```
In [3]:
          import numpy as np # linear algebra
          import pandas as pd # data processing, CSV file I/O (e.g. pd.read csv)
          import matplotlib.pyplot as plt
          import seaborn as sns
          import warnings
          warnings.filterwarnings("ignore")
          import os
          print(os.listdir("C:\\Users\\Admin\\Downloads\\Assignment 5"))
          %matplotlib inline
          ['glass.csv', 'problem_statement(Glass).txt', 'Problem_statement(salary_data).txt', 'Pro
         blem_Statement(Zoo).txt', 'SalaryData_Test.csv', 'SalaryData_Train.csv', 'Zoo.csv']
In [2]:
          zoo=pd.read csv("C:\\Users\\Admin\\Downloads\\Assignment 5\\Zoo.csv")
          zoo.head(10)
                                        eggs milk airborne aquatic predator toothed backbone breathes
Out[2]:
             animalname hair
                               feathers
         0
                aardvark
                            1
                                     0
                                           0
                                                           0
                                                                   0
                                                                             1
                                                                                      1
                                                                                                 1
                                                                                                          1
         1
                antelope
                                     0
                                           0
                                                           0
                                                                   0
                                                                             0
                                                                                                 1
                                                                                                           1
         2
                    bass
                            0
                                     0
                                           1
                                                 0
                                                           0
                                                                   1
                                                                             1
                                                                                                 1
                                                                                                          0
                                                           0
         3
                    bear
                                     0
                                           0
                                                                   0
                                                                             1
                                                                                      1
                                                                                                 1
                                                                                                           1
                                     0
                                           0
                                                           0
                                                                   0
                    boar
                                                 1
                                                                                      1
                                                                                                 1
                                                                                                           1
                  buffalo
                                     0
                                           0
                                                           0
                                                                   0
                                                                             0
         5
                                                 1
                                                                                      1
                                                                                                 1
                                                                                                           1
         6
                     calf
                            1
                                     0
                                           0
                                                 1
                                                           0
                                                                   0
                                                                             0
                                                                                      1
                                                                                                 1
                                                                                                           1
         7
                                                           0
                            0
                                     0
                                           1
                                                 0
                                                                   1
                                                                             0
                                                                                                 1
                                                                                                          0
                    carp
                  catfish
                                     0
                                                           0
                                                                                                          0
         8
                            0
                                           1
                                                 0
                                                                   1
                                                                             1
                                                                                      1
                                                                                                 1
         9
                                     0
                                           0
                                                           0
                                                                   0
                                                                             0
                                                                                      1
                                                                                                 1
                                                                                                           1
                    cavy
                            1
                                                 1
In [4]:
          zoo.head()
Out[4]:
             animalname
                         hair
                               feathers
                                        eggs
                                              milk airborne aquatic predator toothed backbone breathes
         0
                            1
                                     0
                                           0
                                                 1
                                                           0
                                                                   0
                                                                             1
                                                                                      1
                                                                                                 1
                                                                                                          1
                aardvark
         1
                antelope
                            1
                                     0
                                           0
                                                 1
                                                           0
                                                                   0
                                                                             0
                                                                                      1
                                                                                                 1
                                                                                                          1
         2
                            0
                                     0
                                                 0
                                                           0
                                                                                      1
                                                                                                 1
                                                                                                          0
                    bass
                                           1
                                                                   1
                                                                             1
         3
                                     0
                                                           0
                            1
                                           0
                                                 1
                                                                   0
                                                                             1
                                                                                      1
                                                                                                 1
                                                                                                           1
                    bear
                                     0
                                           0
                                                           0
                                                                   0
                                                                                      1
                                                                                                 1
                                                                                                           1
                    boar
                            1
                                                 1
                                                                             1
In [5]:
          zoo.info()
```

```
<class 'pandas.core.frame.DataFrame'>
          RangeIndex: 101 entries, 0 to 100
          Data columns (total 18 columns):
           #
                Column
                             Non-Null Count
                                               Dtype
                             _____
           0
                animalname
                             101 non-null
                                               object
           1
                hair
                             101 non-null
                                               int64
           2
                             101 non-null
                feathers
                                               int64
           3
                             101 non-null
                eggs
                                               int64
           4
                milk
                             101 non-null
                                               int64
           5
                airborne
                             101 non-null
                                               int64
           6
                aquatic
                             101 non-null
                                               int64
           7
                             101 non-null
                predator
                                               int64
           8
                toothed
                             101 non-null
                                               int64
           9
                backbone
                             101 non-null
                                               int64
           10
                breathes
                             101 non-null
                                               int64
           11
                venomous
                             101 non-null
                                               int64
           12
               fins
                             101 non-null
                                               int64
           13
               legs
                             101 non-null
                                               int64
           14
                tail
                             101 non-null
                                               int64
           15
                domestic
                             101 non-null
                                               int64
           16
                catsize
                             101 non-null
                                               int64
           17
                type
                             101 non-null
                                               int64
          dtypes: int64(17), object(1)
          memory usage: 14.3+ KB
 In [6]:
           zoo.describe()
                                                         milk
 Out[6]:
                       hair
                               feathers
                                                                 airborne
                                                                             aquatic
                                                                                        predator
                                                                                                    toothed
                                              eggs
           count 101.000000
                             101.000000
                                        101.000000
                                                    101.000000 101.000000
                                                                          101.000000
                                                                                      101.000000
                                                                                                 101.000000
                               0.198020
                                          0.584158
           mean
                   0.425743
                                                      0.405941
                                                                 0.237624
                                                                            0.356436
                                                                                        0.554455
                                                                                                   0.603960
                   0.496921
                               0.400495
                                          0.495325
                                                      0.493522
             std
                                                                 0.427750
                                                                            0.481335
                                                                                        0.499505
                                                                                                   0.491512
            min
                   0.000000
                               0.000000
                                          0.000000
                                                      0.000000
                                                                 0.000000
                                                                            0.000000
                                                                                        0.000000
                                                                                                   0.000000
            25%
                   0.000000
                               0.000000
                                          0.000000
                                                      0.000000
                                                                 0.000000
                                                                            0.000000
                                                                                        0.000000
                                                                                                   0.000000
            50%
                   0.000000
                               0.000000
                                          1.000000
                                                      0.000000
                                                                 0.000000
                                                                            0.000000
                                                                                        1.000000
                                                                                                   1.000000
                   1.000000
                                                                                        1.000000
            75%
                               0.000000
                                          1.000000
                                                      1.000000
                                                                 0.000000
                                                                            1.000000
                                                                                                   1.000000
                   1.000000
                               1.000000
                                          1.000000
                                                                 1.000000
                                                                            1.000000
                                                                                        1.000000
                                                                                                   1.000000
            max
                                                      1.000000
 In [8]:
           zoo.drop("animalname",axis=1,inplace=True)
 In [9]:
           color list = [("red" if i ==1 else "blue" if i ==0 else "yellow" ) for i in zoo.hair]
In [10]:
           unique list = list(set(color list))
           unique list
          ['blue', 'red']
Out[10]:
```

```
4/22/22, 10:54 AM
                                                                        knn.zoo
                  pd.plotting.scatter_matrix(zoo.iloc[:,:7],
     In [11]:
                                                                  c=color_list,
                                                                  figsize= [20,20],
                                                                  diagonal='hist',
                                                                  alpha=1,
                                                                  s = 300,
                                                                  marker = '*',
                                                                  edgecolor= "black")
                  plt.show()
                         0.0
1.0
                         0.8
                         2.8
                         9.8
                       ≝
0.4
                         0.2
                         0.0
1.0
                         9.8
                         0.8
                         9.8
```

```
In [12]:
          sns.countplot(x="hair", data=zoo)
          plt.xlabel("Hair")
          plt.ylabel("Count")
          plt.show()
          zoo.loc[:,'hair'].value_counts()
```

```
Out[12]: 0 58
1 43
Name: hair, dtype: int64

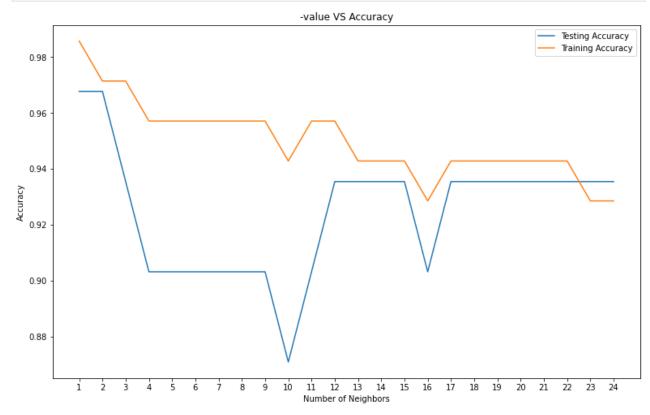
In [13]: from sklearn.neighbors import KNeighborsClassifier
knn = KNeighborsClassifier(n_neighbors = 1)
x,y = zoo.loc[:,zoo.columns != 'hair'], zoo.loc[:,'hair']
knn.fit(x,y)
prediction = knn.predict(x)
print("Prediction = ",prediction)
```

```
from sklearn.model_selection import train_test_split
    x_train,x_test,y_train,y_test = train_test_split(x,y,test_size = 0.3,random_state = 1)
    knn = KNeighborsClassifier(n_neighbors = 1)
    x,y = zoo.loc[:,zoo.columns != 'hair'], zoo.loc[:,'hair']
    knn.fit(x_train,y_train)
    prediction = knn.predict(x_test)
    print('With KNN (K=1) accuracy is: ',knn.score(x_test,y_test)) # accuracy
```

With KNN (K=1) accuracy is: 0.967741935483871

```
In [15]:
          k_values = np.arange(1,25)
          train_accuracy = []
          test_accuracy = []
          for i, k in enumerate(k_values):
              # k from 1 to 25(exclude)
              knn = KNeighborsClassifier(n_neighbors=k)
              # Fit with knn
              knn.fit(x_train,y_train)
              #train accuracy
              train_accuracy.append(knn.score(x_train, y_train))
              # test accuracy
              test_accuracy.append(knn.score(x_test, y_test))
              # Plot
          plt.figure(figsize=[13,8])
          plt.plot(k_values, test_accuracy, label = 'Testing Accuracy')
```

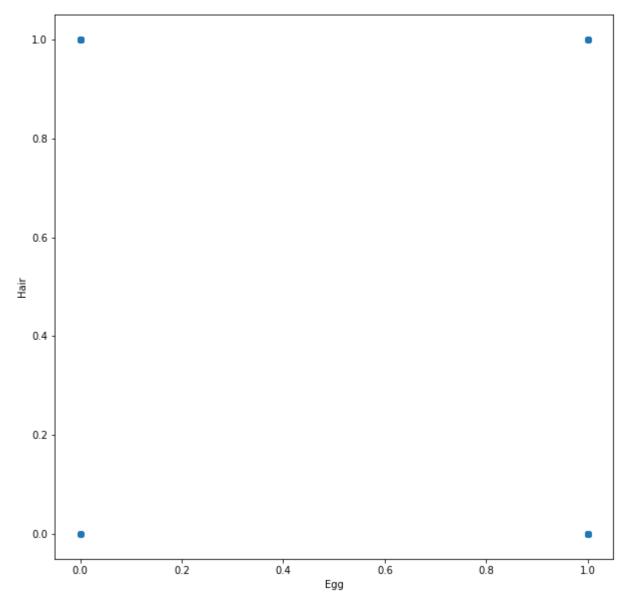
```
plt.plot(k_values, train_accuracy, label = 'Training Accuracy')
plt.legend()
plt.title('-value VS Accuracy')
plt.xlabel('Number of Neighbors')
plt.ylabel('Accuracy')
plt.xticks(k_values)
plt.savefig('graph.png')
plt.show()
print("Best accuracy is {} with K = {}".format(np.max(test_accuracy),1+test_accuracy.in
```



Best accuracy is 0.967741935483871 with K = 1

```
In [16]:
    x = np.array(zoo.loc[:,"eggs"]).reshape(-1,1)
    y = np.array(zoo.loc[:,'hair']).reshape(-1,1)

plt.figure(figsize=[10,10])
    plt.scatter(x=x,y=y)
    plt.xlabel('Egg')
    plt.ylabel('Hair')
    plt.show()
```



```
In [17]:
    from sklearn.linear_model import LinearRegression
    regression = LinearRegression()

    predict_space = np.linspace(min(x),max(x)).reshape(-1,1)
    regression.fit(x,y)
    predicted = regression.predict(predict_space)

    print("R^2 Score: ",regression.score(x,y))

    plt.plot(predict_space, predicted, color='black', linewidth=3)
    plt.scatter(x=x,y=y)
    plt.xlabel('Egg')
    plt.ylabel('Milk')
    plt.show()
```

R^2 Score: 0.6681125904754137

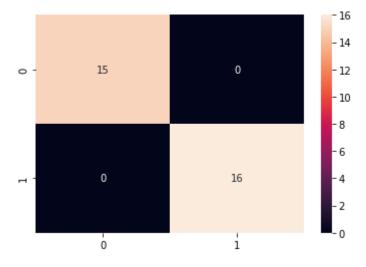
```
1.0 - 0.8 - 0.6 0.8 1.0 Egg
```

```
In [18]:
          from sklearn.model_selection import cross_val_score
          regression = LinearRegression()
          cv_result = cross_val_score(regression,x,y,cv=k)
          print("CV Scores: ",cv_result)
          print("CV Average: ",np.sum(cv_result)/k)
         CV Scores: [0.80171562 0.61914032 0.79243817 0.24939434 0.76176534]
         CV Average: 0.6448907578047475
In [19]:
          from sklearn.linear model import Ridge
          x_train,x_test,y_train,y_test = train_test_split(x,y,random_state = 2, test_size = 0.3)
          ridge = Ridge(alpha= 0.001,normalize = True)
          ridge.fit(x train,y train)
          ridge predict = ridge.predict(x test)
          print("Ridge Score: ",ridge.score(x_test,y_test))
         Ridge Score: 0.930239727992853
In [21]:
          from sklearn.linear_model import Lasso
          x = np.array(zoo.loc[:,['eggs','airborne','fins','legs',"hair","type"]])
          x_train,x_test,y_train,y_test = train_test_split(x,y,random_state = 3, test_size = 0.3)
          lasso = Lasso(alpha = 0.0001, normalize = True)
          lasso.fit(x train,y train)
          ridge_predict = lasso.predict(x_test)
          print('Lasso score: ',lasso.score(x_test,y_test))
          print('Lasso coefficients: ',lasso.coef_)
         Lasso score: 0.9999970989932222
                                                        -0.
                                                                                 0.99830154 -0.
         Lasso coefficients: [-0.
                                            -0.
                                                                     0.
         1
In [22]:
          from sklearn.metrics import classification report,confusion matrix
          from sklearn.ensemble import RandomForestClassifier
          x,y = zoo.loc[:,zoo.columns != "hair"], zoo.loc[:,"hair"]
          x_train,x_test,y_train,y_test = train_test_split(x,y,test_size = 0.3,random_state = 1)
          rf = RandomForestClassifier(random state = 4)
          rf.fit(x train,y train)
          y pred = rf.predict(x test)
          cm = confusion_matrix(y_test,y_pred)
```

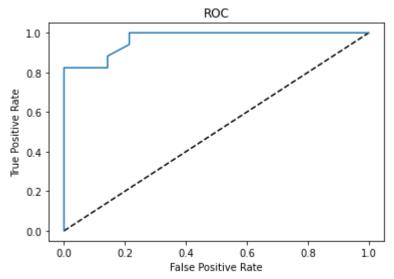
```
print("Confisuon Matrix: \n",cm)
print("Classification Report: \n",classification_report(y_test,y_pred))
```

```
Confisuon Matrix:
 [[15 0]
 [ 0 16]]
Classification Report:
                             recall f1-score
               precision
                                                support
           0
                   1.00
                              1.00
                                        1.00
                                                     15
           1
                   1.00
                              1.00
                                        1.00
                                                     16
    accuracy
                                        1.00
                                                     31
   macro avg
                   1.00
                              1.00
                                        1.00
                                                     31
                                                     31
weighted avg
                   1.00
                              1.00
                                        1.00
```

```
In [23]:
    sns.heatmap(cm,annot=True,fmt="d")
    plt.show()
```



```
In [24]:
          from sklearn.metrics import roc curve
          from sklearn.linear_model import LogisticRegression
          from sklearn.metrics import confusion_matrix, classification_report
          \#hair = 1 no = 0
          x,y = zoo.loc[:,(zoo.columns != 'hair')], zoo.loc[:,'hair']
          x_train,x_test,y_train,y_test = train_test_split(x, y, test_size = 0.3, random_state=42
          logreg = LogisticRegression()
          logreg.fit(x train,y train)
          y pred prob = logreg.predict proba(x test)[:,1]
          fpr, tpr, thresholds = roc_curve(y_test, y_pred_prob)
          # Plot ROC curve
          plt.plot([0, 1], [0, 1], 'k--')
          plt.plot(fpr, tpr)
          plt.xlabel('False Positive Rate')
          plt.ylabel('True Positive Rate')
          plt.title('ROC')
          plt.show()
```



```
In [25]:
          from sklearn.model selection import GridSearchCV
          grid = {'n neighbors': np.arange(1,50)}
          knn = KNeighborsClassifier()
          knn_cv = GridSearchCV(knn, grid, cv=3) # GridSearchCV
          knn_cv.fit(x,y)# Fit
          # Print hyperparameter
          print("Tuned hyperparameter k: {}".format(knn_cv.best_params_))
          print("Best score: {}".format(knn_cv.best_score_))
         Tuned hyperparameter k: {'n neighbors': 1}
         Best score: 0.9402852049910874
In [26]:
          param_grid = {'C': np.logspace(-3, 3, 7), 'penalty': ['11', '12']}
          x_train, x_test, y_train, y_test = train_test_split(x,y,test_size = 0.3,random_state =
          logreg = LogisticRegression()
          logreg_cv = GridSearchCV(logreg,param_grid,cv=3)
          logreg cv.fit(x train,y train)
          # Print the optimal parameters and best score
          print("Tuned hyperparameters : {}".format(logreg_cv.best_params_))
          print("Best Accuracy: {}".format(logreg_cv.best_score_))
```

Tuned hyperparameters : {'C': 0.01, 'penalty': '12'}
Best Accuracy: 0.9299516908212562

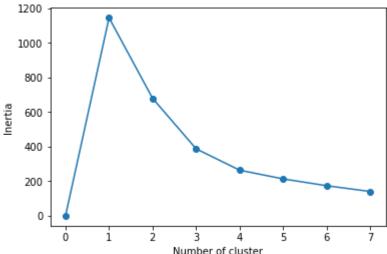
```
In [27]: df = pd.get_dummies(zoo)
    df.head(10)
```

Out[27]:		hair	feathers	eggs	milk	airborne	aquatic	predator	toothed	backbone	breathes	venomous	fi
	0	1	0	0	1	0	0	1	1	1	1	0	
	1	1	0	0	1	0	0	0	1	1	1	0	
	2	0	0	1	0	0	1	1	1	1	0	0	
	3	1	0	0	1	0	0	1	1	1	1	0	
	4	1	0	0	1	0	0	1	1	1	1	0	

```
toothed backbone breathes venomous fi
            hair feathers eggs milk airborne aquatic predator
          5
                        0
                                                    0
                                                             0
                                                                                        1
                                                                                                   0
          6
               1
                        0
                             0
                                   1
                                                    0
                                                             0
                                                                     1
                                                                               1
                                                                                        1
                                                                                                   0
          7
                             1
                                   0
                                                             0
                                                                               1
                                                                                        0
                                                                                                   0
          8
                             1
                                                             1
                                                                                        0
                                                                                                   0
                        0
                             0
                                   1
                                            0
                                                    0
                                                             0
                                                                                        1
                                                                                                   0
In [28]:
          from sklearn.svm import SVC
          from sklearn.preprocessing import StandardScaler
          from sklearn.pipeline import Pipeline
           steps = [('scalar', StandardScaler()),
                    ('SVM', SVC())]
           pipeline = Pipeline(steps)
           parameters = {'SVM_C':[1, 10, 100],
                          'SVM__gamma':[0.1, 0.01]}
          x train, x test, y train, y test = train test split(x,y,test size=0.2,random state = 1)
           cv = GridSearchCV(pipeline,param_grid=parameters,cv=3)
           cv.fit(x_train,y_train)
          y_pred = cv.predict(x_test)
          print("Accuracy: {}".format(cv.score(x test, y test)))
          print("Tuned Model Parameters: {}".format(cv.best_params_))
          Accuracy: 0.9523809523809523
          Tuned Model Parameters: {'SVM__C': 1, 'SVM__gamma': 0.01}
In [29]:
           plt.scatter(zoo['hair'],zoo['tail'])
           plt.xlabel('Hair')
          plt.ylabel('Tail')
           plt.show()
            1.0
            0.8
            0.6
            0.4
            0.2
            0.0
                 0.0
                          0.2
                                  0.4
                                                    0.8
                                                             1.0
                                            0.6
                                       Hair
In [30]:
           data2 = zoo.loc[:,['tail','hair']]
          from sklearn.cluster import KMeans
          kmeans = KMeans(n clusters = 2)
```

```
kmeans.fit(data2)
labels = kmeans.predict(data2)
plt.scatter(zoo['hair'],zoo['tail'],c = labels)
plt.xlabel('Hair')
plt.xlabel('Tail')
plt.show()
```

```
In [31]:
          df = pd.DataFrame({'labels':labels,"hair":zoo['hair']})
          ct = pd.crosstab(df['labels'],df['hair'])
          print(ct)
         hair
                  0
                       1
         labels
         0
                 58
                       0
         1
                   0
                     43
In [32]:
          inertia_list = np.empty(8)
          for i in range(1,8):
              kmeans = KMeans(n_clusters=i)
              kmeans.fit(zoo)
              inertia_list[i] = kmeans.inertia_
          plt.plot(range(0,8),inertia_list,'-o')
          plt.xlabel('Number of cluster')
          plt.ylabel('Inertia')
          plt.show()
```

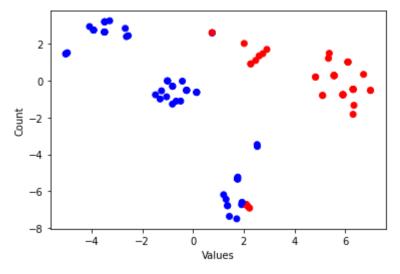


```
Number of cluster
In [33]:
          data2 = zoo.drop("hair",axis=1)
In [34]:
          from sklearn.preprocessing import StandardScaler
          from sklearn.pipeline import make_pipeline
          scalar = StandardScaler()
          kmeans = KMeans(n clusters = 2)
          pipe = make_pipeline(scalar,kmeans)
          pipe.fit(data2)
          labels = pipe.predict(data2)
          df = pd.DataFrame({'labels':labels,"hair":zoo['hair']})
          ct = pd.crosstab(df['labels'],df['hair'])
          print(ct)
         hair
                       1
          labels
                  56
                       4
         1
                   2
                      39
In [35]:
          from scipy.cluster.hierarchy import linkage,dendrogram
          merg = linkage(data2.iloc[:20,0:5],method = 'single')
          dendrogram(merg, leaf rotation = 90, leaf font size = 5)
          plt.show()
          1.4
          1.2
          1.0
          0.8
          0.6
          0.4
```

8 1 8

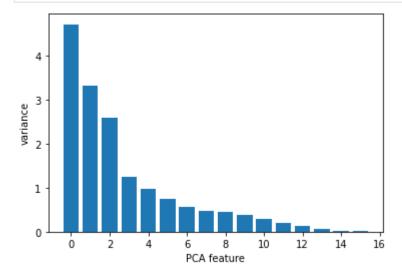
0.2

0.0

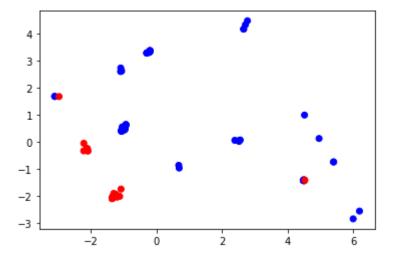


```
In [37]:
          from sklearn.decomposition import PCA
          model = PCA()
          model.fit(data2[0:4])
          transformed = model.transform(data2[0:4])
          print('Principle components: ',model.components )
         Principle components: [[-1.11022302e-16 1.77997984e-01 -1.77997984e-01 0.00000000e+00
            1.77997984e-01 5.75617345e-02 0.00000000e+00 0.00000000e+00
           -1.77997984e-01 0.00000000e+00 1.77997984e-01 -7.11991938e-01
            1.20436250e-01 0.00000000e+00 -1.77997984e-01 5.33993953e-01]
          [-3.33066907e-16 -7.92144437e-03 7.92144437e-03 0.000000000e+00
           -7.92144437e-03 -7.10368323e-01 0.00000000e+00 0.00000000e+00
            7.92144437e-03 0.00000000e+00 -7.92144437e-03 3.16857775e-02
            7.02446879e-01 0.00000000e+00 7.92144437e-03 -2.37643331e-02]
          [ 9.83538848e-01 5.50499658e-02 -4.07082498e-03 -0.000000000e+00
            4.07082498e-03 1.06099015e-01 -0.00000000e+00 -0.00000000e+00
           -4.07082498e-03 -0.00000000e+00 4.07082498e-03 -1.62832999e-02
            1.06099015e-01 -0.00000000e+00 -4.07082498e-03 -8.22121016e-02]
          [ 8.90295760e-02 -9.49149979e-01 -4.23156435e-02 -0.00000000e+00
            4.23156435e-02 -1.55559143e-01 -0.00000000e+00 -0.00000000e+00
           -4.23156435e-02 -0.00000000e+00 4.23156435e-02 -1.69262574e-01
           -1.55559143e-01 -0.00000000e+00 -4.23156435e-02 7.20268693e-02]]
In [38]:
          scaler = StandardScaler()
          pca = PCA()
          pipeline = make pipeline(scaler,pca)
          pipeline.fit(data2)
          plt.bar(range(pca.n_components_), pca.explained_variance_)
          plt.xlabel('PCA feature')
```

```
plt.ylabel('variance')
plt.show()
```



```
pca = PCA(n_components = 2)
pca.fit(data2)
transformed = pca.transform(data2)
x = transformed[:,0]
y = transformed[:,1]
plt.scatter(x,y,c = color_list)
plt.show()
```



```
In [ ]:
```