neural network on a *new* classification task and it achieves 5% test error, we have no straightforward way of knowing if this is the expected behavior or sub-optimal behavior.

A further difficulty is that most machine learning models have multiple parts that are each adaptive. If one part is broken, the other parts can adapt and still achieve roughly acceptable performance. For example, suppose that we are training a neural net with several layers parametrized by weights $\boldsymbol{W}$ and biases $\boldsymbol{b}$. Suppose further that we have manually implemented the gradient descent rule for each parameter separately, and we made an error in the update for the biases:

$$\boldsymbol{b} \leftarrow \boldsymbol{b} - \alpha \tag{11.4}$$

where α is the learning rate. This erroneous update does not use the gradient at all. It causes the biases to constantly become negative throughout learning, which is clearly not a correct implementation of any reasonable learning algorithm. The bug may not be apparent just from examining the output of the model though. Depending on the distribution of the input, the weights may be able to adapt to compensate for the negative biases.

Most debugging strategies for neural nets are designed to get around one or both of these two difficulties. Either we design a case that is so simple that the correct behavior actually can be predicted, or we design a test that exercises one part of the neural net implementation in isolation.

Some important debugging tests include:

Visualize the model in action : When training a model to detect objects in images, view some images with the detections proposed by the model displayed superimposed on the image. When training a generative model of speech, listen to some of the speech samples it produces. This may seem obvious, but it is easy to fall into the practice of only looking at quantitative performance measurements like accuracy or log-likelihood. Directly observing the machine learning model performing its task will help to determine whether the quantitative performance numbers it achieves seem reasonable. Evaluation bugs can be some of the most devastating bugs because they can mislead you into believing your system is performing well when it is not.

Visualize the worst mistakes : Most models are able to output some sort of confidence measure for the task they perform. For example, classifiers based on a softmax output layer assign a probability to each class. The probability assigned to the most likely class thus gives an estimate of the confidence the model has in its classification decision. Typically, maximum likelihood training results in these values being overestimates rather than accurate probabilities of correct prediction,