15B-Classification-II-Demo

November 1, 2016

1 Classification in Practice

Today we'll look at two classification methods in practice:

- Decision Trees, and
- k-Nearest Neighbors.

1.1 k- Nearest Neighbors

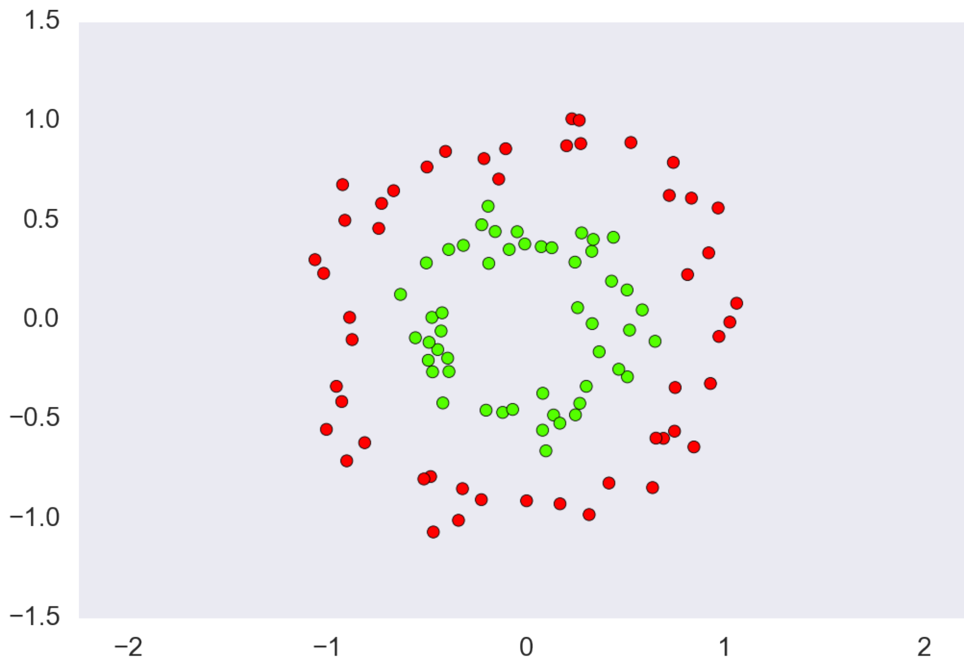
First we'll generate some synthetic data to work with.

```
In [209]: X, y = datasets.make_circles(noise=.1, factor=.5, random_state=1)
          print('Shape of data: {}'.format(X.shape))
          print('Unique labels: {}'.format(np.unique(y)))
```

```
Shape of data: (100, 2)
Unique labels: [0 1]
```

Here is what the data looks like:

```
In [210]: plt.prism()  # this sets a nice color map
          plt.scatter(X[:, 0], X[:, 1], c=y)
          _ = plt.axis('equal')
```



Recall that we always want to test on data separate from our training data. So we will take the first 50 examples for training and the rest for testing.

```
In [211]: X_train = X[:50]
          y_train = y[:50]
          X_test = X[50:]
          y_test = y[50:]
```

```
In [212]: plt.subplot(121)
          plt.scatter(X_train[:, 0], X_train[:, 1], c=y_train, )
          plt.axis('equal')
          plt.title('Training Data')
          plt.subplot(122)
          plt.scatter(X_test[:, 0], X_test[:, 1], c=y_test)
          plt.title('Test Data')
          _=plt.axis('equal')
```

For our first example, we will classify the points (in the two classes) using a k-nn classifier.

We will specify that $k = 5$, i.e., we will classify based on the majority vote of the 5 nearest neighbors.

```
In [213]: k = 5
          knn = KNeighborsClassifier(n_neighbors=k)
```

In the context of supervised learning, the `scikit-learn fit()` function corresponds to **training** and the `predict()` function corresponds to **testing.**

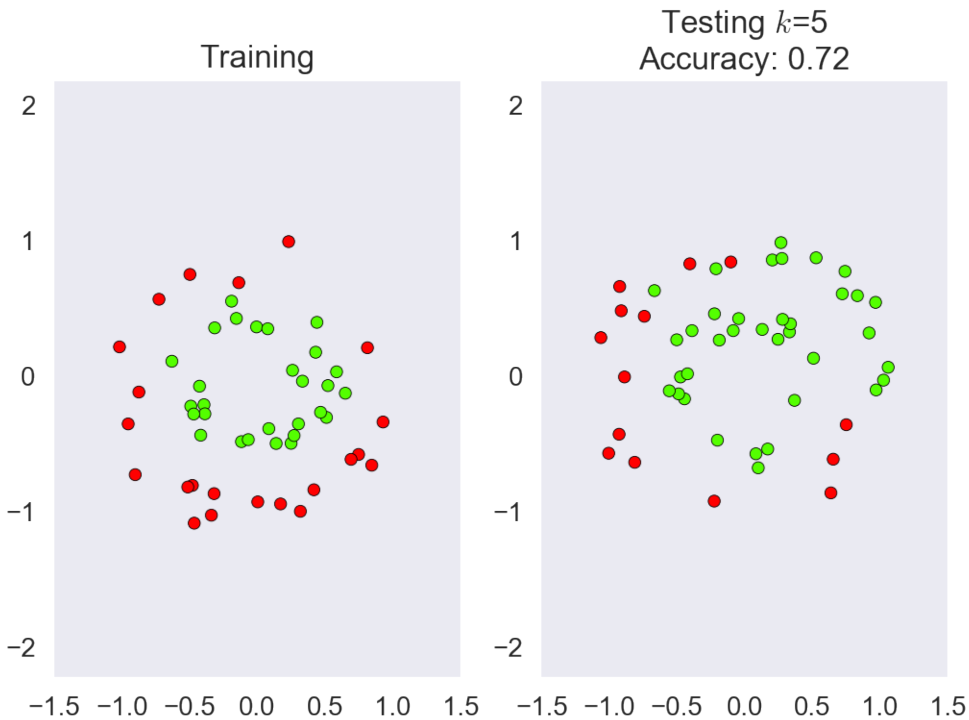
```
In [214]: knn.fit(X_train,y_train)
          y_pred_test = knn.predict(X_test)
          print('Accuracy on test data: {}'.format(knn.score(X_test, y_test)))

Accuracy on test data: 0.72
```

Just for kicks we can see how the classifier does on the training data, although that's not as important as the test data.

```
In [215]: y_pred_train = knn.predict(X_train)
          print('Accuracy on training data: {}'.format(knn.score(X_train, y_train))

Accuracy on training data: 0.94
```

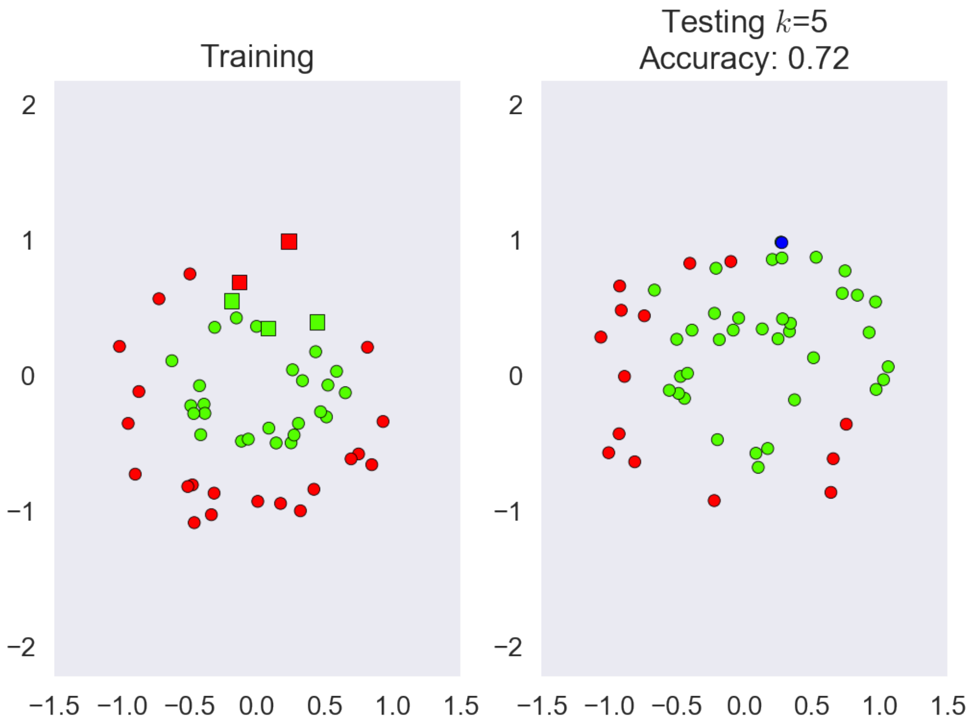
Now let's visualize the results.

In [216]:
```
plt.subplot(121)
plt.scatter(X_train[:, 0], X_train[:, 1], c=y_train)
plt.axis('equal')
plt.title('Training')
plt.subplot(122)
plt.scatter(X_test[:, 0], X_test[:, 1], c=y_pred_test)
plt.title('Testing $k$={}\nAccuracy: {}'.format(k,knn.score(X_test, y_tes
_=plt.axis('equal')
```



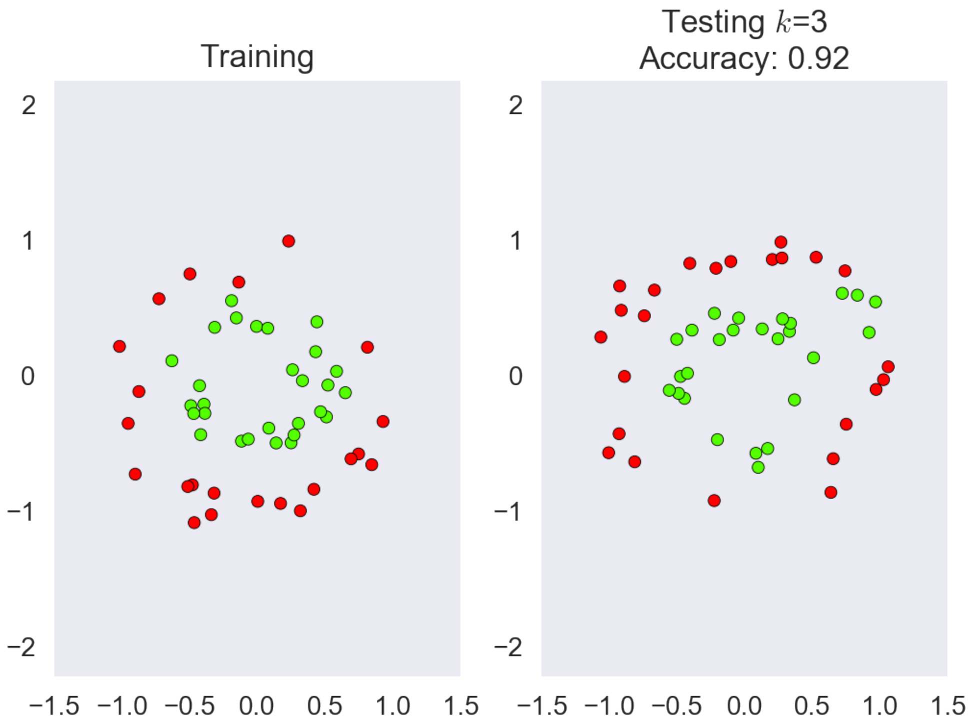
Let's look at one of the points that the classifier got wrong:

In [217]:
```
test_point = np.argmax(X_test[:,1])
X_test[test_point]
neighbors = knn.kneighbors([X_test[test_point]])[1]
plt.subplot(121)
plt.scatter(X_train[:, 0], X_train[:, 1], c=y_train,)
plt.scatter(X_train[neighbors,0], X_train[neighbors,1], c = y_train[neigh
plt.axis('equal')
plt.title(r'Training')
plt.subplot(122)
plt.scatter(X_test[:, 0], X_test[:, 1], c=y_pred_test)
plt.scatter(X_test[test_point,0], X_test[test_point,1], c='b')
plt.title('Testing $k$={}\nAccuracy: {}'.format(k,knn.score(X_test, y_tes
_=plt.axis('equal')
```



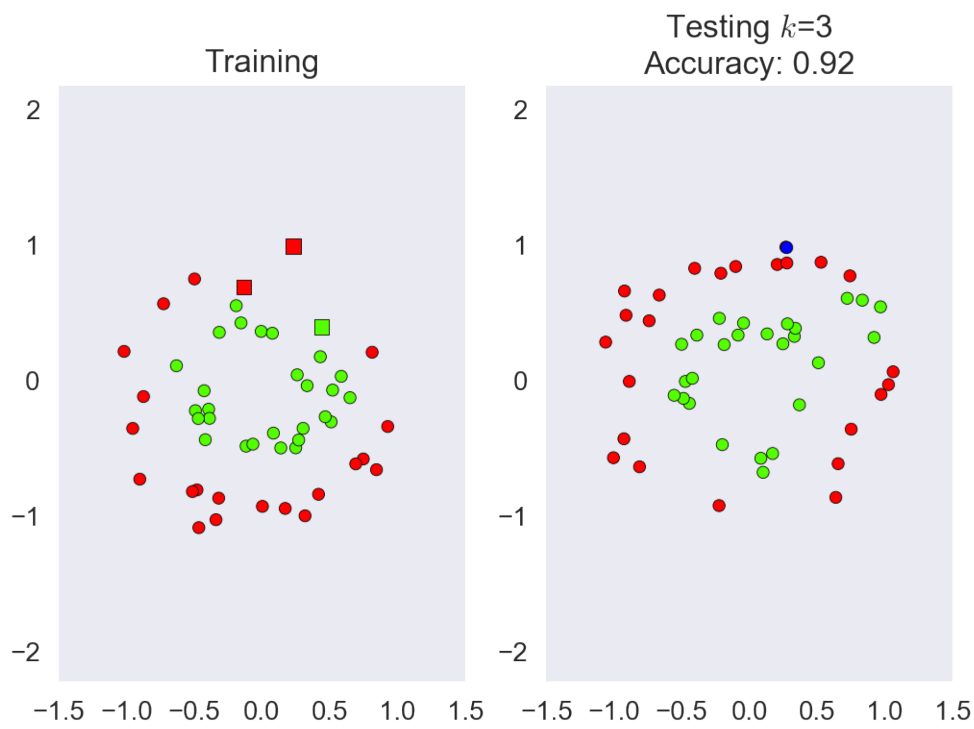
For comparison purposes, let's try $k = 3$.

```
In [218]: k = 3
          knn = KNeighborsClassifier(n_neighbors=k)
          knn.fit(X_train,y_train)
          y_pred_test = knn.predict(X_test)
          plt.subplot(121)
          plt.scatter(X_train[:, 0], X_train[:, 1], c=y_train, )
          plt.axis('equal')
          plt.title(r'Training')
          plt.subplot(122)
          plt.scatter(X_test[:, 0], X_test[:, 1], c=y_pred_test)
          plt.title('Testing $k$={}\nAccuracy: {}'.format(k,knn.score(X_test, y_tes
          _=plt.axis('equal')
```



And let's look at the same individual point as before:

```
In [219]: test_point = np.argmax(X_test[:,1])
          X_test[test_point]
          neighbors = knn.kneighbors([X_test[test_point]])[1]
          plt.subplot(121)
          plt.scatter(X_train[:, 0], X_train[:, 1], c=y_train,)
          plt.scatter(X_train[neighbors,0], X_train[neighbors,1], c = y_train[neigh
          plt.axis('equal')
          plt.title(r'Training')
          plt.subplot(122)
          plt.scatter(X_test[:, 0], X_test[:, 1], c=y_pred_test)
          plt.scatter(X_test[test_point,0], X_test[test_point,1], c='b')
          plt.title('Testing $k$={}\nAccuracy: {}'.format(k,knn.score(X_test, y_tes
          _=plt.axis('equal')
```



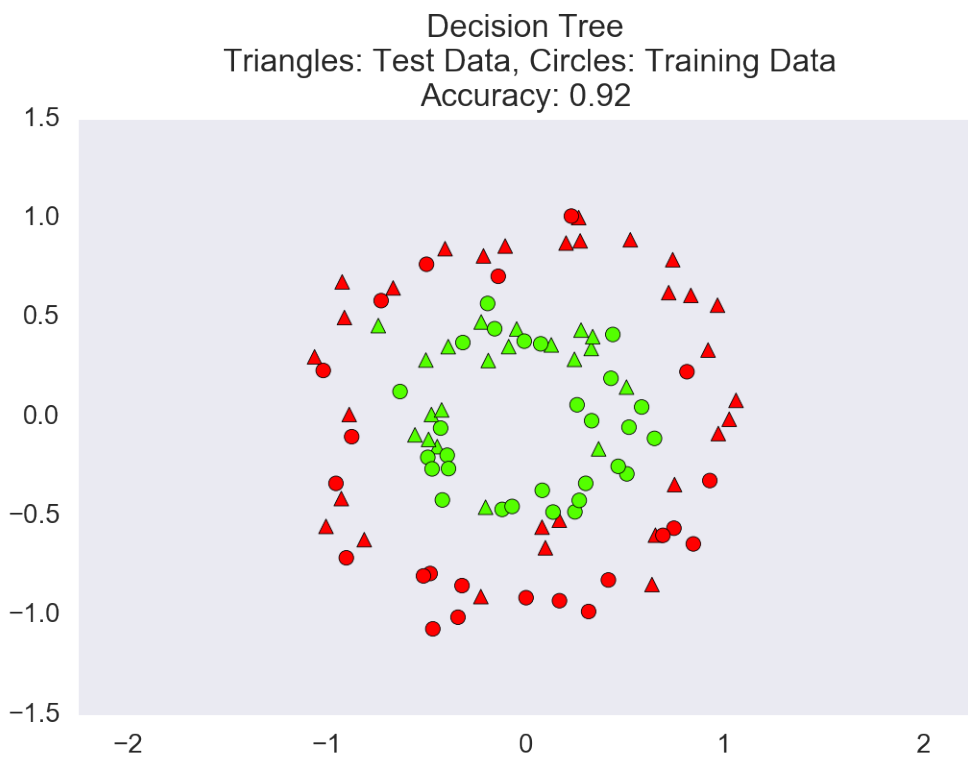
1.2 Decision Tree

Next, we'll use a decision tree on the same data set.

In [220]:
```
dtc = tree.DecisionTreeClassifier()

dtc.fit(X_train,y_train)
y_pred_test = dtc.predict(X_test)
print('DT accuracy on test data: ', dtc.score(X_test, y_test))
y_pred_train = dtc.predict(X_train)
print('DT accuracy on training data: ', dtc.score(X_train, y_train))
```

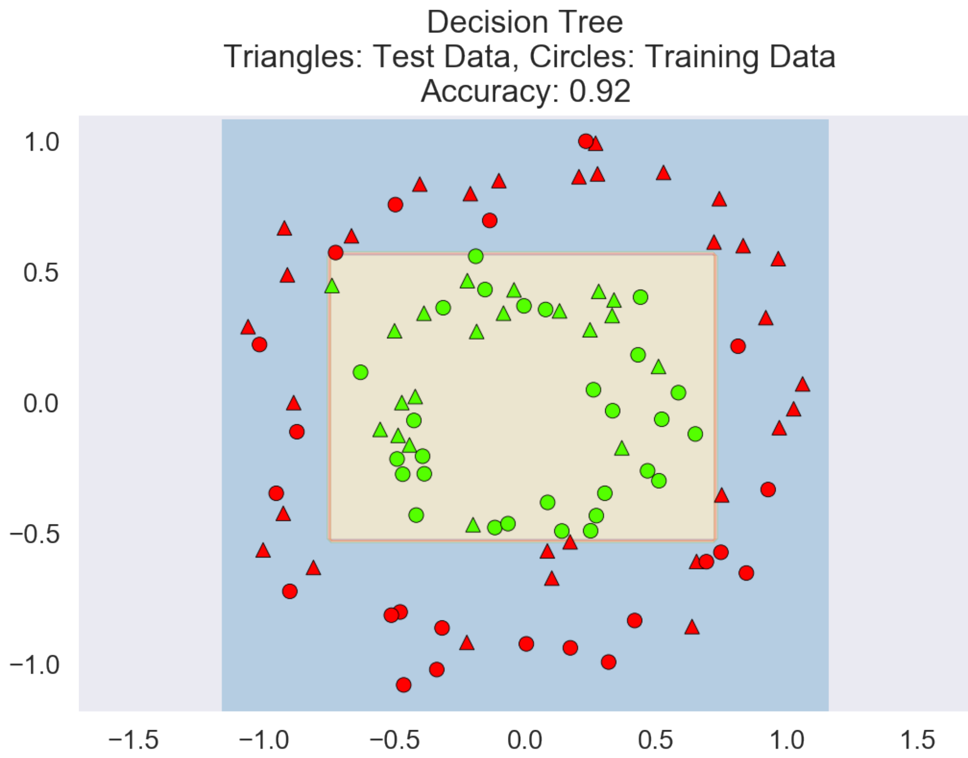
```
DT accuracy on test data:  0.92
DT accuracy on training data:  1.0
```

In [221]:
```
plt.scatter(X_test[:, 0], X_test[:, 1], c=y_pred_test, marker='^',s=30)
plt.scatter(X_train[:, 0], X_train[:, 1], c=y_train, s=30)
plt.axis('equal')
_=plt.title('Decision Tree\n Triangles: Test Data, Circles: Training Data
```



Let's visualize the **decision boundary** of the Decision Tree.

```
In [222]: x_min, x_max = X[:, 0].min() - .1, X[:, 0].max() + .1
          y_min, y_max = X[:, 1].min() - .1, X[:, 1].max() + .1
          plot_step = 0.02
          xx, yy = np.meshgrid(np.arange(x_min, x_max, plot_step),
                               np.arange(y_min, y_max, plot_step))
          Z = dtc.predict(np.c_[xx.ravel(), yy.ravel()])
          Z = Z.reshape(xx.shape)
          cs = plt.contourf(xx, yy, Z, cmap=plt.cm.Paired,alpha=0.3)
          plt.scatter(X_test[:, 0], X_test[:, 1], c=y_pred_test, marker='^',s=30)
          plt.scatter(X_train[:, 0], X_train[:, 1], c=y_train, s=30)
          plt.axis('equal')
          plt.xlim((x_min, x_max))
          plt.ylim((y_min, y_max))
          _=plt.title('Decision Tree\n Triangles: Test Data, Circles: Training Data
```

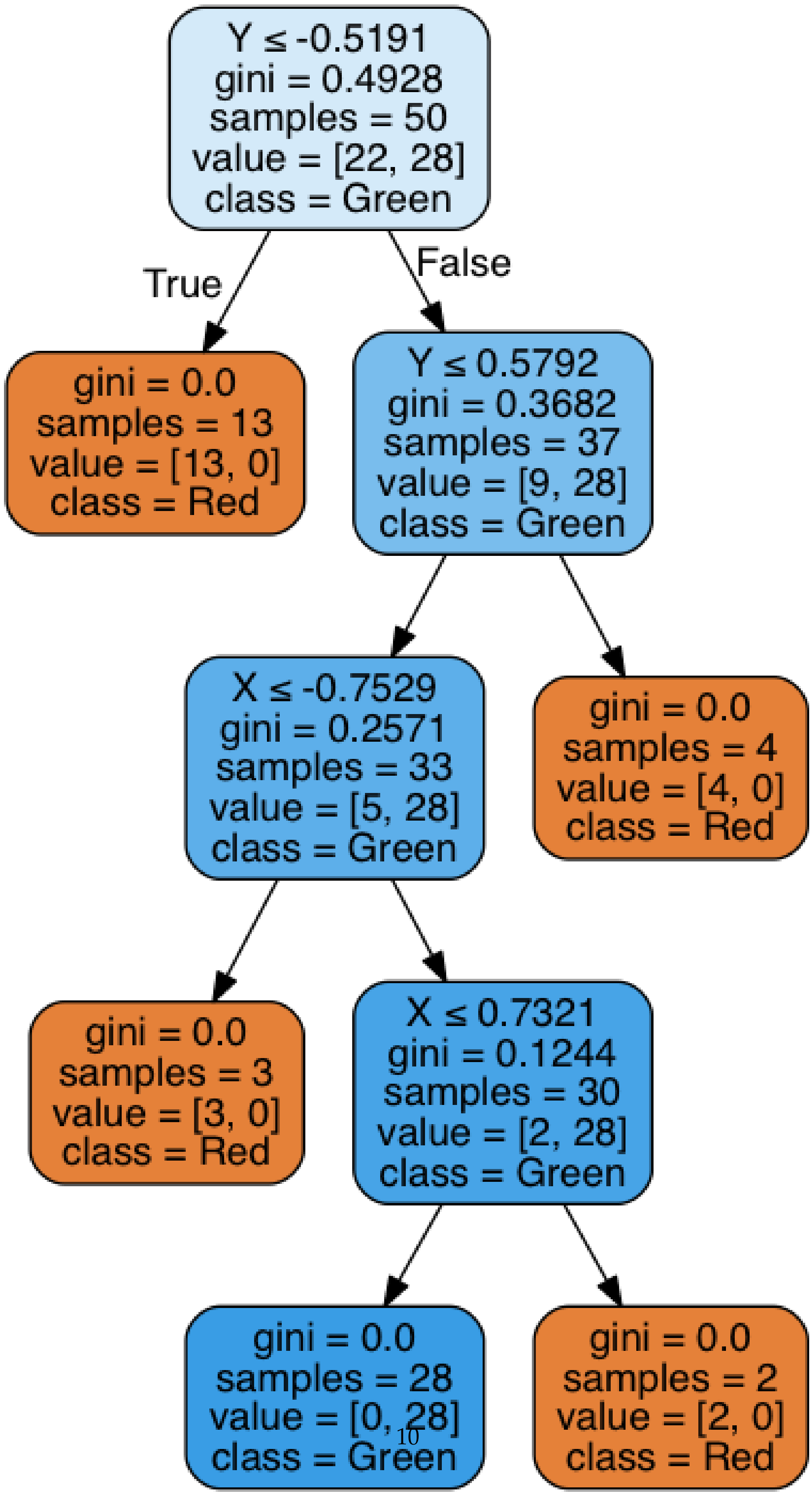


One of the big benefits of a Decision Tree is that we can 'inspect' its process. It is a 'white box' – its decision rule can be interpreted by the user.

Let's do that:

```
In [223]: dot_data = tree.export_graphviz(dtc, out_file=None,
                                          feature_names=['X','Y'],
                                          class_names=['Red','Green'],
                                          filled=True, rounded=True,
                                          special_characters=True)
          import pydotplus
          graph = pydotplus.graph_from_dot_data(dot_data)
          # graph.write_pdf("dt.pdf")
          Image(graph.create_png())
```

Out[223]:


Y ≤ -0.5191
gini = 0.4928
samples = 50
value = [22, 28]
class = Green
True
False
gini = 0.0
samples = 13
value = [13, 0]
class = Red
Y ≤ 0.5792
gini = 0.3682
samples = 37
value = [9, 28]
class = Green
X ≤ -0.7529
gini = 0.2571
samples = 33
value = [5, 28]
class = Green
gini = 0.0
samples = 4
value = [4, 0]
class = Red
gini = 0.0
samples = 3
value = [3, 0]
class = Red
X ≤ 0.7321
gini = 0.1244
samples = 30
value = [2, 28]
class = Green
gini = 0.0
samples = 28
value = [0, 28]
class = Green
gini = 0.0
samples = 2
value = [2, 0]
class = Red

1.3 "Real" data: the IRIS dataset

This is a famous dataset used by Ronald Fisher in a classic 1936 paper on classification. https://archive.ics.uci.edu/ml/datasets/Iris

By http://www.swlearning.com/quant/kohler/stat/biographical_sketches/Fisher_3.jpeg, Public Domain, https://commons.wikimedia.org/w/index.php?curid=4233489

Quoting from Wikipedia:

> The data set consists of 50 samples from each of three species of Iris (Iris setosa, Iris virginica and Iris versicolor). Four features were measured from each sample: the length and the width of the sepals and petals, in centimetres. Based on the combination of these four features, Fisher developed a linear discriminant model to distinguish the species from each other.

```
In [225]: iris = datasets.load_iris()
```

```
In [226]: X = iris.data
          y = iris.target
```

```
ynames = iris.target_names
print(X.shape, y.shape)
print(X[1,:])
print(iris.target_names)
print(y)
```

```
(150, 4) (150,)
[ 4.9  3.   1.4  0.2]
['setosa' 'versicolor' 'virginica']
[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 0
 0 0 0 0 0 0 0 0 0 0 0 0 0 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 2 2 2 2 2 2 2 2 2 2 2
 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2
 2 2]
```

Next we split the data into training and testing:

```
In [227]: X, y = utils.shuffle(X, y, random_state=1)
          y
```

```
Out[227]: array([0, 1, 1, 0, 2, 1, 2, 0, 0, 2, 1, 0, 2, 1, 1, 0, 1, 1, 0, 0, 1, 1,
                 0, 2, 1, 0, 0, 1, 2, 1, 2, 1, 2, 2, 0, 1, 0, 1, 2, 2, 0, 2, 2, 1,
                 0, 0, 0, 1, 0, 0, 2, 2, 2, 2, 2, 1, 2, 1, 0, 2, 2, 0, 0, 2, 0, 2,
                 1, 1, 2, 2, 0, 1, 1, 2, 1, 2, 1, 0, 0, 0, 2, 0, 1, 2, 2, 0, 0, 1,
                 2, 1, 2, 2, 1, 2, 2, 1, 0, 1, 0, 1, 1, 0, 1, 0, 0, 2, 2, 2, 0, 0,
                 0, 2, 0, 2, 2, 0, 2, 0, 1, 0, 1, 1, 0, 0, 1, 0, 1, 1, 0, 1, 1, 1,
                 2, 0, 0, 2, 1, 2, 1, 2, 2, 1, 2, 0])
```

```
In [228]: train_set_size = 100
          X_train = X[:train_set_size]  # selects first 100 rows (examples) for tra
          y_train = y[:train_set_size]
          X_test = X[train_set_size:]   # selects from row 100 until the last one f
          y_test = y[train_set_size:]
          print(X_train.shape), y_train.shape
          print(X_test.shape), y_test.shape
```

```
(100, 4)
(50, 4)
```

```
Out[228]: (None, (50,))
```

Classifying using k-nearest neighbors, with $k = 5$:

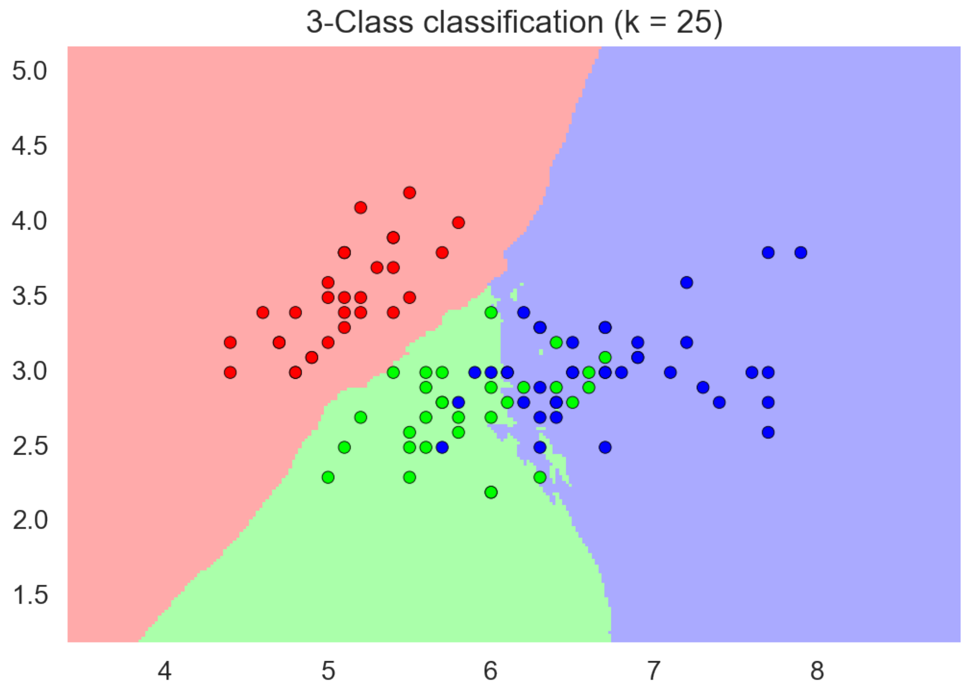
```
In [229]: k = 5
          knn = KNeighborsClassifier(n_neighbors=k)
```

```
In [230]: knn.fit(X_train, y_train)
          y_pred_test = knn.predict(X_test)
          print("Accuracy of KNN test set:", knn.score(X_test, y_test))
```

```
Accuracy of KNN test set: 0.94
```

Again, to gain insight, let's look at the decision boundary.
Note that we will re-run the classifier using only two (of four) features, so we can visualize.

```
In [231]: # Create color maps
          from matplotlib.colors import ListedColormap
          cmap_light = ListedColormap(['#FFAAAA', '#AAFFAA', '#AAAAFF'])
          cmap_bold = ListedColormap(['#FF0000', '#00FF00', '#0000FF'])

          # we will use only the first two (of four) features, so we can visualize
          X = X_train[:, :2]
          h = .02  # step size in the mesh
          k = 25
          knn = KNeighborsClassifier(n_neighbors=k)
          knn.fit(X, y_train)
          # Plot the decision boundary. For that, we will assign a color to each
          # point in the mesh [x_min, x_max]x[y_min, y_max].
          x_min, x_max = X[:, 0].min() - 1, X[:, 0].max() + 1
          y_min, y_max = X[:, 1].min() - 1, X[:, 1].max() + 1
          xx, yy = np.meshgrid(np.arange(x_min, x_max, h),
                               np.arange(y_min, y_max, h))
          Z = knn.predict(np.c_[xx.ravel(), yy.ravel()])

          # Put the result into a color plot
          Z = Z.reshape(xx.shape)
          plt.figure()
          plt.pcolormesh(xx, yy, Z, cmap=cmap_light)

          # Plot also the training points
          plt.scatter(X[:, 0], X[:, 1], c=y_train, cmap=cmap_bold)
          plt.xlim(xx.min(), xx.max())
          plt.ylim(yy.min(), yy.max())
          _ = plt.title("3-Class classification (k = {})".format(k))
```



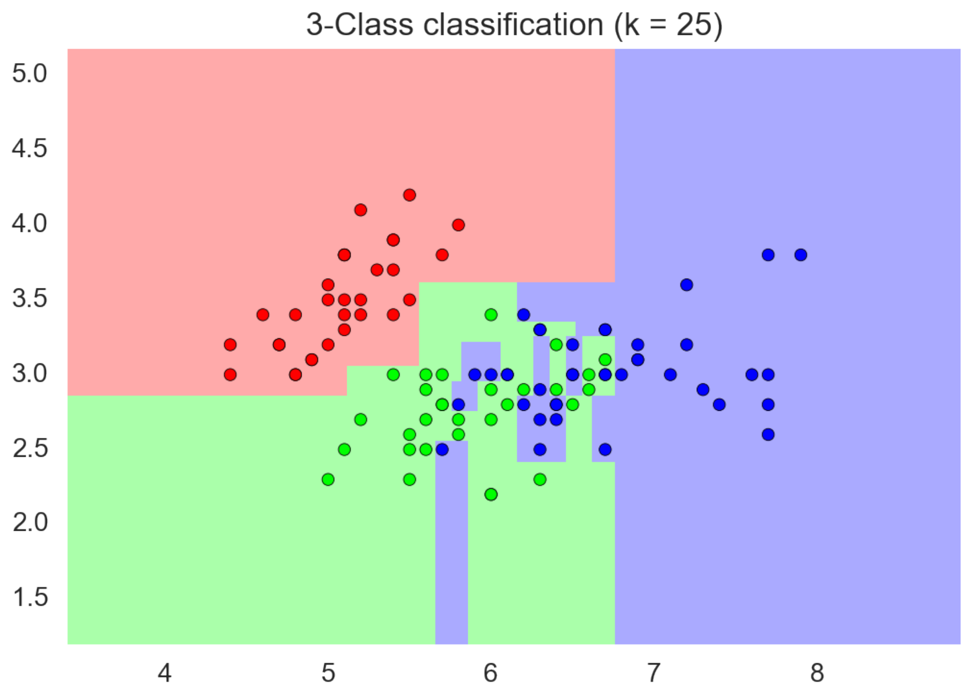

```
In [232]: dtc = tree.DecisionTreeClassifier()
          dtc.fit(X_train,y_train)
          y_pred_test = dtc.predict(X_test)
          print("Accuracy of DTC test set:", dtc.score(X_test, y_test))
```

```
Accuracy of DTC test set: 0.9
```

And now let's visualize the decision boundary for the DT:

```
In [233]: # we will use only the first two (of four) features, so we can visualize
          X = X_train[:, :2]
          h = .02  # step size in the mesh
          dtc.fit(X, y_train)
          # Plot the decision boundary. For that, we will assign a color to each
          # point in the mesh [x_min, x_max]x[y_min, y_max].
          x_min, x_max = X[:, 0].min() - 1, X[:, 0].max() + 1
          y_min, y_max = X[:, 1].min() - 1, X[:, 1].max() + 1
          xx, yy = np.meshgrid(np.arange(x_min, x_max, h),
                               np.arange(y_min, y_max, h))
          Z = dtc.predict(np.c_[xx.ravel(), yy.ravel()])

          # Put the result into a color plot
          Z = Z.reshape(xx.shape)
          plt.figure()
```

```
plt.pcolormesh(xx, yy, Z, cmap=cmap_light)

# Plot also the training points
plt.scatter(X[:, 0], X[:, 1], c=y_train, cmap=cmap_bold)
plt.xlim(xx.min(), xx.max())
plt.ylim(yy.min(), yy.max())
_ = plt.title("3-Class classification (k = {})".format(k))
```



1.4 "Really Real" Data: MNIST dataset

http://yann.lecun.com/exdb/mnist/

NIST used to be called the "National Bureau of Standards." These are the folks who bring you the reference meter, reference kilogram, etc.

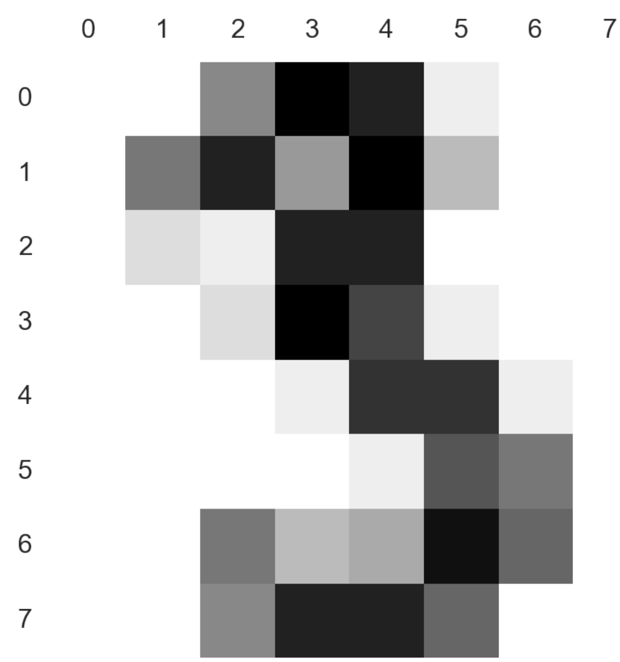
NIST constructed datasets for machine learning of handwritten digits. These were collected from Census Bureau employees and also from high-school students.

```
In [234]: digits = datasets.load_digits()
          X_digits, y_digits = digits.data, digits.target

          print ('Data shape: {}'.format(X_digits.shape))
          print ('Data labels: {}'.format(y_digits))
          print ('Unique labels: {}'.format(digits.target_names))
          X_digits, y_digits = utils.shuffle(X_digits, y_digits, random_state=1)
```

```
Data shape: (1797, 64)
Data labels: [0 1 2 ..., 8 9 8]
Unique labels: [0 1 2 3 4 5 6 7 8 9]
```

```
In [235]: digits.images[3]

Out[235]: array([[  0.,   0.,   7.,  15.,  13.,   1.,   0.,   0.],
                 [  0.,   8.,  13.,   6.,  15.,   4.,   0.,   0.],
                 [  0.,   2.,   1.,  13.,  13.,   0.,   0.,   0.],
                 [  0.,   0.,   2.,  15.,  11.,   1.,   0.,   0.],
                 [  0.,   0.,   0.,   1.,  12.,  12.,   1.,   0.],
                 [  0.,   0.,   0.,   0.,   1.,  10.,   8.,   0.],
                 [  0.,   0.,   8.,   4.,   5.,  14.,   9.,   0.],
                 [  0.,   0.,   7.,  13.,  13.,   9.,   0.,   0.]])
```

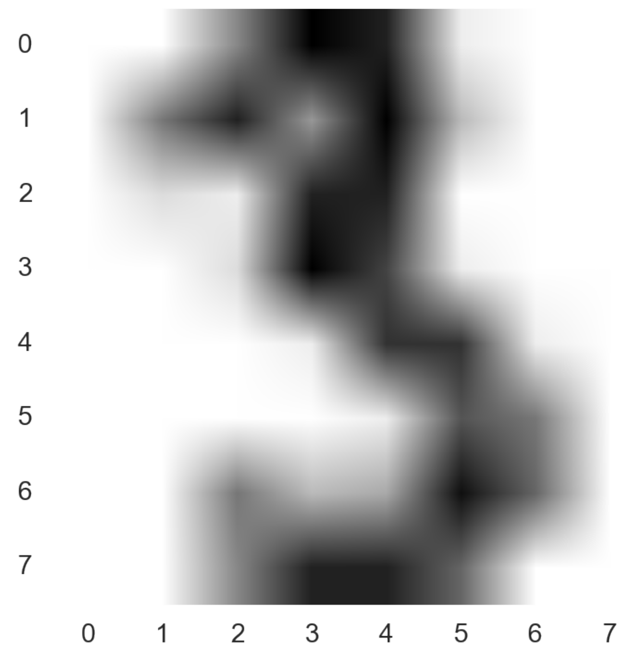
```
In [236]: plt.gray()
          plt.rc('axes', grid=False)
          _=plt.matshow(digits.images[3],cmap=plt.cm.gray_r)

<matplotlib.figure.Figure at 0x1178e13c8>
```



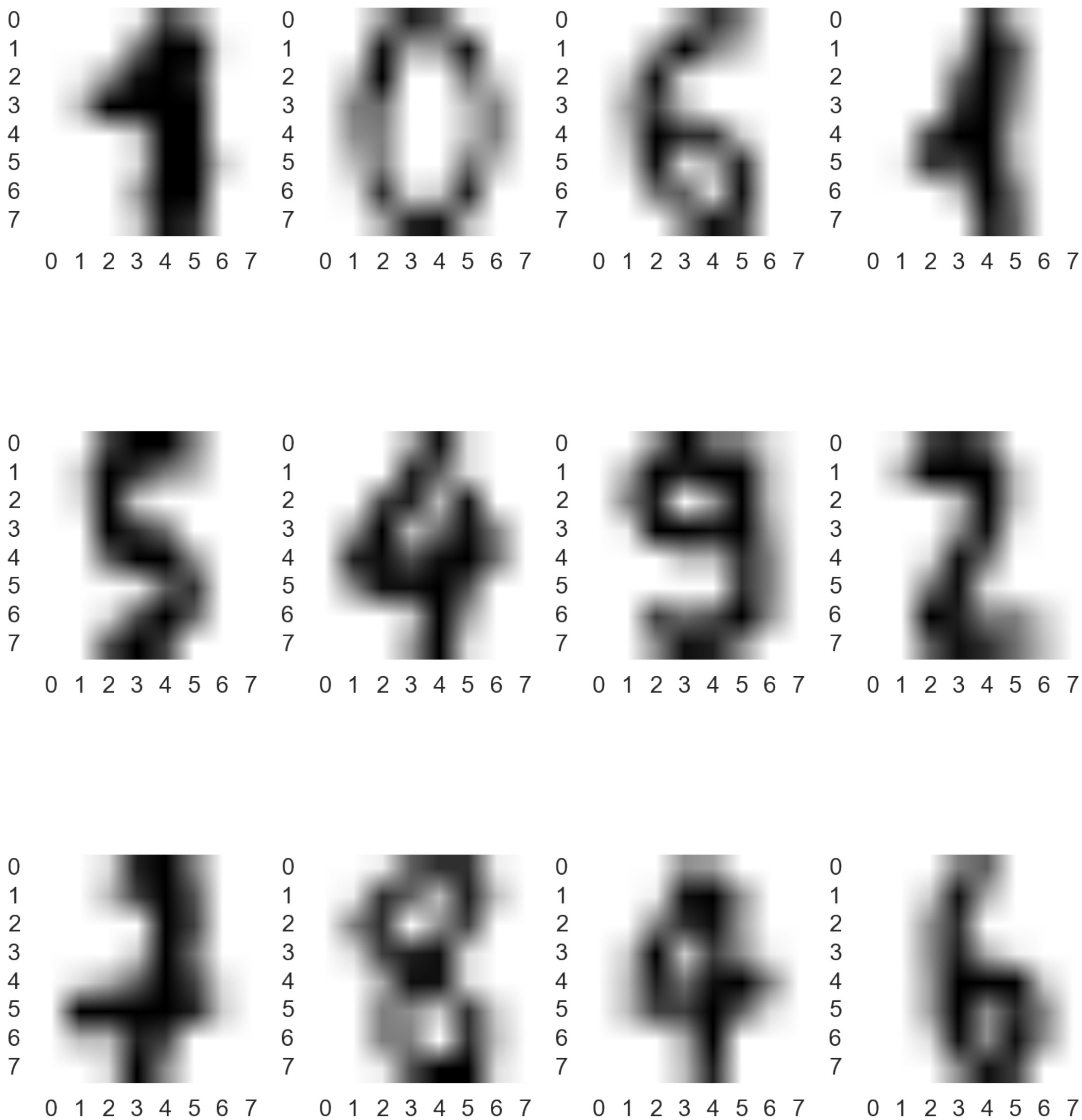
Notice that this is an 8×8 image. However we just treat it as a vector of length 64. It is easier to visualize if we blur the pixels a little bit.

```
In [237]: plt.rc('image', cmap='binary', interpolation='bilinear')
          plt.rc('axes', grid=False)
```

```
plt.figure(figsize=(4,4))
_=plt.imshow(digits.images[3])
```



```
In [238]: for t in range(4):
              plt.figure(figsize=(8,2))
              for j in range(4):
                  plt.subplot(1, 4, 1 + j)
                  plt.imshow(X_digits[4*t + j].reshape(8, 8))
```



This time we will use all classes, but only a small training set.
This points out one issue of KNN: it can be slow on a large training set (why?).
To do model selection, we also create a test set to adjust k.

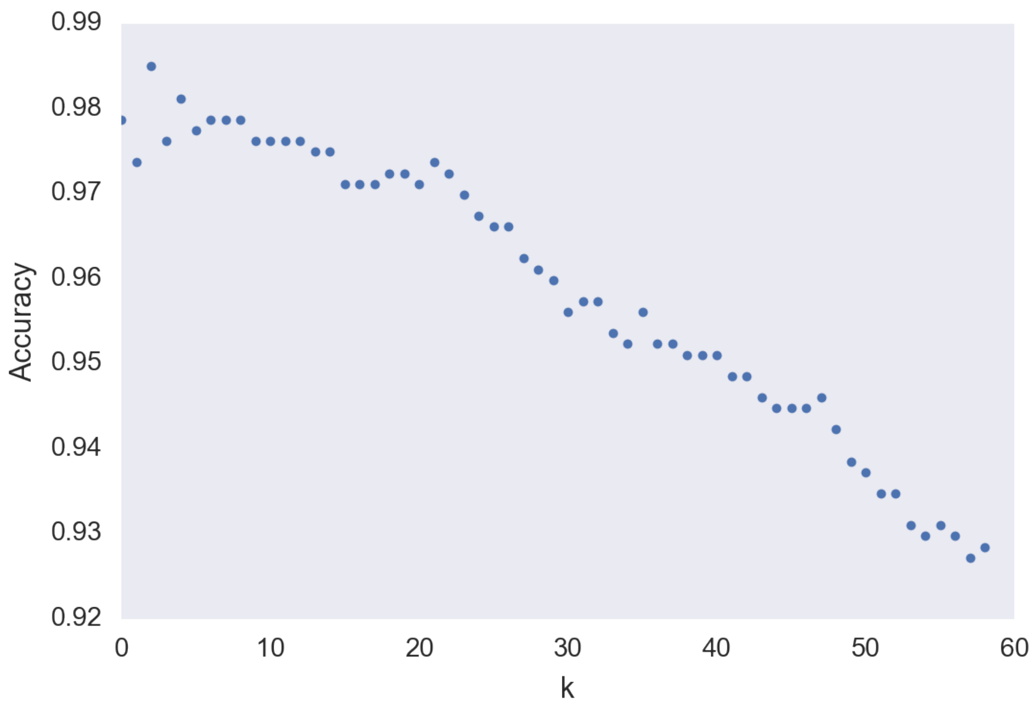
```
In [239]: step = 1000;
          X_digits_train = X_digits[:step]
          y_digits_train = y_digits[:step]
          X_digits_test = X_digits[step:len(y_digits)]
          y_digits_test = y_digits[step:len(y_digits)]
```

Again using the k-NN classifier:

```
In [240]: knn_digits = KNeighborsClassifier(n_neighbors=20)
          _=knn_digits.fit(X_digits_train, y_digits_train)
```

```
In [241]: acc = []
          for k in range(1,60):
              knn_digits = KNeighborsClassifier(n_neighbors=k)
              knn_digits.fit(X_digits_train, y_digits_train)
              y_digits_test_pred = knn_digits.predict(X_digits_test)
              # print("KNN test accuracy on MNIST digits, k = {}, acc = {}: ".forma
                    #k,knn_digits.score(X_digits_test, y_digits_test)))
              acc.append(knn_digits.score(X_digits_test, y_digits_test))
```

```
In [246]: plt.plot(acc,'.')
          plt.xlabel('k')
          _=plt.ylabel('Accuracy')
```



Looking at the nearest neighbors of some points (for k=3):

```
In [243]: neighbors = knn_digits.kneighbors(X_digits_test, n_neighbors=3, return_di
          print(type(neighbors))
          print(neighbors.shape)
```

```
<class 'numpy.ndarray'>
(797, 3)
```

Let's take a look at them...

```
In [244]: plt.rc("image", cmap="binary")  # this sets a black on white colormap
          # plot X_digits_valid[0]
          for t in range(3):
              plt.figure(figsize=(8,2))
              plt.subplot(1, 4, 1)
              plt.imshow(X_digits_test[t].reshape(8, 8))
              plt.title("Query")
              # plot three nearest neighbors from the training set
              for i in [0, 1, 2]:
                  plt.subplot(1, 4, 2 + i)
                  plt.title("neighbor {}".format(i))
                  plt.imshow(X_digits_train[neighbors[t, i]].reshape(8, 8))
```