

```
In [1]: 1 import numpy as np
        2 import pandas as pd
```

```
In [2]: 1 from numpy import array
        2 from numpy import mean
        3 from numpy import cov
        4 from numpy.linalg import eig
```

```
In [4]: 1 mat = array([[1,2],[3,4],[5,6]])
        2 mat

array([[1, 2],
       [3, 4],
       [5, 6]])
```

```
In [5]: 1 mean(mat)

3.5
```

```
In [6]: 1 M = mean(mat.T, axis = 1)
        2 M

array([3., 4.])
```

```
In [7]: 1 c = mat-M
        2 c

array([[ -2.,  -2.],
       [  0.,   0.],
       [  2.,   2.]])
```

```
In [8]: 1 v = cov(c.T)
        2 v

array([[4., 4.],
       [4., 4.]])
```

```
In [9]: 1 values,vectors = eig(v)
        2 print(vectors)
        3 print(values)
```

```
[[ 0.70710678 -0.70710678]
 [ 0.70710678  0.70710678]]
[8. 0.]
```

```
In [10]: 1 P = vectors.T.dot(c.T)
        2 print(P.T)
```

```
[[-2.82842712  0.          ]
 [ 0.          0.          ]
 [ 2.82842712  0.          ]]
```

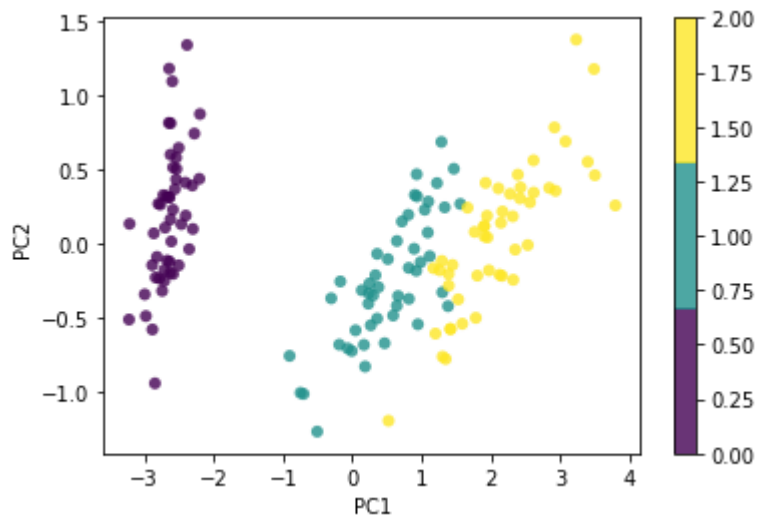
```
In [18]: 1 class pca :
        2     def __init__(self,n_components):
        3         self.n_components = n_components
        4         self.components = None
        5         self.mean= None
        6
        7     def fit(self,x):
        8         self.mean = np.mean(x,axis = 0)
        9         x = x - self.mean
       10         cov = np.cov(x.T)
       11
       12         eigenvalues,eigenvectors = np.linalg.eig(cov)
       13
       14         eigenvectors = eigenvectors.T
       15         idxs = np.argsort(eigenvalues)[::-1]
       16         eigenvalues = eigenvalues[idxs]
       17         eigenvectors = eigenvectors[idxs]
       18
       19         self.components = eigenvectors[0:self.n_components]
       20
       21
       22     def transform(self,x):
       23         x = x - self.mean
       24         return np.dot(x,self.components.T)
```

```
In [14]: 1 from sklearn import datasets
2 import matplotlib.pyplot as plt
3 from sklearn.decomposition import PCA
4 import numpy as np
5
```

```
In [16]: 1 data = datasets.load_iris()
2 x = data.data
3 y = data.target
4
5 pca = PCA(2)
6 pca.fit(x)
7 x_projected = pca.transform(x)
8 print("shape of x : ", x.shape)
9 print("shape of transformed x : ", x_projected.shape)
10 x1 = x_projected[:,0]
11 x2 = x_projected[:,1]
12 plt.scatter(x1,x2, c=y ,edgecolor = 'none',alpha = 0.8 , cmap = plt.cm.get_cmap('magma', 3))
13 plt.xlabel('PC1')
14 plt.ylabel('PC2')
15 plt.colorbar()
16 plt.show()
17
```

shape of x : (150, 4)

shape of transformed x : (150, 2)



```
In [19]: 1 from sklearn.datasets import fetch_openml
2 from sklearn.decomposition import PCA
3 from sklearn.preprocessing import StandardScaler
4 from sklearn import metrics
5 from sklearn.model_selection import train_test_split
6 import pandas as pd
```

```
In [20]: 1 mnist = fetch_openml('mnist_784')
```

```
In [21]: 1 mnist

{'data': array([[0., 0., 0., ..., 0., 0., 0.],
               [0., 0., 0., ..., 0., 0., 0.],
               [0., 0., 0., ..., 0., 0., 0.],
               ...,
               [0., 0., 0., ..., 0., 0., 0.],
               [0., 0., 0., ..., 0., 0., 0.],
               [0., 0., 0., ..., 0., 0., 0.]])
, 'target': array(['5', '0', '4', ..., '4', '5', '6'], dtype=object),
  'frame': None,
  'feature_names': ['pixel1',
                   'pixel2',
                   'pixel3',
                   'pixel4',
                   'pixel5',
                   'pixel6',
                   'pixel7',
                   'pixel8',
                   'pixel9',
                   'pixel10',
                   'pixel11',
                   'pixel12',
                   'pixel13',
                   'pixel14',
                   'pixel15']
}
```

```
In [22]: 1 mnist.data.shape

(70000, 784)
```

```
In [24]: 1 mnist.target.shape

(70000,)
```

```
In [25]: 1 train_img, test_img, train_lbl, test_lbl = train_test_split(
2         mnist.data, mnist.target, test_size=1/7.0, random_state=0)
```

```
In [27]: 1 print(train_img.shape)
          2 print(train_lbl.shape)
          3 print(test_img.shape)
          4 print(test_lbl.shape)
```

```
(60000, 784)
(60000,)
(10000, 784)
(10000,)
```

```
In [28]: 1 from sklearn.preprocessing import StandardScaler
          2 scaler = StandardScaler()
          3 scaler.fit(train_img)
          4 train_img = scaler.transform(train_img)
          5 test_img = scaler.transform(test_img)
```

```
In [29]: 1 pca = PCA(.95)
          2 pca.fit(train_img)
          3 pca.n_components_
```

```
327
```

```
In [30]: 1 train_img = pca.transform(train_img)
          2 test_img = pca.transform(test_img)
```

```
In [33]: 1 from sklearn.linear_model import LogisticRegression
```

```
In [36]: 1 logisticRegr = LogisticRegression(solver = 'lbfgs')
```

```
In [37]: 1 logisticRegr.fit(train_img, train_lbl)
```

C:\Users\hp\anaconda3\lib\site-packages\sklearn\linear_model_logistic.py:940: ConvergenceWarning: lbfgs STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:

<https://scikit-learn.org/stable/modules/preprocessing.html> (<https://scikit-learn.org/stable/modules/preprocessing.html>)

Please also refer to the documentation for alternative solver options:

https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression (https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression)
extra_warning_msg=_LOGISTIC_SOLVER_CONVERGENCE_MSG)

```
LogisticRegression(C=1.0, class_weight=None, dual=False, fit_intercept=True,
                    intercept_scaling=1, l1_ratio=None, max_iter=100,
                    multi_class='auto', n_jobs=None, penalty='l2',
                    random_state=None, solver='lbfgs', tol=0.0001, verbose=0,
                    warm_start=False)
```

```
In [38]: 1 logisticRegr.predict(test_img[0].reshape(1,-1))
```

```
array(['0'], dtype=object)
```

```
In [41]: 1 logisticRegr.predict(test_img[0:10])
```

```
array(['0', '4', '1', '2', '4', '7', '7', '1', '1', '7'], dtype=object)
```

```
In [39]: 1 score = logisticRegr.score(test_img, test_lbl)
         2 print(score)
```

```
0.9201
```

```
In [40]: 1 pd.DataFrame(data = [[1.00, 784, 48.94, .9158],
2                               [.99, 541, 34.69, .9169],
3                               [.95, 330, 13.89, .92],
4                               [.90, 236, 10.56, .9168],
5                               [.85, 184, 8.85, .9156]],
6          columns = ['Variance Retained',
7                    'Number of Components',
8                    'Time (seconds)',
9                    'Accuracy'])
```

| | Variance Retained | Number of Components | Time (seconds) | Accuracy |
|---|-------------------|----------------------|----------------|----------|
| 0 | 1.00 | 784 | 48.94 | 0.9158 |
| 1 | 0.99 | 541 | 34.69 | 0.9169 |
| 2 | 0.95 | 330 | 13.89 | 0.9200 |
| 3 | 0.90 | 236 | 10.56 | 0.9168 |
| 4 | 0.85 | 184 | 8.85 | 0.9156 |