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Experiment 10

Principal Component Analysis (PCA)

In [1]:

```
from sklearn.datasets import load_digits
import pandas as pd

dataset = load_digits()
dataset.keys()
```

Out[1]:

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

In [2]:

```
dataset.data.shape
```

Out[2]:

```
(1797, 64)
```

In [3]:

```
dataset.data[0]
```

Out[3]:

```
array([ 0.,  0.,  5., 13.,  9.,  1.,  0.,  0.,  0.,  0., 13., 15., 10.,
       15.,  5.,  0.,  0.,  3., 15.,  2.,  0., 11.,  8.,  0.,  0.,  4.,
       12.,  0.,  0.,  8.,  8.,  0.,  0.,  5.,  8.,  0.,  0.,  9.,  8.,
        0.,  0.,  4., 11.,  0.,  1., 12.,  7.,  0.,  0.,  2., 14.,  5.,
       10., 12.,  0.,  0.,  0.,  0.,  6., 13., 10.,  0.,  0.,  0.])
```

In [4]:

```
dataset.data[0].reshape(8,8)
```

Out[4]:

```
array([[ 0.,  0.,  5., 13.,  9.,  1.,  0.,  0.],
       [ 0.,  0., 13., 15., 10., 15.,  5.,  0.],
       [ 0.,  3., 15.,  2.,  0., 11.,  8.,  0.],
       [ 0.,  4., 12.,  0.,  0.,  8.,  8.,  0.],
       [ 0.,  5.,  8.,  0.,  0.,  9.,  8.,  0.],
       [ 0.,  4., 11.,  0.,  1., 12.,  7.,  0.],
       [ 0.,  2., 14.,  5., 10., 12.,  0.,  0.],
       [ 0.,  0.,  6., 13., 10.,  0.,  0.,  0.]])
```

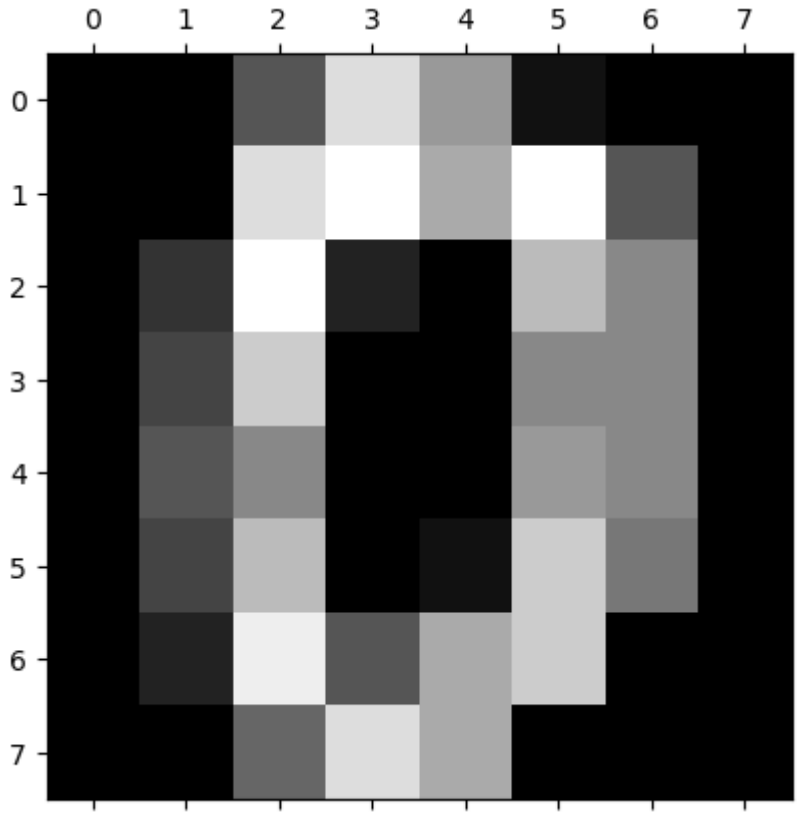
In [5]:

```
from matplotlib import pyplot as plt
%matplotlib inline
plt.gray()
plt.matshow(dataset.data[0].reshape(8,8))
```

Out[5]:

```
<matplotlib.image.AxesImage at 0x1f39b2a5060>
```

```
<Figure size 640x480 with 0 Axes>
```

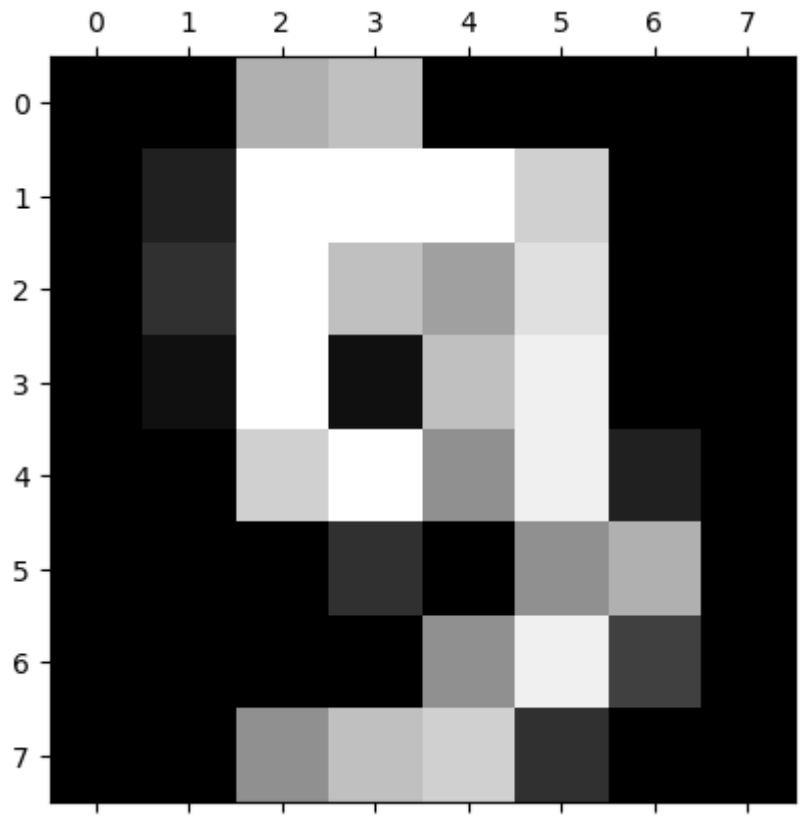


In [6]:

```
plt.matshow(dataset.data[9].reshape(8,8))
```

Out[6]:

```
<matplotlib.image.AxesImage at 0x1f39bbb0d00>
```



In [7]:

```
dataset.target[:5]
```

Out[7]:

```
array([0, 1, 2, 3, 4])
```

In [8]:

```
df = pd.DataFrame(dataset.data, columns=dataset.feature_names)
df.head()
```

Out[8]:

	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_
0	0.0	0.0	5.0	13.0	9.0	1.0	0.0	0.0	
1	0.0	0.0	0.0	12.0	13.0	5.0	0.0	0.0	
2	0.0	0.0	0.0	4.0	15.0	12.0	0.0	0.0	
3	0.0	0.0	7.0	15.0	13.0	1.0	0.0	0.0	
4	0.0	0.0	0.0	1.0	11.0	0.0	0.0	0.0	

5 rows × 64 columns

In [9]:

```
dataset.target
```

Out[9]:

```
array([0, 1, 2, ..., 8, 9, 8])
```

In [10]:

```
df.describe()
```

Out[10]:

	pixel_0_0	pixel_0_1	pixel_0_2	pixel_0_3	pixel_0_4	pixel_0_5	pixel_0
count	1797.0	1797.000000	1797.000000	1797.000000	1797.000000	1797.000000	1797.0000
mean	0.0	0.303840	5.204786	11.835838	11.848080	5.781859	1.3622
std	0.0	0.907192	4.754826	4.248842	4.287388	5.666418	3.3257
min	0.0	0.000000	0.000000	0.000000	0.000000	0.000000	0.0000
25%	0.0	0.000000	1.000000	10.000000	10.000000	0.000000	0.0000
50%	0.0	0.000000	4.000000	13.000000	13.000000	4.000000	0.0000
75%	0.0	0.000000	9.000000	15.000000	15.000000	11.000000	0.0000
max	0.0	8.000000	16.000000	16.000000	16.000000	16.000000	16.0000

8 rows × 64 columns

In [11]:

```
X = df
y = dataset.target
```

In [12]:

```
from sklearn.preprocessing import StandardScaler

scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)
X_scaled
```

Out[12]:

```
array([[ 0.        , -0.33501649, -0.04308102, ..., -1.14664746,
        -0.5056698 , -0.19600752],
       [ 0.        , -0.33501649, -1.09493684, ...,  0.54856067,
        -0.5056698 , -0.19600752],
       [ 0.        , -0.33501649, -1.09493684, ...,  1.56568555,
         1.6951369 , -0.19600752],
       ...,
       [ 0.        , -0.33501649, -0.88456568, ..., -0.12952258,
        -0.5056698 , -0.19600752],
       [ 0.        , -0.33501649, -0.67419451, ...,  0.8876023 ,
        -0.5056698 , -0.19600752],
       [ 0.        , -0.33501649,  1.00877481, ...,  0.8876023 ,
        -0.26113572, -0.19600752]])
```

In [13]:

```
from sklearn.model_selection import train_test_split

X_train, X_test, y_train, y_test = train_test_split(X_scaled, y, test_size=0.2, random_st
```

In [14]:

```
from sklearn.linear_model import LogisticRegression

model = LogisticRegression()
model.fit(X_train, y_train)
model.score(X_test, y_test)
```

Out[14]:

```
0.9722222222222222
```

Use PCA to reduce dimensions

In [15]:

```
X
```

Out[15]:

	pixel_0_0	pixel_0_1	pixel_0_2	pixel_0_3	pixel_0_4	pixel_0_5	pixel_0_6	pixel_0_7	pi
0	0.0	0.0	5.0	13.0	9.0	1.0	0.0	0.0	
1	0.0	0.0	0.0	12.0	13.0	5.0	0.0	0.0	
2	0.0	0.0	0.0	4.0	15.0	12.0	0.0	0.0	
3	0.0	0.0	7.0	15.0	13.0	1.0	0.0	0.0	
4	0.0	0.0	0.0	1.0	11.0	0.0	0.0	0.0	
...	...	...	...	...	...	...	...	...	
1792	0.0	0.0	4.0	10.0	13.0	6.0	0.0	0.0	
1793	0.0	0.0	6.0	16.0	13.0	11.0	1.0	0.0	
1794	0.0	0.0	1.0	11.0	15.0	1.0	0.0	0.0	
1795	0.0	0.0	2.0	10.0	7.0	0.0	0.0	0.0	
1796	0.0	0.0	10.0	14.0	8.0	1.0	0.0	0.0	

1797 rows × 64 columns

Use components such that 95% of variance is retained

In [16]:

```
from sklearn.decomposition import PCA

pca = PCA(0.95)
X_pca = pca.fit_transform(X)
X_pca.shape
```

Out[16]:

```
(1797, 29)
```

In [17]:

```
pca.explained_variance_ratio_
```

Out[17]:

```
array([0.14890594, 0.13618771, 0.11794594, 0.08409979, 0.05782415,
       0.0491691 , 0.04315987, 0.03661373, 0.03353248, 0.03078806,
       0.02372341, 0.02272697, 0.01821863, 0.01773855, 0.01467101,
       0.01409716, 0.01318589, 0.01248138, 0.01017718, 0.00905617,
       0.00889538, 0.00797123, 0.00767493, 0.00722904, 0.00695889,
       0.00596081, 0.00575615, 0.00515158, 0.0048954 ])
```

In [18]:

```
pca.n_components_
```

Out[18]:

```
29
```

PCA created 29 components out of 64 original columns

In [19]:

```
X_pca
```

Out[19]:

```
array([[ -1.25946645,  21.27488348,  -9.46305462, ...,   3.67072108,
         -0.9436689 ,  -1.13250195],
       [  7.9576113 , -20.76869896,   4.43950604, ...,   2.18261819,
         -0.51022719,   2.31354911],
       [  6.99192297,  -9.95598641,   2.95855808, ...,   4.22882114,
          2.1576573 ,   0.8379578 ],
       ...,
       [ 10.8012837 ,  -6.96025223,   5.59955453, ...,  -3.56866194,
          1.82444444,   3.53885886],
       [ -4.87210009,  12.42395362, -10.17086635, ...,   3.25330054,
          0.95484174,  -0.93895602],
       [ -0.34438963,   6.36554919,  10.77370849, ...,  -3.01636722,
          1.29752723,   2.58810313]])
```

In [20]:

```
X_train_pca, X_test_pca, y_train, y_test = train_test_split(X_pca, y, test_size=0.2, rand
```

In [21]:

```
from sklearn.linear_model import LogisticRegression

model = LogisticRegression(max_iter=1000)
model.fit(X_train_pca, y_train)
model.score(X_test_pca, y_test)
```

Out[21]:

```
0.9694444444444444
```

Let's now select only two components

In [22]:

```
pca = PCA(n_components=2)
X_pca = pca.fit_transform(X)
X_pca.shape
```

Out[22]:

```
(1797, 2)
```

In [23]:

```
X_pca
```

Out[23]:

```
array([[ -1.2594657 ,  21.27488402],
       [  7.95761275, -20.76870072],
       [  6.99192146,  -9.95598627],
       ...,
       [ 10.80128274,  -6.96025077],
       [ -4.87209806,  12.42394632],
       [ -0.34439168,   6.36555178]])
```

In [24]:

```
pca.explained_variance_ratio_
```

Out[24]:

```
array([0.14890594, 0.13618771])
```

You can see that both combined retains 0.14+0.13=0.27 or 27% of important feature information

In [25]:

```
X_train_pca, X_test_pca, y_train, y_test = train_test_split(X_pca, y, test_size=0.2, rand

model = LogisticRegression(max_iter=1000)
model.fit(X_train_pca, y_train)
model.score(X_test_pca, y_test)
```

Out[25]:

```
0.6083333333333333
```

We get less accuancy (~60%) as using only 2 components did not retain much of the feature information. However in real life you will find many cases where using 2 or few PCA components can still give you a pretty good accuracy