additional hour of daylight, 129 ± 9 more people choose to ride; a temperature increase of one degree Celsius encourages 65 ± 4 people to grab their bicycle; a dry day means an average of 546 ± 33 more riders; and each inch of precipitation means 665 ± 62 more people leave their bike at home. Once all these effects are accounted for, we see a modest increase of 28 ± 18 new daily riders each year.

Our model is almost certainly missing some relevant information. For example, non-linear effects (such as effects of precipitation *and* cold temperature) and nonlinear trends within each variable (such as disinclination to ride at very cold and very hot temperatures) cannot be accounted for in this model. Additionally, we have thrown away some of the finer-grained information (such as the difference between a rainy morning and a rainy afternoon), and we have ignored correlations between days (such as the possible effect of a rainy Tuesday on Wednesday's numbers, or the effect of an unexpected sunny day after a streak of rainy days). These are all potentially interesting effects, and you now have the tools to begin exploring them if you wish!

In-Depth: Support Vector Machines

Support vector machines (SVMs) are a particularly powerful and flexible class of supervised algorithms for both classification and regression. In this section, we will develop the intuition behind support vector machines and their use in classification problems. We begin with the standard imports:

```
In[1]: %matplotlib inline
       import numpy as np
       import matplotlib.pyplot as plt
       from scipy import stats

       # use Seaborn plotting defaults
       import seaborn as sns; sns.set()
```

Motivating Support Vector Machines

As part of our discussion of Bayesian classification (see "In Depth: Naive Bayes Classification" on page 382), we learned a simple model describing the distribution of each underlying class, and used these generative models to probabilistically determine labels for new points. That was an example of *generative classification*; here we will consider instead *discriminative classification*: rather than modeling each class, we simply find a line or curve (in two dimensions) or manifold (in multiple dimensions) that divides the classes from each other.

As an example of this, consider the simple case of a classification task, in which the two classes of points are well separated (Figure 5-53):