Overfitting

In statistics and machine learning, one of the most common tasks is to fit a "model" to a set of training data, so as to be able to make reliable predictions on general untrained data.

In overfitting, a statistical model describes random error or noise instead of the underlying relationship.

Overfitting occurs when a model is excessively complex, such as having too many parameters relative to the number of observations.

A model that has been overfit has poor predictive performance, as it overreacts to minor fluctuations in the training data.

The possibility of overfitting exists because the criterion used for training the model is not the same as the criterion used to judge the efficacy of a model.

In particular, a model is typically trained by maximizing its performance on some set of training data.

However, its efficacy is determined not by its performance on the training data but by its ability to perform well on unseen data.

Overfitting occurs when a model begins to "memorize" training data rather than "learning" to generalize from trend.

As an extreme example, if the number of parameters is the same as or greater than the number of observations, a simple model or learning process can perfectly predict the training data simply by memorizing the training data in its entirety, but such a model will typically fail drastically when making predictions about new or unseen data, since the simple model has not learned to generalize at all.

The potential for overfitting depends not only on the number of parameters and data but also the conformability of the model structure with the data shape, and the magnitude of model error compared to the expected level of noise or error in the data.

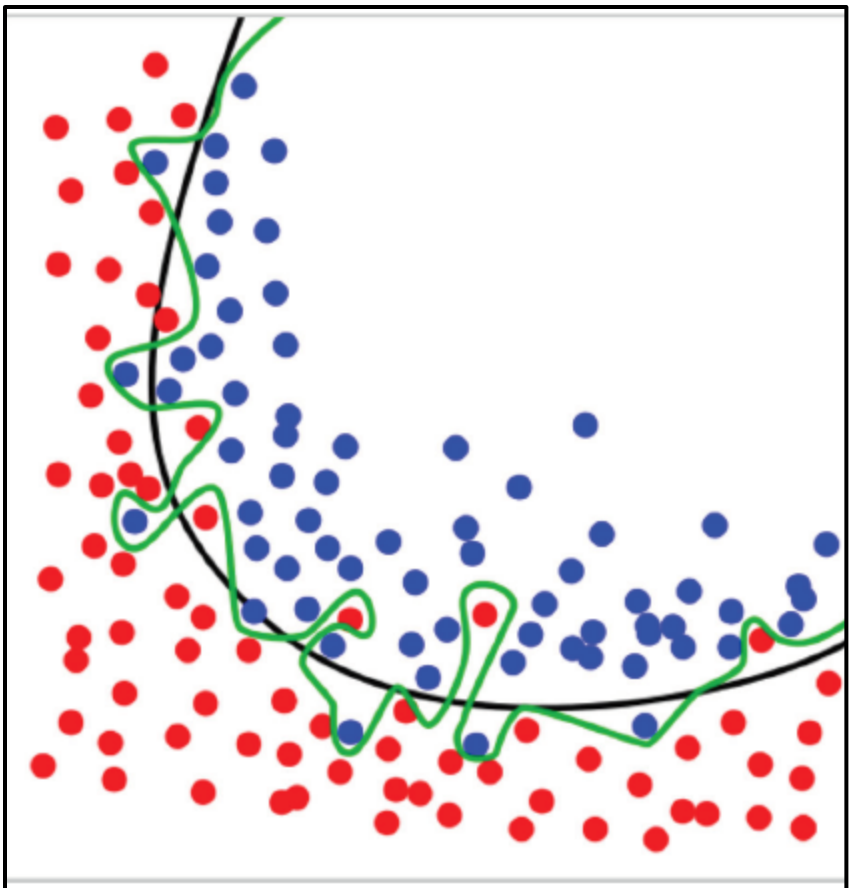
Even when the fitted model does not have an excessive number of parameters, it is to be expected that the fitted relationship will appear to perform less well on a new data set than on the data set used for fitting.

In particular, the value of the coefficient of determination will shrink relative to the original training data.

In order to avoid overfitting, it is necessary to use additional techniques (e.g. cross-validation, regularization, early stopping, pruning, Bayesian priors on parameters or model comparison), that can indicate when further training is not resulting in better generalization.

The basis of some techniques is either (1) to explicitly penalize overly complex models, or (2) to test the model's ability to generalize by evaluating its performance on a set of data not used for training, which is assumed to approximate the typical unseen data that a model will encounter.

A good analogy for the overfitting problem is imagine a baby trying to learn what is a window or what is not a window, we start to show him windows and he detects at an initial phase that all windows have glasses, and a frame and you can look outside, some of them may be opened. If we keep showing the same windows the baby may also falsely deduce that all windows are green, and that all green frames are windows. Thus overfitting the problem.



The green line represents an overfitted model and the black line represents a regularised model. While the green line best follows the training data, it is too dependent on it and it is likely to have a higher error rate on new unseen data, compared to the black line.

Overfitting is especially likely in cases where learning was performed too long or where training examples are rare, causing the learner to adjust to very specific random features of the training data, that have no causal relation to the target function.

In this process of overfitting, the performance on the training examples still increases while the performance on unseen data becomes worse.

As a simple example, consider a database of retail purchases that includes the item bought, the purchaser, and the date and time of purchase.

It's easy to construct a model that will fit the training set perfectly by using the date and time of purchase to predict the other attributes; but this model will not generalize at all to new data, because those past times will never occur again.

Generally, a learning algorithm is said to overfit relative to a simpler one if it is more accurate in fitting known data (hindsight) but less accurate in predicting new data (foresight).

One can intuitively understand overfitting from the fact that information from all past experience can be divided into two groups: information that is relevant for the future and irrelevant information ("noise").

Everything else being equal, the more difficult a criterion is to predict (i.e., the higher its uncertainty), the more noise exists in past information that needs to be ignored.

The problem is determining which part to ignore.

A learning algorithm that can reduce the chance of fitting noise is called robust.

Underfitting occurs when a statistical model or machine learning algorithm cannot capture the underlying trend of the data.

It occurs when the model or algorithm does not fit the data enough.

Underfitting occurs if the model or algorithm shows low variance but high bias (to contrast the opposite, overfitting from high variance and low bias).

It is often a result of an excessively simple model.