```
In[16]: selection = X[indices]  # fancy indexing here
        selection.shape
```

```
Out[16]: (20, 2)
```

Now to see which points were selected, let's over-plot large circles at the locations of the selected points (Figure 2-8):

```
In[17]: plt.scatter(X[:, 0], X[:, 1], alpha=0.3)
        plt.scatter(selection[:, 0], selection[:, 1],
                    facecolor='none', s=200);
```

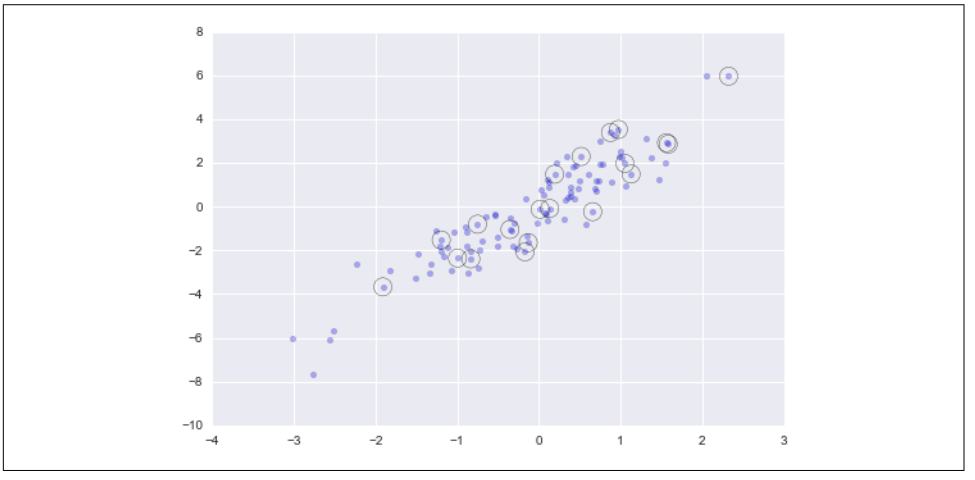

Figure 2-8. Random selection among points

This sort of strategy is often used to quickly partition datasets, as is often needed in train/test splitting for validation of statistical models (see "Hyperparameters and Model Validation" on page 359), and in sampling approaches to answering statistical questions.

Modifying Values with Fancy Indexing

Just as fancy indexing can be used to access parts of an array, it can also be used to modify parts of an array. For example, imagine we have an array of indices and we'd like to set the corresponding items in an array to some value:

```
In[18]: x = np.arange(10)
        i = np.array([2, 1, 8, 4])
        x[i] = 99
        print(x)
```

```
[ 0 99 99  3 99  5  6  7 99  9]
```

We can use any assignment-type operator for this. For example:

```
In[19]: x[i] -= 10
        print(x)
```

```
[ 0 89 89  3 89  5  6  7 89  9]
```

Notice, though, that repeated indices with these operations can cause some potentially unexpected results. Consider the following:

```
In[20]: x = np.zeros(10)
        x[[0, 0]] = [4, 6]
        print(x)
```

```
[ 6.  0.  0.  0.  0.  0.  0.  0.  0.  0.]
```

Where did the 4 go? The result of this operation is to first assign `x[0] = 4`, followed by `x[0] = 6`. The result, of course, is that `x[0]` contains the value 6.

Fair enough, but consider this operation:

```
In[21]: i = [2, 3, 3, 4, 4, 4]
        x[i] += 1
        x
```

```
Out[21]: array([ 6.,  0.,  1.,  1.,  1.,  0.,  0.,  0.,  0.,  0.])
```

You might expect that `x[3]` would contain the value 2, and `x[4]` would contain the value 3, as this is how many times each index is repeated. Why is this not the case? Conceptually, this is because `x[i] += 1` is meant as a shorthand of `x[i] = x[i] + 1`. `x[i] + 1` is evaluated, and then the result is assigned to the indices in `x`. With this in mind, it is not the augmentation that happens multiple times, but the assignment, which leads to the rather nonintuitive results.

So what if you want the other behavior where the operation is repeated? For this, you can use the `at()` method of ufuncs (available since NumPy 1.8), and do the following:

```
In[22]: x = np.zeros(10)
        np.add.at(x, i, 1)
        print(x)
```

```
[ 0.  0.  1.  2.  3.  0.  0.  0.  0.  0.]
```

The `at()` method does an in-place application of the given operator at the specified indices (here, `i`) with the specified value (here, 1). Another method that is similar in spirit is the `reduceat()` method of ufuncs, which you can read about in the NumPy documentation.

Example: Binning Data

You can use these ideas to efficiently bin data to create a histogram by hand. For example, imagine we have 1,000 values and would like to quickly find where they fall within an array of bins. We could compute it using `ufunc.at` like this: