

on the test set. Sometimes these constraints and penalties are designed to encode specific kinds of prior knowledge. Other times, these constraints and penalties are designed to express a generic preference for a simpler model class in order to promote generalization. Sometimes penalties and constraints are necessary to make an underdetermined problem determined. Other forms of regularization, known as ensemble methods, combine multiple hypotheses that explain the training data.

In the context of deep learning, most regularization strategies are based on regularizing estimators. Regularization of an estimator works by trading increased bias for reduced variance. An effective regularizer is one that makes a profitable trade, reducing variance significantly while not overly increasing the bias. When we discussed generalization and overfitting in chapter 5, we focused on three situations, where the model family being trained either (1) excluded the true data generating process—corresponding to underfitting and inducing bias, or (2) matched the true data generating process, or (3) included the generating process but also many other possible generating processes—the overfitting regime where variance rather than bias dominates the estimation error. The goal of regularization is to take a model from the third regime into the second regime.

In practice, an overly complex model family does not necessarily include the target function or the true data generating process, or even a close approximation of either. We almost never have access to the true data generating process so we can never know for sure if the model family being estimated includes the generating process or not. However, most applications of deep learning algorithms are to domains where the true data generating process is almost certainly outside the model family. Deep learning algorithms are typically applied to extremely complicated domains such as images, audio sequences and text, for which the true generation process essentially involves simulating the entire universe. To some extent, we are always trying to fit a square peg (the data generating process) into a round hole (our model family).

What this means is that controlling the complexity of the model is not a simple matter of finding the model of the right size, with the right number of parameters. Instead, we might find—and indeed in practical deep learning scenarios, we almost always do find—that the best fitting model (in the sense of minimizing generalization error) is a large model that has been regularized appropriately.

We now review several strategies for how to create such a large, deep, regularized model.