Support Vector Machine [SVM]

```
    SVM is a powerful and flexible class of supervised algorithm.It fin
ds the line or a curve in two dimension or in
```

multiple dimensions that divides the classes from eachother.

Importing Library

In [1]:
```
%matplotlib inline
import matplotlib.pyplot as plt

import pandas as pd
import numpy as np
from scipy import stats

from sklearn.svm import SVC
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score

import seaborn as sns;sns.set()
```

Reading the Data

In [2]:
```
df=pd.read_csv("ad_data.csv")
df.head()
```

Out[2]:

	relevance_score	ad_length	has_clicked
0	1.412816	1.530335	1
1	1.813361	1.631131	1
2	1.432893	4.376792	0
3	1.872718	4.180692	0
4	2.095178	1.079147	1

In [3]:
```
df.shape
```

Out[3]:
```
(50, 3)
```

In [4]:
```
df.describe()
```

Out[4]:

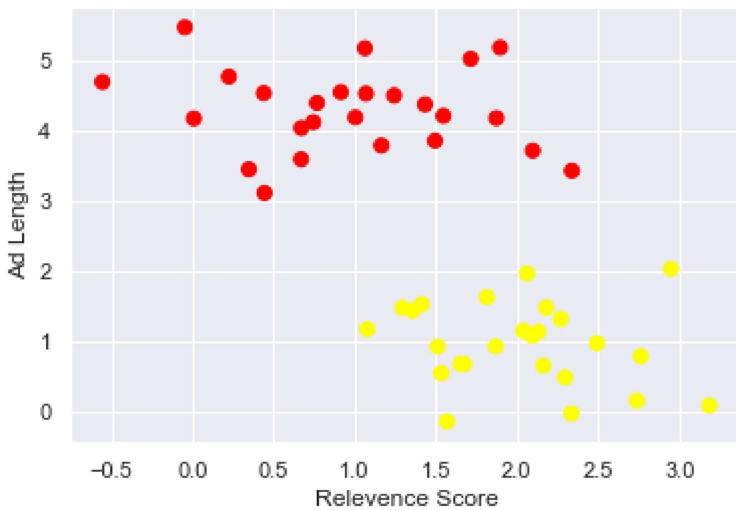
	relevance_score	ad_length	has_clicked
count	50.000000	50.000000	50.000000
mean	1.500291	2.626178	0.500000
std	0.818878	1.773245	0.505076
min	-0.555524	-0.138106	0.000000
25%	1.018468	1.001077	0.000000
50%	1.539556	2.575253	0.500000
75%	2.096398	4.207599	1.000000
max	3.185158	5.474253	1.000000

In [5]:
```
dep="has_clicked"

ind=df.columns.tolist()
ind.remove(dep)
ind
```

Out[5]:
```
['relevance_score', 'ad_length']
```

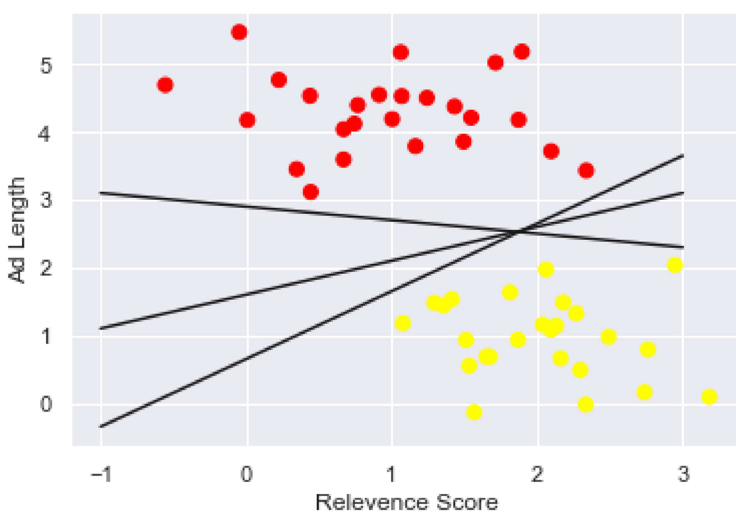
Visualization

In [6]:
```
x=df[ind].values

y=df[dep].values

plt.scatter(x[:,0],x[:,1],c=y,s=50,cmap='autumn')
plt.xlabel("Relevence Score")
plt.ylabel("Ad Length")
plt.show()
```



We can draw these lines manually:

In [7]:
```
xfit=np.linspace(-1,3,5)
plt.scatter(x[:,0],x[:,1],c=y,s=50,cmap='autumn')
plt.xlabel("Relevence Score")
plt.ylabel("Ad Length")


for a,b in [(1,0.65),(0.5,1.6),(-0.2,2.9)]:
    plt.plot(xfit,a*xfit+b,'-k')
```



```
        But there can be many such line.But which is my best decision
    boundary.
```

In SVM the line that maximizes this margin is the one we will choose as a optimal model.

Fitting SVM

In [8]:
```
#Splitting train and test data
xtrain,xtest,ytrain,ytest=train_test_split(x,y,test_size=0.2,random_state=0)
```

In [9]:
```
#Building the model
model=SVC(kernel="linear",C=1E10)
model.fit(xtrain,ytrain)
```

Out[9]:
```
SVC(C=10000000000.0, cache_size=200, class_weight=None, coef0=0.0,
  decision_function_shape='ovr', degree=3, gamma='auto_deprecated',
  kernel='linear', max_iter=-1, probability=False, random_state=None,
  shrinking=True, tol=0.001, verbose=False)
```

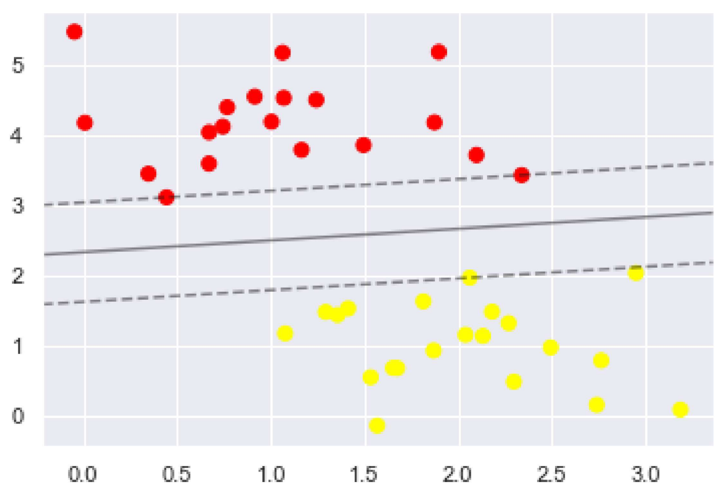
In [10]:
```
pred=model.predict(xtest)

accuracy_score(pred,ytest)
```

Out[10]:
```
1.0
```

To visualize the decision boundary

In [11]:
```
def plot_svc_decision_function(model, ax=None, plot_support=True):
    """Plot the decision function for a 2D SVC"""
    if ax is None:
        ax = plt.gca()
    xlim = ax.get_xlim()
    ylim = ax.get_ylim()

    # create grid to evaluate model
    x = np.linspace(xlim[0], xlim[1], 30)
    y = np.linspace(ylim[0], ylim[1], 30)
    Y, X = np.meshgrid(y, x)
    xy = np.vstack([X.ravel(), Y.ravel()]).T
    P = model.decision_function(xy).reshape(X.shape)

    # plot decision boundary and margins
    ax.contour(X, Y, P, colors='k',
               levels=[-1, 0, 1], alpha=0.5,
               linestyles=['--', '-', '--'])

    # plot support vectors
    if plot_support:
        ax.scatter(model.support_vectors_[:, 0],
                   model.support_vectors_[:, 1],
                   s=300, linewidth=1, facecolors='none');
    ax.set_xlim(xlim)
    ax.set_ylim(ylim)
```

In [12]:
```
plt.scatter(xtrain[:,0],xtrain[:,1],c=ytrain,s=50,cmap='autumn')
plot_svc_decision_function(model);
```



In [13]:
```
model.support_vectors_
```

Out[13]:
```
array([[0.44359863, 3.11530945],
       [2.33812285, 3.43116792],
       [2.06156753, 1.96918596]])
```

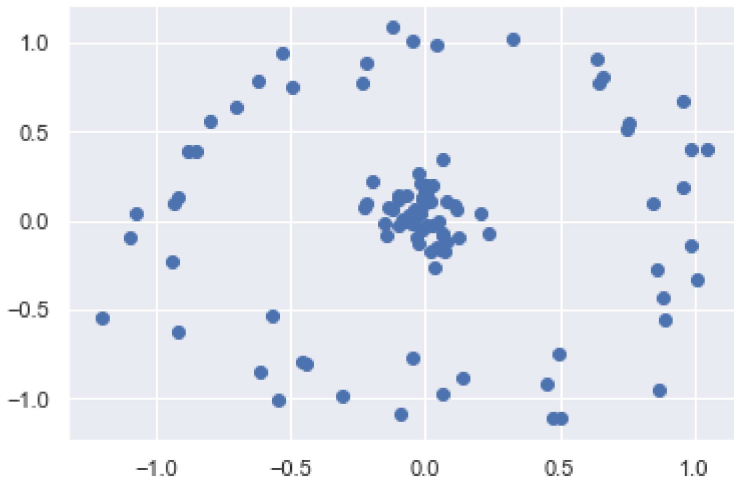
Kernal Tricks

In [14]:
```
from sklearn.datasets.samples_generator import make_circles
```

In [15]:
```
X,Y=make_circles(100,factor=.1,noise=.1)
```

In [16]:
```
plt.scatter(X[:,0],X[:,1])
```

Out[16]:
```
<matplotlib.collections.PathCollection at 0x20d155bc748>
```

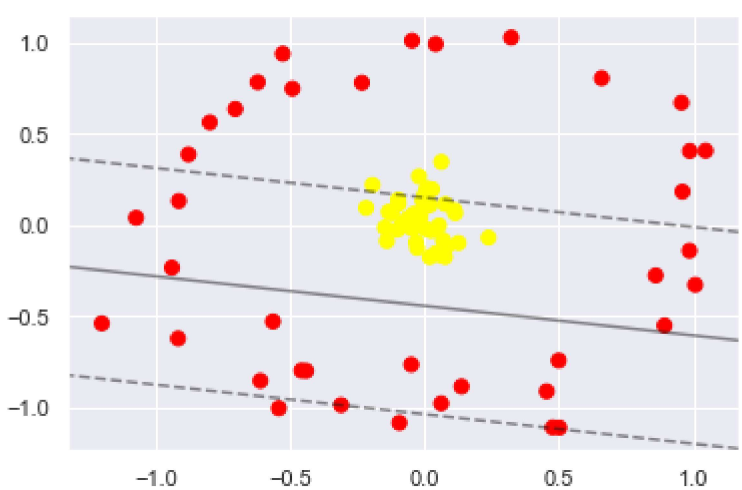


In [17]:
```
xtrain,xtest,ytrain,ytest=train_test_split(X,Y,test_size=0.2,random_state=0)
```

In [18]:
```
model=SVC(kernel="linear")
model.fit(xtrain,ytrain)
```

Out[18]:
```
SVC(C=1.0, cache_size=200, class_weight=None, coef0=0.0,
  decision_function_shape='ovr', degree=3, gamma='auto_deprecated',
  kernel='linear', max_iter=-1, probability=False, random_state=None,
  shrinking=True, tol=0.001, verbose=False)
```

In [19]:
```
plt.scatter(xtrain[:,0],xtrain[:,1],c=ytrain,s=50,cmap="autumn")
plot_svc_decision_function(model,plot_support=False);
```



In [20]:
```
pred=model.predict(xtest)
accuracy_score(pred,ytest)
```

Out[20]:
```
0.45
```

```
        The model is not much accurate so we should play with kernal.We n
eed to transform our datapoint.The video
```

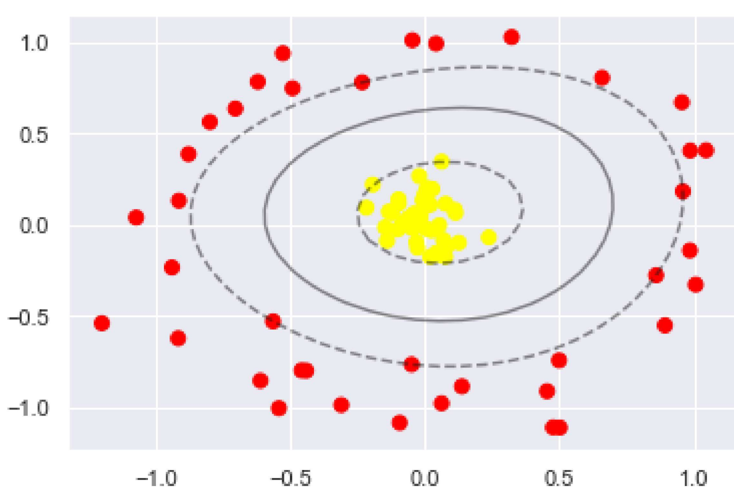
shows how the transformation take place. We here use rbf(Radial Basic Function) for transformation

In [21]:
```
model=SVC(kernel='rbf',C=1E6)
model.fit(xtrain,ytrain)
```

```
C:\Users\Gaurav\Anaconda3\lib\site-packages\sklearn\svm\base.py:196: FutureWarn
ing: The default value of gamma will change from 'auto' to 'scale' in version
0.22 to account better for unscaled features. Set gamma explicitly to 'auto' or
'scale' to avoid this warning.
  "avoid this warning.", FutureWarning)
```

Out[21]:
```
SVC(C=1000000.0, cache_size=200, class_weight=None, coef0=0.0,
  decision_function_shape='ovr', degree=3, gamma='auto_deprecated',
  kernel='rbf', max_iter=-1, probability=False, random_state=None,
  shrinking=True, tol=0.001, verbose=False)
```

In [22]:
```
plt.scatter(xtrain[:,0],xtrain[:,1],c=ytrain,s=50,cmap="autumn")
plot_svc_decision_function(model,plot_support=False);
```



In [23]:
```
pred=model.predict(xtest)
accuracy_score(pred,ytest)
```

Out[23]:
```
1.0
```