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Roll no:-08

Batch:-E1

```
import matplotlib.pyplot as plt
import numpy as np
import pandas as pd
%matplotlib inline
```

1.to avoid the problem of overfitting,pca is used 2.reduce 100 attributes to 10 merge different attributes together which are highly corelated with each other 3.it is a feature extraction techniqe 4.used for dimensionality reduction 5.if the spread is more variance is more than variety of data is high,spread should be more

```
from sklearn import datasets
```

```
digit=datasets.load_digits()
```

```
digit.keys()
```

```
dict_keys(['data', 'target', 'frame', 'feature_names', 'target_names', 'images', 'DESCR'])
```

```
print(digit['DESCR'])
```

```
.. _digits_dataset:
```

```
Optical recognition of handwritten digits dataset
```

```
-----
```

```
**Data Set Characteristics:**
```

```
:Number of Instances: 1797
:Number of Attributes: 64
:Attribute Information: 8x8 image of integer pixels in the range 0..16.
:Missing Attribute Values: None
:Creator: E. Alpaydin (alpaydin '@' boun.edu.tr)
:Date: July; 1998
```

This is a copy of the test set of the UCI ML hand-written digits datasets  
<https://archive.ics.uci.edu/ml/datasets/Optical+Recognition+of+Handwritten+Digits>

The data set contains images of hand-written digits: 10 classes where each class refers to a digit.

Preprocessing programs made available by NIST were used to extract normalized bitmaps of handwritten digits from a preprinted form. From a total of 43 people, 30 contributed to the training set and different 13 to the test set. 32x32 bitmaps are divided into nonoverlapping blocks of 4x4 and the number of on pixels are counted in each block. This generates an input matrix of 8x8 where each element is an integer in the range 0..16. This reduces dimensionality and gives invariance to small distortions.

For info on NIST preprocessing routines, see M. D. Garriis, J. L. Blue, G. T. Candela, D. L. Dimmick, J. Geist, P. J. Grother, S. A. Janet, and C. L. Wilson, NIST Form-Based Handprint Recognition System, NISTIR 5469, 1994.

```
.. topic:: References
```

- C. Kaynak (1995) Methods of Combining Multiple Classifiers and Their Applications to Handwritten Digit Recognition, MSc Thesis, Institute of Graduate Studies in Science and Engineering, Bogazici University.
- E. Alpaydin, C. Kaynak (1998) Cascading Classifiers, Kybernetika.
- Ken Tang and Ponnuthurai N. Suganthan and Xi Yao and A. Kai Qin. Linear dimensionality reduction using relevance weighted LDA. School of Electrical and Electronic Engineering Nanyang Technological University. 2005.
- Claudio Gentile. A New Approximate Maximal Margin Classification Algorithm. NIPS. 2000.

```
print(digit['target_names'])
```

```
[0 1 2 3 4 5 6 7 8 9]
```

```
print(digit['feature_names'])
```

```
['pixel_0_0', 'pixel_0_1', 'pixel_0_2', 'pixel_0_3', 'pixel_0_4', 'pixel_0_5', 'pixel_0_6', 'pixel_0_7', 'pixel_1_0', 'pixel_1_1', 'pixel_1_2', 'pixel_1_3', 'pixel_1_4', 'pixel_1_5', 'pixel_1_6', 'pixel_1_7', 'pixel_2_0', 'pixel_2_1', 'pixel_2_2', 'pixel_2_3', 'pixel_2_4', 'pixel_2_5', 'pixel_2_6', 'pixel_2_7', 'pixel_3_0', 'pixel_3_1', 'pixel_3_2', 'pixel_3_3', 'pixel_3_4', 'pixel_3_5', 'pixel_3_6', 'pixel_3_7', 'pixel_4_0', 'pixel_4_1', 'pixel_4_2', 'pixel_4_3', 'pixel_4_4', 'pixel_4_5', 'pixel_4_6', 'pixel_4_7', 'pixel_5_0', 'pixel_5_1', 'pixel_5_2', 'pixel_5_3', 'pixel_5_4', 'pixel_5_5', 'pixel_5_6', 'pixel_5_7', 'pixel_6_0', 'pixel_6_1', 'pixel_6_2', 'pixel_6_3', 'pixel_6_4', 'pixel_6_5', 'pixel_6_6', 'pixel_6_7']
```

```
feature = digit.data
```

```
target = digit.target
```

```
from sklearn.model_selection import train_test_split
```

```
df=pd.DataFrame(digit['data'],columns=digit['feature_names'])
```

```
df.head()
```

	pixel_0_0	pixel_0_1	pixel_0_2	pixel_0_3	pixel_0_4	pixel_0_5	pixel_0_6	pixel_0_7	pixel_1_0	pixel_1_1	...	pixel_6_6	pixel_6_7
0	0.0	0.0	5.0	13.0	9.0	1.0	0.0	0.0	0.0	0.0	...	0.0	0.0
1	0.0	0.0	0.0	12.0	13.0	5.0	0.0	0.0	0.0	0.0	...	0.0	0.0
2	0.0	0.0	0.0	4.0	15.0	12.0	0.0	0.0	0.0	0.0	...	5.0	0.0
3	0.0	0.0	7.0	15.0	13.0	1.0	0.0	0.0	0.0	8.0	...	9.0	0.0
4	0.0	0.0	0.0	1.0	11.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0

5 rows × 64 columns

```
df.tail()
```

	pixel_0_0	pixel_0_1	pixel_0_2	pixel_0_3	pixel_0_4	pixel_0_5	pixel_0_6	pixel_0_7	pixel_1_0	pixel_1_1	...	pixel_6_6	pixel_6_7
1792	0.0	0.0	4.0	10.0	13.0	6.0	0.0	0.0	0.0	1.0	...	4.0	0.0
1793	0.0	0.0	6.0	16.0	13.0	11.0	1.0	0.0	0.0	0.0	...	1.0	0.0
1794	0.0	0.0	1.0	11.0	15.0	1.0	0.0	0.0	0.0	0.0	...	0.0	0.0
1795	0.0	0.0	2.0	10.0	7.0	0.0	0.0	0.0	0.0	0.0	...	2.0	0.0
1796	0.0	0.0	10.0	14.0	8.0	1.0	0.0	0.0	0.0	2.0	...	8.0	0.0

5 rows × 64 columns

```
X_train, X_test, y_train, y_test = train_test_split(df, target, train_size = 0.7, random_state = 3)
```

```
print(X_train.shape)
```

```
print(X_test.shape)
```

```
print(y_train.shape)
```

```
print(y_test.shape)
```

```
(1257, 64)
```

```
(540, 64)
```

```
(1257,)
```

```
(540,)
```

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

```
my_model = LogisticRegression()
```

```
my_model.fit(X_train,y_train)
```

```
/usr/local/lib/python3.10/dist-packages/sklearn/linear_model/_logistic.py:458: ConvergenceWarning: lbfgs failed to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.
```

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

```
preds = my_model.predict(X_test)
```

```
from sklearn.metrics import accuracy_score, confusion_matrix
```

```
LogisticRegression()
print(accuracy_score(y_test, preds))
```

0.9537037037037037

```
from sklearn.decomposition import PCA
```

```
pca=PCA(n_components=30)
```

```
x_pca=pca.fit_transform(df)
```

```
df.shape
```

(1797, 64)

```
x_pca.shape
```

(1797, 30)

x\_pca

```
array([[ -1.25946644,  21.27488341, -9.46305465, ..., -0.94057806,
        -1.14589241,  2.30963742],
       [ 7.95761133, -20.76869889,  4.43950604, ..., -0.61412919,
        2.43696391,  0.64573521],
       [ 6.99192297, -9.95598631,  2.95855808, ..., 2.14867056,
        0.86555209, -0.44075962],
       ...,
       [10.80128371, -6.96025226,  5.59955449, ..., 1.87382348,
        3.50644345, -4.0235111 ],
       [-4.8721001 , 12.42395363, -10.17086641, ..., 0.98326887,
        -0.95572838, -1.44957216],
       [-0.34438961,  6.36554941, 10.77370858, ..., 1.15742648,
        2.74756365, -6.67833307]])
```

```
explained_variance = np.var(x_pca, axis=0)
print(explained_variance)
```

178.90731578	163.62664073	141.70953623	101.04411456	69.47448269
59.075632	51.85566624	43.99061301	40.28856291	36.99120196
28.5031982	27.30596604	21.89830032	21.31248988	17.62690729
16.93743145	15.84256866	14.99611043	12.22764288	10.88077315
10.687616448	9.57725252	9.1225571	8.68546959	8.36929577
7.16147986	6.91547153	6.18779616	5.88002415	5.149200057

```
explained_variance_ratio = explained_variance / np.sum(explained_variance)
```

```
import matplotlib.pyplot as plt
import numpy as np
```

```
PC_values = np.arange(pca.n_components) + 1
plt.plot(PC_values, explained_variance_ratio, 'o-', linewidth=2, color='blue')
plt.title('Scree Plot')
plt.xlabel('Principal Component')
plt.ylabel('Variance Explained')
plt.show()
```

