**Essential Notes**

Page 30:

The sweet spot in model fitting is where the “generalization curve” is at its peak. It is the classifier/learning algorithm set up that is considered “just right” that is able to achieve this sweet spot. However, this classifier will have less accuracy on the training data than an overfitted one – and that’s completely desired.



The correct curve has generalization at its peak and training data accuracy at something relatively high, but not *too* high.

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The more data points you have, the more complex of a model you can build without overfitting. Yes, it is possible you will have many features but the more data points you have the more chances of less overfitting because of the variety that will be in your dataset.

It is almost always that collecting more datapoints will yield more variety, but simply duplicating the same data (….. -\_-) or collecting suspiciously similar data points will NOT help and thus will contribute to overfitting.

If we added 10,000 more rows of customer data to the table on Page 30, and it was evident that the rule of “customer > 45 and less than 3 children and not divorced” was still there, then we would take this rule with much more open arms.

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“low-dimensional” datasets are those with few features (akin to how many dimensions we would need to plot the dataset). Intuitions (think: trends and patterns) we see from datasets with few features *might not* hold in datasets with many features (high-dimensional).

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In the Boston Dataset, we’ll also look at “interactions” of the dataset. The interactions of a dataset are the relationship between features. Essentially, we will add features to the dataset which are products of one another. The interaction of closeness to the river and crime rate is simply a vector represented by X[:, “CRIME\_RATE”] \* X[:, “CLOSENESS\_TO\_RIVER”]. This new vector would be appended to the end of the dataset. This is called **feature engineering**.

The new shape is (506, 104) because we have added the product of every two distinct feature to the dataset. This is because for every feature we decrease in 1 distinct combination we can make with it

13 (original) + 12 (feature 1 & other 12) + 11 (feature 2 & other 11) + … 1 = **104**

Page 39:

Single neighbor in k-nearest Neighbors corresponds to a more *complex* model (inverse of how many neighbors there are == complexity). By looking at one neighbor, we’re fixating and making decision on just a single data point. As we increased our classifier to accommodate 3 neighbors, and ultimately 9, we notice that our model is actually becoming more *simple*. The decision boundary that separates both of the classes in this binary classification problem actually becomes smoother. On the other extreme, if all of the training data points are considered neighbors, then we run into the problem that our classifier is **completely deterministic**. A prediction on a k-nearest neighbors classifier that has n\_neighbors set to the size of the training set would always lead to the same prediction for any new test set feature set: the majority representative class in the training set would always be predicted.

Confirming relationship between model complexity and generalization is important, otherwise it would seem like this is not the case. Here is a graph that shows the relationship between the increase of neighbors and the accuracy. 