Euclidean distance

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In [2]:
```
%matplotlib inline

import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

Function to compute Euclidean Distance.

In [4]:
```
def euclidean(v1, v2):

    #Convert 1-D Python lists to numpy vectors
    v1 = np.array(v1)
    v2 = np.array(v2)

    #Compute vector which is the element wise square of the difference
    diff = np.power(np.array(v1) - np.array(v2), 2)

    #Perform summation of the elements of the above vector
    sigmal_val = np.sum(diff)

    #Compute square root and return final Euclidean score
    euclid_score = np.sqrt(sigmal_val)

    return euclid_score
```

Define 3 users with ratings for 5 movies

In [5]:
```
u1 = [5,1,2,4,5]
u2 = [1,5,4,2,1]
u3 = [5,2,2,4,4]
```

In [6]:
```
euclidean(u1, u2)
```

Out[6]:
```
7.483314773547883
```

In [7]:
```
euclidean(u1, u3)
```

Out[7]:
```
1.4142135623730951
```

Pearson Correlation

In [8]:
```
alice = [1,1,3,2,4]
bob = [2,2,4,3,5]

euclidean(alice, bob)
```

Out[8]:
```
2.23606797749979
```

In [9]:
```
eve = [5,5,3,4,2]

euclidean(eve, alice)
```

Out[9]:
```
6.324555320336759
```

In [10]:
```
from scipy.stats import pearsonr

pearsonr(alice, bob)
```

Out[10]:
```
(1.0, 0.0)
```

In [11]:
```
pearsonr(alice, eve)
```

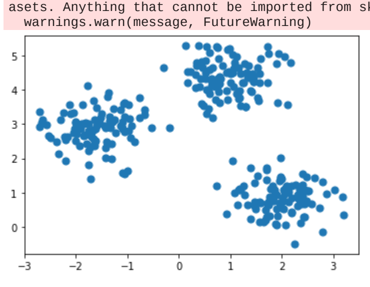
Out[11]:
```
(-1.0, 0.0)
```

Clustering

K-Means

In [13]:
```
# Import the function that enables us to plot clusters
from sklearn.datasets.samples_generator import make_blobs
#https://machinelearningmastery.com/generate-test-datasets-python-scikit-learn/
#https://matplotlib.org/tutorials/introductory/pyplot.html
#https://realpython.com/k-means-clustering-python/

#Get points such that they form 3 visually separable clusters
X, y = make_blobs(n_samples=300, centers=3,
                       cluster_std=0.50, random_state=0)


#Plot the points on a scatterplot
plt.scatter(X[:, 0], X[:, 1], s=50);
```

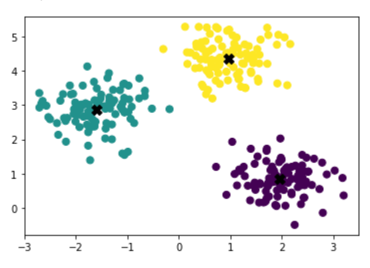
```
c:\users\juand\appdata\local\programs\python\python38\lib\site-packages\sklearn\utils\deprecation.py:143: FutureWarning: The sklearn.datasets.samples_generato
r module is  deprecated in version 0.22 and will be removed in version 0.24. The corresponding classes / functions should instead be imported from sklearn.dat
asets. Anything that cannot be imported from sklearn.datasets is now part of the private API.
  warnings.warn(message, FutureWarning)
```



Import the K-Means Class

In [15]:
```
from sklearn.cluster import KMeans

#Initializr the K-Means object. Set number of clusters to 3,
#centroid initilalization as 'random' and maximum iterations to 10
kmeans = KMeans(n_clusters=3, init='random', max_iter=10)

#Compute the K-Means clustering
kmeans.fit(X)

#Predict the classes for every point
y_pred = kmeans.predict(X)

#Plot the data points again but with different colors for different classes
plt.scatter(X[:, 0], X[:, 1], c=y_pred, s=50)

#Get the list of the final centroids
centroids = kmeans.cluster_centers_

#Plot the centroids onto the same scatterplot.
plt.scatter(centroids[:, 0], centroids[:, 1], c='black', s=100, marker='X')

#https://www.machinelearningplus.com/predictive-modeling/k-means-clustering/
```

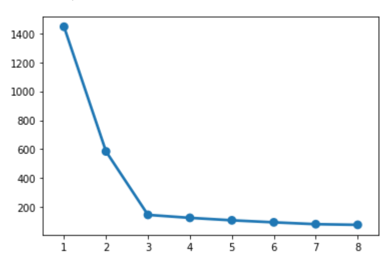
Out[15]:
```
<matplotlib.collections.PathCollection at 0x1c5adba1c40>
```



List that will hold the sum of square values for different cluster sizes

In [17]:
```
ss = []

#We will compute SS for cluster sizes between 1 and 8.
for i in range(1,9):

    #Initlialize the KMeans object and call the fit method to compute clusters
    kmeans = KMeans(n_clusters=i, random_state=0, max_iter=10, init='random').fit(X)

    #Append the value of SS for a particular iteration into the ss list
    ss.append(kmeans.inertia_)

#Plot the Elbow Plot of SS v/s K
sns.pointplot(x=[j for j in range(1,9)], y=ss)

# https://towardsdatascience.com/machine-learning-algorithms-part-9-k-means-example-in-python-f2ad05ed5203
```

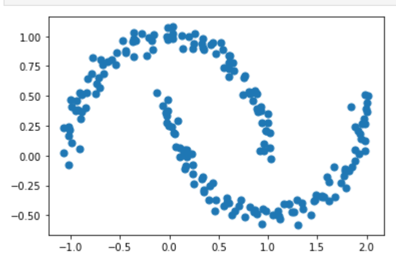
Out[17]:
```
<AxesSubplot:>
```



Other clustering algorithms

Import the half moon function from scikit-learn

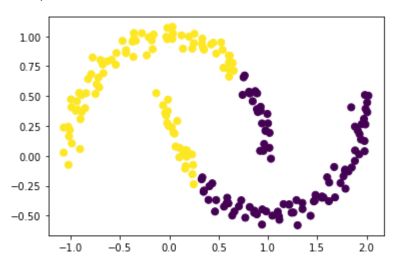
In [18]:
```
from sklearn.datasets import make_moons

#Get access to points using the make_moons function
X_m, y_m = make_moons(200, noise=.05, random_state=0)

#Plot the two half moon clusters
plt.scatter(X_m[:, 0], X_m[:, 1], s=50);
```



Initialize K-Means Object with K=2 (for two half moons) and fit it to our data

In [19]:
```
kmm = KMeans(n_clusters=2, init='random', max_iter=10)
kmm.fit(X_m)

#Predict the classes for the data points
y_m_pred = kmm.predict(X_m)

#Plot the colored clusters as identified by K-Means
plt.scatter(X_m[:, 0], X_m[:, 1], c=y_m_pred, s=50)
```

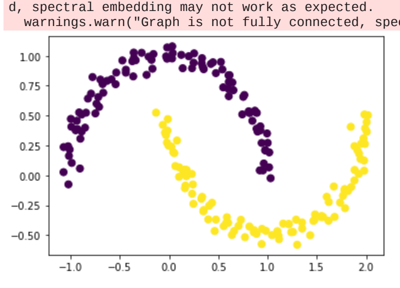
Out[19]:
```
<matplotlib.collections.PathCollection at 0x1c5b1d7c850>
```



Import Spectral Clustering from scikit-learn

In [20]:
```
from sklearn.cluster import SpectralClustering

#Define the Spectral Clustering Model
model = SpectralClustering(n_clusters=2, affinity='nearest_neighbors')

#Fit and predict the labels
y_m_sc = model.fit_predict(X_m)

#Plot the colored clusters as identified by Spectral Clustering
plt.scatter(X_m[:, 0], X_m[:, 1], c=y_m_sc, s=50);
```

```
c:\users\juand\appdata\local\programs\python\python38\lib\site-packages\sklearn\manifold\_spectral_embedding.py:236: UserWarning: Graph is not fully connecte
d, spectral embedding may not work as expected.
  warnings.warn("Graph is not fully connected, spectral embedding"
```



Dimensionality Reduction

Principal Component Analysis

In [21]:
```
# Load the Iris dataset into Pandas DataFrame
iris = pd.read_csv("https://archive.ics.uci.edu/ml/machine-learning-databases/iris/iris.data",
                 names=['sepal_length','sepal_width','petal_length','petal_width','class'])

#Display the head of the dataframe
iris.head()
```

Out[21]:

	sepal_length	sepal_width	petal_length	petal_width	class
0	5.1	3.5	1.4	0.2	Iris-setosa
1	4.9	3.0	1.4	0.2	Iris-setosa
2	4.7	3.2	1.3	0.2	Iris-setosa
3	4.6	3.1	1.5	0.2	Iris-setosa
4	5.0	3.6	1.4	0.2	Iris-setosa

In [22]:
```
#Import Standard Scaler from scikit-learn
from sklearn.preprocessing import StandardScaler

#Separate the features and the class
X = iris.drop('class', axis=1)
y = iris['class']

# Scale the features of X
X = pd.DataFrame(StandardScaler().fit_transform(X),
                 columns = ['sepal_length','sepal_width','petal_length','petal_width'])

X.head()
```

Out[22]:

	sepal_length	sepal_width	petal_length	petal_width
0	-0.900681	1.032057	-1.341272	-1.312977
1	-1.143017	-0.124958	-1.341272	-1.312977
2	-1.385353	0.337848	-1.398138	-1.312977
3	-1.506521	0.106445	-1.284407	-1.312977
4	-1.021849	1.263460	-1.341272	-1.312977

In [23]:
```
#Import PCA
from sklearn.decomposition import PCA

#Intialize a PCA object to transform into the 2D Space.
pca = PCA(n_components=2)

#Apply PCA
pca_iris = pca.fit_transform(X)
pca_iris = pd.DataFrame(data = pca_iris, columns = ['PC1', 'PC2'])

pca_iris.head()
```

Out[23]:

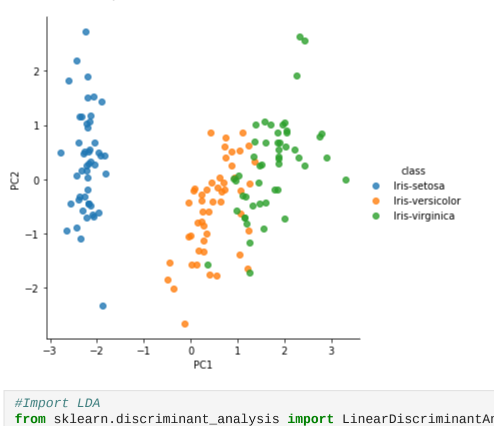
	PC1	PC2
0	-2.264542	0.505704
1	-2.086426	-0.655405
2	-2.367950	-0.318477
3	-2.304197	-0.575368
4	-2.388777	0.674767

In [24]:
```
pca.explained_variance_ratio_
```

Out[24]:
```
array([0.72770452, 0.23030523])
```

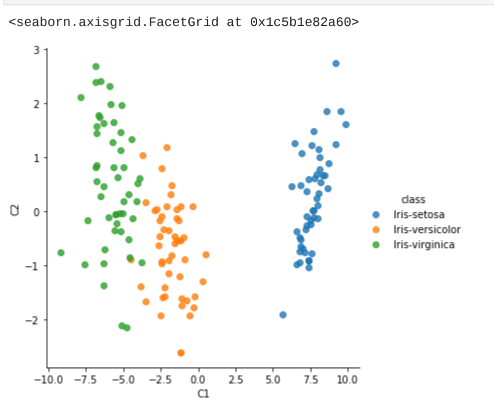
In [25]:
```
#Concatenate the class variable
pca_iris = pd.concat([pca_iris, y], axis = 1)

#Display the scatterplot
sns.lmplot(x='PC1', y='PC2', data=pca_iris, hue='class', fit_reg=False)
```

Out[25]:
```
<seaborn.axisgrid.FacetGrid at 0x1c5ab3d5130>
```



In [26]:
```
#Import LDA
from sklearn.discriminant_analysis import LinearDiscriminantAnalysis

#Define the LDA Object to have two components
lda = LinearDiscriminantAnalysis(n_components = 2)

#Apply LDA
lda_iris = lda.fit_transform(X, y)
lda_iris = pd.DataFrame(data = lda_iris, columns = ['C1', 'C2'])

#Concatenate the class variable
lda_iris = pd.concat([lda_iris, y], axis = 1)

#Display the scatterplot
sns.lmplot(x='C1', y='C2', data=lda_iris, hue='class', fit_reg=False)
```

Out[26]:
```
<seaborn.axisgrid.FacetGrid at 0x1c5b1e82a60>
```



Supervised Learning

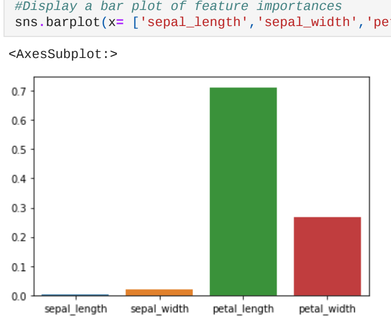
Gradient Boosting

In [28]:
```
#Divide the dataset into the feature dataframe and the target class series.
X, y = iris.drop('class', axis=1), iris['class']

#Split the data into training and test datasets.
#We will train on 75% of the data and assess our performance on 25% of the data

#Import the splitting funnction
from sklearn.model_selection import train_test_split

#Split the data into training and test sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.25, random_state=0)

#Import the Gradient Boosting Classifier
from sklearn.ensemble import GradientBoostingClassifier

#Apply Gradient Boosting to the training data
gbc = GradientBoostingClassifier()
gbc.fit(X_train, y_train)

#Compute the accuracy on the test set
gbc.score(X_test, y_test)
```

Out[28]:
```
0.9736842105263158
```

In [29]:
```
#Display a bar plot of feature importances
sns.barplot(x= ['sepal_length','sepal_width','petal_length','petal_width'], y=gbc.feature_importances_)
```

Out[29]:
```
<AxesSubplot:>
```



In [ ]: