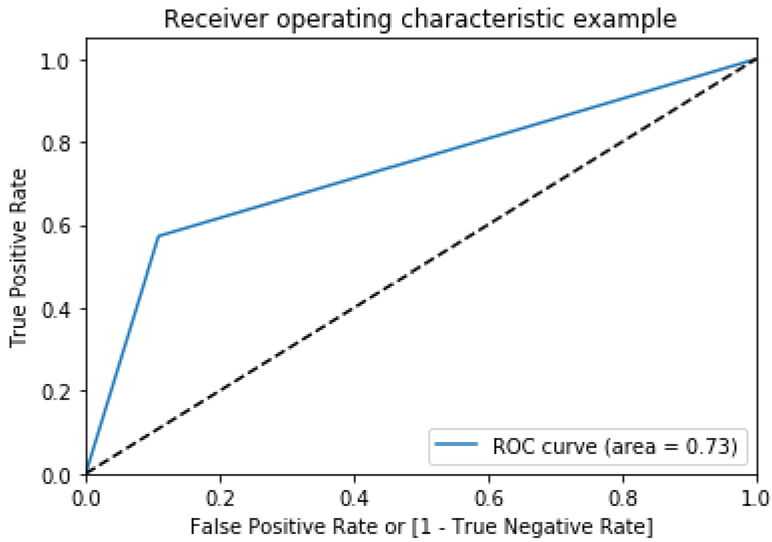
An ROC curve demonstrates several things:

- 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 [180]:
```
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=(6, 4))
    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 fpr, tpr, thresholds
```

In [181]:
```
draw_roc(y_pred_final.Churn, y_pred_final.predicted)
```



Out[181]:
```
(array([ 0.        ,  0.10863874,  1.        ]),
 array([ 0.        ,  0.57216495,  1.        ]),
 array([2, 1, 0], dtype=int64))
```

Finding Optimal Cutoff Point

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

In [182]:
```
# Let's create columns with different probability cutoffs
numbers = [float(x)/10 for x in range(10)]
for i in numbers:
    y_pred_final[i]= y_pred_final.Churn_Prob.map( lambda x: 1 if x > i else 0)
y_pred_final.head()
```

Out[182]:

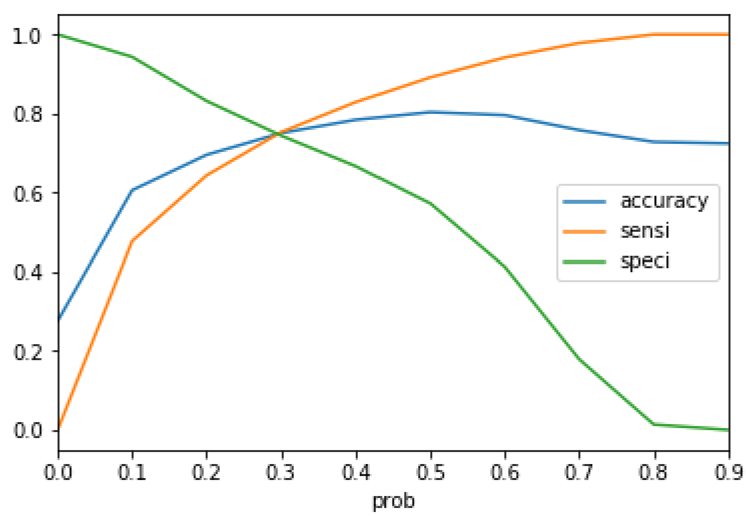
	CustID	Churn	Churn_Prob	predicted	0.0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
0	942	0	0.499083	0	1	1	1	1	1	0	0	0	0	0
1	3730	1	0.372696	0	1	1	1	1	0	0	0	0	0	0
2	1761	0	0.006738	0	1	0	0	0	0	0	0	0	0	0
3	2283	1	0.635453	1	1	1	1	1	1	1	1	0	0	0
4	1872	0	0.007533	0	1	0	0	0	0	0	0	0	0	0

In [183]:
```
# Now let's calculate accuracy sensitivity and specificity for various probabi
lity cutoffs.
cutoff_df = pd.DataFrame( columns = ['prob','accuracy','sensi','speci'])
from sklearn.metrics import confusion_matrix
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_pred_final.Churn, y_pred_final[i] )
    total1=sum(sum(cm1))
    accuracy = (cm1[0,0]+cm1[1,1])/total1
    sensi = cm1[0,0]/(cm1[0,0]+cm1[0,1])
    speci = 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  0.275829  0.000000  1.000000
0.1   0.1  0.605687  0.477094  0.943299
0.2   0.2  0.695261  0.643325  0.831615
0.3   0.3  0.750237  0.752618  0.743986
0.4   0.4  0.783886  0.828534  0.666667
0.5   0.5  0.803318  0.891361  0.572165
0.6   0.6  0.795735  0.941754  0.412371
0.7   0.7  0.757820  0.978403  0.178694
0.8   0.8  0.727962  1.000000  0.013746
0.9   0.9  0.724171  1.000000  0.000000
```

In [184]:
```
# Let's plot accuracy sensitivity and specificity for various probabilities.
cutoff_df.plot.line(x='prob', y=['accuracy','sensi','speci'])
```

Out[184]: <matplotlib.axes._subplots.AxesSubplot at 0x1959961e550>



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

In [185]:
```
y_pred_final['final_predicted'] = y_pred_final.Churn_Prob.map( lambda x: 1 if
x > 0.3 else 0)
```

In [186]:
```
y_pred_final.head()
```

Out[186]:

	CustID	Churn	Churn_Prob	predicted	0.0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	fina
0	942	0	0.499083	0	1	1	1	1	1	0	0	0	0	0	1
1	3730	1	0.372696	0	1	1	1	1	0	0	0	0	0	0	1
2	1761	0	0.006738	0	1	0	0	0	0	0	0	0	0	0	0
3	2283	1	0.635453	1	1	1	1	1	1	1	1	0	0	0	1
4	1872	0	0.007533	0	1	0	0	0	0	0	0	0	0	0	0

In [187]:
```
#Let's check the overall accuracy.
metrics.accuracy_score( y_pred_final.Churn, y_pred_final.final_predicted)
```

Out[187]: 0.75023696682464458

In [188]:
```
metrics.confusion_matrix( y_pred_final.Churn, y_pred_final.final_predicted )
```

Out[188]:
```
array([[1150,  378],
       [ 149,  433]], dtype=int64)
```