

Summary

In this section we have covered the essential features of the Scikit-Learn data representation, and the estimator API. Regardless of the type of estimator, the same import/instantiate/fit/predict pattern holds. Armed with this information about the estimator API, you can explore the Scikit-Learn documentation and begin trying out various models on your data.

In the next section, we will explore perhaps the most important topic in machine learning: how to select and validate your model.

Hyperparameters and Model Validation

In the previous section, we saw the basic recipe for applying a supervised machine learning model:

1. Choose a class of model
2. Choose model hyperparameters
3. Fit the model to the training data
4. Use the model to predict labels for new data

The first two pieces of this—the choice of model and choice of hyperparameters—are perhaps the most important part of using these tools and techniques effectively. In order to make an informed choice, we need a way to *validate* that our model and our hyperparameters are a good fit to the data. While this may sound simple, there are some pitfalls that you must avoid to do this effectively.

Thinking About Model Validation

In principle, model validation is very simple: after choosing a model and its hyperparameters, we can estimate how effective it is by applying it to some of the training data and comparing the prediction to the known value.

The following sections first show a naive approach to model validation and why it fails, before exploring the use of holdout sets and cross-validation for more robust model evaluation.

Model validation the wrong way

Let's demonstrate the naive approach to validation using the Iris data, which we saw in the previous section. We will start by loading the data:

```
In[1]: from sklearn.datasets import load_iris  
iris = load_iris()
```