Importing and merging data

In [1]:

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

In [2]:

```python
import numpy as np
import pandas as pd
```

In [3]:

```python
churn_data=pd.read_csv('machine learning data/churn_data.csv')
churn_data.head()
```

Out[3]:

	customerID	tenure	PhoneService	Contract	PaperlessBilling	PaymentMethod	MonthlyCharges	TotalCharges	Churn
0	7590-VHVEG	1	No	Month-to-month	Yes	Electronic check	29.85	29.85	No
1	5575-GNVDE	34	Yes	One year	No	Mailed check	56.95	1889.5	No
2	3668-QPYBK	2	Yes	Month-to-month	Yes	Mailed check	53.85	108.15	Yes
3	7795-CFOCW	45	No	One year	No	Bank transfer (automatic)	42.30	1840.75	No
4	9237-HQITU	2	Yes	Month-to-month	Yes	Electronic check	70.70	151.65	Yes

In [4]:

```python
customer_data = pd.read_csv("machine learning data/customer_data.csv")
customer_data.head()
```

Out[4]:

	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 [5]:

```python
internet_data = pd.read_csv("machine learning data/internet_data.csv")
internet_data.head()
```

Out[5]:

	customerID	MultipleLines	InternetService	OnlineSecurity	OnlineBackup	DeviceProtection	TechSupport	StreamingTV	StreamingM
0	7590-VHVEG	No phone service	DSL	No	Yes	No	No	No	
1	5575-GNVDE	No	DSL	Yes	No	Yes	No	No	
2	3668-QPYBK	No	DSL	Yes	Yes	No	No	No	
3	7795-	No phone	DSL	Yes	No	Yes	Yes	No	

	customerID	MultipleLines	InternetService	OnlineSecurity	OnlineBackup	DeviceProtection	TechSupport	StreamingTV	StreamingM
4	9237-HQITU	No	Fiber optic	No	No	No	No	No	

In [6]:

```
# Merging on 'customerID'
df_1 = pd.merge(churn_data, customer_data, how='inner', on='customerID')
```

In [7]:

```
telecom = pd.merge(df_1, internet_data, how='inner', on='customerID')
```

Inspecting the data frame

In [8]:

```
telecom.head()
```

Out[8]:

	customerID	tenure	PhoneService	Contract	PaperlessBilling	PaymentMethod	MonthlyCharges	TotalCharges	Churn	gender	...
0	7590-VHVEG	1	No	Month-to-month	Yes	Electronic check	29.85	29.85	No	Female	...
1	5575-GNVDE	34	Yes	One year	No	Mailed check	56.95	1889.5	No	Male	...
2	3668-QPYBK	2	Yes	Month-to-month	Yes	Mailed check	53.85	108.15	Yes	Male	...
3	7795-CFOCW	45	No	One year	No	Bank transfer (automatic)	42.30	1840.75	No	Male	...
4	9237-HQITU	2	Yes	Month-to-month	Yes	Electronic check	70.70	151.65	Yes	Female	...

5 rows × 21 columns

In [9]:

```
telecom.shape
```

Out[9]:

```
(7043, 21)
```

In [10]:

```
telecom.describe()
```

Out[10]:

	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 [11]:

```
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 [12]:

```
varlist =  ['PhoneService', 'PaperlessBilling', 'Churn', 'Partner', 'Dependents']

# 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 [13]:

```
telecom.head()
```

Out[13]:

	customerID	tenure	PhoneService	Contract	PaperlessBilling	PaymentMethod	MonthlyCharges	TotalCharges	Churn	gender	...	I
0	7590-VHVEG	1	0	Month-to-month	1	Electronic check	29.85	29.85	0	Female	...	
1	5575-GNVDE	34	1	One year	0	Mailed check	56.95	1889.5	0	Male	...	
2	3668-QPYBK	2	1	Month-to-month	1	Mailed check	53.85	108.15	1	Male	...	
3	7795-CFOCW	45	0	One year	0	Bank transfer (automatic)	42.30	1840.75	0	Male	...	
4	9237-HQITU	2	1	Month-to-month	1	Electronic check	70.70	151.65	1	Female	...	

5 rows × 21 columns

In [14]:

```
dummy1 = pd.get_dummies(telecom[['Contract', 'PaymentMethod', 'gender', 'InternetService']], drop_f
irst=True)

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

In [15]:

```
telecom.head()
```

Out[15]:

	customerID	tenure	PhoneService	Contract	PaperlessBilling	PaymentMethod	MonthlyCharges	TotalCharges	Churn	gender	...
0	7590-VHVEG	1	0	Month-to-month	1	Electronic check	29.85	29.85	0	Female	...
1	5575-GNVDE	34	1	One year	0	Mailed check	56.95	1889.5	0	Male	...
2	3668-QPYBK	2	1	Month-to-month	1	Mailed check	53.85	108.15	1	Male	...
3	7795-CFOCW	45	0	One year	0	Bank transfer (automatic)	42.30	1840.75	0	Male	...
4	9237-HQITU	2	1	Month-to-month	1	Electronic check	70.70	151.65	1	Female	...

5 rows × 29 columns

In [16]:

```
# 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 [17]:

```
telecom.head()
```

Out[17]:

	customerID	tenure	PhoneService	Contract	PaperlessBilling	PaymentMethod	MonthlyCharges	TotalCharges	Churn	gender	...
0	7590-VHVEG	1	0	Month-to-month	1	Electronic check	29.85	29.85	0	Female	...
1	5575-GNVDE	34	1	One year	0	Mailed check	56.95	1889.5	0	Male	...
2	3668-QPYBK	2	1	Month-to-month	1	Mailed check	53.85	108.15	1	Male	...
3	7795-CFOCW	45	0	One year	0	Bank transfer (automatic)	42.30	1840.75	0	Male	...
4	9237-HQITU	2	1	Month-to-month	1	Electronic check	70.70	151.65	1	Female	...

5 rows × 43 columns

Dropping the repeated variable

In [18]:

```
telecom = telecom.drop(['Contract','PaymentMethod','gender','MultipleLines','InternetService', 'On
lineSecurity', 'OnlineBackup', 'DeviceProtection',
       'TechSupport', 'StreamingTV', 'StreamingMovies'], 1)
```

In [19]:

```
telecom['TotalCharges'] = telecom['TotalCharges'].convert_objects(convert_numeric=True)
```

In [20]:

```
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
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(2), int64(7), object(1), uint8(22)
memory usage: 756.6+ KB
```

In [21]:

```
num_telecom = telecom[['tenure','MonthlyCharges','SeniorCitizen','TotalCharges']]
```

In [22]:

```
num_telecom.describe(percentiles=[.25,.50,.75,.90,.95,.99])
```

Out[22]:

	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

In [23]:

```
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
```

In [24]:

```
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 [25]:

```
telecom=telecom[~np.isnan(telecom['TotalCharges'])]
```

In [26]:

```
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
```

test and train split

In [27]:

```
from sklearn.model_selection import train_test_split
```

In [28]:

```
x=telecom.drop(['Churn','customerID'],axis=1)
x.head()
```

Out[28]:

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

5 rows × 30 columns

In [29]:

```
y=telecom['Churn']
```

In [30]:

```
y.head()
```

Out[30]:

```
0    0
1    0
2    1
3    0
4    1
Name: Churn, dtype: int64
```

In [31]:

```
x_train,x_test,y_train,y_test=train_test_split(x,y,train_size=0.7,test_size=0.3,random_state=100)
```

Feature Scaling

In [32]:

```
from sklearn.preprocessing import StandardScaler
```

In [33]:

```
scaler=StandardScaler()

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

```
x_train.head()
```

Out[33]:

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

5 rows × 30 columns

In [34]:

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

Out[34]:

```
26.578498293515356
```

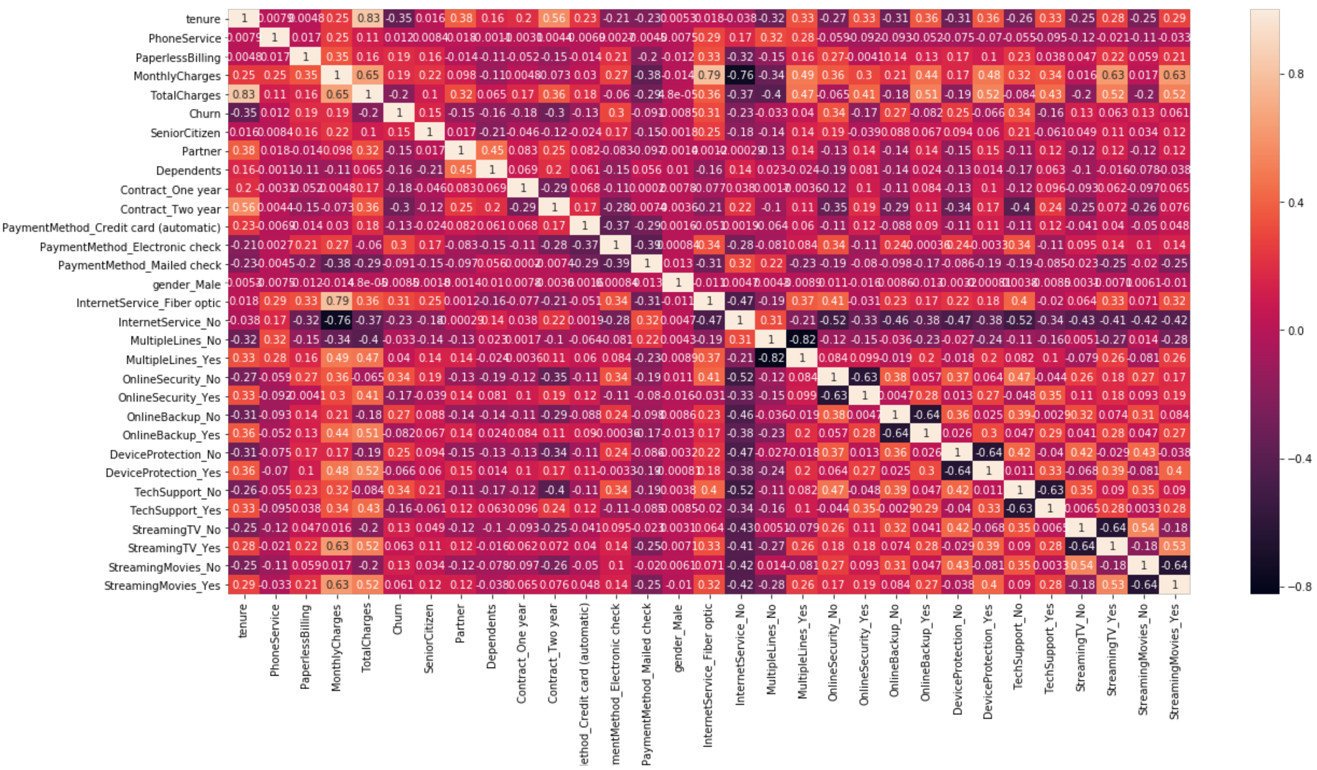
Lookking at correlation

In [35]:

```
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
```

In [36]:

```
plt.figure(figsize = (20,10))        # Size of the figure
sns.heatmap(telecom.corr(),annot = True)
plt.show()
```

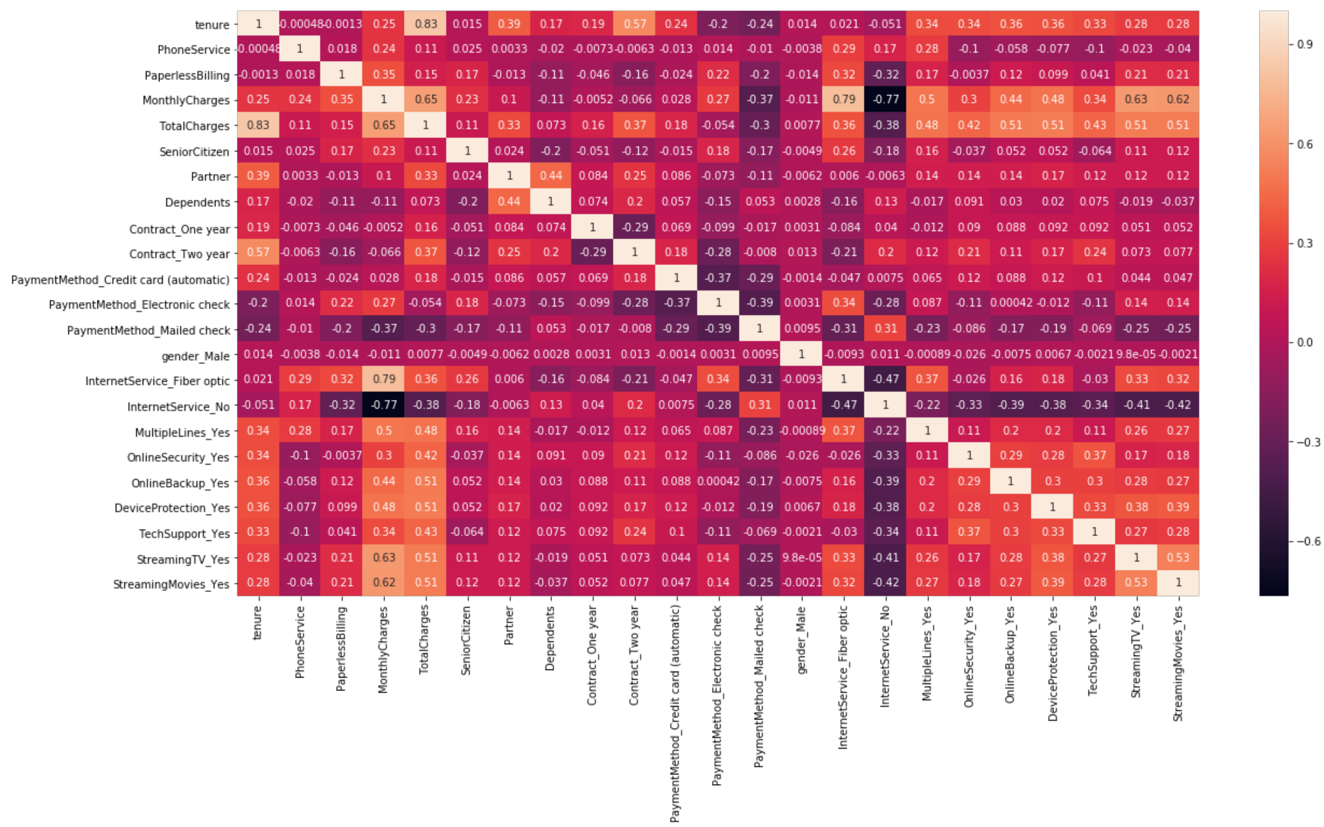


In [37]:

```
x_test =
x_test.drop(['MultipleLines_No','OnlineSecurity_No','OnlineBackup_No','DeviceProtection_No','TechSu
pport_No',
                        'StreamingTV_No','StreamingMovies_No'], 1)
x_train =
x_train.drop(['MultipleLines_No','OnlineSecurity_No','OnlineBackup_No','DeviceProtection_No','Tech
Support_No',
                         'StreamingTV_No','StreamingMovies_No'], 1)
```

In [38]:

```
plt.figure(figsize = (20,10))
sns.heatmap(x_train.corr(),annot = True)
plt.show()
```



Model building

In [39]:

```
import statsmodels.api as sm
```

In [40]:

```
logm1 = sm.GLM(y_train,(sm.add_constant(x_train)), family = sm.families.Binomial())
logm1.fit().summary()
```

Out[40]:

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:	Wed, 20 May 2020	**Deviance:**	4009.4
Time:	13:59:51	**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

feature selection using RFE

In [41]:

```
from sklearn.linear_model import LogisticRegression
logreg = LogisticRegression()
```

In [43]:

```
from sklearn.feature_selection import RFE
rfe = RFE(logreg, 15)             # running RFE with 13 variables as output
rfe = rfe.fit(x_train, y_train)
```

In [44]:

```
rfe.support_
```

Out[44]:

```
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 [45]:

```
list(zip(x_train.columns, rfe.support_, rfe.ranking_))
```

Out[45]:

```
[('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)]
```

In [46]:

```
col = x_train.columns[rfe.support_]
```

In [47]:

```
x_train.columns[~rfe.support_]
```

Out[47]:

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

Accessing with stats model

In [49]:

```
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[49]:

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:	Wed, 20 May 2020	**Deviance:**	4023.5
Time:	14:03:42	**Pearson chi2:**	6.22e+03
No. Iterations:	7	**Covariance Type:**	nonrobust

	coef	std err	z	P>|z|	[0.025	0.975]

	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 [50]:

```
y_train_pred = res.predict(x_train_sm)
y_train_pred[:10]
```

Out[50]:

```
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
```

In [51]:

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

Out[51]:

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

In [52]:

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

Out[52]:

	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

	Churn	Churn_Prob	CustID
4	1	0.645261	2784

In [53]:

```
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[53]:

	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

In [54]:

```
from sklearn import metrics
```

In [55]:

```
# Confusion matrix
confusion = metrics.confusion_matrix(y_train_pred_final.Churn, y_train_pred_final.predicted )
print(confusion)
```

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

In [56]:

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

```
0.8082080455099553
```

checking vif

In [57]:

```
# Check for the VIF values of the feature variables.
from statsmodels.stats.outliers_influence import variance_inflation_factor
```

In [60]:

```
vif = pd.DataFrame()
vif['Features'] = x_train[col].columns
vif['VIF'] = [variance_inflation_factor(x_train[col].values, i) for i in range(x_train[col].shape[1
])]
vif['VIF'] = round(vif['VIF'], 2)
vif = vif.sort_values(by = "VIF", ascending = False)
vif
```

Out[60]:

	Features	VIF
1	PhoneService	8.86
3	TotalCharges	7.37
0	tenure	6.88
9	InternetService_Fiber optic	3.97

	Features	VIF
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

In [61]:

```
col = col.drop('PhoneService', 1)
col
```

Out[61]:

```
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 [63]:

```
#  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[63]:

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:	Wed, 20 May 2020	**Deviance:**	4034.0
Time:	14:11:30	**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 [64]:

```
y_train_pred = res.predict(x_train_sm).values.reshape(-1)
```

In [65]:

```
y_train_pred[:10]
```

Out[65]:

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

In [66]:

```
y_train_pred_final['Churn_Prob'] = y_train_pred
```

In [67]:

```
# 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[67]:

	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 [68]:

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

```
0.8051605038602194
```

checking the vifs again

In [70]:

```
vif = pd.DataFrame()
vif['Features'] = x_train[col].columns
vif['VIF'] = [variance_inflation_factor(x_train[col].values, i) for i in range(x_train[col].shape[1
])]
vif['VIF'] = round(vif['VIF'], 2)
vif = vif.sort_values(by = "VIF", ascending = False)
vif
```

Out[70]:

	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 [71]:

```
col = col.drop('TotalCharges')
col
```

Out[71]:

```
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 [74]:

```
# 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[74]:

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:	Wed, 20 May 2020	**Deviance:**	4044.9
Time:	14:15:59	**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 [76]:

```
y_train_pred = res.predict(x_train_sm).values.reshape(-1)
```

In [77]:

```
y_train_pred[:10]
```

Out[77]:

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

In [78]:

```
y_train_pred_final['Churn_Prob'] = y_train_pred
```

In [79]:

```
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[79]:

	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 [80]:

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

```
0.804754164973588
```

again check the vif

In [82]:

```
vif = pd.DataFrame()
vif['Features'] = x_train[col].columns
vif['VIF'] = [variance_inflation_factor(x_train[col].values, i) for i in range(x_train[col].shape[1
])]
vif['VIF'] = round(vif['VIF'], 2)
vif = vif.sort_values(by = "VIF", ascending = False)
vif
```

Out[82]:

	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

In [83]:

```
# 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[83]:

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

In [84]:

```
metrics.accuracy_score(y_train_pred_final.Churn, y_train_pred_final.predicted)
```

Out[84]:

```
0.804754164973588
```

In [85]:

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

In [86]:

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

Out[86]:

```
0.5376845376845377
```

In [87]:

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

Out[87]:

```
0.8993122420907841
```

In [88]:

```
print(FP/ float(TN+FP))
```

0.10068775790921596

In [89]:

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

0.6540642722117203

In [90]:

```
# Negative predictive value
print (TN / float(TN+ FN))
```

0.8460144927536232

plotting ROC curve

In [91]:

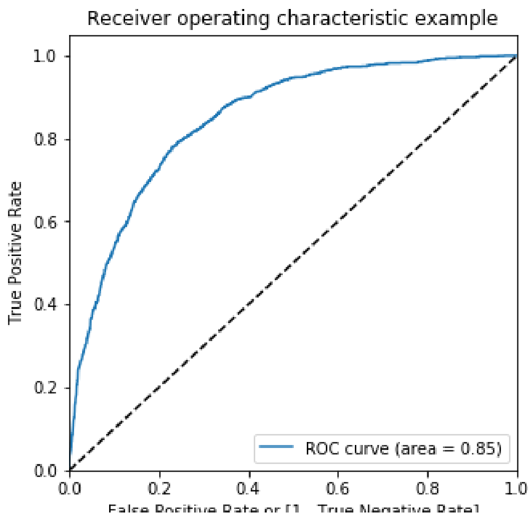
```
def draw_roc( actual, probs ):
    fpr, tpr, thresholds = metrics.roc_curve( actual, probs,
                                              drop_intermediate = False )
    auc_score = metrics.roc_auc_score( actual, probs )
    plt.figure(figsize=(5, 5))
    plt.plot( fpr, tpr, label='ROC curve (area = %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 [92]:

```
fpr, tpr, thresholds = metrics.roc_curve( y_train_pred_final.Churn, y_train_pred_final.Churn_Prob,
drop_intermediate = False )
```

In [93]:

```
draw_roc(y_train_pred_final.Churn, y_train_pred_final.Churn_Prob)
```



False Positive Rate or [1 - True Negative Rate]

finding the optimal cutoff point

In [94]:

```
# 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[94]:

	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

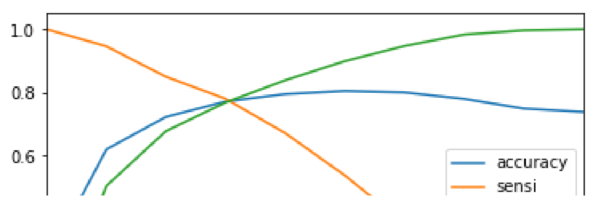
In [95]:

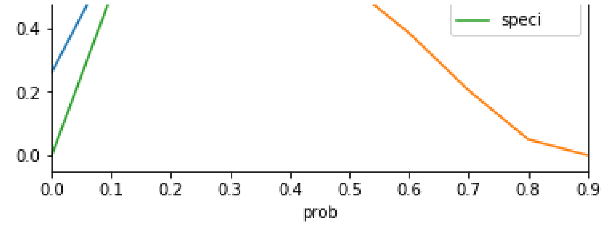
```
# Now let's calculate accuracy sensitivity and specificity for various probability cutoffs.
cutoff_df = pd.DataFrame( columns = ['prob','accuracy','sensi','speci'])
from sklearn.metrics import confusion_matrix

# 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_final[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 [96]:

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





In [97]:

```
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[97]:

	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 [98]:

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

Out[98]:

```
0.771434376269809
```

In [99]:

```
confusion2 = metrics.confusion_matrix(y_train_pred_final.Churn, y_train_pred_final.final_predicted
)
confusion2
```

Out[99]:

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

In [101]:

```
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 [102]:

```
TP / float(TP+FN)
```

Out[102]:

```
0.7801087801087802
```

In [103]:

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

Out[103]:

```
0.768363136176066
```

In [104]:

```
print(FP/ float(TN+FP))
```

```
0.23163686382393398
```

In [105]:

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

```
0.5438786565547129
```

In [106]:

```
# Negative predictive value
print (TN / float(TN+ FN))
```

```
0.907997399219766
```

precision and recall

In [107]:

```
confusion = metrics.confusion_matrix(y_train_pred_final.Churn, y_train_pred_final.predicted )
confusion
```

Out[107]:

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

In [108]:

```
#precision
confusion[1,1]/(confusion[0,1]+confusion[1,1])
```

Out[108]:

```
0.6540642722117203
```

In [109]:

```
#recall
confusion[1,1]/(confusion[1,0]+confusion[1,1])
```

Out[109]:

```
0.5376845376845377
```

In [110]:

```
from sklearn.metrics import precision_score, recall_score
```

In [111]:

```
?precision_score
```

In [112]:

```
precision_score(y_train_pred_final.Churn, y_train_pred_final.predicted)
```

Out[112]:

```
0.6540642722117203
```

In [113]:

```
recall_score(y_train_pred_final.Churn, y_train_pred_final.predicted)
```

Out[113]:

```
0.5376845376845377
```

In [114]:

```
from sklearn.metrics import precision_recall_curve
```

In [115]:

```
y_train_pred_final.Churn, y_train_pred_final.predicted
```

Out[115]:

```
(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
```

```
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
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    0
4893    1
4894    0
4895    0
4896    0
4897    0
4898    0
4899    0
4900    0
4901    0
4902    0
4903    0
4904    1
4905    0
4906    1
4907    0
4908    0
4909    1
4910    0
4911    0
4912    0
4913    0
4914    0
4915    0
4916    0
4917    0
4918    0
4919    0
4920    0
4921    0
Name: predicted, Length: 4922, dtype: int64)
```

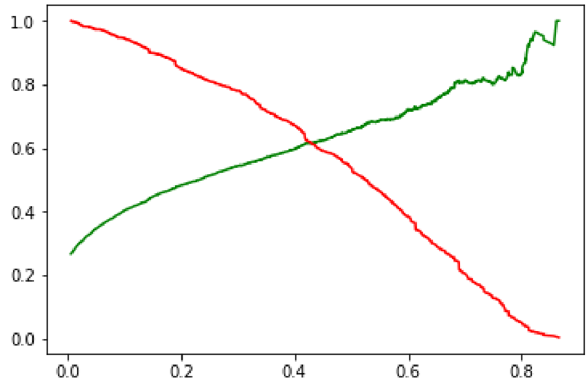
In [116]:

```
p, r, thresholds = precision_recall_curve(y_train_pred_final.Churn, y_train_pred_final.Churn_Prob)
```

```
p, r, thresholds = precision_recall_curve(y_train_pred_final.Churn, y_train_pred_final.Churn_Prob)
```

In [118]:

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



making precisoin on test data

In [119]:

```
x_test[['tenure','MonthlyCharges','TotalCharges']] =
scaler.transform(x_test[['tenure','MonthlyCharges','TotalCharges']])
```

```
C:\Users\Pujitha\Anaconda3\lib\site-packages\ipykernel_launcher.py:1: DataConversionWarning: Data
with input dtype int64, float64 were all converted to float64 by StandardScaler.
  """Entry point for launching an IPython kernel.
```

In [120]:

```
x_test = x_test[col]
x_test.head()
```

Out[120]:

	tenure	PaperlessBilling	SeniorCitizen	Contract_One year	Contract_Two year	PaymentMethod_Credit card (automatic)	PaymentMethod_Mailed check	InternetS
942	-0.347623	1	0	0	0	1	0	
3730	0.999203	1	0	0	0	1	0	
1761	1.040015	1	0	0	1	1	0	
2283	-1.286319	1	0	0	0	0	1	
1872	0.346196	0	0	0	1	0	0	

In [121]:

```
x_test_sm = sm.add_constant(x_test)
```

In [122]:

```
y_test_pred = res.predict(x_test_sm)
```

In [123]:

```
y_test_pred[:10]
```

Out[123]:

```
942     0.397413
3730    0.270295
1761    0.010238
2283    0.612692
1872    0.015869
1970    0.727206
2532    0.302131
1616    0.010315
2485    0.632881
5914    0.126451
dtype: float64
```

In [124]:

```python
# Converting y_pred to a dataframe which is an array
y_pred_1 = pd.DataFrame(y_test_pred)
```

In [125]:

```python
# Let's see the head
y_pred_1.head()
```

Out[125]:

	0
942	0.397413
3730	0.270295
1761	0.010238
2283	0.612692
1872	0.015869

In [126]:

```python
# Converting y_test to dataframe
y_test_df = pd.DataFrame(y_test)
```

In [127]:

```python
# Putting CustID to index
y_test_df['CustID'] = y_test_df.index
```

In [128]:

```python
# 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 [129]:

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

In [130]:

```python
y_pred_final.head()
```

Out[130]:

	Churn	CustID	0
0	0	942	0.397413
1	1	3730	0.270295
2	0	1761	0.010238

	Churn	CustID	0
3	1	2283	0.612692
~~4~~	~~0~~	~~1872~~	~~0.015869~~

In [131]:

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

In [132]:

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

In [133]:

```
# Let's see the head of y_pred_final
y_pred_final.head()
```

Out[133]:

	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 [134]:

```
y_pred_final['final_predicted'] = y_pred_final.Churn_Prob.map(lambda x: 1 if x > 0.42 else 0)
```

In [135]:

```
y_pred_final.head()
```

Out[135]:

	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 [136]:

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

Out[136]:

```
0.7834123222748816
```

In [137]:

```
confusion2 = metrics.confusion_matrix(y_pred_final.Churn, y_pred_final.final_predicted )
confusion2
```

Out[137]:

```
array([[1294,  234],
```

```
       [ 223,   359]], dtype=int64)
```

In [138]:

```
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 [139]:

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

Out[139]:

```
0.6168384879725086
```

In [140]:

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

Out[140]:

```
0.8468586387434555
```

In [ ]: