CHAPTER 10

Improving Models and Data Extraction 模型的改进以及数据提取

How do you go about improving upon a simple machine learning algorithm such as Naive Bayesian Classifiers, SVMs, or really any method? That is what we will delve into in this chapter, by talking about four major ways of improving models:

• Feature selection

• Feature transformation

• Ensemble learning

• Bootstrapping

关于如何改进一个已知的简单模型的机器学习算法，比如贝叶斯分类器、SVMs支持向量机等等，我们将在这章从以下4个方面进行探讨如何改进：

* 特征选择
* 特征转换
* 集成学习
* 数据重抽样

I’ll outline the benefits of each of these methods but in general they reduce entanglement, overcome the curse of dimensionality, and reduce correction cascades and sensitivity to data changes.

我将分别概述这些优化方法的好处，总的来说，这些方法的目的都是为了减少数据间的耦合相关性，降低数据维度，并减少校正级联和数据变化的敏感性。

They each have certain pros and cons and should be used when there is a purpose behind it. Sometimes problems are so sufficiently complex that tweaking and improvement are warranted at this level, other times they are not. That is a judgment people must make depending on the business context.

每个方法都有各自的优点和缺点，因此都有其特定的使用场景。如果是比较复杂的问题就需要进行必要的调整和改进，必须根据每个商业案例的情况进行具体情况具体分析。

Debate Club

辩论俱乐部

I’m not sure if this is common throughout the world, but in the United States, debate club is a high school fixture. For those of you who haven’t heard of this, it’s a simple idea: high schoolers will take polarizing issues and debate their side. This serves as a great way for students who want to become lawyers to try out their skills arguing for a case.

我不确定辩论俱乐部在全世界其他高校是否都存在，但是在美国每个高校都有这样一个俱乐部。其实这只是一个非常简单的场所，就是提供给高中生一个能够将他们对问题的看法坚持下来并且与他们意见不一致的同学进行辩论的场所。这也给那些将来立志当律师的学生尝试就某些案例进行相关辩论的一个最好的实践方式。

The fascinating thing about this is just how rigorous and disciplined these kids are. Usually they study all kinds of facts to put together a dossier of important points to

make. Sometimes they argue for a side they don’t agree with but they do so with conviction.

比较有趣的地方是孩子们都会严格遵守相关的辩论规则，通常他们会收集各种事件相关的事实案例并且规整成卷宗。有些时候其实他们的真实想法与他们辩论时所处的正反方并不一致，但是他们也会按照的辩论规则捍卫他们当前的正方(或者反方)的结论。

Why am I telling you this? These debate club skills are the key to making machine learning algorithms (and many cases any algorithm) work better:

• Collecting factual and important data

• Arguing different points of view in multiple ways

为什么我要告诉你辩论俱乐部的事情？事实上辩论俱乐部的核心技能就是我们解开机器学习算法的钥匙，即如何使大多数情况下算法更好的工作取决于下面两点：

* 收集相关事实和重要数据
* 争论不同的观点(以多种方式)

As you can imagine, if we could collect important or relevant data to feed into our models, and try different methods or approaches to the same problem, we will itera‐ tively get better as we find the best model combination.

你可以想象一下，假如我们能够收集到各种重要数据或者相关数据用以补充我们的模型，并且对于同样一个问题可以尝试各种不同的方法和解决途径进行多次迭代，那么我们终究可以找到一个最优模型解

This gets us into what we will be talking about: picking better data or arguing for solutions more effectively.

下面我们将分两方面继续进行深入探讨：如何选择更好的数据以及如何有效的解决争论性的问题

Picking Better Data

选择更好的数据

In this section we’ll be discussing how to pick better data. Basically we want to find the most compact, simplest amount of data that backs up what we are trying to solve. Some of that intuitively means that we want the data that supports our conclusion, which is a bit of cart before the horse; regardless, there are two great methods to improve the data one is using: feature selection and feature transformation algorithms.

在本节中我们将讨论如何选择更好的数据。基本原则是我们希望找到最紧凑最简单的数据集合用以支持我们所试图解决的问题。直观意义上就是指我们试图找到那些最能支持我们结论的那些数据，但是这听上去似乎有些本末倒置(即有了结论以后反过来去找数据支撑)。尽管如此，我们将使用特征选择以及特征转换这两个伟大的方法来改善我们数据并依此做出选择。

This sounds like a great idea, but what is the motivation behind picking better data?

上述的方法听上去好像是个好主意，但是选取数据背后的动机究竟是什么？

Generally speaking, machine learning methods are better suited for smaller dimen‐ sions that are well correlated with the data. As we have discussed, data can become extremely overfit, entangled, or track improperly with many dimensions. We don’t want to under- or overfit our data, so finding the best set to map is the best use of our time.

通常来说，机器学习方法更适用于低维度并且数据之间依赖关系比较大的集合。正如我们之前所讨论的过，数据模型的构建中常常会出现过拟、或者关联了无关的冗余维度导致过拟等现象。我们并不希望出现欠拟或者过拟问题，因此需要找到最佳的数据集才是节省时间的最优方案。

Feature Selection

Let’s think about some data that doesn’t make a whole lot of sense. Say we want to measure weather data and want to be able to predict temperature given three variables: “Matt’s Coffee Consumption,” “Ice Cream Consumption,” and “Season” (see Table 10-1 and Figure 10-1).

特征选择

我们以一组看上去并没有太大意义的数据来讨论如何进行特征选择。假如我们想测量的对象是气象数据，而我们预测气温的依据基于给定的三个变量：Matt咖啡的消费、冰淇淋的消费、季节

Table 10-1. Weather data for Seattle

表10-1 西雅图天气数据

Obviously you can see that I generally drink about 4 cups of coffee a day. I tend to eat

more ice cream in the summertime and it’s generally hotter around that time.

通过数据表你显然可以看到我通常每天会喝掉大概4杯咖啡。如果天气变热或者是夏天的时候我会吃掉更多的冰淇淋。

But what can we do with this data? There are at most N choose K solutions to any

data set, so given N dimensions, we can find an enormous number of combinations

of various-sized subsets.

但是我们能用这些数据做什么呢？从N维数据中尝试找到K种解决方式，对于指定的N维数据，我们可以找到通过排列组合出巨量的包含各种长度子集。

At this point we want to reduce the amount of dimensions we are looking at but don’t

know where to start. In general we want to minimize the redundancy of our data

while maximizing the relevancy. As you can imagine this is a tradeoff: if we keep all

the data, then we’ll know 100% that we have relevant data whereas if we reduce some number of dimensions we might have redundancy—especially if we have lots and lots of dimensions.

基于这点，我们希望降低维度以方便我们更好的观测数据，但是我们并不知道如何开始。简而言之，我们希望在最大限度的减少冗余数据的同时最大限度的提高数据的相关性。你可以把这想象成是一种权衡：如果保留了全部的数据以及维度信息，我们确实能够100%的了解数据间的相关性，但是庞大的维度和巨量的数据会给我们模型计算带来困难。因此必须进行一些数据和维度上的裁剪，而且我们相信某些数据和维度存在冗余关系(这些冗余的数据和维度显然是可以被裁剪的)，特别是当维度非常非常大的时候。

We have talked about this before as being an entanglement problem with having too

many data points that point to the same thing.

我们之前已经谈论过这个问题，很多数据往往会指向同一个问题。

In general, redundancy and relevancy are calculated using the same metrics and on a spectrum:

•Correlation

•Mutual information

•Distance from some point (Euclidean distance from reference)

在一般情况下，冗余性和相关性通常从下面几个范围进行度量：

•相关性

•互信息

•点之间的距离(参考欧式距离)

So they actually end up measuring the same thing. How do we solve this?

其实依据这些度量标准所测量的都是同一个东西，我们如何解决这个问题？

Let’s first take a step back and think about what would happen if we just looked at all possibilities.

我们可以先退一步，首先想想所有发生的可能性是什么？

Exhaustive Search

穷举法搜索

Let’s imagine that in this case we want to find the best possible dimensions to train

on. We could realistically just search through all possibilities. In this case we have

three dimensions which would equate to seven models (123, 12, 13, 23, 1, 2, 3). From

here we could say that we want to find the model that has the highest accuracy

(Figure 10-2).

首先想象一下在下面这个例子中我们希望找到一个最佳的维度模型进行训练。我们可以实事求是的搜索所有的可能性（穷举法）。在这个情况下，我们有三个维度，这将等同于七个模型 (123, 12, 13, 23, 1, 2, 3）。基于这点，我们可以认为我们想找到的模型具有较高的精度。

Figure 10-2. Exhaustive search for best features

穷举法去搜索最佳的功能特性

This unfortunately doesn’t work as well as you go up in dimensions. If for instance

you have 10 dimensions, the possibilities from selecting 10 dimensions, to 1 dimen‐

sion would be 2^10– 1. This can be denoted in Pascal’s triangle (Figure 10-3) as a sum of combinations where:

不幸的消息是如果随着维度持续增加，穷举法将无法正常工作。例如你有10个维度，穷举选择10个维度的所有可能性需要2的10次方-1.这可以在帕斯卡三角(Pascal’s triangle)表示成一个组合

Figure 10-3. Pascal’s triangle

图10-3 帕斯卡三角

Pascal’s triangle shows all combinations for a given row. Since each row sums up to

2^n, all we need to do is subtract 1, so we don’t account for zero dimensions.

帕斯卡三角显示了给定行的所有组合。由于每行的总和是2的N次方，

So as you add dimensions you would have to account for 2^n– 1 possible data sets. If

you had 3,000 dimensions (which would be a good reason to use feature selection),

you would have roughly a trecentillion (10^903) models to run through!

Surely there is a better way. We don’t need to try every model. Instead, what if we just randomly selected features?