```
from sklearn.datasets import load_breast_cancer
breast=load breast cancer()
breast
             1, 1, 1, 1, 1, 1, 0, 0, 0, 1, 0, 0, 1, 1, 1, 0, 0, 1, 0, 1, 0,
             1, 1, 0, 1, 1, 1, 1, 0, 0, 1, 0, 1, 1, 0, 0, 1, 1, 0, 0, 1, 1, 1,
             1, 0, 1, 1, 0, 0, 0, 1, 0, 1, 0, 1, 1, 1, 0, 1, 1, 0, 0, 1, 0, 0,
             0, 0, 1, 0, 0, 0, 1, 0, 1, 0, 1, 1, 0, 1, 0, 0, 0, 0, 1, 1, 0, 0,
             1, 1, 1, 0, 1, 1, 1, 1, 0, 0, 1, 1, 0, 1, 1, 0, 0, 1, 0, 1, 1,
             1, 1, 0, 1, 1, 1, 1, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
             0, 0, 1, 1, 1, 1, 1, 0, 1, 0, 1, 1, 0, 1, 1, 0, 1, 0, 0, 1, 1,
             1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 1, 0, 1, 0, 1, 1, 1, 1, 1,
             1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 1, 1, 1, 0, 1, 0, 1, 1, 1, 1, 1, 0, 0,
             0, 1, 1, 1, 1, 0, 1, 0, 1, 0, 1, 1, 1, 0, 1, 1, 1, 1, 1, 1, 1, 0,
             0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0, 1, 0, 0, 1, 0, 0,
             1, 1, 1, 1, 1, 0, 1, 1, 1, 1, 0, 1, 1, 1, 0, 1, 1, 0, 0, 1, 1,
             1, 1, 1, 1, 0, 1, 1, 1, 1, 1, 1, 0, 1, 1, 1, 1, 0, 1, 1, 0,
             1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 1, 0, 0, 1, 0, 1, 1, 1, 1,
             1, 0, 1, 1, 0, 1, 0, 1, 1, 0, 1, 0, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0,
             1, 1, 1, 0, 1, 0, 1, 1, 0, 1, 1, 1, 1, 1, 0, 0, 1, 0, 1, 0, 1, 1,
             1, 1, 1, 0, 1, 1, 0, 1, 0, 1, 0, 0, 1, 1, 1, 0, 1, 1, 1, 1, 1,
             1, 1, 1, 1, 0, 1, 0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
             1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0, 0, 0, 0, 0, 1]),
      'frame': None,
      'target_names': array(['malignant', 'benign'], dtype='<U9'),
      'DESCR': '.. _breast_cancer_dataset:\n\nBreast cancer wisconsin (diagnostic) dataset\n--------
     ---\n\n**Data Set Characteristics:**\n\n :Number of Instances: 569\n\n :Number of Attributes: 30 numeric, predictive
     attributes and the class\n\n :Attribute Information:\n - radius (mean of distances from center to points on the
     perimeter)\n - texture (standard deviation of gray-scale values)\n - perimeter\n - area\n
     smoothness (local variation in radius lengths)\n - compactness (perimeter^2 / area - 1.0)\n
     of concave portions of the contour)\n - concave points (number of concave portions of the contour)\n - symmetry\n - fractal dimension ("coastline approximation" - 1)\n\n The mean, standard error, and "worst" or largest (mean of the three\n worst/largest values) of these features were computed for each image,\n resulting in 30 features. For
     of concave portions of the contour)\n
     instance, field 0 is Mean Radius, field\n 10 is Radius SE, field 20 is Worst Radius.\n\n - class:\n
     - WDBC-Malignant\n
                                      Min Max\n =======\n
     =====\n
                                           6.981 28.11\n texture (mean): 9.71 39.28\n perimeter.

143.5 2501.0\n smoothness (mean):

0.0 0.
     radius (mean):
                                43.79 188.5\n area (mean):
     (mean):
                                                          mean): 143.5 25
0.019 0.345\n concavity (mean):
     0.053 0.163\n compactness (mean):
                                                                                                                     0.0 0.427\n
    concave points (mean):

0.0 0.201\n symmetry (mean):

0.0 0.201\n symmetry (mean):

0.05 0.097\n radius (standard error):

0.36 4.885\n perimeter (standard error):

0.36 4.885\n perimeter (standard error):

0.3757 21.98\n area (standard error):

0.3802 542.2\n smoothness (standard error):

0.396\n concavity (standard error):

0.00 0.396\n concave points (standard error):

0.00 0.053\n symmetry
                                                                                                                     0.002 0.135\n
    concavity (standard error): 0.0 0.396\n concave points (standard error). 0.001 0.03\n radius (worst): (standard error): 0.008 0.079\n fractal dimension (standard error): 0.001 0.03\n radius (worst): 50.41
                                           12.02 49.54\n perimeter (worst):
185.2 4254.0\n smoothness (worst):
     7.93 36.04\n texture (worst):
                                                                                                                      50.41 251.2\n
                                                                                                    0.071 0.223\n compactness
     area (worst):
                                                                                       0.0 1.252\n concave points (worst):
     (worst):
                              0.027 1.058\n concavity (worst):
                                                                            fractal dimension (worst):
                                                            0.156 0.664\n
     0.0 0.291\n symmetry (worst):
                                                                                                                     0.055 0.208\n
     Malignant, 357 - Benign\n\n :Creator: Dr. William H. Wolberg, W. Nick Street, Olvi L. Mangasarian\n\n :Donor: Nick
     Street\n\n :Date: November, 1995\n\nThis is a copy of UCI ML Breast Cancer Wisconsin (Diagnostic)
     datasets.\nhttps://goo.gl/U2Uwz2\n\nFeatures are computed from a digitized image of a fine needle\naspirate (FNA) of a breast
     mass. They describe\ncharacteristics of the cell nuclei present in the image.\n\nSeparating plane described above was obtained
     using\nMultisurface Method-Tree (MSM-T) [K. P. Bennett, "Decision Tree\nConstruction Via Linear Programming." Proceedings of the
     4th\nMidwest Artificial Intelligence and Cognitive Science Society,\npp. 97-101, 1992], a classification method which uses
     linear\nprogramming to construct a decision tree. Relevant features\nwere selected using an exhaustive search in the space of
     1-4\nfeatures and 1-3 separating planes.\n\nThe actual linear program used to obtain the separating plane\nin the 3-dimensional
     space is that described in:\n[K. P. Bennett and O. L. Mangasarian: "Robust Linear\nProgramming Discrimination of Two Linearly
     Inseparable Sets",\nOptimization Methods and Software 1, 1992, 23-34].\n\nThis database is also available through the UW CS ftp
     server:\n\nftn ftn cs wisc edu\ncd math-nrog/cno-dataset/machine-learn/WDRC/\n\n
                                                                                        tonic. References\n\n
breast data=breast.data
breast_data
     array([[1.799e+01, 1.038e+01, 1.228e+02, ..., 2.654e-01, 4.601e-01,
             1.189e-011.
            [2.057e+01, 1.777e+01, 1.329e+02, ..., 1.860e-01, 2.750e-01,
             8.902e-02],
            [1.969e+01, 2.125e+01, 1.300e+02, ..., 2.430e-01, 3.613e-01,
            [1.660e+01, 2.808e+01, 1.083e+02, ..., 1.418e-01, 2.218e-01,
             7.820e-021,
            [2.060e+01, 2.933e+01, 1.401e+02, ..., 2.650e-01, 4.087e-01,
            1.240e-01],
[7.760e+00, 2.454e+01, 4.792e+01, ..., 0.000e+00, 2.871e-01,
```

7.039e-02]])

```
breast.data.shape
    (569, 30)
breast_data
    array([[1.799e+01, 1.038e+01, 1.228e+02, ..., 2.654e-01, 4.601e-01,
            1.189e-01],
           [2.057e+01, 1.777e+01, 1.329e+02, ..., 1.860e-01, 2.750e-01,
            8.902e-02],
           [1.969e+01, 2.125e+01, 1.300e+02, ..., 2.430e-01, 3.613e-01,
           8.758e-02],
           [1.660e+01, 2.808e+01, 1.083e+02, ..., 1.418e-01, 2.218e-01,
            7.820e-02],
           [2.060e+01, 2.933e+01, 1.401e+02, ..., 2.650e-01, 4.087e-01,
            1.240e-01],
           [7.760e+00, 2.454e+01, 4.792e+01, ..., 0.000e+00, 2.871e-01,
            7.039e-02]])
breast_label=breast.target
breast label
    0,\ 0,\ 1,\ 0,\ 1,\ 1,\ 1,\ 1,\ 0,\ 0,\ 1,\ 0,\ 0,\ 1,\ 1,\ 1,\ 1,\ 0,\ 0,\ 0,
           1, 1, 1, 1, 0, 1, 0, 0, 1, 0, 1, 0, 0, 1, 1, 1, 0, 0, 1, 0, 0,
           1, 1, 1, 0, 1, 1, 0, 0, 1, 1, 1, 0, 0, 1, 1, 1, 1, 0, 1, 1, 0, 1,
           1, 1, 1, 1, 1, 1, 0, 0, 0, 1, 0, 0, 1, 1, 1, 0, 0, 1, 0, 1, 0,
           1, 1, 0, 1, 1, 1, 1, 0, 0, 1, 0, 1, 1, 0, 0, 1, 1, 0, 0, 1, 1, 1,
           1, 0, 1, 1, 0, 0, 0, 1, 0, 1, 0, 1, 1, 1, 0, 1, 1, 0, 0, 1, 0, 0,
           0, 0, 1, 0, 0, 0, 1, 0, 1, 0, 1, 1, 0, 1, 0, 0, 0, 0, 1, 1, 0, 0,
           1, 1, 1, 0, 1, 1, 1, 1, 1, 0, 0, 1, 1, 0, 1, 1, 0, 0, 1, 0, 1, 1,
           1, 1, 0, 1, 1, 1, 1, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
           0,\ 0,\ 1,\ 1,\ 1,\ 1,\ 1,\ 0,\ 1,\ 0,\ 1,\ 1,\ 0,\ 1,\ 1,\ 0,\ 1,\ 1,
           1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 1, 1, 0, 1, 0, 1, 1, 1, 1, 1,
           1, 1, 1, 1, 1, 1, 1, 1, 0, 1, 1, 0, 1, 0, 1, 1, 1, 1, 0, 0,
           0, 1, 1, 1, 1, 0, 1, 0, 1, 1, 1, 1, 0, 1, 1, 1, 1, 1, 1, 1, 0,
           0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0, 1, 0, 0, 1, 0, 0,
           1, 1, 1, 1, 1, 0, 1, 1, 1, 1, 0, 1, 1, 1, 0, 1, 1, 0, 0, 1, 1,
           1, 1, 1, 1, 0, 1, 1, 1, 1, 1, 1, 0, 1, 1, 1, 1, 0, 1, 1, 0,
           1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 1, 0, 0, 1, 0, 1, 1, 1, 1,
           1, 0, 1, 1, 0, 1, 0, 1, 0, 1, 0, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0,
           1, 1, 1, 1, 1, 1, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 1, 1, 1,
           1, 1, 1, 0, 1, 0, 1, 1, 0, 1, 1, 1, 1, 1, 0, 0, 1, 0, 1, 0, 1, 1,
           1, 1, 1, 0, 1, 1, 0, 1, 0, 1, 0, 0, 1, 1, 1, 0, 1, 1, 1, 1, 1,
           1, 1, 1, 1, 0, 1, 0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
           1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0, 0, 0, 0, 0, 1])
breast_label.shape
    (569,)
import numpy as np
labels=np.reshape(breast_label,(569,1))
labels
```

```
[1],
             [1],
             [1],
             [1],
             [1],
             [1],
              [1],
              [1],
              [1],
             [1],
             [1],
             [1],
[1],
             [1],
             [1],
             [1],
             [1],
             [1],
             [1],
             [1],
             [0],
             [0],
             [0],
             [0],
             [0],
             [0],
             [1]])
final_breast_data=np.concatenate([breast_data, labels], axis=1)
```

```
final_breast_data.shape
     (569, 31)
```

import pandas as pd breast_dataset=pd.DataFrame(final_breast_data)

breast_dataset

```
6
                                                                                  9 ..
  0
      17.99
            10.38
                   122.80
                          1001.0
                                  0.11840
                                          0.27760
                                                   0.30010
                                                            0.14710
                                                                    0.2419
                                                                            0.07871
  1
      20 57 17 77
                   132 90
                          1326 0 0 08474
                                          0.07864
                                                   0.08690
                                                           0.07017 0.1812 0.05667
      19.69
           21.25
                   130.00
                          1203.0 0.10960
                                          0.15990
                                                   0.19740
                                                            0.12790
 3
      11 42 20 38
                    77 58
                           386 1 0 14250
                                          0.28390
                                                   0.24140
                                                           0.10520 0.2597
                                                                            0.09744
  4
      20.29
            14.34
                   135.10
                          1297.0 0.10030 0.13280
                                                  0.19800
                                                           0.10430 0.1809
                                                                           0.05883
     21.56 22.39
                   142.00 1479.0
                                 0.11100 0.11590
                                                  0.24390
                                                           0.13890 0.1726 0.05623
 564
      20.13 28.25
                   131.20
                          1261.0 0.09780
                                          0.10340
                   108.30
 566
      16.60 28.08
                           858 1
                                  0.08455
                                          0.10230
                                                   0.09251
                                                            0.05302 0.1590
                                                                            0.05648
     20.60 29.33
                   140.10
                          1265.0 0.11780 0.27700
                                                   0.35140
 567
                                                           0.15200 0.2397
                                                                           0.07016
 568
      7.76 24.54
                    47.92
                           181.0 0.05263 0.04362
                                                  0.00000
                                                           0.00000 0.1587 0.05884
569 rows × 31 columns
4
```

final_breast_data

```
array([[1.799e+01, 1.038e+01, 1.228e+02, ..., 4.601e-01, 1.189e-01,
       0.000e+00],
      [2.057e+01, 1.777e+01, 1.329e+02, ..., 2.750e-01, 8.902e-02,
       0.000e+00],
      [1.969e+01, 2.125e+01, 1.300e+02, ..., 3.613e-01, 8.758e-02,
       0.000e+00],
      [1.660e+01, 2.808e+01, 1.083e+02, ..., 2.218e-01, 7.820e-02,
       0.000e+00],
       [2.060e+01, 2.933e+01, 1.401e+02, ..., 4.087e-01, 1.240e-01,
       0.000e+00],
      [7.760e+00, 2.454e+01, 4.792e+01, ..., 2.871e-01, 7.039e-02,
        1.000e+00]])
```

```
features=breast.feature_names
features
```

```
array(['mean radius', 'mean texture', 'mean perimeter', 'mean area',
    'mean smoothness', 'mean compactness', 'mean concavity',
    'mean concave points', 'mean symmetry', 'mean fractal dimension',
    'radius error', 'texture error', 'perimeter error', 'area error',
    'smoothness error', 'compactness error', 'concavity error',
    'concave points error', 'symmetry error',
    'fractal dimension error', 'worst radius', 'worst texture',
    'worst perimeter', 'worst area', 'worst smoothness',
    'worst compactness', 'worst concavity', 'worst concave points',
    'worst symmetry', 'worst fractal dimension'], dtype='<U23')
```

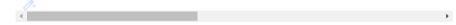
features_labels=np.append(features, 'label')

breast_dataset.columns=features_labels

breast_dataset.head()

	mean radius	mean texture	mean perimeter	mean area	mean smoothness	mean compactness	mean concavity	mean concave points	s)
0	17.99	10.38	122.80	1001.0	0.11840	0.27760	0.3001	0.14710	
1	20.57	17.77	132.90	1326.0	0.08474	0.07864	0.0869	0.07017	
2	19.69	21.25	130.00	1203.0	0.10960	0.15990	0.1974	0.12790	
3	11.42	20.38	77.58	386.1	0.14250	0.28390	0.2414	0.10520	
4	20.29	14.34	135.10	1297.0	0.10030	0.13280	0.1980	0.10430	

5 rows × 31 columns

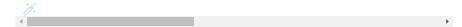


breast_dataset['label'].replace(0,'Benign', inplace=True)
breast_dataset['label'].replace(1,'Malignant', inplace=True)

breast_dataset.tail()

		mean radius	mean texture	mean perimeter	mean area	mean smoothness	mean compactness	mean concavity	mean concave points
į	564	21.56	22.39	142.00	1479.0	0.11100	0.11590	0.24390	0.13890
į	565	20.13	28.25	131.20	1261.0	0.09780	0.10340	0.14400	0.09791
Ę	566	16.60	28.08	108.30	858.1	0.08455	0.10230	0.09251	0.05302
į	567	20.60	29.33	140.10	1265.0	0.11780	0.27700	0.35140	0.15200
į	568	7.76	24.54	47.92	181.0	0.05263	0.04362	0.00000	0.00000

5 rows × 31 columns



from sklearn.preprocessing import StandardScaler
x=breast_dataset.loc[:,features].values
x=StandardScaler().fit_transform(x) #normalizing the features

x.shape

(569, 30)

np.mean(x),np.std(x)

(-6.826538293184326e-17, 1.0)

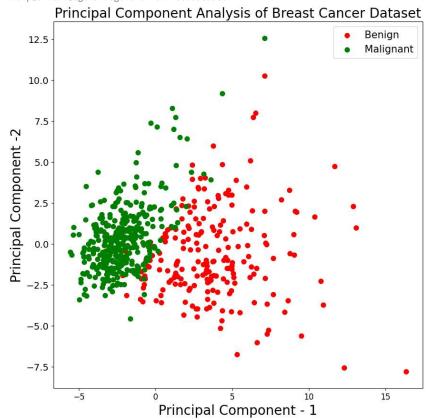
feat_cols=['feature'+str(i) for i in range(x.shape[1])]

normalised_breast=pd.DataFrame(x,columns=feat_cols)

normalised_breast.tail()

```
feature0 feature1 feature2 feature3 feature4 feature5 feature6 feature7
           2.110995
                    0.721473
                              2.060786
                                        2.343856
                                                 1.041842
                                                           0.219060
                                                                    1.947285
                                                                              2.320965
      565
           1.704854
                    2.085134
                              1.615931
                                       1.723842
                                                 0.102458
                                                          -0.017833
                                                                    0.693043
                                                                              1.263669
          0.702284
                    2.045574
                              0.672676
                                       0.577953 -0.840484 -0.038680
                                                                    0.046588
                                                                              0.105777
      566
      567
           1.838341 2.336457
                              1.982524
                                       1.735218
                                                 1.525767
                                                           3.272144
                                                                    3.296944
                                                                              2.658866
      5 rows × 30 columns
from sklearn.decomposition import PCA
pca_breast=PCA(n_components=2)
principalComponent_breast=pca_breast.fit_transform(x)
principal_breast_Df=pd.DataFrame(data=principalComponent_breast, columns=['+', 'principal component 2'])
principal_breast_Df.tail()
                  + principal component 2
      564
           6.439315
                                 -3.576817
      565
           3.793382
                                 -3.584048
      566
           1.256179
                                 -1.902297
         10.374794
                                 1.672010
      567
      568
          -5.475243
                                 -0.670637
print('Explained variation per principal component : {}',format(pca_breast.explained_variance_ratio_))
     Explained variation per principal component : {} [0.44272026 0.18971182]
import matplotlib.pyplot as plt
plt.figure(figsize=(10,10))
plt.xticks(fontsize=12)
plt.yticks(fontsize=14)
plt.xlabel('Principal Component - 1',fontsize=20)
plt.ylabel('Principal Component -2', fontsize=20)
plt.title("Principal Component Analysis of Breast Cancer Dataset", fontsize=20)
targets=['Benign', 'Malignant']
colors=['r','g']
for target,color in zip(targets, colors):
 indicesToKeep=breast_dataset['label']==target
 plt.scatter(principal_breast_Df.loc[indicesToKeep, '+'], principal_breast_Df.loc[indicesToKeep, 'principal component 2'], c=color, s=50)
plt.legend(targets, prop={'size':15})
```

<matplotlib.legend.Legend at 0x7f681a5e25e0>



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