DATA ANALYTICS LAB EXPERIMENT 8: Support Vector Machine

Objective: Understanding Support Vector Machine algorithm through building SVM algorithm in Python

Introduction: An SVM is a numeric classifier. That means that all of the features of the data must be numeric, not symbolic. Furthermore, in this class, we'll assume that the SVM is a binary classifier: that is, it classifies points as one of two classifications. We'll typically call the classifications "+" and " -".
A trained SVM is defined by two values:
• A normal vector w (also called the weight vector), which solely determines the shape and direction of the decision boundary.
• A scalar offset b, which solely determines the position of the decision boundary with respect to the origin.
A trained SVM can then classify a point x by computing w · x + b. If this value is positive, x is classified as +; otherwise, x is classified as -.
The decision boundary is coerced by support vectors, so called because these vectors (data points) support the boundary: if any of these points are moved or eliminated, the decision boundary changes! All support vectors lie on a gutter, which can be thought of as a line running parallel to the decision boundary. There are two gutters: one gutter hosts positive support vectors, and the other, negative support vectors.
Note that, though a support vector is always on a gutter, it's not necessarily true that every data point on a gutter is a support vector.
Below are the five principle SVM equations, as taught in lecture and recitation. Equations 1-3 define the decision boundary and the margin width, while Equations 4 and 5 can be used to calculate the alpha (supportiveness) values for the training points.

```
#importing all packages
import pandas as pd
import numpy as np
import matplotlib as mpl
import matplotlib.pyplot as plt
from sklearn.metrics import confusion_matrix
from sklearn.svm import SVC

%matplotlib inline
```

```
# Function to plot SVC
def plot_svc(svc, X, y, h=0.02, pad=0.25):
    x_min, x_max = X[:, 0].min()-pad, X[:, 0].max()+pad
    y_min, y_max = X[:, 1].min()-pad, X[:, 1].max()+pad
    xx, yy = np.meshgrid(np.arange(x_min, x_max, h), np.arange(y_min, y_max, h))
    Z = svc.predict(np.c_[xx.ravel(), yy.ravel()])
    Z = Z.reshape(xx.shape)
    plt.contourf(xx, yy, Z, cmap=plt.cm.Paired, alpha=0.2)

    plt.scatter(X[:,0], X[:,1], s=70, c=y, cmap=mpl.cm.Paired)
    # Support vectors indicated in plot by vertical lines
    sv = svc.support_vectors_
    plt.scatter(sv[:,0], sv[:,1], c='k', marker='x', s=100, linewidths='1')
    plt.xlim(x_min, x_max)
    plt.ylim(y_min, y_max)
    plt.xlabel('X1')
    plt.ylabel('X2')
    plt.show()
```

```
#reading the dataset
data = pd.read_csv("d.csv",index_col=[0])
data.head()
```

User ID	Gender	Age	EstimatedSalary	Purchased
15624510	Male	19	19000	0
15810944	Male	35	20000	0
15668575	Female	26	43000	0
15603246	Female	27	57000	0
15804002	Male	19	76000	0

```
#attribute selection for support vector classifier model
X = data.loc[:,['Age','EstimatedSalary']]
y = data.iloc[:,-1]
```

```
#removing the mean of X and scaling it's variance to 1
from sklearn.preprocessing import StandardScaler
sc = StandardScaler()
X = sc.fit_transform(X)
```

```
#train-test split
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, random_state = 0)
```

Linear

```
#linear svc
from sklearn.svm import SVC
classifier = SVC(kernel = 'linear', random_state = 0)
classifier.fit(X_train, y_train)
```

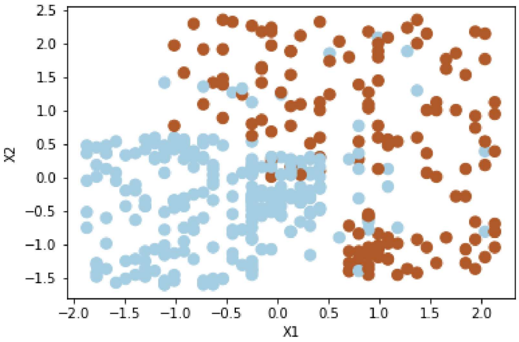
```
SVC(kernel='linear', random_state=0)
```

```
#print accuracy score
from sklearn.metrics import accuracy_score
y_pred = classifier.predict(X_test)
print('Accuracy of the model is %.2f%%' %(accuracy_score(y_test, y_pred)*100))
```

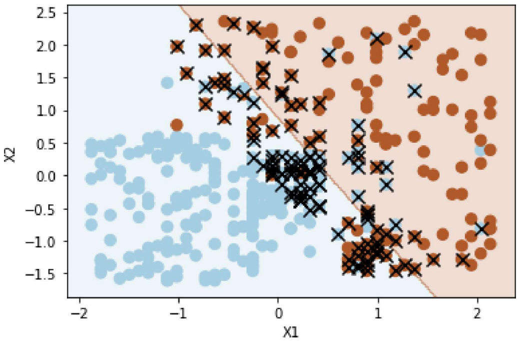
```
Accuracy of the model is 90.00%
```

```
#scatter plot of dataset, so that data can be seen clearly
plt.scatter(X[:,0], X[:,1], s=70, c=y, cmap=mpl.cm.Paired)
plt.xlabel('X1')
plt.ylabel('X2')
```

```
Text(0, 0.5, 'X2')
```




```
#plot linear svc
plot_svc(classifier,X,y)
```



Non-Linear

```
#non-linear svc
from sklearn.svm import SVC
classifier = SVC(kernel = 'rbf', random_state = 0)
classifier.fit(X_train, y_train)
```

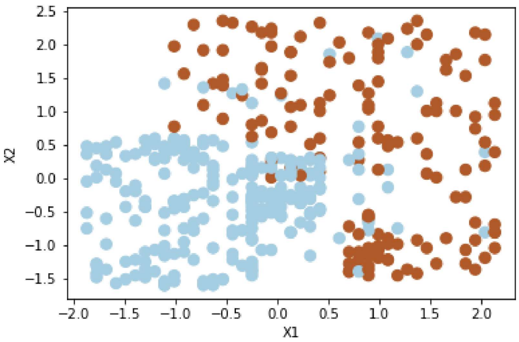
```
SVC(random_state=0)
```

```
#print accuracy score
from sklearn.metrics import accuracy_score
y_pred = classifier.predict(X_test)
print('Accuracy of the model is %.2f%%' %(accuracy_score(y_test, y_pred)*100))
```

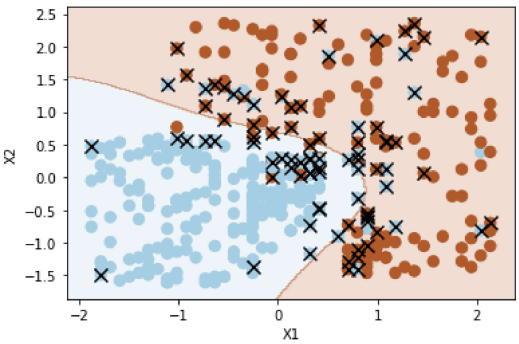
```
Accuracy of the model is 93.00%
```

```
#scatter plot of dataset, so that data can be seen clearly
plt.scatter(X[:,0], X[:,1], s=70, c=y, cmap=mpl.cm.Paired)
plt.xlabel('X1')
plt.ylabel('X2')
```

```
Text(0, 0.5, 'X2')
```




```
#plot non linear svc
plot_svc(classifier,X,y)
```



ROC

```
#importing all packages
from sklearn.metrics import auc
from sklearn.metrics import roc_curve
```

```
# More constrained model
svm3 = SVC(C=1, kernel='rbf', gamma=1)
svm3.fit(X_train, y_train)
```

```
SVC(C=1, gamma=1)
```

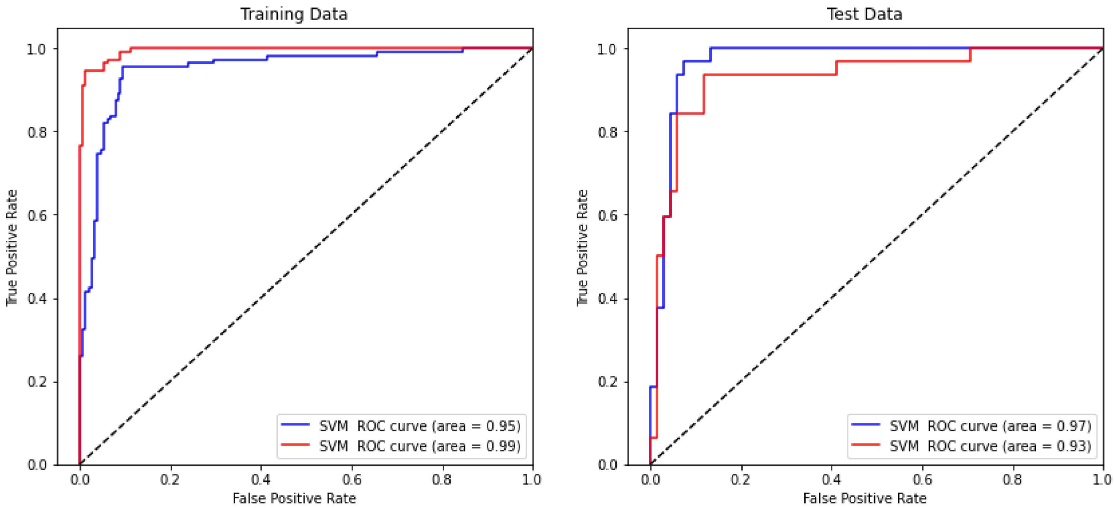
```
# More flexible model
svm4 = SVC(C=1, kernel='rbf', gamma=50)
svm4.fit(X_train, y_train)
```

```
SVC(C=1, gamma=50)
```

```
#train-test split
y_train_score3 = svm3.decision_function(X_train)
y_train_score4 = svm4.decision_function(X_train)
```

```
y_train_score3 = svm3.decision_function(X_train)
y_train_score4 = svm4.decision_function(X_train)

false_pos_rate3, true_pos_rate3, _ = roc_curve(y_train, y_train_score3)
roc_auc3 = auc(false_pos_rate3, true_pos_rate3)

false_pos_rate4, true_pos_rate4, _ = roc_curve(y_train, y_train_score4)
roc_auc4 = auc(false_pos_rate4, true_pos_rate4)

fig, (ax1,ax2) = plt.subplots(1, 2, figsize=(14,6))
ax1.plot(false_pos_rate3, true_pos_rate3, label='SVM  ROC curve (area = %0.2f)' % roc_auc3, color='b')
ax1.plot(false_pos_rate4, true_pos_rate4, label='SVM  ROC curve (area = %0.2f)' % roc_auc4, color='r')
ax1.set_title('Training Data')

y_test_score3 = svm3.decision_function(X_test)
y_test_score4 = svm4.decision_function(X_test)
```

```
false_pos_rate3, true_pos_rate3, _ = roc_curve(y_test, y_test_score3)
roc_auc3 = auc(false_pos_rate3, true_pos_rate3)

false_pos_rate4, true_pos_rate4, _ = roc_curve(y_test, y_test_score4)
roc_auc4 = auc(false_pos_rate4, true_pos_rate4)

ax2.plot(false_pos_rate3, true_pos_rate3, label='SVM  ROC curve (area = %0.2f)' % roc_auc3, color='b')
ax2.plot(false_pos_rate4, true_pos_rate4, label='SVM  ROC curve (area = %0.2f)' % roc_auc4, color='r')
ax2.set_title('Test Data')

for ax in fig.axes:
    ax.plot([0, 1], [0, 1], 'k--')
    ax.set_xlim([-0.05, 1.0])
    ax.set_ylim([0.0, 1.05])
    ax.set_xlabel('False Positive Rate')
    ax.set_ylabel('True Positive Rate')
    ax.legend(loc="lower right")
```



OBSERVATION:

- Linear SVC has 90% accuracy.
- Non-Linear SVC has 93% accuracy.
- The third model has 95% accuracy in training set and 97% accuracy in test set.
- The fourth model has 99% accuracy in training set and 93% accuracy in test set.

INFERENCE:

- Non-linear SVC is more efficient than linear SVC
- The third model is more accurate than the fourth model according to the roc score for the test data.
- I have learnt how svm works and now I know the difference between linear and non-linear svm.
- I have learnt about ROC score and AUC score which are used to check accuracy of SVM models.