In [1]:

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

In [2]:

```
from sklearn import datasets
```

In [3]:

```
digits = datasets.load_digits()
```

Info about Dataset

In [6]:

```
print(digits.DESCR)
```

```
.. _digits_dataset:

Optical recognition of handwritten digits dataset
--------------------------------------------------

**Data Set Characteristics:**

    :Number of Instances: 5620
    :Number of Attributes: 64
    :Attribute Information: 8x8 image of integer pixels in the ran
ge 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 d
atasets
https://archive.ics.uci.edu/ml/datasets/Optical+Recognition+of+Han
dwritten+Digits

The data set contains images of hand-written digits: 10 classes wh
ere
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. F
rom a
total of 43 people, 30 contributed to the training set and differe
nt 13
to the test set. 32x32 bitmaps are divided into nonoverlapping blo
cks of
4x4 and the number of on pixels are counted in each block. This ge
nerates
an input matrix of 8x8 where each element is an integer in the ran
ge
0..16. This reduces dimensionality and gives invariance to small
distortions.

For info on NIST preprocessing routines, see M. D. Garris, J. L. B
lue, G.
T. Candela, D. L. Dimmick, J. Geist, P. J. Grother, S. A. Janet, a
nd C.
L. Wilson, NIST Form-Based Handprint Recognition System, NISTIR 54
69,
1994.

.. topic:: References

  - C. Kaynak (1995) Methods of Combining Multiple Classifiers and
Their
    Applications to Handwritten Digit Recognition, MSc Thesis, Ins
titute of
    Graduate Studies in Science and Engineering, Bogazici Universi
ty.
  - E. Alpaydin, C. Kaynak (1998) Cascading Classifiers, Kyberneti
```

```
ka.
  - Ken Tang and Ponnuthurai N. Suganthan and Xi Yao and A. Kai Qi
n.
    Linear dimensionalityreduction using relevance weighted LDA. S
chool of
    Electrical and Electronic Engineering Nanyang Technological Un
iversity.
    2005.
  - Claudio Gentile. A New Approximate Maximal Margin Classificati
on
    Algorithm. NIPS. 2000.
```

In [48]:

```
main_data = digits['data']
targets = digits['target']
```

In [9]:

```
len(main_data)
```

Out[9]:

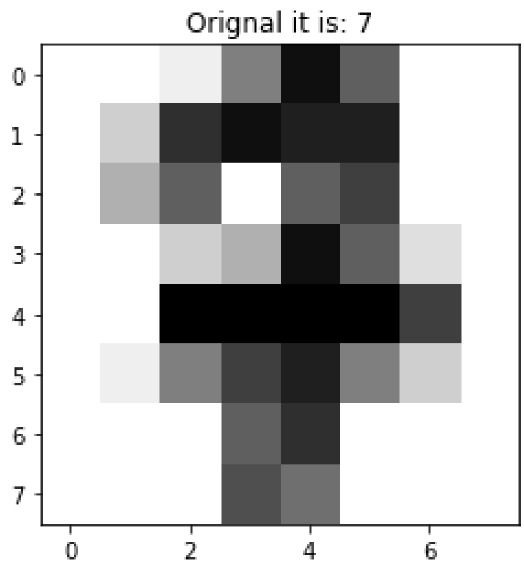
1797

In [34]:

```
def view_digit(index):
    plt.imshow(digits.images[index] , cmap = plt.cm.gray_r , interpolation = 'n
earest')
    plt.title('Orignal it is: '+ str(digits.target[index]))
    plt.show()
```

In [38]:

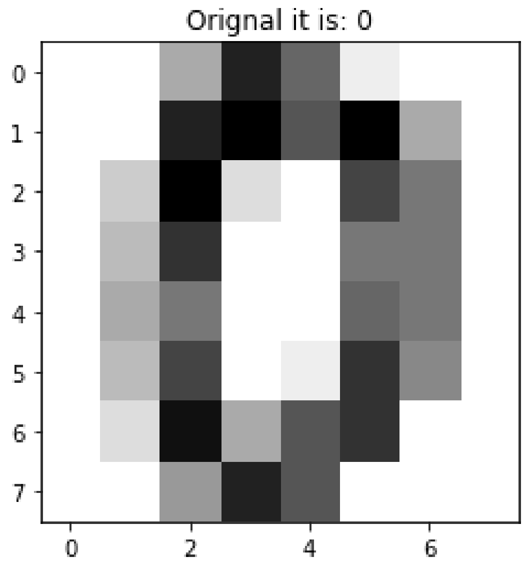
```
view_digit(17)
```



For this 1797 data we have to consider only 1791 as training dataset and last 6 data for validation dataset

In [106]:

```
number = 0
plt.imshow(main_data[number].reshape(8,8,1) , cmap = plt.cm.gray_r)
plt.title('Orignal : '+ str(digits.target[number]))
plt.show()
# we can also print images from data by reshaping
```

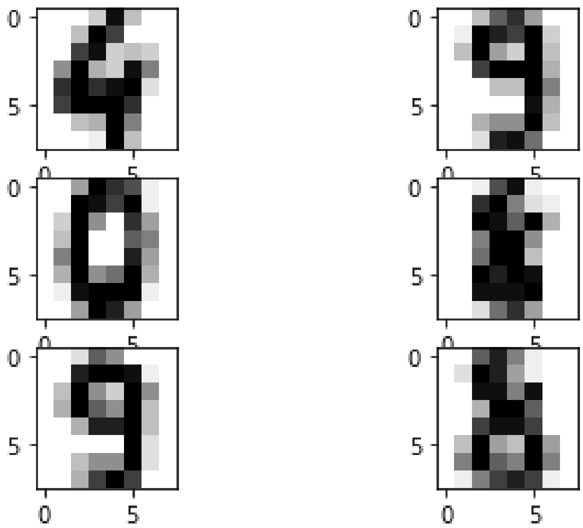


In [70]:

```
%matplotlib inline

plt.subplot(321)
plt.imshow(digits.images[1791], cmap=plt.cm.gray_r,
interpolation='nearest')

plt.subplot(322)
plt.imshow(digits.images[1792], cmap=plt.cm.gray_r,
interpolation='nearest')

plt.subplot(323)
plt.imshow(digits.images[1793], cmap=plt.cm.gray_r,
interpolation='nearest')

plt.subplot(324)
plt.imshow(digits.images[1794], cmap=plt.cm.gray_r,
interpolation='nearest')

plt.subplot(325)
plt.imshow(digits.images[1795], cmap=plt.cm.gray_r,
interpolation='nearest')

plt.subplot(326)
plt.imshow(digits.images[1796], cmap=plt.cm.gray_r,
interpolation='nearest')
```

Out[70]:

```
<matplotlib.image.AxesImage at 0x1fe8ee88fa0>
```



Support Vector Classifier

In [46]:

```
from sklearn import svm
svc = svm.SVC(gamma=0.001 , C = 100.)
```

In [49]:

```
svc.fit(main_data[:1790] , targets[:1790])
```

Out[49]:

```
SVC(C=100.0, gamma=0.001)
```

In [50]:

```
predictions = svc.predict(main_data[1791:])
```

In [52]:

```
predictions , targets[1791:]
```

Out[52]:

```
(array([4, 9, 0, 8, 9, 8]), array([4, 9, 0, 8, 9, 8]))
```

From SVC we get 100% accuracy
Training Data : 1790
Test Data : 6

Decision Tree Classifier

In [53]:

```
from sklearn.tree import DecisionTreeClassifier
```

In [65]:

```
dt = DecisionTreeClassifier(criterion = 'gini')
```

In [66]:

```
dt.fit(main_data[:1600] , targets[:1600]) # this time we only use 1600 as train and 197 as test
```

Out[66]:

```
DecisionTreeClassifier()
```

In [67]:

```
predictions2 = dt.predict(main_data[1601:])
```

In [71]:

```
from sklearn.metrics import accuracy_score
```

In [69]:

```
confusion_matrix(targets[1601:] , predictions2) # as you can we have some wrong
predictions
```

Out[69]:

```
array([[17,  0,  0,  0,  0,  0,  0,  0,  0,  0],
       [ 0, 17,  0,  0,  1,  0,  0,  0,  2,  0],
       [ 0,  0, 13,  1,  0,  1,  0,  1,  1,  0],
       [ 0,  2,  2,  9,  0,  3,  2,  4,  0,  0],
       [ 0,  0,  0,  0, 18,  0,  1,  2,  0,  1],
       [ 0,  0,  0,  1,  2, 15,  0,  0,  1,  0],
       [ 0,  0,  0,  1,  2,  0, 19,  0,  0,  0],
       [ 0,  0,  0,  2,  1,  0,  0, 17,  0,  0],
       [ 0,  2,  1,  0,  0,  0,  0,  1, 13,  0],
       [ 0,  1,  0,  0,  0,  0,  0,  2,  1, 16]], dtype=int64)
```

In [72]:

```
accuracy_score(targets[1601:] , predictions2)
```

Out[72]:

```
0.7857142857142857
```

From Decision Tree Classifier we get 78 % Accuracy
Training Data : 1600
Test_data : 197

Random Forest Classifier

In [74]:

```
from sklearn.ensemble import RandomForestClassifier
```

In [100]:

```
rc = RandomForestClassifier(n_estimators = 150)
```

In [101]:

```
rc.fit(main_data[:1500] , targets[:1500])
```

Out[101]:

```
RandomForestClassifier(n_estimators=150)
```

In [102]:

```
predictions3 = rc.predict(main_data[1501:])
```

In [103]:

```
accuracy_score(targets[1501:] , predictions3)
```

Out[103]:

```
0.9222972972972973
```

From Random Forest Classifier we get high accuracy for n_estimators = 150
Training data : 1500
Test Data : 297

Conclusion

Data maters the most we need a good amount of data for modal.if we have a less data then we can use some other machine learning classifier algorithms like random forest which is also give 92 % accuracy on 1500 trainset which is less data compare to Support vector classifier

In [ ]:

```

```