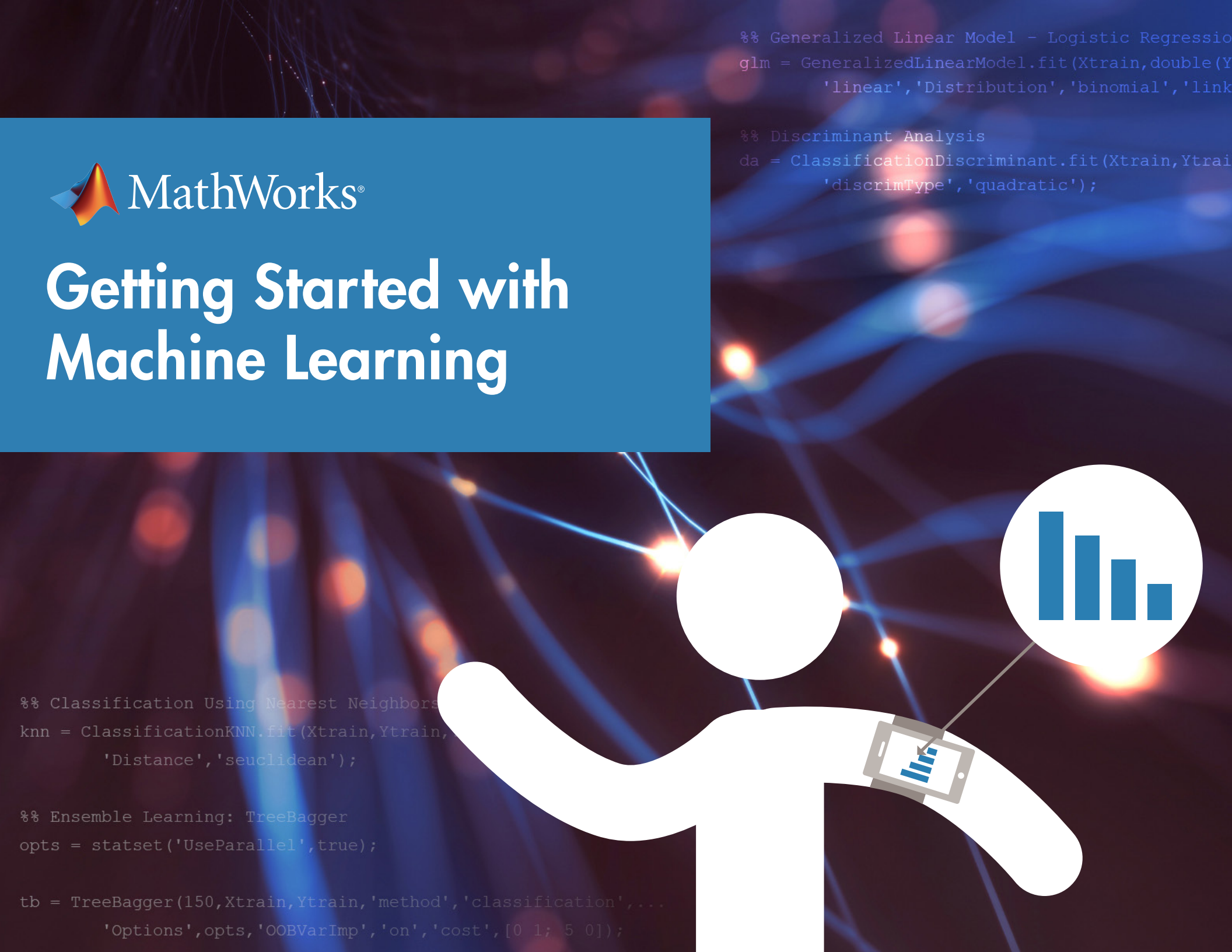
MathWorks®

Getting Started with Machine Learning



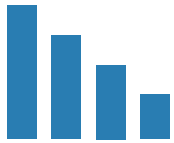
Rarely a Straight Line

With machine learning there's rarely a straight line from start to finish—you'll find yourself constantly iterating and trying different ideas and approaches. This chapter describes a systematic machine learning workflow, highlighting some key decision points along the way.

Machine Learning Challenges

Most machine learning challenges relate to handling your data and finding the right model.

Data comes in all shapes and sizes. Real-world datasets can be messy, incomplete, and in a variety of formats. You might just have simple numeric data. But sometimes you're combining several different data types, such as sensor signals, text, and streaming images from a camera.



Preprocessing your data might require specialized knowledge and tools. For example, to select features to train an object detection algorithm requires specialized knowledge of image processing. Different types of data require different approaches to preprocessing.

It takes time to find the best model to fit the data. Choosing the right model is a balancing act. Highly flexible models tend to overfit data by modeling minor variations that could be noise. On the other hand, simple models may assume too much. There are always tradeoffs between model speed, accuracy, and complexity.

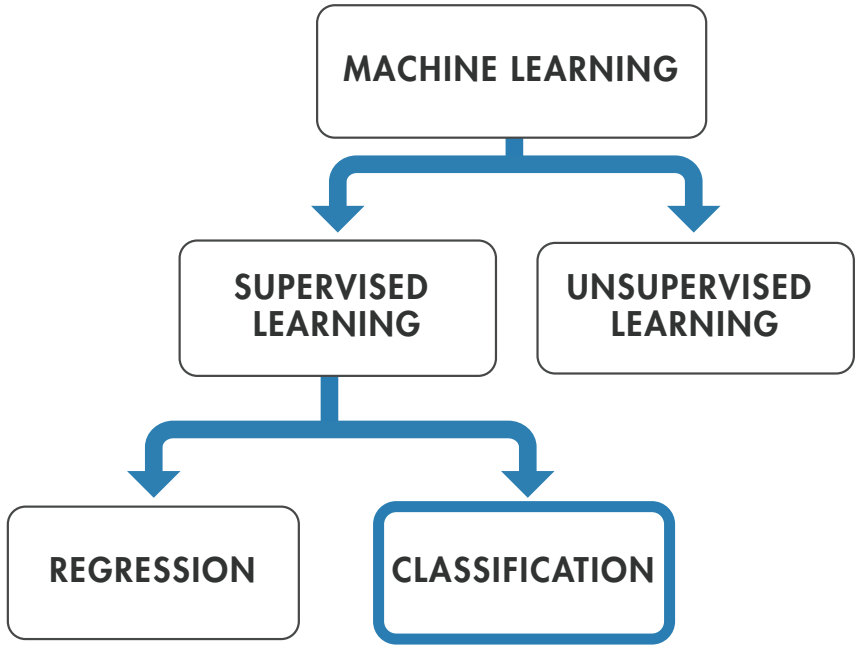
Sounds daunting? Don't be discouraged. Remember that trial and error is at the core of machine learning—if one approach or algorithm doesn't work, you simply try another. But a systematic workflow will help you get off to a smooth start.

Questions to Consider Before You Start

Every machine learning workflow begins with three questions:

- What kind of data are you working with?
- What insights do you want to get from it?
- How and where will those insights be applied?

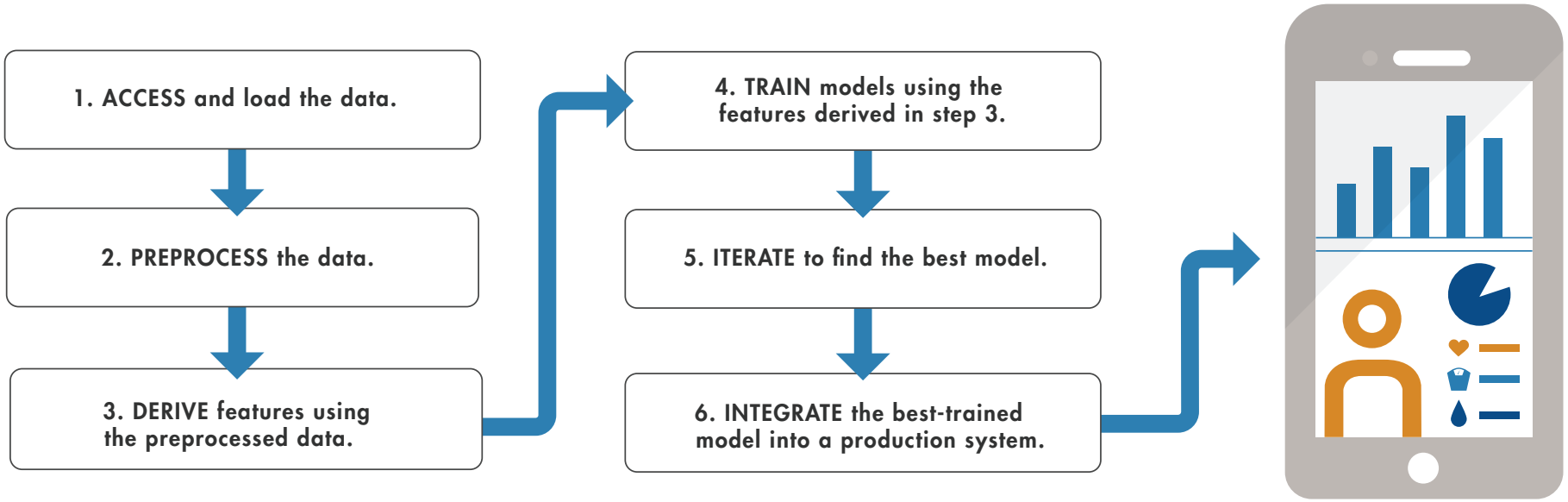
Your answers to these questions help you decide whether to use supervised or unsupervised learning.



Choose supervised learning if you need to train a model to make a prediction--for example, the future value of a continuous variable, such as temperature or a stock price, or a classification—for example, identify makes of cars from webcam video footage.

Choose unsupervised learning if you need to explore your data and want to train a model to find a good internal representation, such as splitting data up into clusters.

Workflow at a Glance



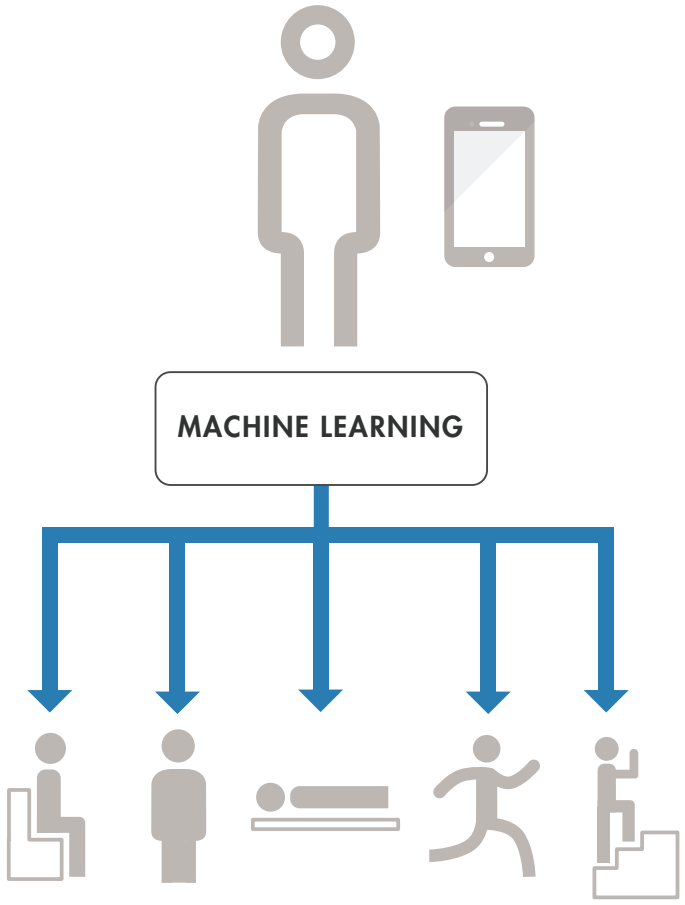
In the next sections we'll look at the steps in more detail, using a health monitoring app for illustration. The entire workflow will be completed in MATLAB®.

Training a Model to Classify Physical Activities

This example is based on a cell phone health-monitoring app. The input consists of three-axial sensor data from the phone's accelerometer and gyroscope. The responses, (or output), are the activities performed–walking, standing, running, climbing stairs, or lying down.

We want to use the input data to train a classification model to identify these activities. Since our goal is classification, we'll be applying supervised learning.

The trained model (or classifier) will be integrated into an app to help users track their activity levels throughout the day.



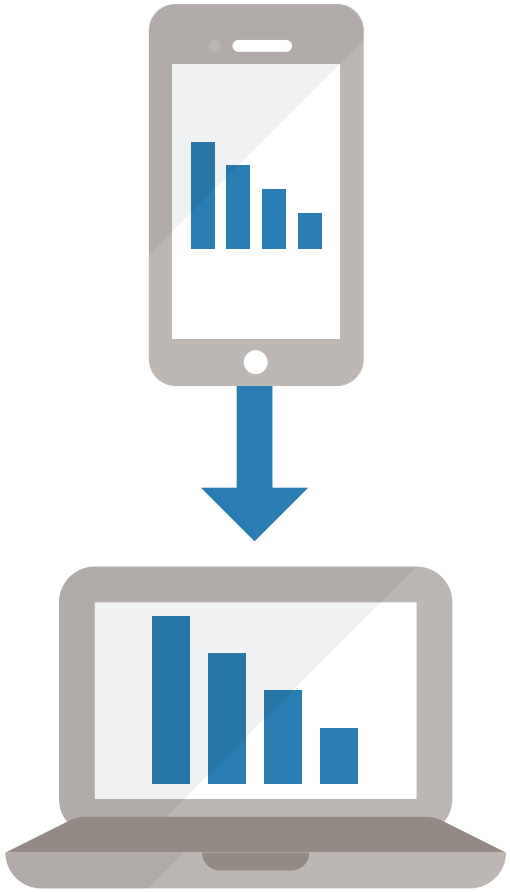
1 Step One: Load the Data

To load data from the accelerometer and gyroscope we do the following:

1. Sit down holding the phone, log data from the phone, and store it in a text file labeled "Sitting."
2. Stand up holding the phone, log data from the phone, and store it in a second text file labeled "Standing."
3. Repeat the steps until we have data for each activity we want to classify.

We store the labeled data sets in a text file. A flat file format such as text or CSV is easy to work with and makes it straightforward to import data.

Machine learning algorithms aren't smart enough to tell the difference between noise and valuable information. Before using the data for training, we need to make sure it's clean and complete.



2 Step Two: Preprocess the Data

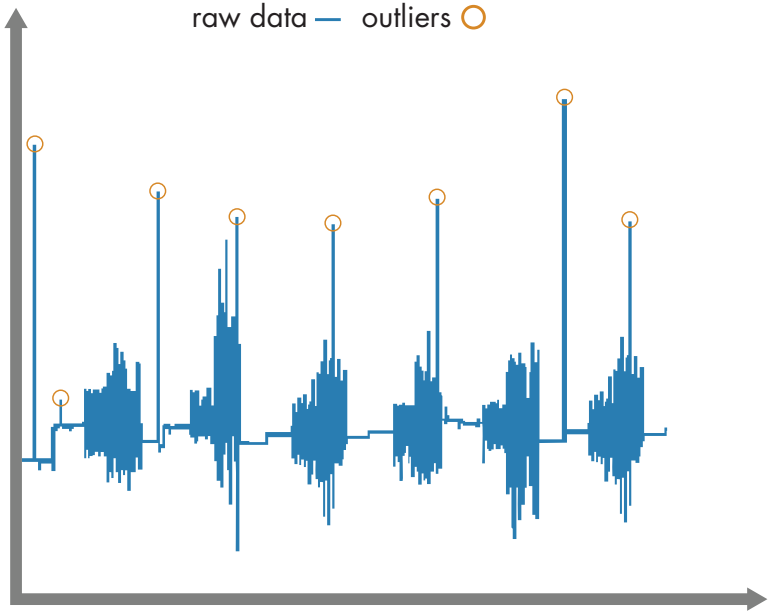
We import the data into MATLAB and plot each labeled set. To preprocess the data we do the following:

1. Look for outliers–data points that lie outside the rest of the data.

We must decide whether the outliers can be ignored or whether they indicate a phenomenon that the model should account for. In our example, they can safely be ignored (it turns out that we moved unintentionally while recording the data).

2. Check for missing values (perhaps we lost data because the connection dropped during recording).

We could simply ignore the missing values, but this will reduce the size of the data set. Alternatively, we could substitute approximations for the missing values by interpolating or using comparable data from another sample.



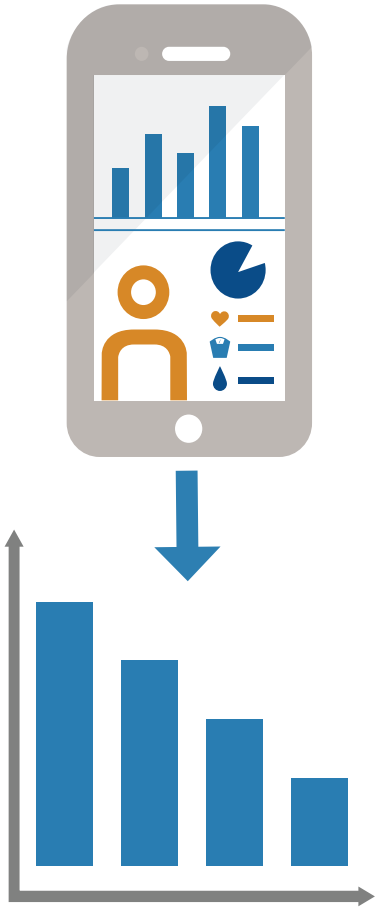
Outliers in the activity-tracking data.

In many applications, outliers provide crucial information. For example, in a credit card fraud detection app, they indicate purchases that fall outside a customer's usual buying patterns.

2 Step Two: Preprocess the Data *continued*

3. Remove gravitational effects from the accelerometer data so that our algorithm will focus on the movement of the subject, not the movement of the phone. A simple high-pass filter such as a biquad filter is commonly used for this.
4. Divide the data into two sets. We save part of the data for testing (the test set) and use the rest (the training set) to build models. This is referred to as holdout, and is a useful cross-validation technique.

By testing your model against data that wasn't used in the modeling process, you see how it will perform with unknown data.



3 Step Three: Derive Features

Deriving features (also known as feature engineering or feature extraction) is one of the most important parts of machine learning. It turns raw data into information that a machine learning algorithm can use.

For the activity tracker, we want to extract features that capture the frequency content of the accelerometer data. These features will help the algorithm distinguish between walking (low frequency) and running (high frequency). We create a new table that includes the selected features.

Use feature selection to:

- Improve the accuracy of a machine learning algorithm
- Boost model performance for high-dimensional data sets
- Improve model interpretability
- Prevent overfitting

3 Step Three: Derive Features *continued*

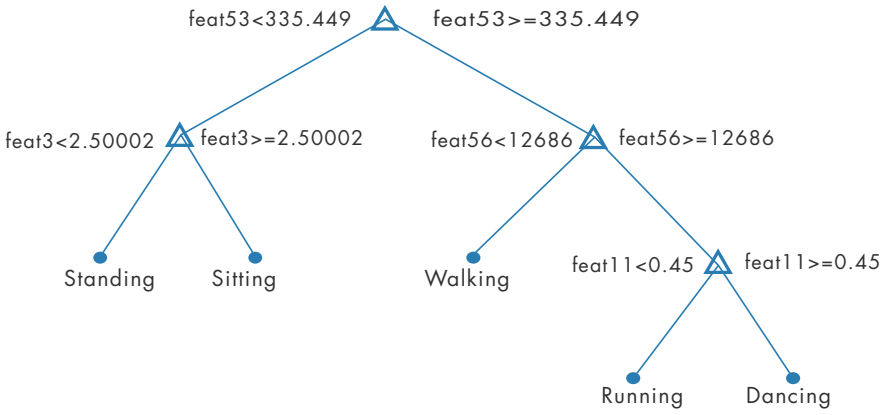
The number of features that you could derive is limited only by your imagination. However, there are a lot of techniques commonly used for different types of data.

Data Type	Feature Selection Task	Techniques
Sensor data	Extract signal properties from raw sensor data to create higher-level information	**Peak analysis** – perform an fft and identify dominant frequencies **Pulse and transition metrics** – derive signal characteristics such as rise time, fall time, and settling time **Spectral measurements** – plot signal power, bandwidth, mean frequency, and median frequency
Image and video data	Extract features such as edge locations, resolution, and color	**Bag of visual words** – create a histogram of local image features, such as edges, corners, and blobs **Histogram of oriented gradients (HOG)** – create a histogram of local gradient directions **Minimum eigenvalue algorithm** – detect corner locations in images **Edge detection** – identify points where the degree of brightness changes sharply
Transactional data	Calculate derived values that enhance the information in the data	**Timestamp decomposition** – break timestamps down into components such as day and month **Aggregate value calculation** – create higher-level features such as the total number of times a particular event occurred

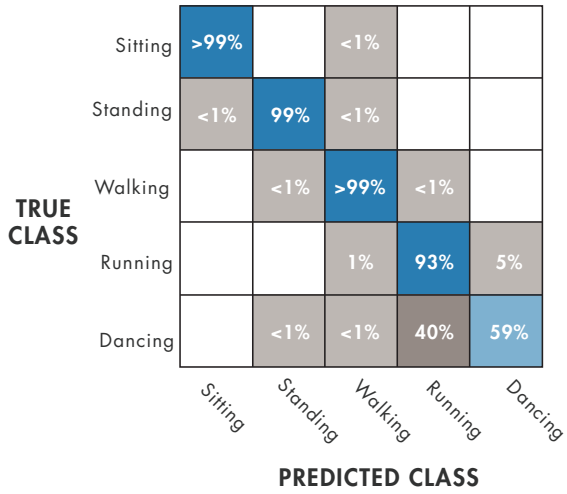
4 Step Four: Build and Train the Model

When building a model, it's a good idea to start with something simple; it will be faster to run and easier to interpret.

We start with a basic decision tree.



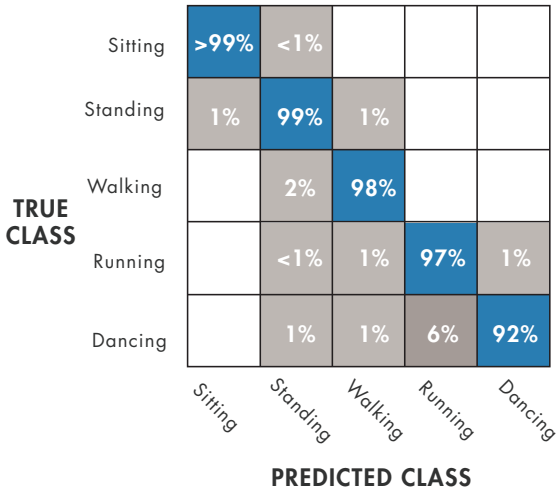
To see how well it performs, we plot the confusion matrix, a table that compares the classifications made by the model with the actual class labels that we created in step 1.



The confusion matrix shows that our model is having trouble distinguishing between walking and running. Maybe a decision tree doesn't work for this type of data. We'll try a few different algorithms.

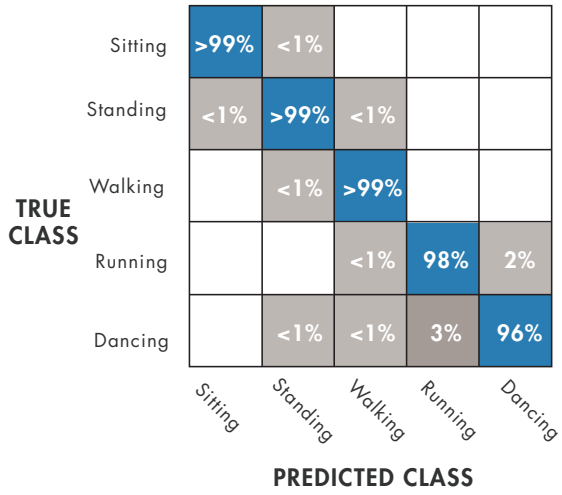
4 Step Four: Build and Train the Model *continued*

We start with a K-nearest neighbors (KNN), a simple algorithm that stores all the training data, compares new points to the training data, and returns the most frequent class of the "K" nearest points. That gives us 98% accuracy compared to 94.1% for the simple decision tree. The confusion matrix looks better, too:



However, KNNs take a considerable amount of memory to run, since they require all the training data to make a prediction.

We try a linear discriminant model, but that doesn't improve the results. Finally, we try a multiclass support vector machine (SVM). The SVM does very well—we now get 99% accuracy:



We achieved our goal by iterating on the model and trying different algorithms. If our classifier still couldn't reliably differentiate between walking and running, we'd look into ways to improve the model.

5 Step Five: Improve the Model

Improving a model can take two different directions: make the model simpler or add complexity.

Simplify

First, we look for opportunities to reduce the number of features. Popular feature reduction techniques include:

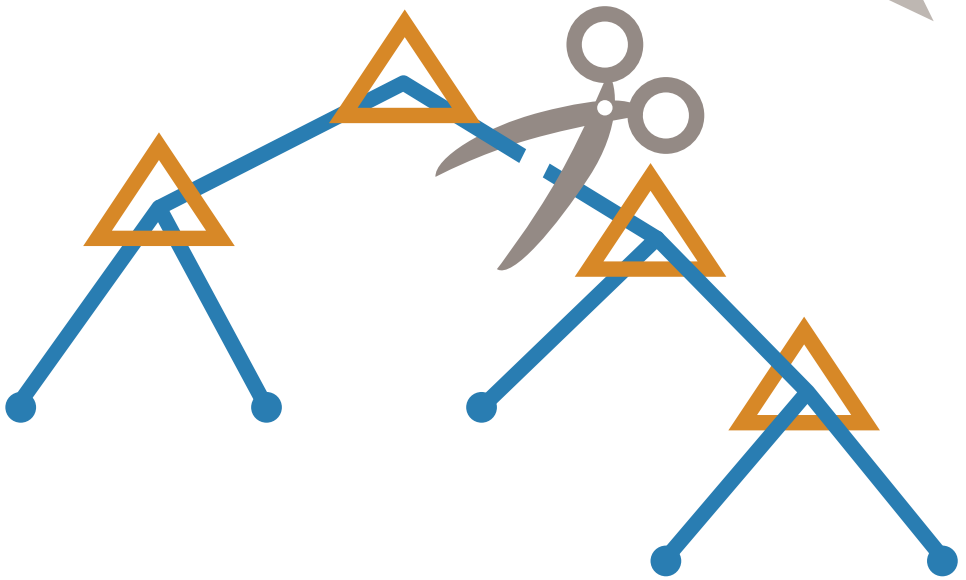
- Correlation matrix – shows the relationship between variables, so that variables (or features) that are not highly correlated can be removed.
- Principal component analysis (PCA) – eliminates redundancy by finding a combination of features that captures key distinctions between the original features and brings out strong patterns in the dataset.
- Sequential feature reduction – reduces features iteratively on the model until there is no improvement in performance.

Next, we look at ways to reduce the model itself. We can do this by:

- Pruning branches from a decision tree
- Removing learners from an ensemble

A good model includes only the features with the most predictive power. A simple model that generalizes well is better than a complex model that may not generalize or train well to new data.

In machine learning, as in many other computational processes, simplifying the model makes it easier to understand, more robust, and more computationally efficient.



5 Step Five: Improve the Model *continued*

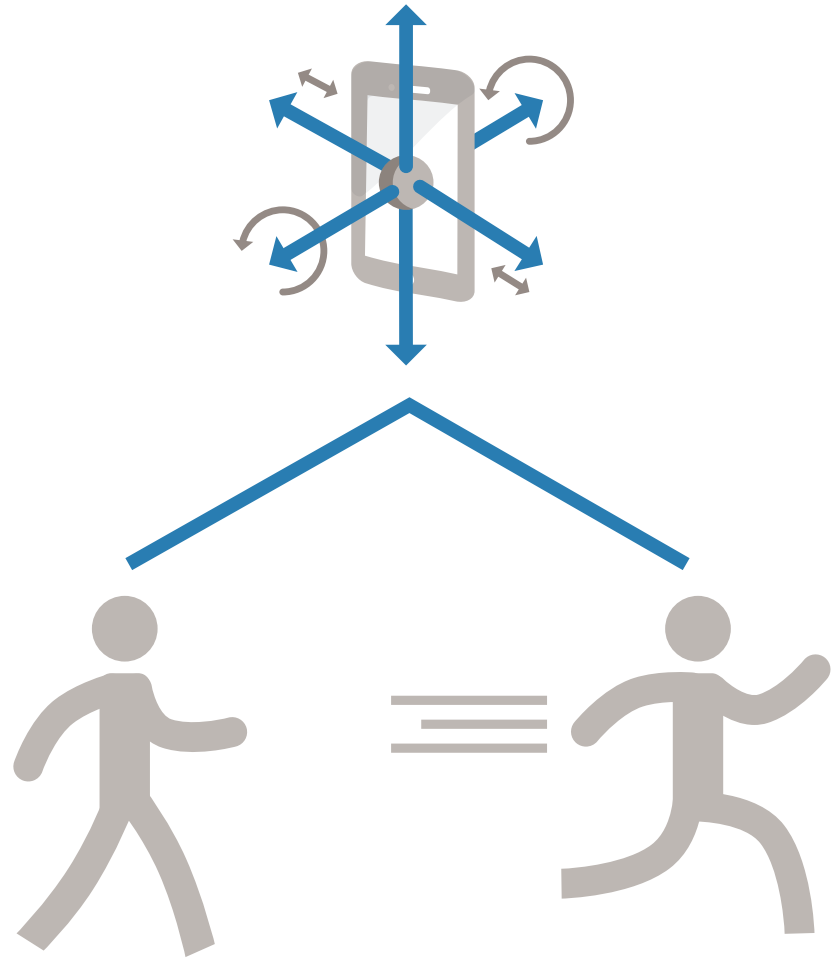
Add Complexity

If our model can't differentiate walking from running because it is over-generalizing, then we need find ways to make it more fine-tuned. To do this we can either:

- Use model combination – merge multiple simpler models into a larger model that is better able to represent the trends in the data than any of the simpler models could on their own.
- Add more data sources – look at the gyroscope data as well as the acceleromter data. The gyroscope records the orientation of the cell phone during activity. This data might provide unique signatures for the different activities; for example, there might be a combination of acceleration and rotation that's unique to running.

Once we've adjusted the model, we validate its performance on the test data that we set aside during preprocessing.

If the model can reliably classify activities on the test data, we're ready to move it to the phone and start tracking.



Learn More

Ready for a deeper dive? Explore these resources to learn more about machine learning methods, examples, and tools.

Watch

Machine Learning Made Easy 34:34

Signal Processing and Machine Learning Techniques for Sensor Data Analytics 42:45

Read

Supervised Learning Workflow and Algorithms

Data-Driven Insights with MATLAB Analytics: An Energy Load Forecasting Case Study

Explore

MATLAB Machine Learning Examples

Classify Data with the Classification Learner App

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