In sample and out of sample error

Jeffrey Leek
Johns Hopkins Bloomberg School of Public Health

In sample versus out of sample

In Sample Error: The error rate you get on the same data set you used to build your predictor. Sometimes called resubstitution error.

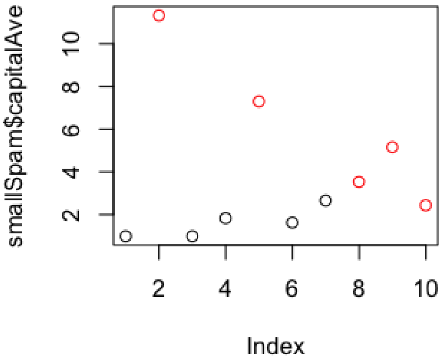
Out of Sample Error: The error rate you get on a new data set. Sometimes called generalization error.

Key ideas

1. Out of sample error is what you care about
2. In sample error $<$ out of sample error
3. The reason is overfitting
   - Matching your algorithm to the data you have

In sample versus out of sample errors

```r
library(kernlab); data(spam); set.seed(333)
smallSpam <- spam[sample(dim(spam)[1],size=10),]
spamLabel <- (smallSpam$type=="spam")*1 + 1
plot(smallSpam$capitalAve,col=spamLabel)
```



Prediction rule 1

- capitalAve > 2.7 = "spam"
- capitalAve < 2.40 = "nonspam"
- capitalAve between 2.40 and 2.45 = "spam"
- capitalAve between 2.45 and 2.7 = "nonspam"

zwei Spezialregeln, die die beiden Spezialfaelle _dieses_ Datensatzes beruecksichtigen!
-> massgeschneidert

daher perfekte Accuracy im Test-Datensatz

Apply Rule 1 to smallSpam

```
rule1 <- function(x){
  prediction <- rep(NA,length(x))
  prediction[x > 2.7] <- "spam"
  prediction[x < 2.40] <- "nonspam"
  prediction[(x >= 2.40 & x <= 2.45)] <- "spam"
  prediction[(x > 2.45 & x <= 2.70)] <- "nonspam"
  return(prediction)
}
table(rule1(smallSpam$capitalAve),smallSpam$type)
```

```
           
          nonspam spam
  nonspam       5    0
  spam          0    5
```

Prediction rule 2

- capitalAve > 2.40 = "spam"
- capitalAve ≤ 2.40 = "nonspam"

`simpler`

Apply Rule 2 to smallSpam

```
rule2 <- function(x){
  prediction <- rep(NA,length(x))
  prediction[x > 2.8] <- "spam"
  prediction[x <= 2.8] <- "nonspam"
  return(prediction)
}
table(rule2(smallSpam$capitalAve),smallSpam$type)
```

```

           nonspam spam
  nonspam        5    1
  spam           0    4
```

Apply to complete spam data

```
table(rule1(spam$capitalAve),spam$type)
```

```
          nonspam spam
  nonspam    2141  588
  spam        647 1225
```

```
table(rule2(spam$capitalAve),spam$type)
```

```
          nonspam spam
  nonspam    2224  642
  spam        564 1171
```

```
mean(rule1(spam$capitalAve)==spam$type)
```

Look at accuracy

```
sum(rule1(spam$capitalAve)==spam$type)
```

```
[1] 3366
```

```
sum(rule2(spam$capitalAve)==spam$type)
```

```
[1] 3395
```

-> einfachere Regel schneidet sogar etwas besser ab.

What's going on?

Overfitting

- Data have two parts
  - Signal
  - Noise
- The goal of a predictor is to find signal
- You can always design a perfect in-sample predictor
- You capture both signal + noise when you do that
- Predictor won't perform as well on new samples

http://en.wikipedia.org/wiki/Overfitting