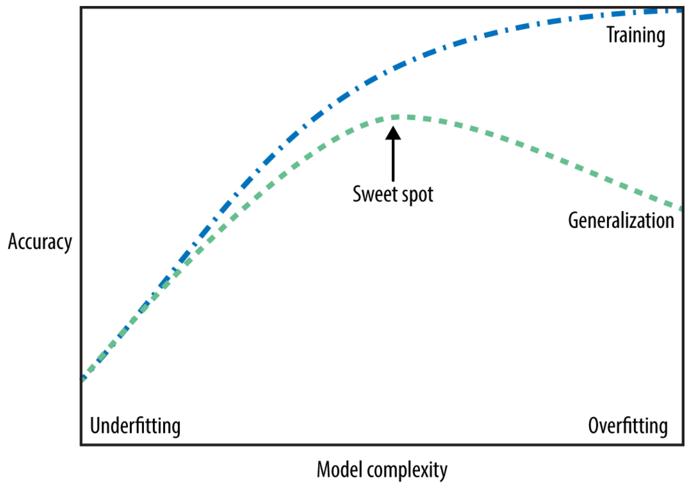

Figure 2-1. Trade-off of model complexity against training and test accuracy

Relation of Model Complexity to Dataset Size

It's important to note that model complexity is intimately tied to the variation of inputs contained in your training dataset: the larger variety of data points your dataset contains, the more complex a model you can use without overfitting. Usually, collecting more data points will yield more variety, so larger datasets allow building more complex models. However, simply duplicating the same data points or collecting very similar data will not help.

Going back to the boat selling example, if we saw 10,000 more rows of customer data, and all of them complied with the rule "If the customer is older than 45, and has less than 3 children or is not divorced, then they want to buy a boat," we would be much more likely to believe this to be a good rule than when it was developed using only the 12 rows in Table 2-1.

Having more data and building appropriately more complex models can often work wonders for supervised learning tasks. In this book, we will focus on working with datasets of fixed sizes. In the real world, you often have the ability to decide how much data to collect, which might be more beneficial than tweaking and tuning your model. Never underestimate the power of more data.

Supervised Machine Learning Algorithms

We will now review the most popular machine learning algorithms and explain how they learn from data and how they make predictions. We will also discuss how the concept of model complexity plays out for each of these models, and provide an overview of how each algorithm builds a model. We will examine the strengths and weaknesses of each algorithm, and what kind of data they can best be applied to. We will also explain the meaning of the most important parameters and options.[4] Many algorithms have a classification and a regression variant, and we will describe both.

It is not necessary to read through the descriptions of each algorithm in detail, but understanding the models will give you a better feeling for the different ways machine learning algorithms can work. This chapter can also be used as a reference guide, and you can come back to it when you are unsure about the workings of any of the algorithms.

Some Sample Datasets

We will use several datasets to illustrate the different algorithms. Some of the datasets will be small and synthetic (meaning made-up), designed to highlight particular aspects of the algorithms. Other datasets will be large, real-world examples.

An example of a synthetic two-class classification dataset is the `forge` dataset, which has two features. The following code creates a scatter plot (Figure 2-2) visualizing all of the data points in this dataset. The plot has the first feature on the x-axis and the second feature on the y-axis. As is always the case in scatter plots, each data point is represented as one dot. The color and shape of the dot indicates its class:

In[2]:

```
# generate dataset
X, y = mglearn.datasets.make_forge()
# plot dataset
mglearn.discrete_scatter(X[:, 0], X[:, 1], y)
plt.legend(["Class 0", "Class 1"], loc=4)
plt.xlabel("First feature")
plt.ylabel("Second feature")
print("X.shape: {}".format(X.shape))
```

Out[2]:

```
X.shape: (26, 2)
```

4 Discussing all of them is beyond the scope of the book, and we refer you to the `scikit-learn` documentation for more details.