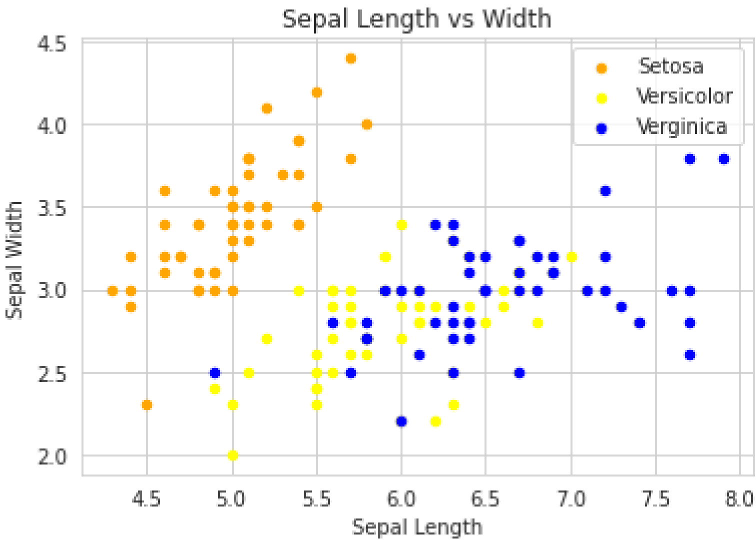
```
import sklearn
import matplotlib.pyplot as plt
import numpy as np
import pandas as pd
import seaborn as sns


from sklearn.datasets import load_iris
iris = load_iris()
y1=iris.target
x1= iris.data


df = pd.DataFrame(x1,
                  columns = iris.feature_names)


df['species']=y1
df
```

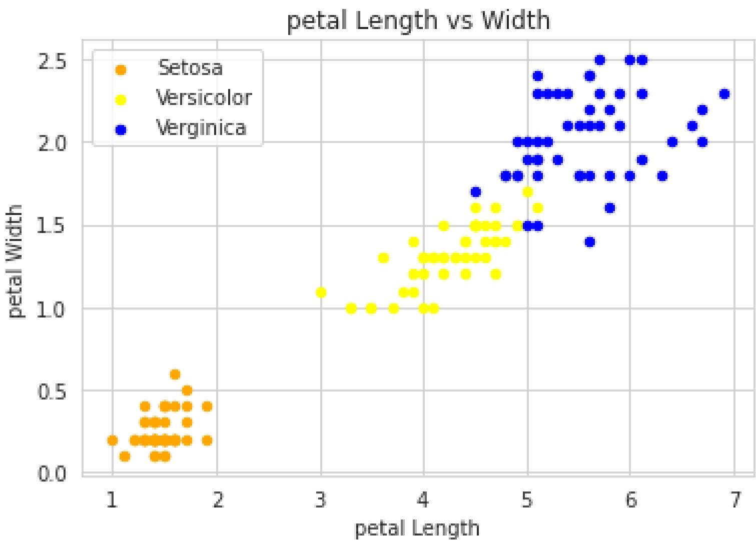
	sepal length (cm)	sepal width (cm)	petal length (cm)	petal width (cm)	specie
0	5.1	3.5	1.4	0.2	
1	4.9	3.0	1.4	0.2	
2	4.7	3.2	1.3	0.2	
3	4.6	3.1	1.5	0.2	
4	5.0	3.6	1.4	0.2	
...	...	...	...	...	
145	6.7	3.0	5.2	2.3	
146	6.3	2.5	5.0	1.9	
147	6.5	3.0	5.2	2.0	
148	6.2	3.4	5.4	2.3	
149	5.9	3.0	5.1	1.8	

150 rows × 5 columns

```
fig = df[df['species'] == 0].plot(kind='scatter', x='sepal length (cm)', y='sepal width (c
df[df['species'] == 1].plot(kind='scatter', x='sepal length (cm)', y='sepal width (cm)', c
df[df['species'] == 2].plot(kind='scatter', x='sepal length (cm)', y='sepal width (cm)', c
fig.set_ylabel('Sepal Width')
fig.set_xlabel('Sepal Length')
fig.set_title('Sepal Length vs Width')

fig = plt.gcf()
plt.show()
```

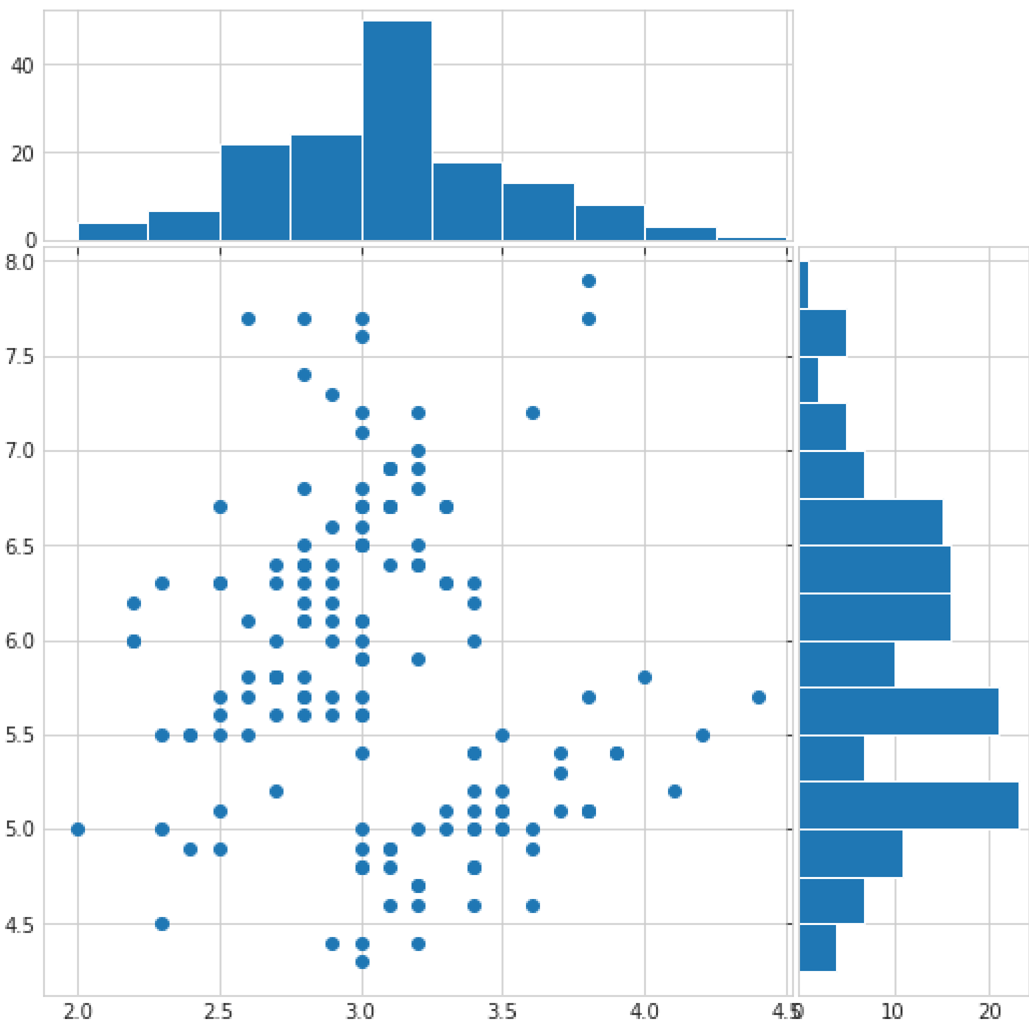



```
fig = df[df['species'] == 0].plot(kind='scatter', x='petal length (cm)', y='petal width (c
df[df['species'] == 1].plot(kind='scatter', x='petal length (cm)', y='petal width (cm)', c
df[df['species'] == 2].plot(kind='scatter', x='petal length (cm)', y='petal width (cm)', c
fig.set_ylabel('petal Width')
fig.set_xlabel('petal Length')
fig.set_title('petal Length vs Width')

fig = plt.gcf()
plt.show()
```



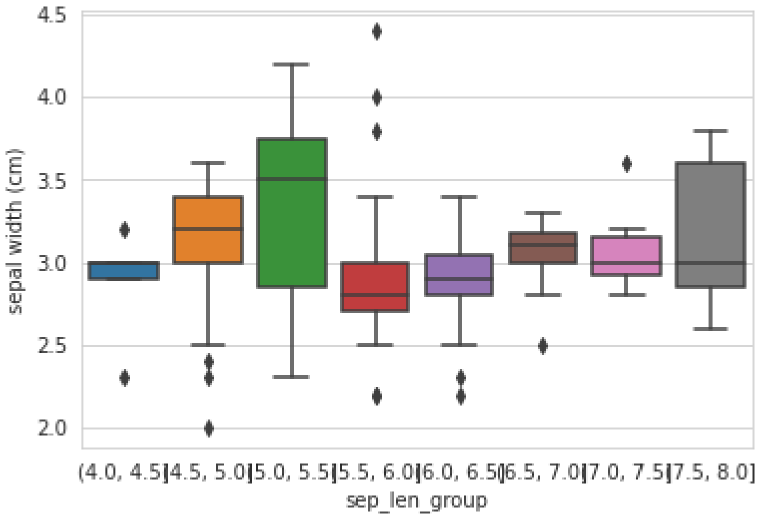

```
x = df['sepal width (cm)']
y = df['sepal length (cm)']
left, width = 0.1, 0.65
bottom, height = 0.1, 0.65
spacing = 0.005
rect_scatter = [left, bottom, width, height]
rect_histx = [left, bottom + height + spacing, width, 0.2]
rect_histy = [left + width + spacing, bottom, 0.2, height]

#rectangular Figure
plt.figure(figsize=(8, 8))
```

```
ax_scatter = plt.axes(rect_scatter)
ax_scatter.tick_params(direction='in', top=True, right=True)
ax_histx = plt.axes(rect_histx)
ax_histx.tick_params(direction='in', labelbottom=False)
ax_histy = plt.axes(rect_histy)
ax_histy.tick_params(direction='in', labelleft=False)

# the scatter plot:
ax_scatter.scatter(x,y,)
binwidth = 0.25
lim = np.ceil(np.abs([x, y]).max() / binwidth) * binwidth
bins = np.arange(-lim, lim + binwidth, binwidth)
ax_histx.hist(x, bins=bins)
ax_histy.hist(y, bins=bins, orientation='horizontal')

ax_histx.set_xlim(ax_scatter.get_xlim())
ax_histy.set_ylim(ax_scatter.get_ylim())

plt.show()
#reference taken from sikit learn to plot this graph
```



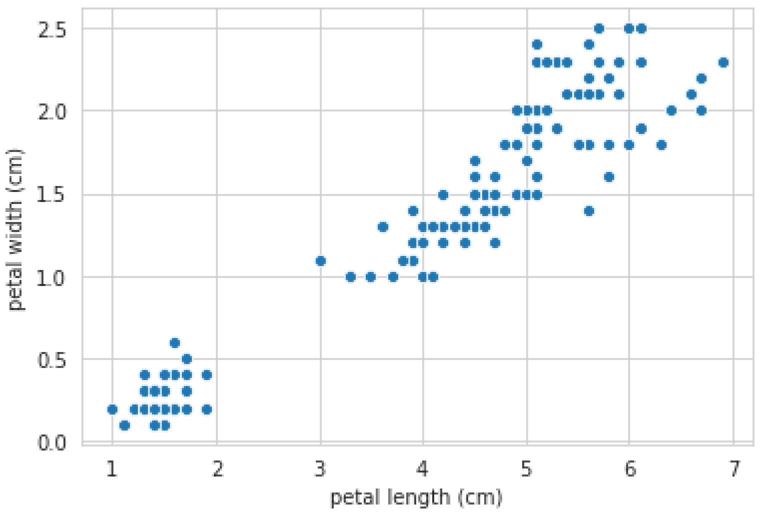

```
#visualizing sepal width by grouping sepal lengths into 5 bins
import seaborn as sns
sbin=pd.DataFrame(df['sepal width (cm)'])
sbin['sepal length (cm)']= df['sepal length (cm)']
sbin.sort_values(inplace=True,by='sepal length (cm)')
```

```
sbin['sep_len_group'] = pd.cut(sbin['sepal length (cm)'], bins=[4,4.5,5,5.5,6,6.5,7,7.5,8]
ax = sns.boxplot(x="sep_len_group", y="sepal width (cm)", data=sbin)
```



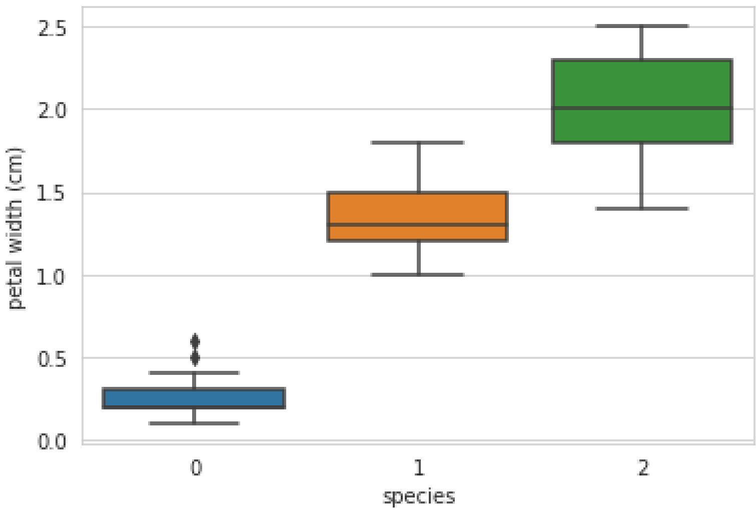

```
#scatter plot petal length vs width
sns.scatterplot(data=df,x='petal length (cm)',y='petal width (cm)')
```

<matplotlib.axes._subplots.AxesSubplot at 0x7fbf391dc9e8>

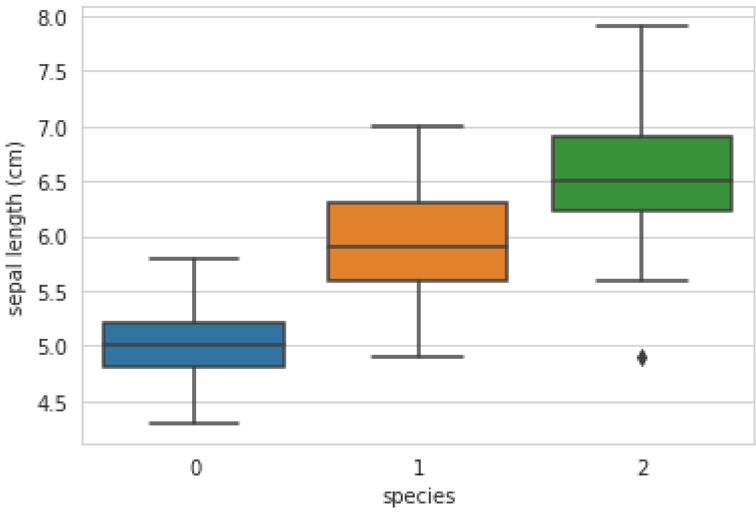



```
sns.boxplot(x="species",y="petal length (cm)",data=df)
plt.show()
```


```
sns.boxplot(x="species",y="petal width (cm)",data=df)
plt.show()
```

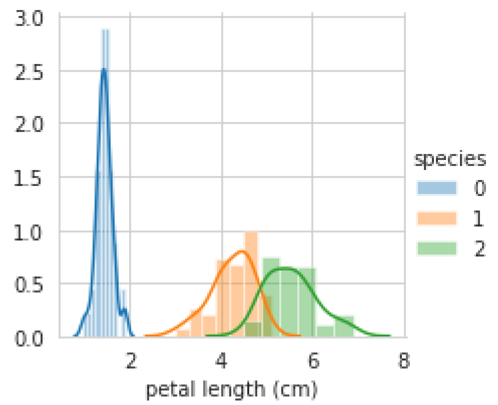


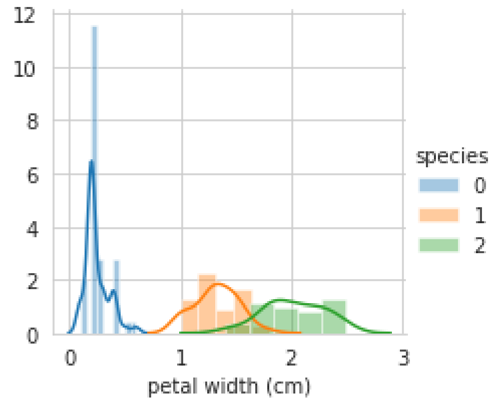

```
sns.boxplot(x="species",y="sepal length (cm)",data=df)
plt.show()
```

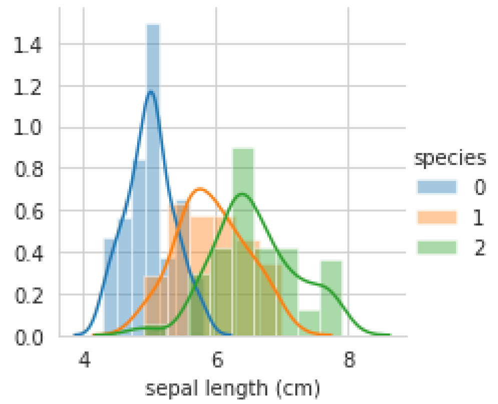


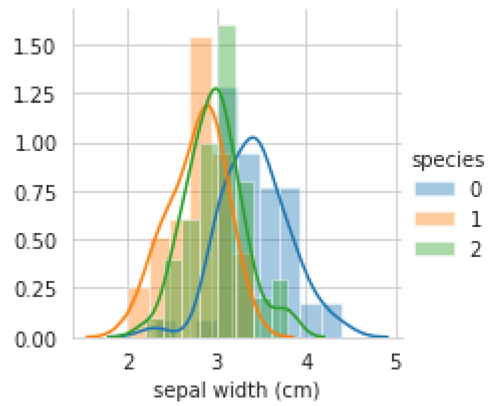

```
sns.boxplot(x="species",y="sepal width (cm)",data=df)
plt.show()
```

```
sns.FacetGrid(df,hue="species",height=3).map(sns.distplot,"petal length (cm)").add_legend(
sns.FacetGrid(df,hue="species",height=3).map(sns.distplot,"petal width (cm)").add_legend()
sns.FacetGrid(df,hue="species",height=3).map(sns.distplot,"sepal length (cm)").add_legend(
sns.FacetGrid(df,hue="species",height=3).map(sns.distplot,"sepal width (cm)").add_legend()
plt.show()
```










```
sns.set_style("whitegrid")
sns.pairplot(df,hue="species",height=3);
```

```
plt.show()
```


sepal length (cm)
sepal width (cm)
petal length (cm)
petal width (cm)
sepal length (cm)
sepal width (cm)
petal length (cm)

```
#standardize x1 reduced accuracy but if still needed uncomment
#from sklearn.preprocessing import StandardScaler
#sc_x = StandardScaler()
#x1 = sc_x.fit_transform(x1)
```

```
import sklearn.model_selection
X_train, X_test, Y_train, Y_test = sklearn.model_selection.train_test_split(x1, y1, test_s
#print(X_train.shape)
#print(X_test.shape)
#print(Y_train.shape)
#print(Y_test.shape)
```

```
from sklearn.linear_model import LogisticRegression
```

```
clf=LogisticRegression(multi_class='ovr',solver='lbfgs',C=10.0,)
```

```
#cross val predict makes iterations with different test and train sets each time and in th
#was considered as a test point at some stage
from sklearn.model_selection import cross_val_predict
predicts=cross_val_predict(clf, x1, y1, cv=5)
predicts.size
```

```
150
```

```
#clf.fit(X_train,Y_train)
#Y_predict=clf.predict(X_test)
from sklearn.metrics import confusion_matrix
print (confusion_matrix(y1,predicts))
print (sklearn.metrics.classification_report(y1,predicts))
```

```
[[50  0  0]
 [ 0 47  3]
 [ 0  3 47]]
              precision    recall  f1-score   support

           0       1.00      1.00      1.00        50
           1       0.94      0.94      0.94        50
           2       0.94      0.94      0.94        50

    accuracy                           0.96       150
   macro avg       0.96      0.96      0.96       150
weighted avg       0.96      0.96      0.96       150
```

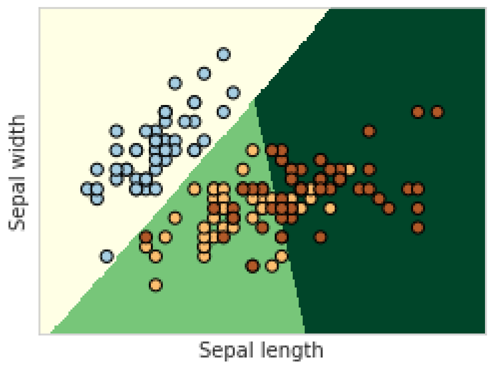
```
#here I am printing accuracy scores for each iteratin of the k fold split. We can also tak
# the same as accuracy obtained above
scores = sklearn.model_selection.cross_val_score(clf, x1, y1, cv=5)
print(scores)
```

```
print(scores)
print(scores.mean())
```

```
[0.96666667 0.96666667 0.93333333 0.93333333 1.         ]
0.96
```

```
X = iris.data[:, :2]
Y = iris.target
#reference taken from sikit learn to plot this graph
# Plot the decision boundary. For that, we will assign a color to each
# point in the mesh [x_min, x_max]x[y_min, y_max].
x_min, x_max = X[:, 0].min() - .5, X[:, 0].max() + .5
y_min, y_max = X[:, 1].min() - .5, X[:, 1].max() + .5
h = .02  # step size in the mesh
xx, yy = np.meshgrid(np.arange(x_min, x_max, h), np.arange(y_min, y_max, h))
Z = logreg.predict(np.c_[xx.ravel(), yy.ravel()])
print(Z.shape)
# Put the result into a color plot
Z = Z.reshape(xx.shape)
plt.figure(1, figsize=(4, 3))
plt.pcolormesh(xx, yy, Z, cmap='YlGn')

# Plot also the training points
plt.scatter(X[:, 0], X[:, 1], c=Y, edgecolors='k', cmap=plt.cm.Paired)
plt.xlabel('Sepal length')
plt.ylabel('Sepal width')

plt.xlim(xx.min(), xx.max())
plt.ylim(yy.min(), yy.max())
plt.xticks(())
plt.yticks(())

plt.show()
```

```
(39501,)
```




```
#logistic complete
#naive bayes
from sklearn.naive_bayes import GaussianNB
```

```
gnb =GaussianNB()

#cross val predict makes iterations with different test and train sets each time and in th
#was considered as a test point at some stage
from sklearn.model_selection import cross_val_predict
predicts=cross_val_predict(gnb, x1, y1, cv=5)
predicts.size
```

```
150
```

```
#clf.fit(X_train,Y_train)
#Y_predict=clf.predict(X_test)
from sklearn.metrics import confusion_matrix
print (confusion_matrix(y1,predicts))
print (sklearn.metrics.classification_report(y1,predicts))
```

```
[[50  0  0]
 [ 0 47  3]
 [ 0  4 46]]
              precision    recall  f1-score   support

           0       1.00      1.00      1.00        50
           1       0.92      0.94      0.93        50
           2       0.94      0.92      0.93        50

    accuracy                           0.95       150
   macro avg       0.95      0.95      0.95       150
weighted avg       0.95      0.95      0.95       150
```

```
#here I am printing accuracy scores for each iteratin of the k fold split. We can also tak
# the same as accuracy obtained above
scores = sklearn.model_selection.cross_val_score(gnb, x1, y1, cv=5)
print(scores)
print(scores.mean())
```

```
[0.93333333 0.96666667 0.93333333 0.93333333 1.        ]
0.9533333333333334
```

```
#gnb finshed
#k means clustering
from sklearn.cluster import KMeans
```

```
KMclf = KMeans(n_clusters=3,)
KMclf.fit(X_train)
```

```
KMeans(algorithm='auto', copy_x=True, init='k-means++', max_iter=300,
       n_clusters=3, n_init=10, n_jobs=None, precompute_distances='auto',
       random_state=None, tol=0.0001, verbose=0)
```

```
KMclf.labels_# not that these labels are cluster numbers and not actual labels
```

```
array([1, 2, 0, 2, 1, 2, 0, 2, 2, 2, 1, 0, 1, 0, 0, 2, 1, 1, 2, 1, 2, 1,
       2, 2, 2, 2, 2, 2, 1, 1, 2, 0, 2, 2, 2, 2, 2, 1, 0, 0, 1, 2, 0, 0,
       1, 0, 2, 2, 0, 2, 1, 2, 0, 1, 1, 1, 1, 0, 0, 1, 1, 0, 1, 0, 2, 1,
       0, 0, 1, 0, 0, 0, 2, 1, 1, 0, 0, 0, 2, 2, 0, 0, 2, 0, 1, 2, 1, 2,
       0, 2, 0, 1, 0, 0, 1, 0, 1, 2, 2, 2, 1, 1, 2, 1, 0, 2, 1, 2, 0, 2,
       2, 2, 2, 0, 0, 0, 1, 2, 1, 0], dtype=int32)
```

```
#now we figure out the actual cluster labels
def GetActualLabels(cluster_labels,Y_train):
 # Initializing
 reference_labels = {}
 # For loop to run through each label of cluster label
 for i in range(len(np.unique(KMclf.labels_))):
  index = np.where(cluster_labels == i,1,0)
  num = np.bincount(Y_train[index==1]).argmax()
  reference_labels[i] = num
 return reference_labels
```

```
reference_labels = GetActualLabels(KMclf.labels_,Y_train)
reference_labels
```

```
{0: 0, 1: 2, 2: 1}
```

```
number_labels = np.random.rand(len(KMclf.labels_))
for i in range(len(KMclf.labels_)):
  number_labels[i] = reference_labels[KMclf.labels_[i]]
```

```
print(number_labels[:20].astype('int'))
print(Y_train[:20])
```

```
[2 1 0 1 2 1 0 1 1 1 2 0 2 0 0 1 2 2 1 2]
[2 1 0 2 2 1 0 1 1 1 2 0 2 0 0 1 2 2 2 2]
```

```
from sklearn.metrics import accuracy_score
print(accuracy_score(number_labels,Y_train))
```

```
0.8833333333333333
```

```
#now we see if no of clusters affect accuracy
#below is a funct to print metrics for the model
def calculate_metrics(model,output):
 print('Number of clusters is {}'.format(model.n_clusters))
 print('Inertia : {}'.format(model.inertia_))
 print('Homogeneity :       {}'.format(metrics.homogeneity_score(output,model.labels_)))
```

```
from sklearn import metrics
cluster_number = [3,16,32,64,77]#no of clusters<=no of samples
for i in cluster_number:
 total_clusters = 3
 # Initialize the K-Means model
 KMclf = KMeans(n_clusters = i)
 # Fitting the model to training set
```

```
KMclf.fit(X_train)
# Calculating the metrics

calculate_metrics(KMclf,Y_train)
# Calculating reference_labels
reference_labels = GetActualLabels(KMclf.labels_,Y_train)
# ‘number_labels’ is a list which denotes the number displayed in image
number_labels = np.random.rand(len(KMclf.labels_))
for i in range(len(KMclf.labels_)):

 number_labels[i] = reference_labels[KMclf.labels_[i]]

print('Accuracy score : {}'.format(accuracy_score(number_labels,Y_train)))
print('\n')
```

```
Number of clusters is 3
Inertia : 63.196666666666665
Homogeneity :       0.7311815209297751
Accuracy score : 0.8833333333333333


Number of clusters is 16
Inertia : 13.505057081807081
Homogeneity :       0.8980093601978169
Accuracy score : 0.95


Number of clusters is 32
Inertia : 6.153595238095238
Homogeneity :       0.9538564169309326
Accuracy score : 0.975


Number of clusters is 64
Inertia : 1.6358333333333337
Homogeneity :       0.9723550663340088
Accuracy score : 0.9833333333333333


Number of clusters is 77
Inertia : 0.9078333333333337
Homogeneity :       0.9999999999999998
Accuracy score : 1.0
```

```
#we found highest accuracy for 77 clusters but our no of test samples is only 30 so we can
# Testing model on Testing set of size 30
KMclf = KMeans(n_clusters =27)

KMclf.fit(X_test)
calculate_metrics(KMclf,Y_test)
reference_labels = GetActualLabels(KMclf.labels_,Y_test)
number_labels = np.random.rand(len(KMclf.labels_))
for i in range(len(KMclf.labels_)):

 number_labels[i] = reference_labels[KMclf.labels_[i]]
```

```
print('Accuracy score : {}'.format(accuracy_score(number_labels,Y_test)))
print('\n')
```

```
Number of clusters is 27
Inertia : 0.09833333333333329
Homogeneity :       0.9999999999999998
Accuracy score : 1.0
```

```
#running on test set with cluster size 3
KMclf = KMeans(n_clusters =3)

KMclf.fit(X_test)
calculate_metrics(KMclf,Y_test)
reference_labels = GetActualLabels(KMclf.labels_,Y_test)
number_labels = np.random.rand(len(KMclf.labels_))
for i in range(len(KMclf.labels_)):

 number_labels[i] = reference_labels[KMclf.labels_[i]]

print('Accuracy score : {}'.format(accuracy_score(number_labels,Y_test)))
print('\n')
```

```
Number of clusters is 3
Inertia : 13.892878787878793
Homogeneity :       0.8133923344775366
Accuracy score : 0.9333333333333333
```

```
# Testing model on Testing set of size 30 with k fold cross validation
KMclf = KMeans(n_clusters =30)
from sklearn.model_selection import KFold # import KFold
kf = KFold(n_splits=5) # Define the split - into 2 folds
kf.get_n_splits(x1) # returns the number of splitting iterations in the cross-validator
print(kf)
KFold(n_splits=2, random_state=None, shuffle=False)
for train_index, test_index in kf.split(x1):
  X_train, X_test = x1[train_index], x1[test_index]
  Y_train, Y_test = y1[train_index], y1[test_index]
  KMclf.fit(X_test)
  calculate_metrics(KMclf,Y_test)
  reference_labels = GetActualLabels(KMclf.labels_,Y_test)
  number_labels = np.random.rand(len(KMclf.labels_))
  for i in range(len(KMclf.labels_)):
    number_labels[i] = reference_labels[KMclf.labels_[i]]

  print (confusion_matrix(Y_test,number_labels))
  print (sklearn.metrics.classification_report(Y_test,number_labels))
```

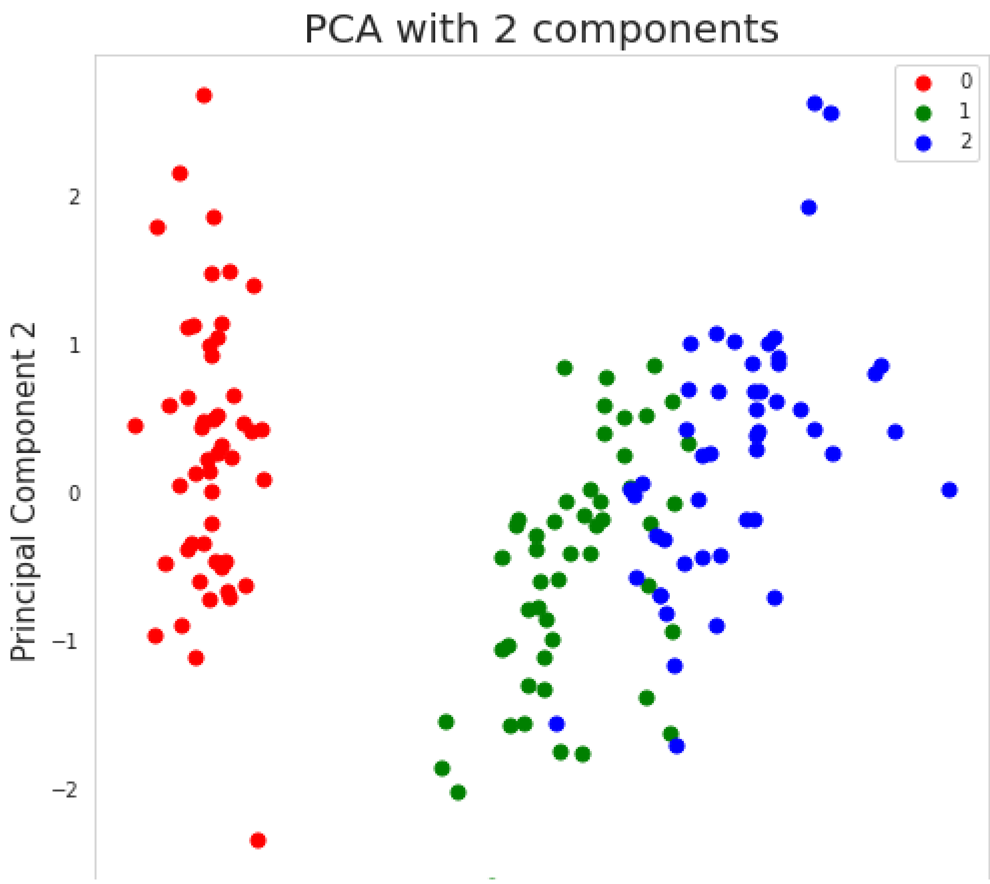
```
           0       1.00      1.00      1.00        30

    accuracy                           1.00        30
   macro avg       1.00      1.00      1.00        30
weighted avg       1.00      1.00      1.00        30

Number of clusters is 30
Inertia : 0.0
Homogeneity :       1.0000000000000007
[[20  0]
 [ 0 10]]
              precision    recall  f1-score   support

           0       1.00      1.00      1.00        20
           1       1.00      1.00      1.00        10

    accuracy                           1.00        30
   macro avg       1.00      1.00      1.00        30
weighted avg       1.00      1.00      1.00        30

Number of clusters is 30
Inertia : 0.0
Homogeneity :       1.0
[[30]]
              precision    recall  f1-score   support

           1       1.00      1.00      1.00        30

    accuracy                           1.00        30
   macro avg       1.00      1.00      1.00        30
weighted avg       1.00      1.00      1.00        30

Number of clusters is 30
Inertia : 0.0
Homogeneity :       1.0000000000000004
[[10  0]
 [ 0 20]]
              precision    recall  f1-score   support

           1       1.00      1.00      1.00        10
           2       1.00      1.00      1.00        20

    accuracy                           1.00        30
   macro avg       1.00      1.00      1.00        30
weighted avg       1.00      1.00      1.00        30

Number of clusters is 30
Inertia : 0.0
Homogeneity :       1.0
[[30]]
              precision    recall  f1-score   support

           2       1.00      1.00      1.00        30

    accuracy                           1.00        30
   macro avg       1.00      1.00      1.00        30
weighted avg       1.00      1.00      1.00        30
```

```
# Testing model on Testing set of size 30 with k fold cross validation
KMclf = KMeans(n_clusters =3)
from sklearn.model_selection import KFold # import KFold
kf = KFold(n_splits=5) # Define the split - into 2 folds
kf.get_n_splits(x1) # returns the number of splitting iterations in the cross-validator
print(kf)
KFold(n_splits=2, random_state=None, shuffle=False)
for train_index, test_index in kf.split(x1):
  #print("TRAIN:", train_index, "TEST:", test_index)
  X_train, X_test = x1[train_index], x1[test_index]
  Y_train, Y_test = y1[train_index], y1[test_index]
  KMclf.fit(X_test)
  calculate_metrics(KMclf,Y_test)
  reference_labels = GetActualLabels(KMclf.labels_,Y_test)
  number_labels = np.random.rand(len(KMclf.labels_))
  for i in range(len(KMclf.labels_)):
    number_labels[i] = reference_labels[KMclf.labels_[i]]

  print (confusion_matrix(Y_test,number_labels))
  print (sklearn.metrics.classification_report(Y_test,number_labels))
```

```
KFold(n_splits=5, random_state=None, shuffle=False)
Number of clusters is 3
Inertia : 2.9441608391608396
Homogeneity :       1.0
[[30]]
              precision    recall  f1-score   support

           0       1.00      1.00      1.00        30

    accuracy                           1.00        30
   macro avg       1.00      1.00      1.00        30
weighted avg       1.00      1.00      1.00        30

Number of clusters is 3
Inertia : 8.284333333333333
Homogeneity :       1.0000000000000002
[[20  0]
 [ 0 10]]
              precision    recall  f1-score   support

           0       1.00      1.00      1.00        20
           1       1.00      1.00      1.00        10

    accuracy                           1.00        30
   macro avg       1.00      1.00      1.00        30
weighted avg       1.00      1.00      1.00        30

Number of clusters is 3
Inertia : 5.95275
Homogeneity :       1.0
[[30]]
              precision    recall  f1-score   support

           1       1.00      1.00      1.00        30

    accuracy                           1.00        30
   macro avg       1.00      1.00      1.00        30
weighted avg       1.00      1.00      1.00        30

Number of clusters is 3
Inertia : 12.45993006993007
Homogeneity :       0.8245130934624357
[[10  0]
 [ 1 19]]
              precision    recall  f1-score   support

           1       0.91      1.00      0.95        10
           2       1.00      0.95      0.97        20

    accuracy                           0.97        30
   macro avg       0.95      0.97      0.96        30
weighted avg       0.97      0.97      0.97        30

Number of clusters is 3
Inertia : 5.798571428571428
Homogeneity :       1.0
[[30]]
              precision    recall  f1-score   support

           2       1.00      1.00      1.00        30
```

```
    accuracy                           1.00        30
   macro avg       1.00      1.00      1.00        30
weighted avg       1.00      1.00      1.00        30
```

```
from sklearn.preprocessing import StandardScaler
# Standardizing the features
x = StandardScaler().fit_transform(x1)
#principal component analysis
from sklearn.decomposition import PCA
pca = PCA(n_components=2)
principalComponents = pca.fit_transform(x)
principalDf = pd.DataFrame(data = principalComponents
             , columns = ['principal component 1', 'principal component 2'])
finalDf = pd.concat([principalDf, df[['species']]], axis = 1)
fig = plt.figure(figsize = (8,8))
ax = fig.add_subplot(1,1,1)
ax.set_xlabel('Principal Component 1', fontsize = 15)
ax.set_ylabel('Principal Component 2', fontsize = 15)
ax.set_title('PCA with 2 components', fontsize = 20)
targets = [0, 1, 2]
colors = ['r', 'g', 'b']
for target, color in zip(targets,colors):
    indicesToKeep = finalDf['species'] == target
    ax.scatter(finalDf.loc[indicesToKeep, 'principal component 1']
               , finalDf.loc[indicesToKeep, 'principal component 2']
               , c = color
               , s = 50)
ax.legend(targets)
ax.grid()
```


PCA with 2 components
Principal Component 2
2
1
0
−1
−2
0
1
2