baggingBoostingRFs

November 12, 2019

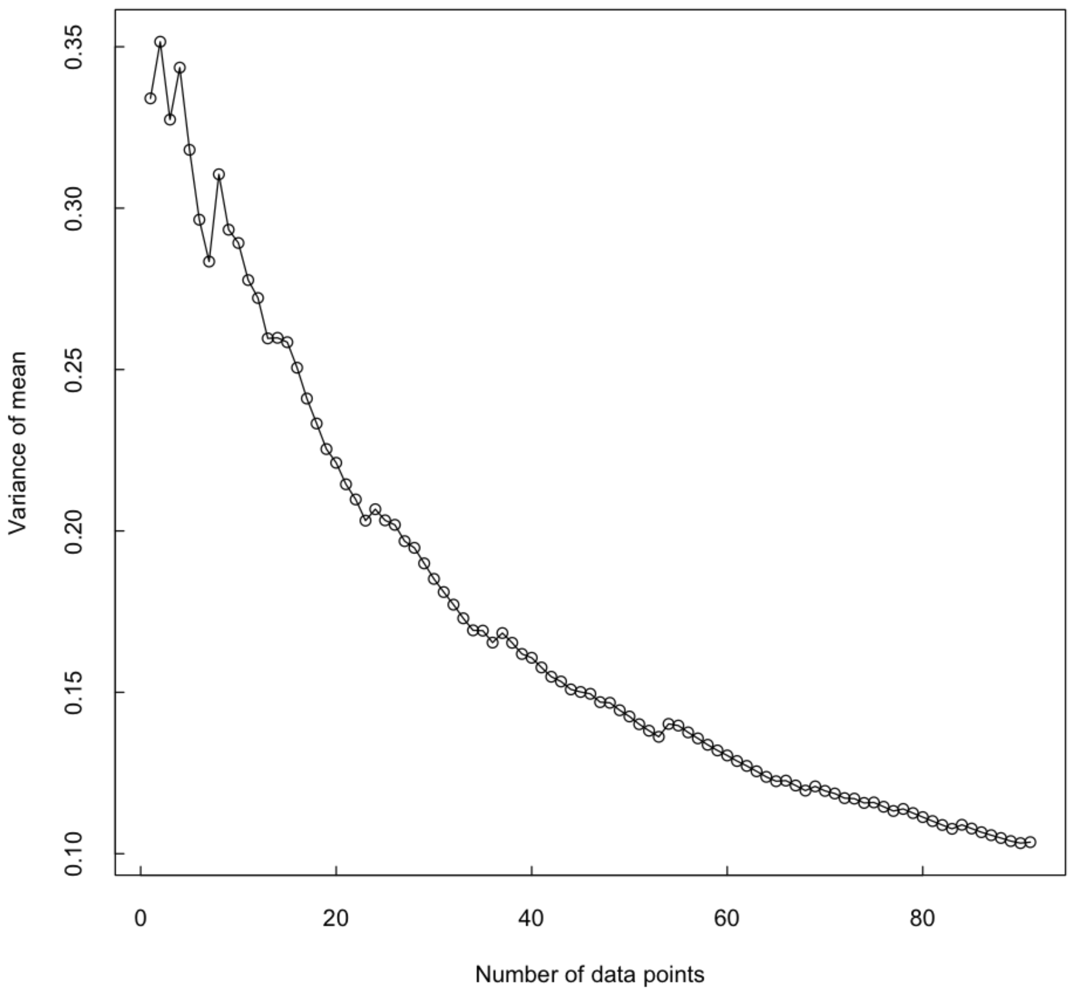
1 Bagging, Boosting, and Random Forests

Decision trees have many advantages. They are easy to interpret. To make a prediction, you only need to follow a set of rules. Predictions are also data-driven, not having to follow a more structured linear pattern like the past model we studied. Regression trees also have two big disadvantages: (i) they typically have poor performance compared to other regression models, and (ii) suffer from high variance.

1.1 Goal of an ensemble

The goal of an ensemble model is to combine many weak predictors, and in doing so, build a model that has lower variance and bias. This phenomena occurs in simple statistics. Given a sample of data $Y_1, Y_2, \cdots, Y_n$ the average $\bar{Y}$ has a Normal distribution with variance σ^2/n. The average lowers the variance. A single regression tree tends to have high variance, and by combining many different regression trees in an ensemble, attempts to lower the variance.

[1]:
```
y = rnorm(10^2)
N = length(y)
vars = rep(0,N-10)

j=1
for(i in 10:N){
    vars[j] = sd(y[1:i])/sqrt(i)
    j=j+1
}

#plot
options(repr.plot.width=8,repr.plot.height=8)
plot(vars, ylab="Variance of mean", xlab="Number of data points",tck=0.01)
lines(vars)
```



1.2 Bagging for a continuous target

Boot-strap aggregation (bagging) constructs B training data sets by sampling, at random, observations from our original dataset until we generate a Bootstrapped dataset of the same size as our original training data. A TBR model is trained on each bootstrapped dataset ($\text{TBR}_b(x)$), and the final Bagged TBR model is defined as the average of all individual TBR_b models

$$\text{TBR}_{\text{bagged}}(x) = \frac{1}{B}\sum_{b=1}^{B}\text{TBR}_b(x)$$

[23]:

```
#require(MASS)
#data(Boston)
#plot(Boston$rm,Boston$medv)

d = read.csv('exampleData.csv')
plot(d$x,d$y)

# Single tree
require(rpart)
TBR = rpart(y~x,data=d)
#TBR = prune(TBR,cp=0.01)

examples       = d[order(d$x),]
yhatsSingle    = predict(TBR,examples)

truthAndPredictions=data.frame(truth=examples$x,predicted=yhatsSingle)
sum((truthAndPredictions$truth-truthAndPredictions$predicted)^2)

# bootstrap function
bootstrapTrainingData = function(){
    nObs = 1:nrow(d)
    boostrap = d[sample(nObs,replace=TRUE),]
    return(boostrap)
}

# Bagged TBR model
B=400
TBR_boostrap = list()
for (b in 1:B){
    bStrap = bootstrapTrainingData()
    TBR_b = rpart(y~x,data=bStrap)
    TBR_b = prune(TBR_b,cp=0.01)
    TBR_boostrap[[b]] = TBR_b
}

# make a prediction
yhats  = predict(TBR_boostrap[[1]],examples)
for (b in 2:B){
    yhats  = yhats+predict(TBR_boostrap[[b]],examples)

    predictions = predict(TBR_boostrap[[b]],examples)
    lines(examples$x,predictions,col='green')
}
yhats = yhats/B
lines(examples$x,yhats,col='blue',lwd=2)

lines(examples$x,yhatsSingle,col='red',lwd=2)
```

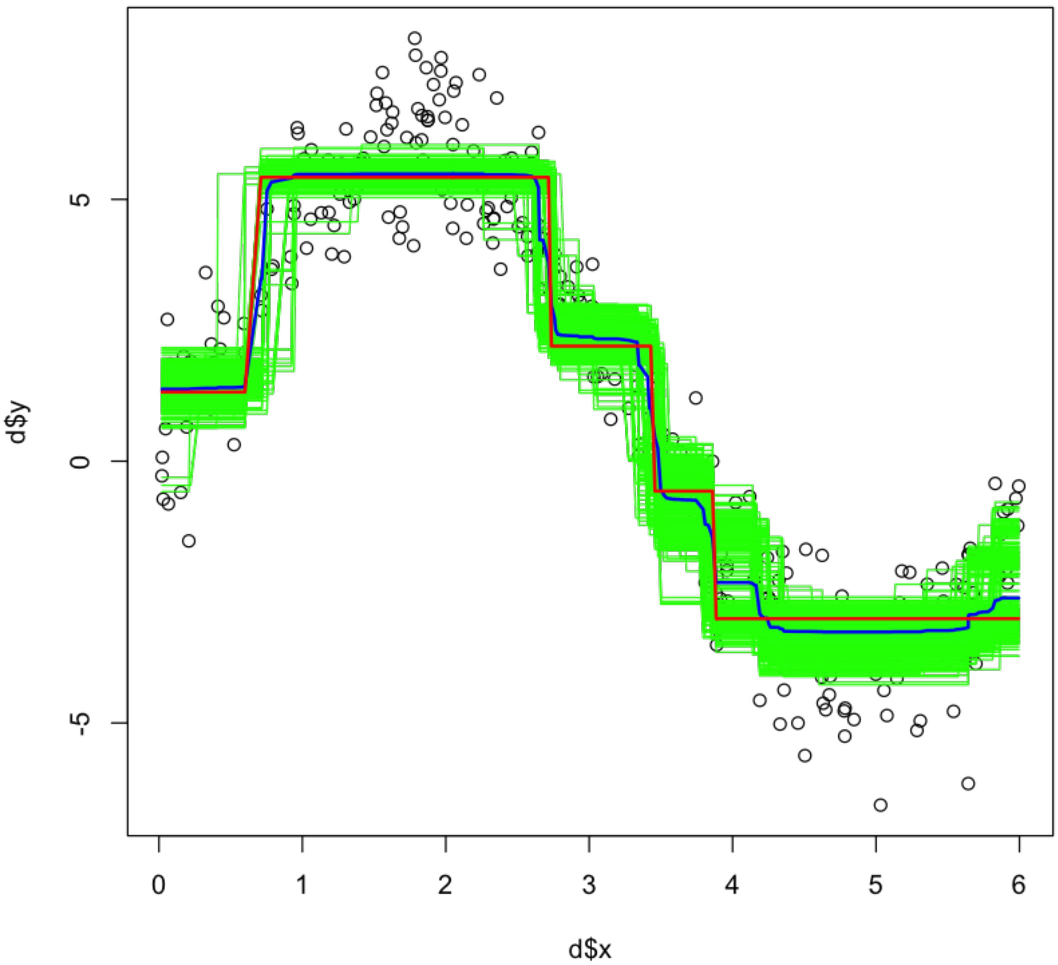
```r
truthAndPredictions=data.frame(truth=examples$medv,predicted=yhats)
sum((truthAndPredictions$truth-truthAndPredictions$predicted)^2)
```

8468.54690681599

```
Error in data.frame(truth = examples$medv, predicted = yhats): arguments␣
↪imply differing number of rows: 0, 300
Traceback:
```

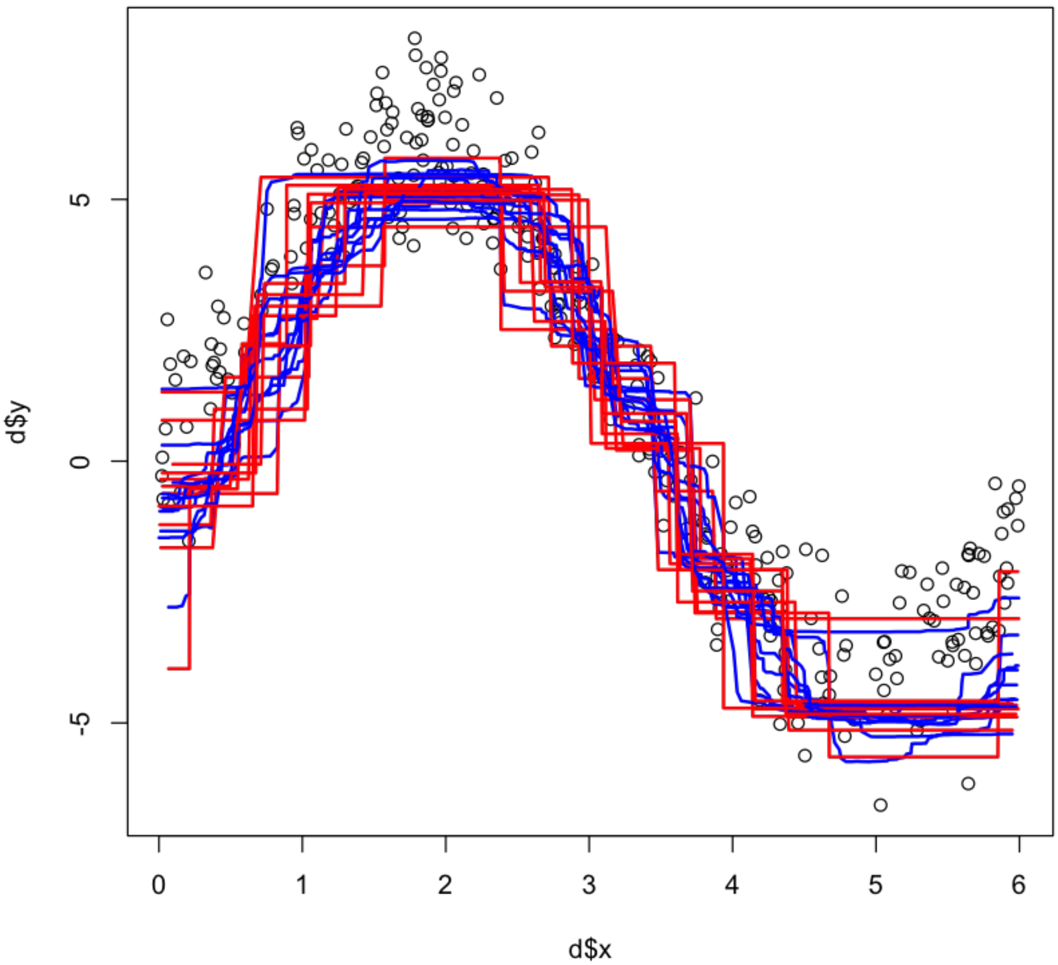
1. `data.frame(truth = examples$medv, predicted = yhats)`

2. `stop(gettextf("arguments imply differing number of rows: %s",`
   `.     paste(unique(nrows), collapse = ", ")), domain = NA)`



[24]:
```
plot(d$x,d$y)
lines(examples$x,yhats,col='blue',lwd=2)
lines(examples$x,yhatsSingle,col='red',lwd=2)

for (k in 1:10){
    d = read.csv(sprintf('exampleData_%02d.csv',k))
#     par(new=TRUE)
#     plot(d$x,d$y)

    TBR_1 = TBR
    yhatsSingle1 = yhatsSingle

    TBRnew = rpart(y~x,data=d)
```

```
    TBRnew = prune(TBRnew,cp=0.01)

    examples        = d[order(d$x),]
    yhatsSingle     = predict(TBRnew,examples)


    TBR_bootStrap1 = TBR_boostrap
    yhats1 = yhats

    # bootstrap function
    bootstrapTrainingData = function(){
        nObs = 1:nrow(d)
        boostrap = d[sample(nObs,replace=TRUE),]
        return(boostrap)
    }

    # Bagged TBR model
    B=500
    TBR_boostrap = list()
    for (b in 1:B){
        bStrap = bootstrapTrainingData()
        TBR_b = rpart(y~x,data=bStrap)
        TBR_b = prune(TBR_b,cp=0.01)
        TBR_boostrap[[b]] = TBR_b
    }

    # make a prediction
    yhats  = predict(TBR_boostrap[[1]],examples)
    for (b in 2:B){
        yhats  = yhats+predict(TBR_boostrap[[b]],examples)

        predictions = predict(TBR_boostrap[[b]],examples)
    }
    yhats = yhats/B

    lines(examples$x,yhats,col='blue',lwd=2)
    lines(examples$x,yhatsSingle,col='red',lwd=2)
}
```



1.3 Random forests

Random forests are similar to Bagged trees, except for a minor tweak. Every time a new split in our tree is considered, the random forest model only considers a randomly chosen subset of variables. By choosing from a random subset of variables to split, the RF model attempts to decorrelate individual trees from one another. The more independent each tree in the ensemble, the better the average.

[ ]:
```
require(MASS)
data(Boston)
plot(Boston$rm,Boston$medv)
```

```r
# Single tree
require(rpart)
TBR = rpart(medv~rm,data=Boston)
TBR = prune(TBR,cp=0.01)

examples = Boston[order(Boston$rm),]
yhatsSingle    = predict(TBR,examples)

d=data.frame(truth=examples$medv,predicted=yhats)
sum((d$truth-d$predicted)^2)


require(randomForest)
RF <- randomForest(medv ~ ., data = Boston, importance = TRUE)
yhats = predict(RF,examples)

lines( examples$rm, yhats,col='green' )
lines( examples$rm, yhatsSingle,col='blue' )

d=data.frame(truth=examples$medv,predicted=yhats)
sum((d$truth-d$predicted)^2)
```

1.4 Bagging for a categorical target

1.4.1 Majority Vote

1.5 Measuring out of sample error