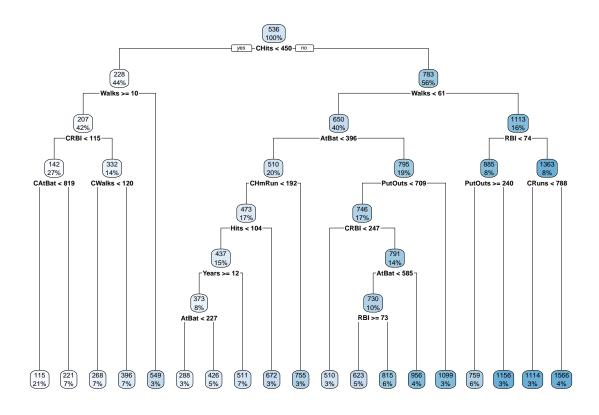
## Decision Tree and Random Forest

Aylin Mumcular 14th May 2018

```
res.rp <- rpart(Salary~.,d,cp=0.001)
res.rp
## n=263 (59 observations deleted due to missingness)
##
  node), split, n, deviance, yval
##
         * denotes terminal node
##
##
     1) root 263 53319110.00 535.9259
##
       2) CHits< 450 117 5931094.00 227.8547
##
         4) Walks>=10 110 1754378.00 207.4470
##
           8) CRBI< 114.5 72
                               284426.40 141.6343
##
            16) CAtBat< 818.5 54
                                    76731.04 115.0926 *
##
            17) CAtBat>=818.5 18
                                    55531.94
                                              221.2593 *
##
           9) CRBI>=114.5 38
                               567215.00 332.1447
##
            18) CWalks< 120 19
                                 119848.20
                                            268.2368 *
##
            19) CWalks>=120 19
                                 292166.40
##
         5) Walks< 10 7 3410996.00 548.5476 *
##
       3) CHits>=450 146 27385210.00 782.8048
         6) Walks< 61 104 9469906.00 649.6232
##
          12) AtBat< 395.5 53 2859476.00 510.0157
##
            24) CHmRun< 192 46 1613745.00 472.7718
##
##
              48) Hits< 103.5 39 1192870.00 436.9872
##
                96) Years>=11.5 21
                                     354508.20 373.4127
##
                 192) AtBat< 226.5 8
                                         26150.00 287.5000 *
                                         232973.10 426.2821 *
##
                 193) AtBat>=226.5 13
##
                97) Years< 11.5 18
                                     654463.60 511.1574 *
##
              49) Hits>=103.5 7
                                   92692.86 672.1429 *
##
            25) CHmRun>=192 7
                                762619.10
                                           754.7619 *
##
          13) AtBat>=395.5 51 4503956.00
                                           794.7054
            26) PutOuts< 709 44 2358329.00 746.3631
##
##
              52) CRBI< 246.5 7
                                  292530.40 509.6429 *
##
              53) CRBI>=246.5 37 1599333.00 791.1480
##
               106) AtBat< 585 27
                                    975014.60 729.9065
##
                 212) RBI>=72.5 12
                                     353972.80 623.4702 *
##
                 213) RBI< 72.5 15
                                     376342.30
                                                815.0555 *
##
               107) AtBat>=585 10
                                    249641.40 956.5000 *
            27) PutOuts>=709 7 1396458.00 1098.5710 *
##
##
         7) Walks>=61 42 11502830.00 1112.5880
##
          14) RBI< 73.5 22 3148182.00 885.2651
##
            28) PutOuts>=239.5 15
                                    656292.30 758.8889 *
            29) PutOuts< 239.5 7 1738973.00 1156.0710 *
##
##
          15) RBI>=73.5 20 5967231.00 1362.6430
##
            30) CRuns< 788 9
                               581309.70 1114.4440 *
##
            31) CRuns>=788 11
                               4377879.00 1565.7150 *
rpart.plot(res.rp)
```

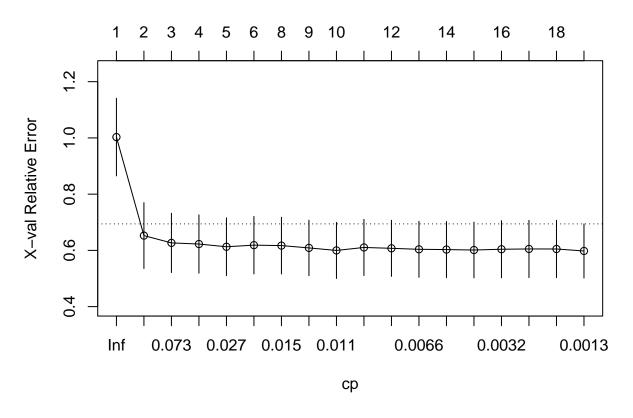


```
#Recursive partitioning
predict(res.rp,newdata=d[17,]) #First grow a very large tree, then prune it
## -Buddy Bell
##
      1565.715
printcp(res.rp)
##
## Regression tree:
## rpart(formula = Salary ~ ., data = d, cp = 0.001)
##
## Variables actually used in tree construction:
                                CHmRun CRBI
##
   [1] AtBat
                CAtBat CHits
                                                CRuns
                                                        CWalks Hits
##
   [9] PutOuts RBI
                        Walks
                                Years
##
## Root node error: 53319113/263 = 202734
##
## n=263 (59 observations deleted due to missingness)
##
##
             CP nsplit rel error xerror
## 1 0.3751526
                     0
                         1.00000 1.00296 0.138011
## 2 0.1202660
                     1
                         0.62485 0.65261 0.117220
## 3 0.0447760
                     2
                         0.50458 0.62667 0.105404
    0.0395069
                     3
                         0.45981 0.62259 0.103688
## 5 0.0189058
                         0.42030 0.61289 0.102734
```

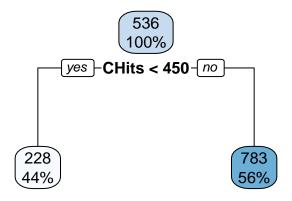
```
## 6 0.0156460
                         0.40139 0.61865 0.102423
     0.0141210
                         0.37010 0.61703 0.100734
## 7
                     7
     0.0140507
                         0.35598 0.60881 0.098552
     0.0090608
                         0.34193 0.59981 0.099742
## 9
                     9
                         0.33287 0.61039 0.099877
## 10 0.0087486
                    10
## 11 0.0070271
                    11
                         0.32412 0.60739 0.099788
## 12 0.0061551
                    12
                         0.31709 0.60381 0.099624
## 13 0.0045893
                         0.31094 0.60293 0.099682
                    13
## 14 0.0034490
                    14
                         0.30635 0.60124 0.099191
## 15 0.0029108
                    15
                         0.30290 0.60407 0.101550
## 16 0.0028538
                    16
                         0.29999 0.60509 0.101883
## 17 0.0017889
                    17
                         0.29713 0.60494 0.101853
## 18 0.0010000
                    18
                         0.29535 0.59787 0.096345
```

plotcp(res.rp) #Anything below the line is statistically indifferent. I make a choice in favor of a simple statistically indifferent.

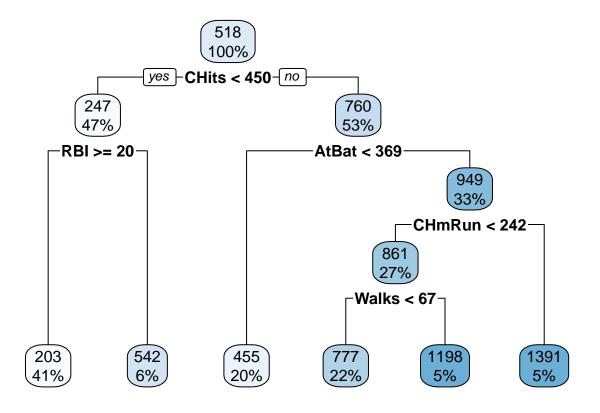
## size of tree



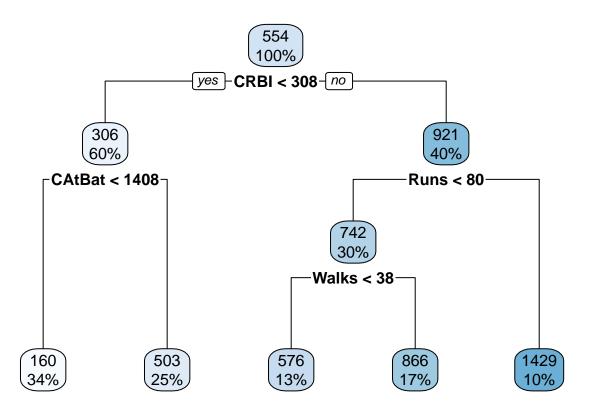
```
res.pruned <- prune(res.rp,cp=.2)
rpart.plot(res.pruned)</pre>
```



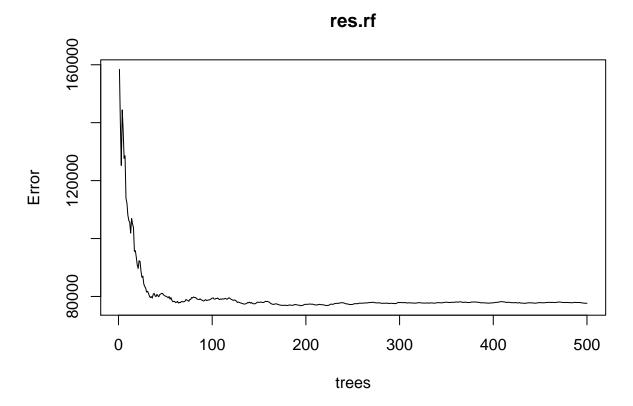
```
predict(res.pruned,newdata=d[17,])
## -Buddy Bell
      782.8048
#Use MSE to check goodness of fit. This is a nonparametric model, I can just use predictions. Pick the
set.seed(1)
id <- sample(c(FALSE,TRUE),nrow(d),rep=TRUE)</pre>
table(id)
## id
## FALSE TRUE
##
     162
           160
d1 <- d[id,]</pre>
d2 <- d[!id,]
res.rp1 <- rpart(Salary~.,d1,cp=0.02)</pre>
res.rp2 <- rpart(Salary~.,d2,cp=0.02)</pre>
rpart.plot(res.rp1)
```



rpart.plot(res.rp2)



```
set.seed(3)
s <- sample(1:40,rep=TRUE)</pre>
table(s) #T1 and T2 are not independent
## s
## 2 3 4 5 6 8 9 10 11 12 15 16 18 19 20 22 23 25 29 31 33 36 37 39 40
## 1 1 1 2 1 3 2 3 1 2 1 1 1 1 1 1 1 2 1 1 1 3 1 6
Bagging
res.rf <- randomForest(Salary~.,na.omit(d),mtry=ncol(d)-1)
res.rf
##
   randomForest(formula = Salary ~ ., data = na.omit(d), mtry = ncol(d) -
##
                                                                              1)
##
                 Type of random forest: regression
                       Number of trees: 500
##
## No. of variables tried at each split: 19
##
##
            Mean of squared residuals: 79865.04
##
                      % Var explained: 60.61
RandomForest
res.rf <- randomForest(Salary~.,na.omit(d))</pre>
res.rf
```



## importance(res.rf,type=1) #first column ## %IncMSE 8.3053494 ## AtBat ## Hits 6.4552783 6.0570968 ## HmRun ## Runs 6.6815317 ## RBI 6.1764620 ## Walks 5.2095354 ## Years 7.0732857 ## CAtBat 14.1930385 ## CHits 13.2423782 ## CHmRun 7.8666030 ## CRuns 10.5996034 ## CRBI 11.1924379 ## CWalks 6.9982971 ## League -1.0493647 ## Division 0.7546720 ## PutOuts 4.4171769 ## Assists 0.1772433 ## Errors 1.7773874 ## NewLeague 1.3284999

varImpPlot(res.rf,type=1)

## res.rf

