Classification on Provided Dataset

```
from google.colab import files
import io
import pandas as pd

pd.set_option('display.max_columns', None)
uploaded = files.upload()
```

Choose Files Churn_Modelling.csv

- **Churn_Modelling.csv**(application/vnd.ms-excel) - 684858 bytes, last modified: 4/12/2020 - 100% done

```
Saving Churn_Modelling.csv to Churn_Modelling (1).csv
```

```
data = pd.read_csv(io.BytesIO(uploaded['Churn_Modelling.csv']))
data.head()
```

	RowNumber	CustomerId	Surname	CreditScore	Geography	Gender	Age	Tenure	Balanc
0	1	15634602	Hargrave	619	France	Female	42	2	0.0
1	2	15647311	Hill	608	Spain	Female	41	1	83807.8
2	3	15619304	Onio	502	France	Female	42	8	159660.8
3	4	15701354	Boni	699	France	Female	39	1	0.0
4	5	15737888	Mitchell	850	Spain	Female	43	2	125510.8

```
import sklearn
import matplotlib.pyplot as plt
import numpy as np


import seaborn as sns
```

```
/usr/local/lib/python3.6/dist-packages/statsmodels/tools/_testing.py:19: FutureWarning:
  import pandas.util.testing as tm
```

```
# Plot a confusion matrix.
# cm is the confusion matrix, names are the names of the classes.
def plot_confusion_matrix(cm, names, title='confusion matrix', cmap=plt.cm.PuBuGn):
    plt.imshow(cm, interpolation='nearest', cmap=cmap)
    plt.title(title)
    plt.colorbar()
    tick_marks = np.arange(len(names))
    plt.xticks(tick_marks, names, rotation=45)
    plt.yticks(tick_marks, names)
    plt.tight_layout()
```

```
    plt.tight_layout()
    plt.ylabel('True label')
    plt.xlabel('Predicted label')
```

Churn_Modelling Dataset

```
import pandas as pd
import pandas.util.testing as tm
import seaborn as sns

data = pd.read_csv('Churn_Modelling.csv',header='infer')
data
```

	RowNumber	CustomerId	Surname	CreditScore	Geography	Gender	Age	Tenure	Ba
0	1	15634602	Hargrave	619	France	Female	42	2	
1	2	15647311	Hill	608	Spain	Female	41	1	83
2	3	15619304	Onio	502	France	Female	42	8	159
3	4	15701354	Boni	699	France	Female	39	1	
4	5	15737888	Mitchell	850	Spain	Female	43	2	125
...	...	...	...	...	...	...	...	...	
9995	9996	15606229	Obijiaku	771	France	Male	39	5	
9996	9997	15569892	Johnstone	516	France	Male	35	10	57
9997	9998	15584532	Liu	709	France	Female	36	7	
9998	9999	15682355	Sabbatini	772	Germany	Male	42	3	75
9999	10000	15628319	Walker	792	France	Female	28	4	130

10000 rows × 14 columns

Suppose we convert the problem into a binary classification task (Exited versus Continued), given lim
by replacing the class labels of the instances 0 to Continued and 1 to Exited

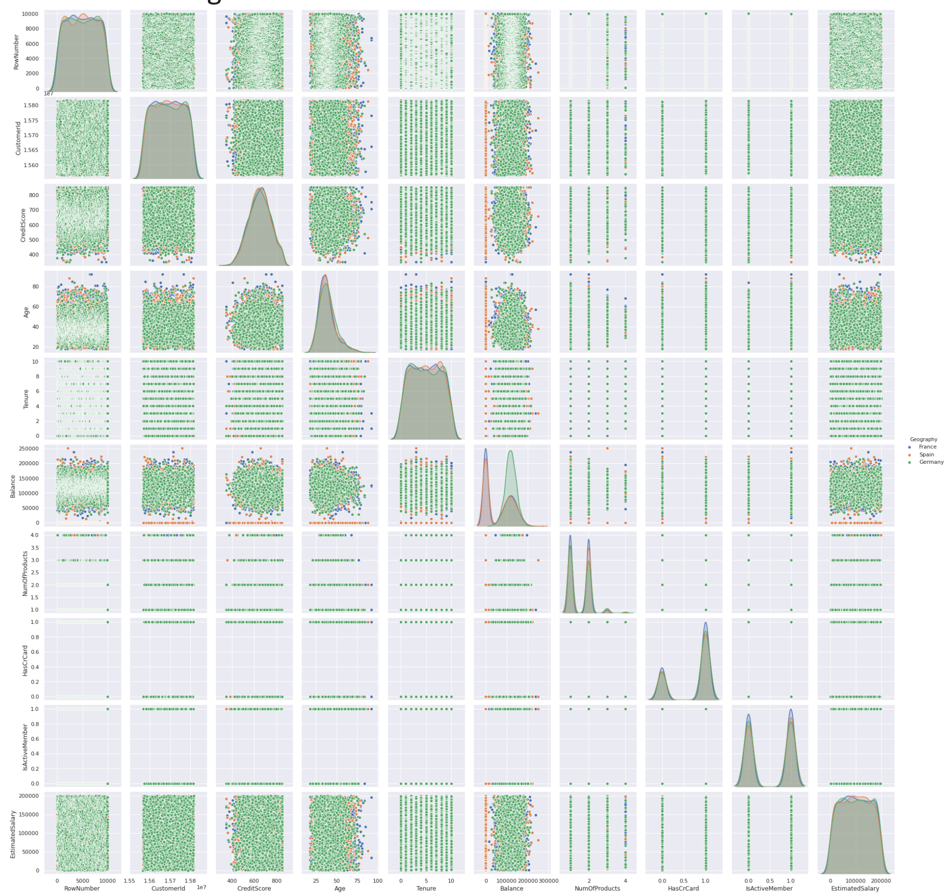
```
data['Exited'] = data['Exited'].replace([0],'Continued')
data['Exited'] = data['Exited'].replace([1],'Exited')

data
```

	RowNumber	CustomerId	Surname	CreditScore	Geography	Gender	Age	Tenure	Ba
0	1	15634602	Hargrave	619	France	Female	42	2	
1	2	15647311	Hill	608	Spain	Female	41	1	838
2	3	15619304	Onio	502	France	Female	42	8	159
3	4	15701354	Boni	699	France	Female	39	1	
4	5	15737888	Mitchell	850	Spain	Female	43	2	125
...	...	...	...	...	...	...	...	...	
9995	9996	15606229	Obijiaku	771	France	Male	39	5	
9996	9997	15569892	Johnstone	516	France	Male	35	10	57
9997	9998	15584532	Liu	709	France	Female	36	7	
9998	9999	15682355	Sabbatini	772	Germany	Male	42	3	75
9999	10000	15628319	Walker	792	France	Female	28	4	130

10000 rows × 14 columns

```
# Paired plot using seaborn
sns.set()
sns.pairplot(data[['RowNumber', 'CustomerId', 'Surname', 'CreditScore', 'Geography', 'Gender'
```

```
<seaborn.axisgrid.PairGrid at 0x7fb7c5e96f28>
```



Applying Pandas cross-tabulation to examine the relationship between the Gender and Age attributes

```
pd.crosstab([data['Gender'],data['Age']],data['Exited'])
```

	Exited	Continued	Exited
Gender	**Age**		
Female	**18**	4	0
	19	8	1
	20	12	1
	21	31	2
	22	36	6
...	**...**	...	...
Male	**81**	2	0
	83	1	0
	84	1	0
	88	1	0
	92	2	0

135 rows × 2 columns

Decision Tree Classifier

In this section, we apply a decision tree classifier to the Churn_Modelling dataset described in the pre

```
from sklearn import tree

Y = pd.DataFrame(data, columns=['Exited'])
X = data.drop(['Gender', 'Surname', 'Geography', 'Exited'],axis=1)

clf = tree.DecisionTreeClassifier(criterion='entropy',max_depth=3)
clf = clf.fit(X, Y)
```

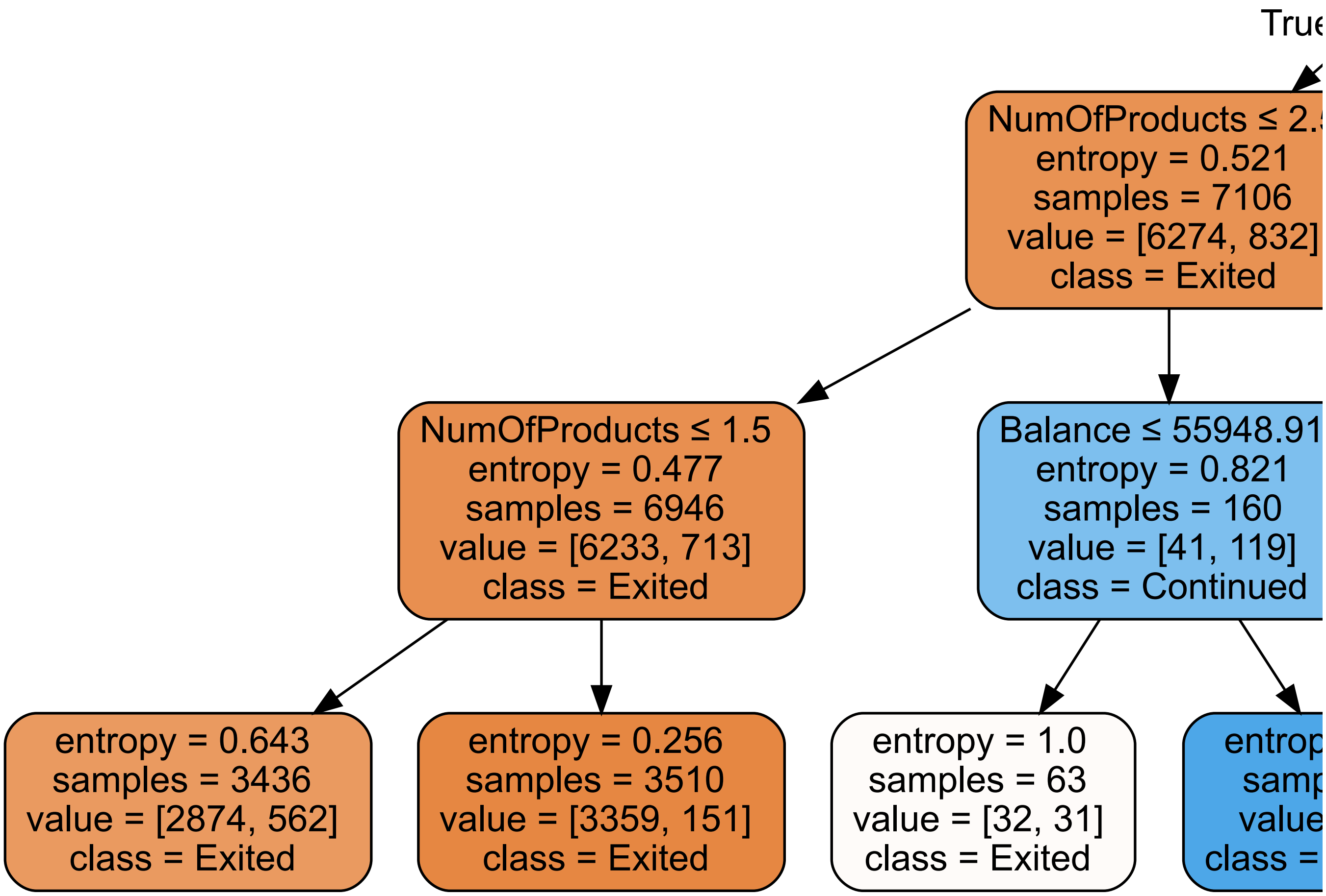
```
X
```

	RowNumber	CustomerId	CreditScore	Age	Tenure	Balance	NumOfProducts	HasCrCa
0	1	15634602	619	42	2	0.00	1	
1	2	15647311	608	41	1	83807.86	1	
2	3	15619304	502	42	8	159660.80	3	
3	4	15701354	699	39	1	0.00	2	
4	5	15737888	850	43	2	125510.82	1	
...	...	...	...	...	...	...	...	
9995	9996	15606229	771	39	5	0.00	2	
9996	9997	15569892	516	35	10	57369.61	1	
9997	9998	15584532	709	36	7	0.00	1	
9998	9999	15682355	772	42	3	75075.31	2	
9999	10000	15628319	792	28	4	130142.79	1	

10000 rows × 10 columns

```
import graphviz
dot_data = tree.export_graphviz(clf, out_file=None)
graph = graphviz.Source(dot_data)
```

```
dot_data = tree.export_graphviz(clf, out_file=None,
                     feature_names=X.columns,
                     class_names=['Exited','Continued'],
                     filled=True, rounded=True,
                     special_characters=True)
graph = graphviz.Source(dot_data)
graph
```



Next, suppos decision tree is applied to classify the following test examples.

```
test_Data = [[5,15737888,'Mitchell',850,'Spain','Female',43,2,122510.82,1,1,1,79084.10,'Conti
           [6,15574012,'chu',645,'Spain','Male',44,8,113755.78,2,1,0,149756.71,'Exited'],
           [7,15592531,'Bartlett',822,'France','Male',50,7,0.00,2,1,1,10062.80,'Continued'],
           [8,15656148,'Oblnna',376,'Germany','Female',29,4,115046.74,4,1,0,119346.88,'Exited
test_Data = pd.DataFrame(test_Data, columns=data.columns)
test_Data
```

We first extract the predictor and target class attributes from the test data and then apply the decisio

```
testY = pd.DataFrame(test_Data, columns=['Exited'])
testX = test_Data.drop(['Surname','Gender','Geography','Exited'],axis=1)
predY = clf.predict(testX)
predictions = pd.concat([test_Data['Exited'],pd.Series(predY,name='Predicted Exit')], axis=1)
predictions
```

	Exited	Predicted Exit
0	Continued	Continued
1	Exited	Continued
2	Continued	Continued
3	Exited	Exited

```
print('Number of instances remaining in D1 = %d' % (data.shape[0]))
numInstances = (data.shape[0])
```

```
Number of instances remaining in D1 = 10000
```

```
from sklearn.model_selection import train_test_split
numTrain = 49730  # number of training instances
numTest = numInstances - numTrain

Y = pd.DataFrame(data, columns=['Exited'])
X = data.drop(['Gender', 'Surname', 'Geography', 'Exited'],axis=1)


print('X size \n', X.size)
print('Y size \n', Y.size)
```

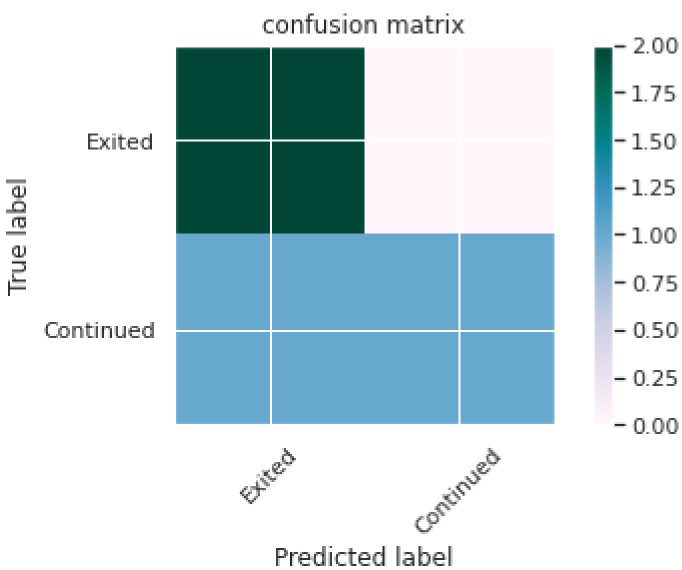
```
X size
 100000
Y size
 10000
```

Splitting the data

```
X_train, X_test, Y_train, Y_test = train_test_split(X, Y, test_size=0.2, random_state=123)
```

```
from sklearn.metrics import accuracy_score, confusion_matrix, f1_score, precision_score,recal

confusion = confusion_matrix(testY, predY)
print(confusion)

plot_confusion_matrix(confusion, data.Exited.unique(), title ='confusion matrix', cmap=plt.cm
print('Accuracy on test data is %.2f' % (accuracy_score(testY, predY)))
print('F1 score on test data is %.2f' % (f1_score(testY, predY,pos_label='Exited')))
print('Precision Score on test data is %.2f' % (precision_score(testY, predY,pos_label='Exite
print('Recall score on test data is %.2f' % (recall_score(testY, predY,pos_label='Exited')))
print( classification_report(testY,predY))
```

```
[[2 0]
 [1 1]]
Accuracy on test data is 0.75
F1 score on test data is 0.67
Precision Score on test data is 1.00
Recall score on test data is 0.50
              precision    recall  f1-score   support

   Continued       0.67      1.00      0.80         2
      Exited       1.00      0.50      0.67         2

    accuracy                           0.75         4
   macro avg       0.83      0.75      0.73         4
weighted avg       0.83      0.75      0.73         4
```




```
list(data.Exited.unique())
```

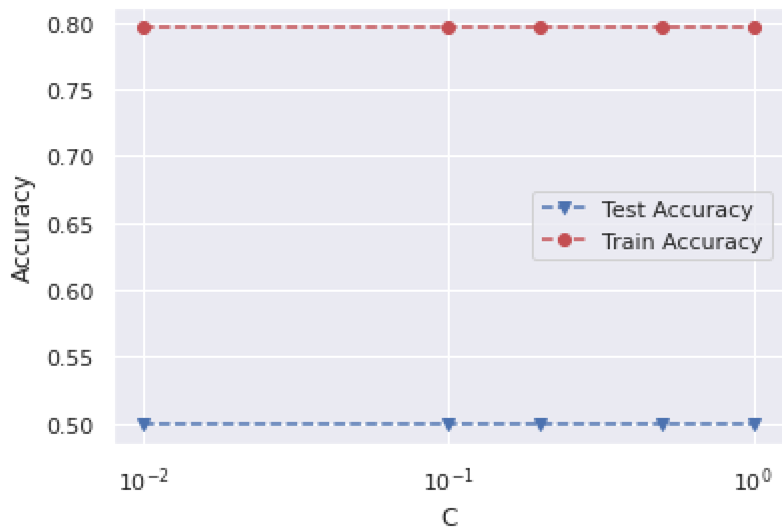
```
['Exited', 'Continued']
```

Logistic Regression

In this section, we apply a Logistic Regression to the Churn_Modelling dataset described in the previo

```
from sklearn.linear_model import LogisticRegression


C = [0.01, 0.1, 0.2, 0.5,1]

LRtestAcc = []
LRtrainAcc = []

for param in C:
    clf = LogisticRegression(C=param)
    clf.fit(X,Y)

    log_reg_pred = clf.predict(testX)
    log_reg_pred_train = clf.predict(X)
    print(log_reg_pred)
    LRtestAcc.append(accuracy_score(testY, log_reg_pred))
    LRtrainAcc.append(accuracy_score(Y,log_reg_pred_train))



plt.plot(C, LRtestAcc,'bv--',C,LRtrainAcc,'ro--')
plt.legend(['Test Accuracy','Train Accuracy'])
plt.xlabel('C')
plt.xscale('log')
plt.ylabel('Accuracy')
```

```
/usr/local/lib/python3.6/dist-packages/sklearn/utils/validation.py:760: DataConversionWa
  y = column_or_1d(y, warn=True)
/usr/local/lib/python3.6/dist-packages/sklearn/utils/validation.py:760: DataConversionWa
  y = column_or_1d(y, warn=True)
['Continued' 'Continued' 'Continued' 'Continued']
['Continued' 'Continued' 'Continued' 'Continued']
/usr/local/lib/python3.6/dist-packages/sklearn/utils/validation.py:760: DataConversionWa
  y = column_or_1d(y, warn=True)
/usr/local/lib/python3.6/dist-packages/sklearn/utils/validation.py:760: DataConversionWa
  y = column_or_1d(y, warn=True)
['Continued' 'Continued' 'Continued' 'Continued']
['Continued' 'Continued' 'Continued' 'Continued']
['Continued' 'Continued' 'Continued' 'Continued']
/usr/local/lib/python3.6/dist-packages/sklearn/utils/validation.py:760: DataConversionWa
  y = column_or_1d(y, warn=True)
Text(0, 0.5, 'Accuracy')
```




```
model_lg=clf.fit(X_train,Y_train).predict(X_test)
```

```
/usr/local/lib/python3.6/dist-packages/sklearn/utils/validation.py:760: DataConversionWa
  y = column_or_1d(y, warn=True)
```

```
print('Accuracy on test data is %.2f for logistic regression' % (accuracy_score(Y_test,model_
```

```
Accuracy on test data is 0.79 for logistic regression
```

Naive Bayes Classifier

In this section, we apply a Naise Bayes classifier to the Churn _Modelling dataset described in the pre

```
from sklearn.naive_bayes import GaussianNB

clf_NB = GaussianNB()
```

```
clf_NB = GaussianNB()
clf_NB.fit(X,Y)
NB_pred = clf_NB.predict(testX)
print(NB_pred)

# print('Accuracy on test data is %.2f' % (accuracy_score(testY, NB_pred)))
```

```
['Continued' 'Continued' 'Continued' 'Continued']
/usr/local/lib/python3.6/dist-packages/sklearn/naive_bayes.py:206: DataConversionWarning
  y = column_or_1d(y, warn=True)
```

```
model_nb=clf_NB.fit(X_train,Y_train).predict(X_test)
```

```
/usr/local/lib/python3.6/dist-packages/sklearn/naive_bayes.py:206: DataConversionWarning
  y = column_or_1d(y, warn=True)
```

```
print('Accuracy on test data is %.2f for Naive Bayes' % (accuracy_score(Y_test,model_nb)))
```

```
Accuracy on test data is 0.78 for Naive Bayes
```

Decision Tree Classifier

```
from sklearn.tree import DecisionTreeClassifier
dt=DecisionTreeClassifier()
```

```
model_dt=dt.fit(X_train,Y_train).predict(X_test)
```

```
accuracy_score(Y_test,model_dt)
```

```
0.766
```

```
print('Accuracy on test data is %.2f for Decision Tree Classifier' % (accuracy_score(Y_test,m
```

```
Accuracy on test data is 0.77 for Decision Tree Classifier
```

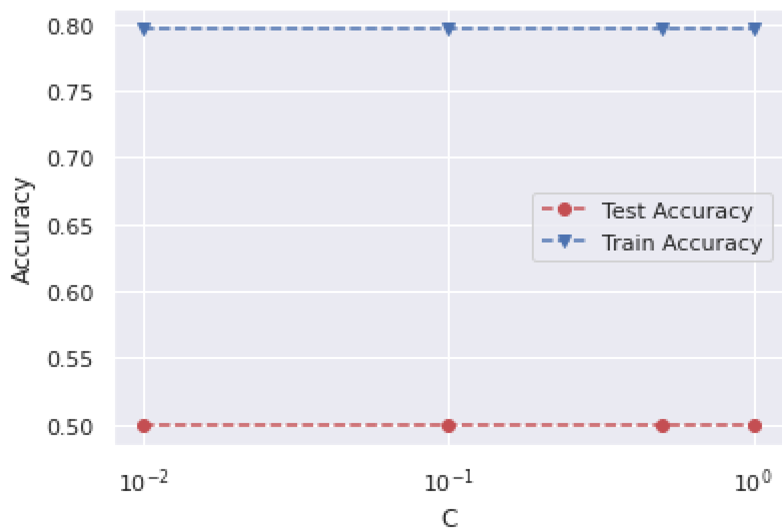
Support Vector Machine (SVM) Classifier

In this section, we apply a SVM classifier to the Churn_Modelling dataset described in the previous su
parameter and different kernals and see how it effects the performance of the model.

Linear Decision Boundary

```
from sklearn.svm import SVC


C = [0.01, 0.1, 0.5,1]


SVMLtestAcc = []
SVMLtrainAcc = []

for param in C:
    clf_linear = SVC(param,kernel='linear')
    clf_linear.fit(X,Y)
    svml_pred = clf_linear.predict(testX)
    svml_pred_train = clf_linear.predict(X)
    print(svml_pred)
    SVMLtestAcc.append(accuracy_score(testY, svml_pred))
    SVMLtrainAcc.append(accuracy_score(Y,svml_pred_train))

plt.plot(C, SVMLtestAcc,'ro--', C,SVMLtrainAcc,'bv--')
plt.legend(['Test Accuracy','Train Accuracy'])
plt.xlabel('C')
plt.xscale('log')
plt.ylabel('Accuracy')
```

```
/usr/local/lib/python3.6/dist-packages/sklearn/utils/validation.py:760: DataConversionWa
  y = column_or_1d(y, warn=True)
['Continued' 'Continued' 'Continued' 'Continued']
/usr/local/lib/python3.6/dist-packages/sklearn/utils/validation.py:760: DataConversionWa
  y = column_or_1d(y, warn=True)
['Continued' 'Continued' 'Continued' 'Continued']
/usr/local/lib/python3.6/dist-packages/sklearn/utils/validation.py:760: DataConversionWa
  y = column_or_1d(y, warn=True)
['Continued' 'Continued' 'Continued' 'Continued']
/usr/local/lib/python3.6/dist-packages/sklearn/utils/validation.py:760: DataConversionWa
  y = column_or_1d(y, warn=True)
['Continued' 'Continued' 'Continued' 'Continued']
Text(0, 0.5, 'Accuracy')
```




```
model_svml=clf_linear.fit(X_train,Y_train).predict(X_test)
```

```
/usr/local/lib/python3.6/dist-packages/sklearn/utils/validation.py:760: DataConversionWa
  y = column_or_1d(y, warn=True)
```

```
print('Accuracy on test data is %.3f for SVM Linear' % (accuracy_score(Y_test, model_svml)))
```

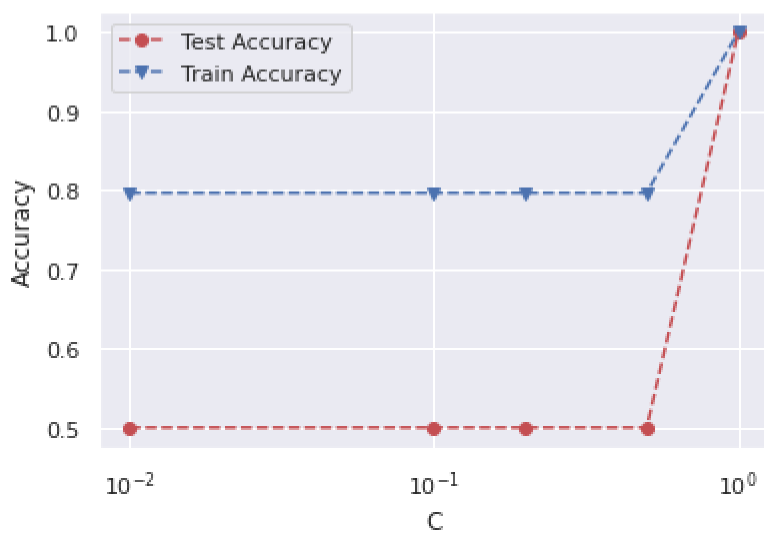
```
Accuracy on test data is 0.793 for SVM Linear
```

Non Linear Decision Boundary

```
C = [0.01, 0.1, 0.2, 0.5,1]

SVMLtestAcc = []
SVMLtrainAcc = []
```

```
for param in C:
    clf_non = SVC(C=param,kernel='rbf',gamma='auto')
    clf_non.fit(X,Y)
    svml_pred_n = clf_non.predict(testX)
    svml_pred_train_n = clf_non.predict(X)
    print(svml_pred)
    SVMLtestAcc.append(accuracy_score(testY, svml_pred_n))
    SVMLtrainAcc.append(accuracy_score(Y,svml_pred_train_n))

plt.plot(C, SVMLtestAcc,'ro--', C,SVMLtrainAcc,'bv--')
plt.legend(['Test Accuracy','Train Accuracy'])
plt.xlabel('C')
plt.xscale('log')
plt.ylabel('Accuracy')
```

```
/usr/local/lib/python3.6/dist-packages/sklearn/utils/validation.py:760: DataConversionWa
  y = column_or_1d(y, warn=True)
['Continued' 'Continued' 'Continued' 'Continued']
/usr/local/lib/python3.6/dist-packages/sklearn/utils/validation.py:760: DataConversionWa
  y = column_or_1d(y, warn=True)
['Continued' 'Continued' 'Continued' 'Continued']
/usr/local/lib/python3.6/dist-packages/sklearn/utils/validation.py:760: DataConversionWa
  y = column_or_1d(y, warn=True)
['Continued' 'Continued' 'Continued' 'Continued']
/usr/local/lib/python3.6/dist-packages/sklearn/utils/validation.py:760: DataConversionWa
  y = column_or_1d(y, warn=True)
['Continued' 'Continued' 'Continued' 'Continued']
/usr/local/lib/python3.6/dist-packages/sklearn/utils/validation.py:760: DataConversionWa
  y = column_or_1d(y, warn=True)
['Continued' 'Continued' 'Continued' 'Continued']
Text(0, 0.5, 'Accuracy')
```




```
model_svmnl=clf_non.fit(X_train,Y_train).predict(X_test)
print('Accuracy on test data is %.3f for SVM non Linear' % (accuracy_score(Y_test, model_svmn
```

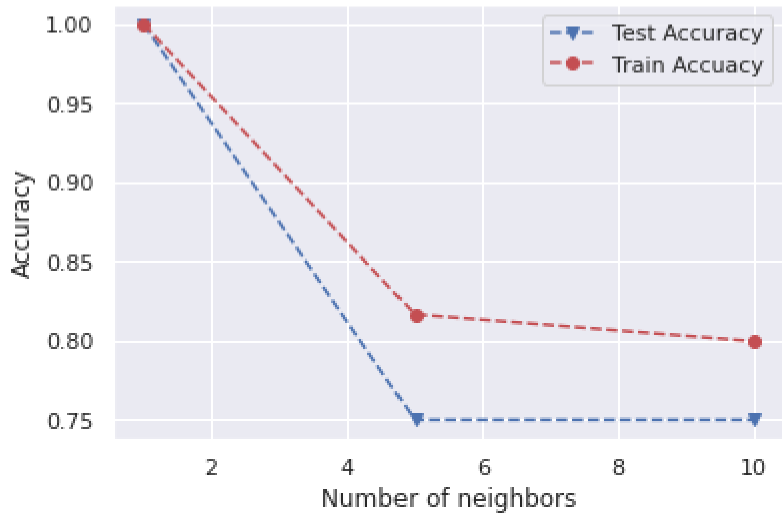
```
/usr/local/lib/python3.6/dist-packages/sklearn/utils/validation.py:760: DataConversionWa
  y = column_or_1d(y, warn=True)
Accuracy on test data is 0.793 for SVM non Linear
```

K Nearest Neighbor (KNN) Classifier

In this section, we apply a K - Nearest Neighbor classifier to the Churn_Modelling dataset described ir look at how the K value effect the performance of the Model.

```
from sklearn.neighbors import KNeighborsClassifier

numNeighbors = [1, 5, 10]
testAcc = []
trainAcc = []

for k in numNeighbors:
  clf_k = KNeighborsClassifier(n_neighbors=k, metric='minkowski', p=2)
  clf_k.fit(X, Y)
  knn_pred = clf_k.predict(testX)
  knn_pred_train = clf_k.predict(X)
  print(knn_pred)
  testAcc.append(accuracy_score(testY, knn_pred))
  trainAcc.append(accuracy_score(Y,knn_pred_train))

plt.plot(numNeighbors, testAcc,'bv--',numNeighbors, trainAcc, 'ro--')
plt.legend(['Test Accuracy','Train Accuacy'])
plt.xlabel('Number of neighbors')
plt.ylabel('Accuracy')
```

```
/usr/local/lib/python3.6/dist-packages/ipykernel_launcher.py:9: DataConversionWarning: A
  if __name__ == '__main__':
['Continued' 'Exited' 'Continued' 'Exited']
/usr/local/lib/python3.6/dist-packages/ipykernel_launcher.py:9: DataConversionWarning: A
  if __name__ == '__main__':
['Continued' 'Continued' 'Continued' 'Exited']
/usr/local/lib/python3.6/dist-packages/ipykernel_launcher.py:9: DataConversionWarning: A
  if __name__ == '__main__':
['Continued' 'Continued' 'Continued' 'Exited']
Text(0, 0.5, 'Accuracy')
```




```
model_kn=clf_k.fit(X_train,Y_train).predict(X_test)
print('Accuracy on test data is %.2f for KNN' % (accuracy_score(Y_test, model_kn)))
```

```
Accuracy on test data is 0.79 for KNN
/usr/local/lib/python3.6/dist-packages/ipykernel_launcher.py:1: DataConversionWarning: A
  """Entry point for launching an IPython kernel.
```