

also obtain equivalent information by measuring the **error rate**, the proportion of examples for which the model produces an incorrect output. We often refer to the error rate as the expected 0-1 loss. The 0-1 loss on a particular example is 0 if it is correctly classified and 1 if it is not. For tasks such as density estimation, it does not make sense to measure accuracy, error rate, or any other kind of 0-1 loss. Instead, we must use a different performance metric that gives the model a continuous-valued score for each example. The most common approach is to report the average log-probability the model assigns to some examples.

Usually we are interested in how well the machine learning algorithm performs on data that it has not seen before, since this determines how well it will work when deployed in the real world. We therefore evaluate these performance measures using a **test set** of data that is separate from the data used for training the machine learning system.

The choice of performance measure may seem straightforward and objective, but it is often difficult to choose a performance measure that corresponds well to the desired behavior of the system.

In some cases, this is because it is difficult to decide what should be measured. For example, when performing a transcription task, should we measure the accuracy of the system at transcribing entire sequences, or should we use a more fine-grained performance measure that gives partial credit for getting some elements of the sequence correct? When performing a regression task, should we penalize the system more if it frequently makes medium-sized mistakes or if it rarely makes very large mistakes? These kinds of design choices depend on the application.

In other cases, we know what quantity we would ideally like to measure, but measuring it is impractical. For example, this arises frequently in the context of density estimation. Many of the best probabilistic models represent probability distributions only implicitly. Computing the actual probability value assigned to a specific point in space in many such models is intractable. In these cases, one must design an alternative criterion that still corresponds to the design objectives, or design a good approximation to the desired criterion.

5.1.3 The Experience, E

Machine learning algorithms can be broadly categorized as **unsupervised** or **supervised** by what kind of experience they are allowed to have during the learning process.

Most of the learning algorithms in this book can be understood as being allowed to experience an entire **dataset**. A dataset is a collection of many examples, as