ML | Using SVM to perform classification on a non-linear dataset

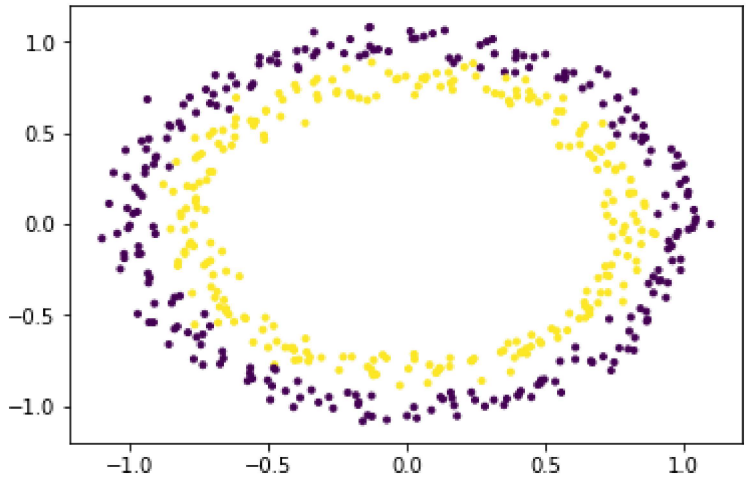
Prerequisite: Support Vector Machines

Definition of a hyperplane and SVM classifier:
For a linearly separable dataset having n features (thereby needing n dimensions for representation), a hyperplane is basically an (n – 1) dimensional subspace used for separating the dataset into two sets, each set containing data points belonging to a different class. For example, for a dataset having two features X and Y (therefore lying in a 2-dimensional space), the separating hyperplane is a line (a 1-dimensional subspace). Similarly, for a dataset having 3-dimensions, we have a 2-dimensional separating hyperplane, and so on.
In machine learning, Support Vector Machine (SVM) is a non-probabilistic, linear, binary classifier used for classifying data by learning a hyperplane separating the data.

Classifying a non-linearly separable dataset using a SVM – a linear classifier:
As mentioned above SVM is a linear classifier which learns an (n – 1)-dimensional classifier for classification of data into two classes. However, it can be used for classifying a non-linear dataset. This can be done by projecting the dataset into a higher dimension in which it is linearly separable!

To get a better understanding, let's consider circles dataset.

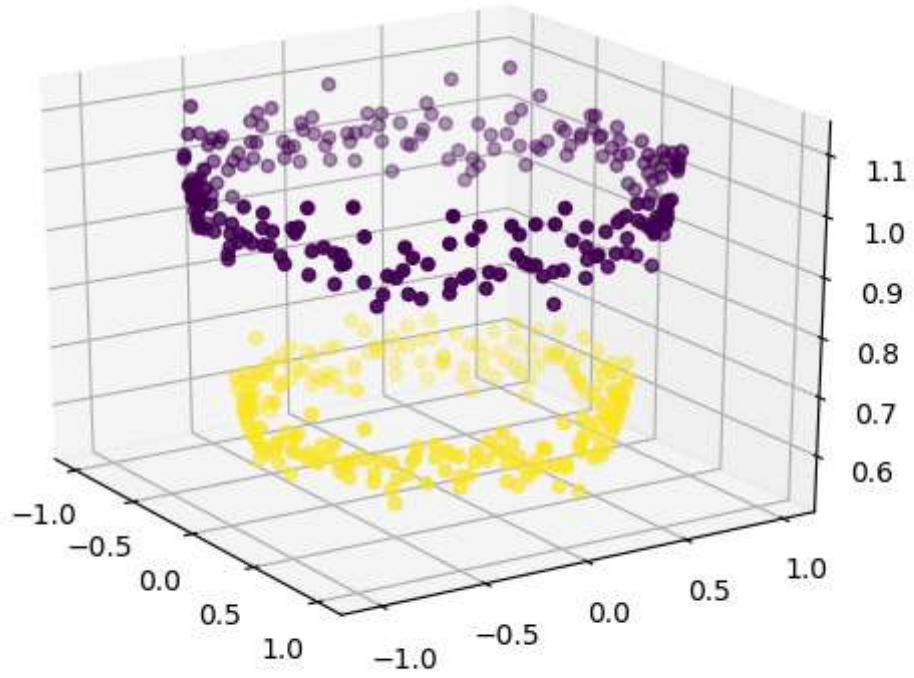
```
import  numpy as np

import  matplotlib.pyplot as plt

from  sklearn.datasets  import  make_circles

from  mpl_toolkits.mplot3d  import  Axes3D

X, Y  =  make_circles(n_samples  =  500``, noise  =  0.02``)

plt.scatter(X[:,  0``], X[:,  1``], c  =  Y, marker  =  '.'``)

plt.show()
```



The dataset is clearly a non-linear dataset and consists of two features (say, X and Y).

In order to use SVM for classifying this data, introduce another feature Z = X2 + Y2 into the dataset. Thus, projecting the 2-dimensional data into 3-dimensional space. The first dimension representing the feature X, second representing Y and third representing Z (which, mathematically, is equal to the radius of the circle of which the point (x, y) is a part of). Now, clearly, for the data shown above, the 'yellow' data points belong to a circle of smaller radius and the 'purple' data points belong to a circle of larger radius. Thus, the data becomes linearly separable along the Z-axis.

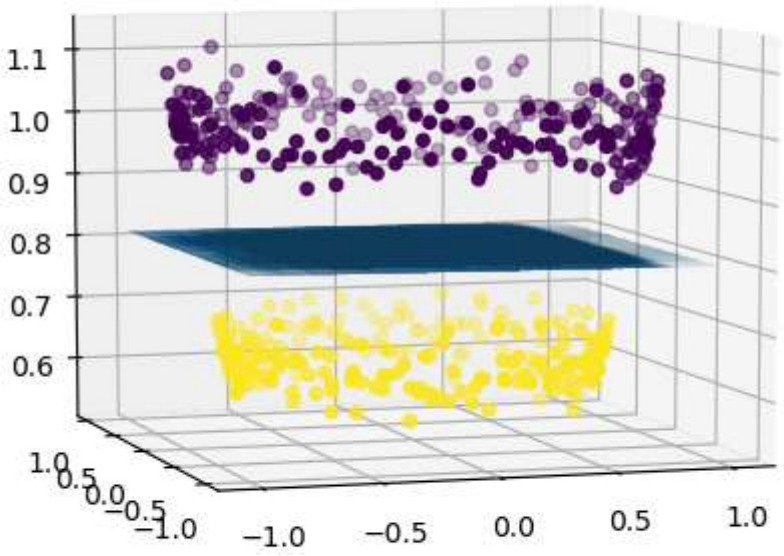
```
X1  =  X[:,  0``].reshape((``-``1``,  1``))

X2  =  X[:,  1``].reshape((``-``1``,  1``))

X3  =  (X1``*``*``2  +  X2``*``*``2``)

X  =  np.hstack((X, X3))

fig  =  plt.figure()

axes  =  fig.add_subplot(``111``, projection  =  '3d'``)

axes.scatter(X1, X2, X1``*``*``2  +  X2``*``*``2``, c  =  Y, depthshade  =  True``)

plt.show()
```



Now, we can use SVM (or, for that matter, any other linear classifier) to learn a 2-dimensional separating hyperplane. This is how the hyperplane would look like:

```
from sklearn import svm

svc = svm.SVC(kernel = 'linear```)

svc.fit(X, Y)

w = svc.coef_

b = svc.intercept_

x1 = X[:, 0``].reshape((``-``1``, 1``))

x2 = X[:, 1``].reshape((``-``1``, 1``))

x1, x2 = np.meshgrid(x1, x2)

x3 = -``(w[``0``][``0``]``*``x1 + w[``0``][``1``]``*``x2 + b) / w[``0``][``2``]

fig = plt.figure()
```

```
axes2  =  fig.add_subplot(``111``, projection  =  '3d'``)

axes2.scatter(X1, X2, X1``*``*``2  +  X2``*``*``2``, c  =  Y, depthshade  =  True``)

axes1  =  fig.gca(projection  =  '3d'``)

axes1.plot_surface(x1, x2, x3, alpha  =  0.01``)

plt.show()
```



Thus, using a linear classifier we can separate a non-linearly separable dataset.

A brief introduction to kernels in machine learning:
In machine learning, a trick known as “kernel trick” is used to learn a linear classifier to classify a non-linear dataset. It transforms the linearly inseparable data into a linearly separable one by projecting it into a higher dimension. A kernel function is applied on each data instance to map the original non-linear data points into some higher dimensional space in which they become linearly separable.