Handwritten Digit Recognition using SVM

This example is about Handwritten Digit recognition using SVM. You'll use a dataset with 1797 observations, each of which is an image of one handwritten digit. Each image has 64 px, with a width of 8 px and a height of 8 px.

The inputs ($\mathbf{x}$) are vectors with 64 dimensions or values. Each input vector describes one image. Each of the 64 values represents one pixel of the image. The input values are the integers between 0 and 16, depending on the shade of gray for the corresponding pixel. The output (y) for each observation is an integer between 0 and 9, consistent with the digit on the image. There are ten classes in total, each corresponding to one image.

In [1]:
```
#Importing the dataset
from sklearn.datasets import load_digits
digits = load_digits()
```

In [2]:
```
print(digits.keys())
```

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

In [3]:
```
print(digits.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 (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. Garris, 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 dimensionalityreduction 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.
```

In [4]:
```
print(type(digits.data))
```

```
<class 'numpy.ndarray'>
```

In [5]:
```
print(digits.data.shape)
```
```
(1797, 64)
```

In [6]:
```
print(digits.target.shape)
```
```
(1797,)
```

In [7]:
```
print(type(digits.data[0]))
print(digits.data[0].shape)
print(digits.data[0])
```
```
<class 'numpy.ndarray'>
(64,)
[ 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 [8]:
```
print(type(digits.images))
```
```
<class 'numpy.ndarray'>
```

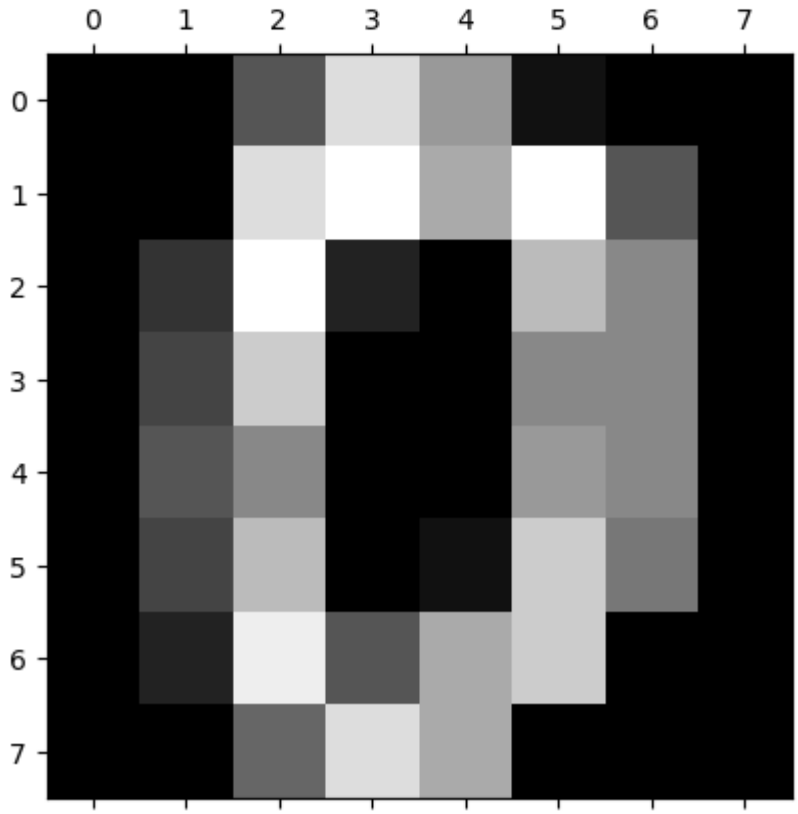
In [9]:
```
print(digits.images[0].shape)
```
```
(8, 8)
```

In [10]:
```
print(digits.images[0])
```
```
[[ 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 [11]:
```
import matplotlib.pyplot as plt
plt.gray()
plt.matshow(digits.images[0])
```

Out[11]:
```
<matplotlib.image.AxesImage at 0x23983901370>

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



In [12]:
```
print(digits.target_names)
```

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

In [13]:
```
digits.data
```

Out[13]:
```
array([[ 0.,  0.,  5., ...,  0.,  0.,  0.],
       [ 0.,  0.,  0., ..., 10.,  0.,  0.],
       [ 0.,  0.,  0., ..., 16.,  9.,  0.],
       ...,
       [ 0.,  0.,  1., ...,  6.,  0.,  0.],
       [ 0.,  0.,  2., ..., 12.,  0.,  0.],
       [ 0.,  0., 10., ..., 12.,  1.,  0.]])
```

In [14]:
```
print(digits.target)
```

```
[0 1 2 ... 8 9 8]
```

In [15]:
```
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(digits.data, digits.target
```

In [16]:
```
print(X_train.shape, y_train.shape, X_test.shape, y_test.shape)
```

```
(1347, 64) (1347,) (450, 64) (450,)
```

In [17]:
```
# Train a SVM classification model
from sklearn.svm import SVC
classifier=SVC(kernel='linear', random_state=0)
classifier.fit(X_train,y_train)
```

Out[17]:
```
SVC(kernel='linear', random_state=0)
```

In [18]:
```
#help(SVC)
```

In [19]:
```
y_pred= classifier.predict(X_test)
```

In [20]:
```
print(y_pred)
```

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

In [21]:
```
print(y_test)
```

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

In [22]:
```
for i in range(len(y_test)):
    if (y_test[i] != y_pred[i]):
        print(i, y_test[i], y_pred[i])
```

```
109 7 4
118 6 1
124 8 1
130 9 5
181 5 9
196 8 1
211 9 3
331 1 8
335 8 2
378 3 8
398 8 1
429 9 8
430 3 9
```

In [23]:
```
print("classes", classifier.classes_)
```

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

In [24]:
```
print(classifier.support_vectors_)
```

```
[[ 0.  0.  2. ...  6.  0.  0.]
 [ 0.  0.  0. ...  8.  0.  0.]
 [ 0.  0. 10. ... 10.  0.  0.]
 ...
 [ 0.  0.  0. ...  7.  0.  0.]
 [ 0.  0.  9. ... 13.  3.  0.]
 [ 0.  0.  7. ...  5.  0.  0.]]
```

In [25]:
```
print(len(classifier.support_vectors_))
```

```
385
```

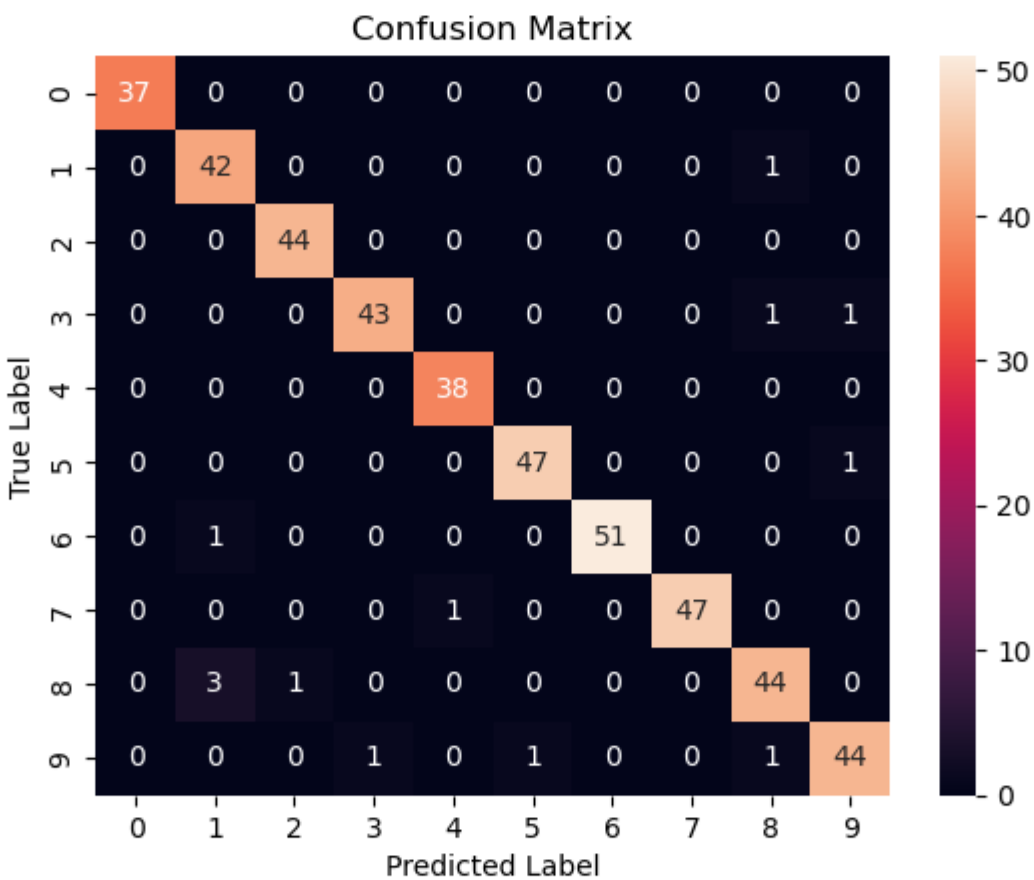
In [26]:
```
#Making the Confusion Matrix
from sklearn.metrics import confusion_matrix
cm = confusion_matrix(y_test, y_pred)
```

In [27]:
```
print ("Confusion Matrix : \n", cm)
```

```
Confusion Matrix :
 [[37  0  0  0  0  0  0  0  0  0]
 [ 0 42  0  0  0  0  0  0  1  0]
 [ 0  0 44  0  0  0  0  0  0  0]
 [ 0  0  0 43  0  0  0  0  1  1]
 [ 0  0  0  0 38  0  0  0  0  0]
 [ 0  0  0  0  0 47  0  0  0  1]
 [ 0  1  0  0  0  0 51  0  0  0]
 [ 0  0  0  0  1  0  0 47  0  0]
 [ 0  3  1  0  0  0  0  0 44  0]
 [ 0  0  0  1  0  1  0  0  1 44]]
```

In [28]:
```python
#It’s often useful to visualize the confusion matrix using Heatmap.
import seaborn as sn
sn.heatmap(cm, annot=True)
plt.ylabel('True Label')
plt.xlabel('Predicted Label')
plt.title('Confusion Matrix')
```

Out[28]:
```
Text(0.5, 1.0, 'Confusion Matrix')
```



In [29]:
```python
#Performance measure - Accuracy
from sklearn.metrics import accuracy_score
print ("Accuracy : ", accuracy_score(y_test, y_pred))
```

```
Accuracy :  0.9711111111111111
```

In [30]:
```python
classifier.score(X_test, y_test)
```

Out[30]:
```
0.9711111111111111
```

In [31]:
```
from sklearn.metrics import classification_report
print(classification_report(y_test, y_pred))
```

```
              precision    recall  f1-score   support

           0       1.00      1.00      1.00        37
           1       0.91      0.98      0.94        43
           2       0.98      1.00      0.99        44
           3       0.98      0.96      0.97        45
           4       0.97      1.00      0.99        38
           5       0.98      0.98      0.98        48
           6       1.00      0.98      0.99        52
           7       1.00      0.98      0.99        48
           8       0.94      0.92      0.93        48
           9       0.96      0.94      0.95        47

    accuracy                           0.97       450
   macro avg       0.97      0.97      0.97       450
weighted avg       0.97      0.97      0.97       450
```

In [ ]: