

Jin Kweon - lab 12 (3032235207)

Jin Kweon

11/17/2017

Decision Trees

Q. So, when I output the “plot(tree_carseats),” then does the condition on the parents node true is on the left, and false on the right? ==> True!!!

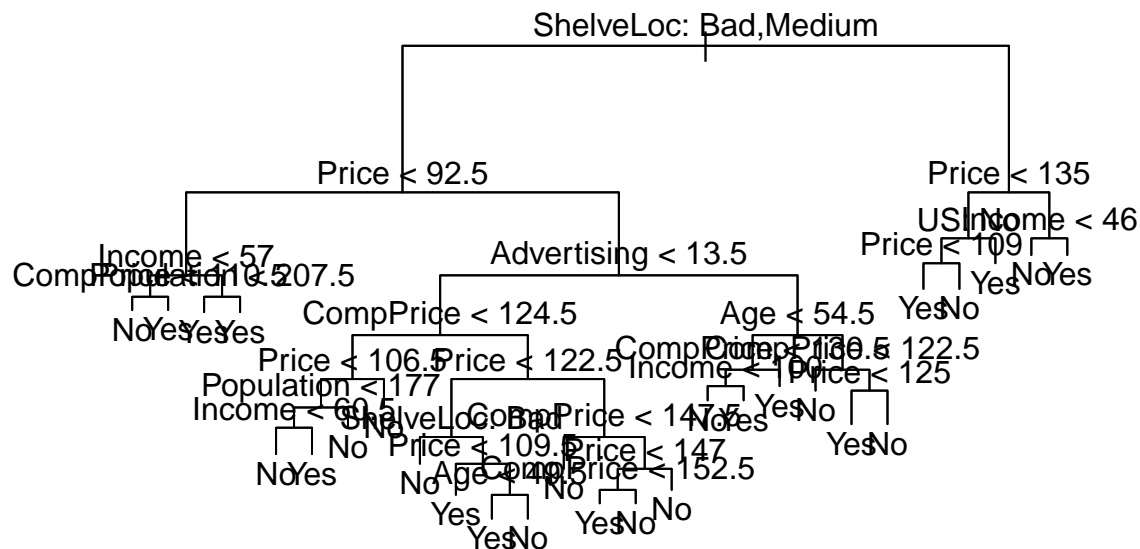
Q. Why do I see error message when I run `library(ParallelForest)???` ==> no worry.

```
attach(Carseats)
High <- ifelse(Sales <= 8, "No", "Yes")
carseats <- data.frame(Carseats, High)

tree_carseats <- tree(High ~.-Sales, data = carseats)
summary(tree_carseats)
```

```
##
## Classification tree:
## tree(formula = High ~ . - Sales, data = carseats)
## Variables actually used in tree construction:
## [1] "ShelveLoc" "Price" "Income" "CompPrice" "Population"
## [6] "Advertising" "Age" "US"
## Number of terminal nodes: 27
## Residual mean deviance: 0.4575 = 170.7 / 373
## Misclassification error rate: 0.09 = 36 / 400
```

```
plot(tree_carseats)
text(tree_carseats, pretty=0)
```



tree_carseats

```
## node), split, n, deviance, yval, (yprob)
##      * denotes terminal node
```

```

##
## 1) root 400 541.500 No ( 0.59000 0.41000 )
##      2) ShelfLoc: Bad,Medium 315 390.600 No ( 0.68889 0.31111 )
##          4) Price < 92.5 46 56.530 Yes ( 0.30435 0.69565 )
##              8) Income < 57 10 12.220 No ( 0.70000 0.30000 )
##                  16) CompPrice < 110.5 5 0.000 No ( 1.00000 0.00000 ) *
##                  17) CompPrice > 110.5 5 6.730 Yes ( 0.40000 0.60000 ) *
##              9) Income > 57 36 35.470 Yes ( 0.19444 0.80556 )
##                  18) Population < 207.5 16 21.170 Yes ( 0.37500 0.62500 ) *
##                  19) Population > 207.5 20 7.941 Yes ( 0.05000 0.95000 ) *
##          5) Price > 92.5 269 299.800 No ( 0.75465 0.24535 )
##              10) Advertising < 13.5 224 213.200 No ( 0.81696 0.18304 )
##                  20) CompPrice < 124.5 96 44.890 No ( 0.93750 0.06250 )
##                      40) Price < 106.5 38 33.150 No ( 0.84211 0.15789 )
##                          80) Population < 177 12 16.300 No ( 0.58333 0.41667 )
##                              160) Income < 60.5 6 0.000 No ( 1.00000 0.00000 ) *
##                              161) Income > 60.5 6 5.407 Yes ( 0.16667 0.83333 ) *
##                          81) Population > 177 26 8.477 No ( 0.96154 0.03846 ) *
##                  41) Price > 106.5 58 0.000 No ( 1.00000 0.00000 ) *
##          21) CompPrice > 124.5 128 150.200 No ( 0.72656 0.27344 )
##              42) Price < 122.5 51 70.680 Yes ( 0.49020 0.50980 )
##                  84) ShelfLoc: Bad 11 6.702 No ( 0.90909 0.09091 ) *
##                  85) ShelfLoc: Medium 40 52.930 Yes ( 0.37500 0.62500 )
##                      170) Price < 109.5 16 7.481 Yes ( 0.06250 0.93750 ) *
##                      171) Price > 109.5 24 32.600 No ( 0.58333 0.41667 )
##                          342) Age < 49.5 13 16.050 Yes ( 0.30769 0.69231 ) *
##                          343) Age > 49.5 11 6.702 No ( 0.90909 0.09091 ) *
##              43) Price > 122.5 77 55.540 No ( 0.88312 0.11688 )
##                  86) CompPrice < 147.5 58 17.400 No ( 0.96552 0.03448 ) *
##                  87) CompPrice > 147.5 19 25.010 No ( 0.63158 0.36842 )
##                      174) Price < 147 12 16.300 Yes ( 0.41667 0.58333 )
##                          348) CompPrice < 152.5 7 5.742 Yes ( 0.14286 0.85714 ) *
##                          349) CompPrice > 152.5 5 5.004 No ( 0.80000 0.20000 ) *
##                      175) Price > 147 7 0.000 No ( 1.00000 0.00000 ) *
##          11) Advertising > 13.5 45 61.830 Yes ( 0.44444 0.55556 )
##              22) Age < 54.5 25 25.020 Yes ( 0.20000 0.80000 )
##                  44) CompPrice < 130.5 14 18.250 Yes ( 0.35714 0.64286 )
##                      88) Income < 100 9 12.370 No ( 0.55556 0.44444 ) *
##                      89) Income > 100 5 0.000 Yes ( 0.00000 1.00000 ) *
##                  45) CompPrice > 130.5 11 0.000 Yes ( 0.00000 1.00000 ) *
##          23) Age > 54.5 20 22.490 No ( 0.75000 0.25000 )
##              46) CompPrice < 122.5 10 0.000 No ( 1.00000 0.00000 ) *
##              47) CompPrice > 122.5 10 13.860 No ( 0.50000 0.50000 )
##                  94) Price < 125 5 0.000 Yes ( 0.00000 1.00000 ) *
##                  95) Price > 125 5 0.000 No ( 1.00000 0.00000 ) *
##      3) ShelfLoc: Good 85 90.330 Yes ( 0.22353 0.77647 )
##          6) Price < 135 68 49.260 Yes ( 0.11765 0.88235 )
##              12) US: No 17 22.070 Yes ( 0.35294 0.64706 )
##                  24) Price < 109 8 0.000 Yes ( 0.00000 1.00000 ) *
##                  25) Price > 109 9 11.460 No ( 0.66667 0.33333 ) *
##              13) US: Yes 51 16.880 Yes ( 0.03922 0.96078 ) *
##          7) Price > 135 17 22.070 No ( 0.64706 0.35294 )
##              14) Income < 46 6 0.000 No ( 1.00000 0.00000 ) *
##              15) Income > 46 11 15.160 Yes ( 0.45455 0.54545 ) *

```

Random Forests

Q. What does it mean by “Random forests are considered one of the best “off-the-shelf” classifiers with minimal tuning.”?? ==> There is no tuning parameter, but you do not need to tune a lot. The default parameter already did good job.

Q. What is really “importance = T”??

Q. The textbook says “In the case of a classification tree, the argument type=“class” instructs R to return the actual class prediction.” Do I need to include type = class for my exercise? But seems like I got the same result regardless I include this or not...

Q. So, I guess the OOB error rate is the mean prediction error in the training data set? But, why do we really need to get training error rate...? And, I want to get some intuition of rf\$err.rate...?

Q. Why my importance() function gives different outputs with the one in pg.330??? And, can you help me interpret it?

Q. Why are we doing variable selection here though... I dont really understand.....

```
set.seed(10)
train <- as.vector(createDataPartition(carseats[,2], p = 0.8))[[1]]
rf <- randomForest(High ~ .-Sales, data = carseats[train, ], importance = T)
rf

##
## Call:
## randomForest(formula = High ~ . - Sales, data = carseats[train,      ], importance = T)
##              Type of random forest: classification
##              Number of trees: 500
## No. of variables tried at each split: 3
##
##              OOB estimate of  error rate: 19.69%
## Confusion matrix:
##              No Yes class.error
## No  166  23   0.1216931
## Yes  40  91   0.3053435

rf$err.rate

##              OOB              No              Yes
## [1,] 0.3442623 0.3150685 0.3877551
## [2,] 0.3092784 0.2678571 0.3658537
## [3,] 0.3020408 0.2620690 0.3600000
## [4,] 0.2977941 0.2562500 0.3571429
## [5,] 0.2808219 0.2011834 0.3902439
## [6,] 0.2662338 0.1944444 0.3671875
## [7,] 0.2683706 0.1902174 0.3798450
## [8,] 0.2666667 0.1945946 0.3692308
## [9,] 0.2807571 0.1818182 0.4230769
## [10,] 0.2704403 0.1861702 0.3923077
## [11,] 0.2735849 0.1968085 0.3846154
## [12,] 0.2515723 0.1861702 0.3461538
## [13,] 0.2389937 0.1702128 0.3384615
## [14,] 0.2327044 0.1648936 0.3307692
## [15,] 0.2351097 0.1587302 0.3461538
## [16,] 0.2437500 0.1746032 0.3435115
## [17,] 0.2343750 0.1693122 0.3282443
```

```

## [18,] 0.2375000 0.1640212 0.3435115
## [19,] 0.2312500 0.1534392 0.3435115
## [20,] 0.2312500 0.1481481 0.3511450
## [21,] 0.2375000 0.1534392 0.3587786
## [22,] 0.2375000 0.1587302 0.3511450
## [23,] 0.2343750 0.1481481 0.3587786
## [24,] 0.2406250 0.1534392 0.3664122
## [25,] 0.2312500 0.1428571 0.3587786
## [26,] 0.2375000 0.1534392 0.3587786
## [27,] 0.2406250 0.1693122 0.3435115
## [28,] 0.2375000 0.1587302 0.3511450
## [29,] 0.2406250 0.1587302 0.3587786
## [30,] 0.2406250 0.1587302 0.3587786
## [31,] 0.2343750 0.1481481 0.3587786
## [32,] 0.2406250 0.1587302 0.3587786
## [33,] 0.2250000 0.1428571 0.3435115
## [34,] 0.2218750 0.1375661 0.3435115
## [35,] 0.2125000 0.1269841 0.3358779
## [36,] 0.2281250 0.1481481 0.3435115
## [37,] 0.2218750 0.1481481 0.3282443
## [38,] 0.2218750 0.1428571 0.3358779
## [39,] 0.2218750 0.1534392 0.3206107
## [40,] 0.2187500 0.1534392 0.3129771
## [41,] 0.2250000 0.1481481 0.3358779
## [42,] 0.2218750 0.1375661 0.3435115
## [43,] 0.2187500 0.1375661 0.3358779
## [44,] 0.2281250 0.1428571 0.3511450
## [45,] 0.2312500 0.1587302 0.3358779
## [46,] 0.2281250 0.1534392 0.3358779
## [47,] 0.2375000 0.1587302 0.3511450
## [48,] 0.2312500 0.1534392 0.3435115
## [49,] 0.2187500 0.1481481 0.3206107
## [50,] 0.2312500 0.1534392 0.3435115
## [51,] 0.2187500 0.1428571 0.3282443
## [52,] 0.2343750 0.1746032 0.3206107
## [53,] 0.2218750 0.1481481 0.3282443
## [54,] 0.2343750 0.1693122 0.3282443
## [55,] 0.2187500 0.1428571 0.3282443
## [56,] 0.2250000 0.1534392 0.3282443
## [57,] 0.2218750 0.1481481 0.3282443
## [58,] 0.2156250 0.1481481 0.3129771
## [59,] 0.2250000 0.1587302 0.3206107
## [60,] 0.2187500 0.1534392 0.3129771
## [61,] 0.2250000 0.1534392 0.3282443
## [62,] 0.2156250 0.1428571 0.3206107
## [63,] 0.2187500 0.1534392 0.3129771
## [64,] 0.2218750 0.1481481 0.3282443
## [65,] 0.2281250 0.1587302 0.3282443
## [66,] 0.2250000 0.1640212 0.3129771
## [67,] 0.2218750 0.1534392 0.3206107
## [68,] 0.2187500 0.1587302 0.3053435
## [69,] 0.2218750 0.1587302 0.3129771
## [70,] 0.2218750 0.1587302 0.3129771
## [71,] 0.2218750 0.1534392 0.3206107

```

```

## [72,] 0.2281250 0.1587302 0.3282443
## [73,] 0.2281250 0.1587302 0.3282443
## [74,] 0.2281250 0.1640212 0.3206107
## [75,] 0.2375000 0.1746032 0.3282443
## [76,] 0.2250000 0.1534392 0.3282443
## [77,] 0.2250000 0.1534392 0.3282443
## [78,] 0.2218750 0.1481481 0.3282443
## [79,] 0.2218750 0.1428571 0.3358779
## [80,] 0.2281250 0.1534392 0.3358779
## [81,] 0.2218750 0.1428571 0.3358779
## [82,] 0.2187500 0.1428571 0.3282443
## [83,] 0.2156250 0.1428571 0.3206107
## [84,] 0.2187500 0.1428571 0.3282443
## [85,] 0.2093750 0.1375661 0.3129771
## [86,] 0.2093750 0.1428571 0.3053435
## [87,] 0.2125000 0.1428571 0.3129771
## [88,] 0.2187500 0.1481481 0.3206107
## [89,] 0.2156250 0.1375661 0.3282443
## [90,] 0.2156250 0.1428571 0.3206107
## [91,] 0.2062500 0.1428571 0.2977099
## [92,] 0.2125000 0.1375661 0.3206107
## [93,] 0.2156250 0.1375661 0.3282443
## [94,] 0.2218750 0.1534392 0.3206107
## [95,] 0.2062500 0.1428571 0.2977099
## [96,] 0.2093750 0.1428571 0.3053435
## [97,] 0.2156250 0.1481481 0.3129771
## [98,] 0.2062500 0.1375661 0.3053435
## [99,] 0.2125000 0.1375661 0.3206107
## [100,] 0.2093750 0.1375661 0.3129771
## [101,] 0.2125000 0.1428571 0.3129771
## [102,] 0.2093750 0.1428571 0.3053435
## [103,] 0.2093750 0.1428571 0.3053435
## [104,] 0.2125000 0.1428571 0.3129771
## [105,] 0.2093750 0.1428571 0.3053435
## [106,] 0.2125000 0.1428571 0.3129771
## [107,] 0.2093750 0.1428571 0.3053435
## [108,] 0.2062500 0.1375661 0.3053435
## [109,] 0.2062500 0.1322751 0.3129771
## [110,] 0.2062500 0.1322751 0.3129771
## [111,] 0.2000000 0.1269841 0.3053435
## [112,] 0.2000000 0.1269841 0.3053435
## [113,] 0.2031250 0.1269841 0.3129771
## [114,] 0.2031250 0.1269841 0.3129771
## [115,] 0.2062500 0.1322751 0.3129771
## [116,] 0.2031250 0.1269841 0.3129771
## [117,] 0.2000000 0.1269841 0.3053435
## [118,] 0.2000000 0.1269841 0.3053435
## [119,] 0.2031250 0.1322751 0.3053435
## [120,] 0.1968750 0.1269841 0.2977099
## [121,] 0.2000000 0.1269841 0.3053435
## [122,] 0.1968750 0.1216931 0.3053435
## [123,] 0.2031250 0.1322751 0.3053435
## [124,] 0.2031250 0.1269841 0.3129771
## [125,] 0.2000000 0.1216931 0.3129771

```

```

## [126,] 0.2000000 0.1216931 0.3129771
## [127,] 0.2000000 0.1269841 0.3053435
## [128,] 0.1968750 0.1216931 0.3053435
## [129,] 0.1968750 0.1216931 0.3053435
## [130,] 0.1968750 0.1216931 0.3053435
## [131,] 0.1937500 0.1216931 0.2977099
## [132,] 0.1968750 0.1269841 0.2977099
## [133,] 0.2031250 0.1375661 0.2977099
## [134,] 0.2000000 0.1322751 0.2977099
## [135,] 0.2031250 0.1322751 0.3053435
## [136,] 0.2031250 0.1375661 0.2977099
## [137,] 0.2031250 0.1322751 0.3053435
## [138,] 0.2031250 0.1375661 0.2977099
## [139,] 0.2062500 0.1375661 0.3053435
## [140,] 0.2000000 0.1269841 0.3053435
## [141,] 0.1937500 0.1269841 0.2900763
## [142,] 0.2000000 0.1269841 0.3053435
## [143,] 0.1968750 0.1216931 0.3053435
## [144,] 0.1968750 0.1164021 0.3129771
## [145,] 0.1968750 0.1164021 0.3129771
## [146,] 0.1968750 0.1216931 0.3053435
## [147,] 0.1968750 0.1269841 0.2977099
## [148,] 0.1906250 0.1164021 0.2977099
## [149,] 0.2000000 0.1322751 0.2977099
## [150,] 0.1937500 0.1164021 0.3053435
## [151,] 0.1968750 0.1216931 0.3053435
## [152,] 0.1937500 0.1164021 0.3053435
## [153,] 0.1937500 0.1216931 0.2977099
## [154,] 0.1968750 0.1216931 0.3053435
## [155,] 0.1968750 0.1216931 0.3053435
## [156,] 0.1937500 0.1164021 0.3053435
## [157,] 0.1937500 0.1164021 0.3053435
## [158,] 0.1937500 0.1164021 0.3053435
## [159,] 0.2000000 0.1216931 0.3129771
## [160,] 0.2000000 0.1216931 0.3129771
## [161,] 0.1968750 0.1216931 0.3053435
## [162,] 0.1937500 0.1164021 0.3053435
## [163,] 0.2000000 0.1269841 0.3053435
## [164,] 0.1968750 0.1216931 0.3053435
## [165,] 0.1937500 0.1216931 0.2977099
## [166,] 0.2031250 0.1269841 0.3129771
## [167,] 0.2000000 0.1216931 0.3129771
## [168,] 0.2000000 0.1216931 0.3129771
## [169,] 0.1968750 0.1164021 0.3129771
## [170,] 0.1937500 0.1216931 0.2977099
## [171,] 0.1968750 0.1216931 0.3053435
## [172,] 0.1968750 0.1216931 0.3053435
## [173,] 0.1968750 0.1164021 0.3129771
## [174,] 0.1937500 0.1164021 0.3053435
## [175,] 0.1937500 0.1216931 0.2977099
## [176,] 0.2000000 0.1269841 0.3053435
## [177,] 0.1968750 0.1216931 0.3053435
## [178,] 0.1937500 0.1216931 0.2977099
## [179,] 0.1937500 0.1216931 0.2977099

```

```

## [180,] 0.1937500 0.1216931 0.2977099
## [181,] 0.1906250 0.1216931 0.2900763
## [182,] 0.1906250 0.1216931 0.2900763
## [183,] 0.1906250 0.1216931 0.2900763
## [184,] 0.1937500 0.1216931 0.2977099
## [185,] 0.1937500 0.1216931 0.2977099
## [186,] 0.1906250 0.1216931 0.2900763
## [187,] 0.1906250 0.1164021 0.2977099
## [188,] 0.1937500 0.1216931 0.2977099
## [189,] 0.2000000 0.1269841 0.3053435
## [190,] 0.2000000 0.1269841 0.3053435
## [191,] 0.2000000 0.1269841 0.3053435
## [192,] 0.2000000 0.1269841 0.3053435
## [193,] 0.1968750 0.1216931 0.3053435
## [194,] 0.1968750 0.1216931 0.3053435
## [195,] 0.2000000 0.1269841 0.3053435
## [196,] 0.1937500 0.1216931 0.2977099
## [197,] 0.2031250 0.1269841 0.3129771
## [198,] 0.2031250 0.1269841 0.3129771
## [199,] 0.2000000 0.1216931 0.3129771
## [200,] 0.1968750 0.1216931 0.3053435
## [201,] 0.1968750 0.1164021 0.3129771
## [202,] 0.1937500 0.1111111 0.3129771
## [203,] 0.1937500 0.1111111 0.3129771
## [204,] 0.1937500 0.1164021 0.3053435
## [205,] 0.2031250 0.1269841 0.3129771
## [206,] 0.2031250 0.1216931 0.3206107
## [207,] 0.2031250 0.1269841 0.3129771
## [208,] 0.2000000 0.1216931 0.3129771
## [209,] 0.2000000 0.1216931 0.3129771
## [210,] 0.2000000 0.1216931 0.3129771
## [211,] 0.1968750 0.1216931 0.3053435
## [212,] 0.2031250 0.1322751 0.3053435
## [213,] 0.2031250 0.1322751 0.3053435
## [214,] 0.2000000 0.1216931 0.3129771
## [215,] 0.2062500 0.1322751 0.3129771
## [216,] 0.1968750 0.1216931 0.3053435
## [217,] 0.1968750 0.1216931 0.3053435
## [218,] 0.2031250 0.1269841 0.3129771
## [219,] 0.2031250 0.1269841 0.3129771
## [220,] 0.2031250 0.1269841 0.3129771
## [221,] 0.2000000 0.1216931 0.3129771
## [222,] 0.2031250 0.1269841 0.3129771
## [223,] 0.1968750 0.1216931 0.3053435
## [224,] 0.2000000 0.1269841 0.3053435
## [225,] 0.2031250 0.1269841 0.3129771
## [226,] 0.1968750 0.1216931 0.3053435
## [227,] 0.1968750 0.1216931 0.3053435
## [228,] 0.2031250 0.1322751 0.3053435
## [229,] 0.2000000 0.1269841 0.3053435
## [230,] 0.2000000 0.1216931 0.3129771
## [231,] 0.1968750 0.1216931 0.3053435
## [232,] 0.2000000 0.1216931 0.3129771
## [233,] 0.2000000 0.1216931 0.3129771

```

```

## [234,] 0.2000000 0.1216931 0.3129771
## [235,] 0.1968750 0.1216931 0.3053435
## [236,] 0.1968750 0.1164021 0.3129771
## [237,] 0.1968750 0.1164021 0.3129771
## [238,] 0.2000000 0.1216931 0.3129771
## [239,] 0.1968750 0.1216931 0.3053435
## [240,] 0.1968750 0.1216931 0.3053435
## [241,] 0.1968750 0.1216931 0.3053435
## [242,] 0.2000000 0.1216931 0.3129771
## [243,] 0.1937500 0.1164021 0.3053435
## [244,] 0.1968750 0.1216931 0.3053435
## [245,] 0.1968750 0.1269841 0.2977099
## [246,] 0.1968750 0.1269841 0.2977099
## [247,] 0.1937500 0.1216931 0.2977099
## [248,] 0.1937500 0.1216931 0.2977099
## [249,] 0.1968750 0.1269841 0.2977099
## [250,] 0.1937500 0.1216931 0.2977099
## [251,] 0.1968750 0.1216931 0.3053435
## [252,] 0.1968750 0.1216931 0.3053435
## [253,] 0.1937500 0.1216931 0.2977099
## [254,] 0.1968750 0.1216931 0.3053435
## [255,] 0.1968750 0.1216931 0.3053435
## [256,] 0.2000000 0.1216931 0.3129771
## [257,] 0.2000000 0.1216931 0.3129771
## [258,] 0.1937500 0.1216931 0.2977099
## [259,] 0.1968750 0.1216931 0.3053435
## [260,] 0.1937500 0.1216931 0.2977099
## [261,] 0.1937500 0.1164021 0.3053435
## [262,] 0.1937500 0.1216931 0.2977099
## [263,] 0.1937500 0.1164021 0.3053435
## [264,] 0.1937500 0.1164021 0.3053435
## [265,] 0.1937500 0.1164021 0.3053435
## [266,] 0.1906250 0.1164021 0.2977099
## [267,] 0.1906250 0.1164021 0.2977099
## [268,] 0.1937500 0.1164021 0.3053435
## [269,] 0.1906250 0.1164021 0.2977099
## [270,] 0.1906250 0.1164021 0.2977099
## [271,] 0.1906250 0.1164021 0.2977099
## [272,] 0.1906250 0.1164021 0.2977099
## [273,] 0.1906250 0.1164021 0.2977099
## [274,] 0.1937500 0.1164021 0.3053435
## [275,] 0.1906250 0.1164021 0.2977099
## [276,] 0.1906250 0.1164021 0.2977099
## [277,] 0.1937500 0.1164021 0.3053435
## [278,] 0.1906250 0.1164021 0.2977099
## [279,] 0.1937500 0.1164021 0.3053435
## [280,] 0.1906250 0.1164021 0.2977099
## [281,] 0.1906250 0.1164021 0.2977099
## [282,] 0.1906250 0.1164021 0.2977099
## [283,] 0.1875000 0.1164021 0.2900763
## [284,] 0.1875000 0.1164021 0.2900763
## [285,] 0.1875000 0.1164021 0.2900763
## [286,] 0.1875000 0.1164021 0.2900763
## [287,] 0.1906250 0.1164021 0.2977099

```


[288,] 0.1875000 0.1164021 0.2900763
[289,] 0.1875000 0.1164021 0.2900763
[290,] 0.1875000 0.1164021 0.2900763
[291,] 0.1906250 0.1164021 0.2977099
[292,] 0.1875000 0.1164021 0.2900763
[293,] 0.1875000 0.1164021 0.2900763
[294,] 0.1875000 0.1164021 0.2900763
[295,] 0.1906250 0.1164021 0.2977099
[296,] 0.1875000 0.1164021 0.2900763
[297,] 0.1875000 0.1164021 0.2900763
[298,] 0.1906250 0.1164021 0.2977099
[299,] 0.1875000 0.1164021 0.2900763
[300,] 0.1937500 0.1164021 0.3053435
[301,] 0.1875000 0.1164021 0.2900763
[302,] 0.1875000 0.1164021 0.2900763
[303,] 0.1875000 0.1164021 0.2900763
[304,] 0.1875000 0.1164021 0.2900763
[305,] 0.1875000 0.1164021 0.2900763
[306,] 0.1875000 0.1164021 0.2900763
[307,] 0.1875000 0.1164021 0.2900763
[308,] 0.1875000 0.1164021 0.2900763
[309,] 0.1875000 0.1164021 0.2900763
[310,] 0.1906250 0.1216931 0.2900763
[311,] 0.1906250 0.1216931 0.2900763
[312,] 0.1906250 0.1216931 0.2900763
[313,] 0.1906250 0.1216931 0.2900763
[314,] 0.1937500 0.1216931 0.2977099
[315,] 0.1906250 0.1216931 0.2900763
[316,] 0.1906250 0.1216931 0.2900763
[317,] 0.1906250 0.1216931 0.2900763
[318,] 0.1875000 0.1216931 0.2824427
[319,] 0.1875000 0.1216931 0.2824427
[320,] 0.1906250 0.1216931 0.2900763
[321,] 0.1906250 0.1216931 0.2900763
[322,] 0.1875000 0.1216931 0.2824427
[323,] 0.1906250 0.1216931 0.2900763
[324,] 0.1875000 0.1216931 0.2824427
[325,] 0.1875000 0.1216931 0.2824427
[326,] 0.1875000 0.1216931 0.2824427
[327,] 0.1875000 0.1216931 0.2824427
[328,] 0.1906250 0.1216931 0.2900763
[329,] 0.1906250 0.1216931 0.2900763
[330,] 0.1937500 0.1216931 0.2977099
[331,] 0.1937500 0.1216931 0.2977099
[332,] 0.1937500 0.1216931 0.2977099
[333,] 0.1906250 0.1216931 0.2900763
[334,] 0.1906250 0.1216931 0.2900763
[335,] 0.1906250 0.1216931 0.2900763
[336,] 0.1906250 0.1216931 0.2900763
[337,] 0.1906250 0.1216931 0.2900763
[338,] 0.1875000 0.1216931 0.2824427
[339,] 0.1906250 0.1216931 0.2900763
[340,] 0.1906250 0.1216931 0.2900763
[341,] 0.1906250 0.1216931 0.2900763

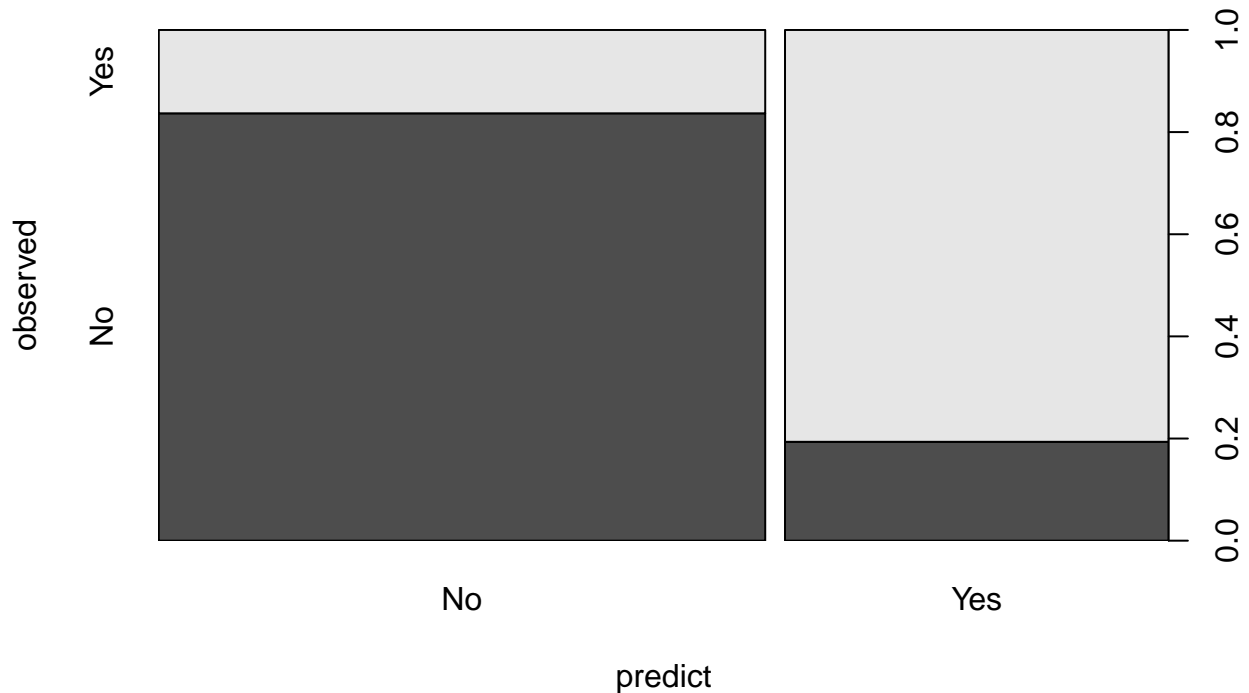
[342,] 0.1875000 0.1164021 0.2900763
[343,] 0.1906250 0.1164021 0.2977099
[344,] 0.1906250 0.1164021 0.2977099
[345,] 0.1906250 0.1164021 0.2977099
[346,] 0.1937500 0.1216931 0.2977099
[347,] 0.1906250 0.1164021 0.2977099
[348,] 0.1906250 0.1216931 0.2900763
[349,] 0.1906250 0.1216931 0.2900763
[350,] 0.1906250 0.1216931 0.2900763
[351,] 0.1875000 0.1164021 0.2900763
[352,] 0.1875000 0.1164021 0.2900763
[353,] 0.1906250 0.1164021 0.2977099
[354,] 0.1875000 0.1164021 0.2900763
[355,] 0.1906250 0.1216931 0.2900763
[356,] 0.1906250 0.1164021 0.2977099
[357,] 0.1875000 0.1164021 0.2900763
[358,] 0.1906250 0.1164021 0.2977099
[359,] 0.1906250 0.1164021 0.2977099
[360,] 0.1875000 0.1164021 0.2900763
[361,] 0.1875000 0.1164021 0.2900763
[362,] 0.1937500 0.1216931 0.2977099
[363,] 0.1937500 0.1216931 0.2977099
[364,] 0.1937500 0.1216931 0.2977099
[365,] 0.1937500 0.1216931 0.2977099
[366,] 0.1906250 0.1164021 0.2977099
[367,] 0.1906250 0.1164021 0.2977099
[368,] 0.1906250 0.1164021 0.2977099
[369,] 0.1906250 0.1164021 0.2977099
[370,] 0.1906250 0.1164021 0.2977099
[371,] 0.1906250 0.1164021 0.2977099
[372,] 0.1906250 0.1164021 0.2977099
[373,] 0.1906250 0.1164021 0.2977099
[374,] 0.1875000 0.1164021 0.2900763
[375,] 0.1906250 0.1164021 0.2977099
[376,] 0.1906250 0.1164021 0.2977099
[377,] 0.1906250 0.1164021 0.2977099
[378,] 0.1906250 0.1164021 0.2977099
[379,] 0.1906250 0.1164021 0.2977099
[380,] 0.1875000 0.1164021 0.2900763
[381,] 0.1906250 0.1164021 0.2977099
[382,] 0.1875000 0.1164021 0.2900763
[383,] 0.1875000 0.1164021 0.2900763
[384,] 0.1875000 0.1164021 0.2900763
[385,] 0.1843750 0.1164021 0.2824427
[386,] 0.1875000 0.1164021 0.2900763
[387,] 0.1875000 0.1164021 0.2900763
[388,] 0.1843750 0.1164021 0.2824427
[389,] 0.1875000 0.1164021 0.2900763
[390,] 0.1906250 0.1164021 0.2977099
[391,] 0.1906250 0.1164021 0.2977099
[392,] 0.1906250 0.1164021 0.2977099
[393,] 0.1906250 0.1164021 0.2977099
[394,] 0.1906250 0.1164021 0.2977099
[395,] 0.1937500 0.1164021 0.3053435

[396,] 0.1937500 0.1164021 0.3053435
[397,] 0.1968750 0.1164021 0.3129771
[398,] 0.1937500 0.1164021 0.3053435
[399,] 0.1937500 0.1164021 0.3053435
[400,] 0.1968750 0.1164021 0.3129771
[401,] 0.1968750 0.1164021 0.3129771
[402,] 0.1937500 0.1164021 0.3053435
[403,] 0.1968750 0.1164021 0.3129771
[404,] 0.1968750 0.1164021 0.3129771
[405,] 0.1968750 0.1164021 0.3129771
[406,] 0.1937500 0.1164021 0.3053435
[407,] 0.1937500 0.1164021 0.3053435
[408,] 0.1937500 0.1164021 0.3053435
[409,] 0.1937500 0.1164021 0.3053435
[410,] 0.1937500 0.1164021 0.3053435
[411,] 0.1937500 0.1164021 0.3053435
[412,] 0.1906250 0.1164021 0.2977099
[413,] 0.1906250 0.1164021 0.2977099
[414,] 0.1937500 0.1164021 0.3053435
[415,] 0.1906250 0.1164021 0.2977099
[416,] 0.1906250 0.1164021 0.2977099
[417,] 0.1906250 0.1164021 0.2977099
[418,] 0.1906250 0.1164021 0.2977099
[419,] 0.1906250 0.1164021 0.2977099
[420,] 0.1906250 0.1164021 0.2977099
[421,] 0.1906250 0.1164021 0.2977099
[422,] 0.1906250 0.1164021 0.2977099
[423,] 0.1906250 0.1164021 0.2977099
[424,] 0.1906250 0.1164021 0.2977099
[425,] 0.1906250 0.1164021 0.2977099
[426,] 0.1906250 0.1164021 0.2977099
[427,] 0.1906250 0.1164021 0.2977099
[428,] 0.1906250 0.1164021 0.2977099
[429,] 0.1906250 0.1164021 0.2977099
[430,] 0.1906250 0.1164021 0.2977099
[431,] 0.1906250 0.1164021 0.2977099
[432,] 0.1937500 0.1164021 0.3053435
[433,] 0.1937500 0.1216931 0.2977099
[434,] 0.1906250 0.1164021 0.2977099
[435,] 0.1906250 0.1164021 0.2977099
[436,] 0.1906250 0.1164021 0.2977099
[437,] 0.1906250 0.1164021 0.2977099
[438,] 0.1906250 0.1164021 0.2977099
[439,] 0.1906250 0.1164021 0.2977099
[440,] 0.1906250 0.1164021 0.2977099
[441,] 0.1906250 0.1164021 0.2977099
[442,] 0.1906250 0.1164021 0.2977099
[443,] 0.1937500 0.1164021 0.3053435
[444,] 0.1906250 0.1164021 0.2977099
[445,] 0.1937500 0.1164021 0.3053435
[446,] 0.1937500 0.1164021 0.3053435
[447,] 0.1906250 0.1164021 0.2977099
[448,] 0.1937500 0.1164021 0.3053435
[449,] 0.1937500 0.1164021 0.3053435

```
## [450,] 0.1968750 0.1216931 0.3053435
## [451,] 0.1968750 0.1216931 0.3053435
## [452,] 0.1968750 0.1216931 0.3053435
## [453,] 0.1968750 0.1216931 0.3053435
## [454,] 0.1968750 0.1216931 0.3053435
## [455,] 0.2000000 0.1269841 0.3053435
## [456,] 0.1968750 0.1216931 0.3053435
## [457,] 0.2000000 0.1269841 0.3053435
## [458,] 0.1968750 0.1216931 0.3053435
## [459,] 0.1968750 0.1216931 0.3053435
## [460,] 0.1968750 0.1216931 0.3053435
## [461,] 0.1968750 0.1216931 0.3053435
## [462,] 0.1937500 0.1216931 0.2977099
## [463,] 0.1937500 0.1216931 0.2977099
## [464,] 0.1937500 0.1216931 0.2977099
## [465,] 0.1968750 0.1216931 0.3053435
## [466,] 0.1968750 0.1216931 0.3053435
## [467,] 0.1937500 0.1216931 0.2977099
## [468,] 0.1937500 0.1216931 0.2977099
## [469,] 0.1968750 0.1269841 0.2977099
## [470,] 0.1968750 0.1269841 0.2977099
## [471,] 0.1968750 0.1269841 0.2977099
## [472,] 0.1968750 0.1269841 0.2977099
## [473,] 0.1968750 0.1269841 0.2977099
## [474,] 0.1968750 0.1269841 0.2977099
## [475,] 0.1968750 0.1216931 0.3053435
## [476,] 0.1968750 0.1269841 0.2977099
## [477,] 0.1968750 0.1216931 0.3053435
## [478,] 0.1968750 0.1216931 0.3053435
## [479,] 0.1937500 0.1216931 0.2977099
## [480,] 0.1937500 0.1216931 0.2977099
## [481,] 0.1937500 0.1216931 0.2977099
## [482,] 0.1968750 0.1216931 0.3053435
## [483,] 0.1937500 0.1216931 0.2977099
## [484,] 0.1937500 0.1216931 0.2977099
## [485,] 0.1968750 0.1216931 0.3053435
## [486,] 0.1937500 0.1216931 0.2977099
## [487,] 0.1937500 0.1216931 0.2977099
## [488,] 0.1937500 0.1216931 0.2977099
## [489,] 0.1937500 0.1216931 0.2977099
## [490,] 0.1937500 0.1216931 0.2977099
## [491,] 0.1937500 0.1216931 0.2977099
## [492,] 0.1968750 0.1216931 0.3053435
## [493,] 0.1968750 0.1216931 0.3053435
## [494,] 0.1937500 0.1216931 0.2977099
## [495,] 0.1968750 0.1216931 0.3053435
## [496,] 0.1968750 0.1216931 0.3053435
## [497,] 0.1968750 0.1216931 0.3053435
## [498,] 0.1968750 0.1216931 0.3053435
## [499,] 0.1968750 0.1216931 0.3053435
## [500,] 0.1968750 0.1216931 0.3053435
```

```
yhat <- predict(rf, newdata = carseats[-train, ])
hightest <- carseats[-train, "High"]
```

```
plot(yhat, hightest, xlab = "predict", ylab = "observed")
```



```
confusion <- table(yhat, hightest)
(confusion[1,2] + confusion[2,1]) / (confusion[1,2] + confusion[1,1] + confusion[2,1] + confusion[2,2])
```

```
## [1] 0.175
```

```
mean((as.numeric(yhat) - as.numeric(hightest))^2) #other way to do it...
```

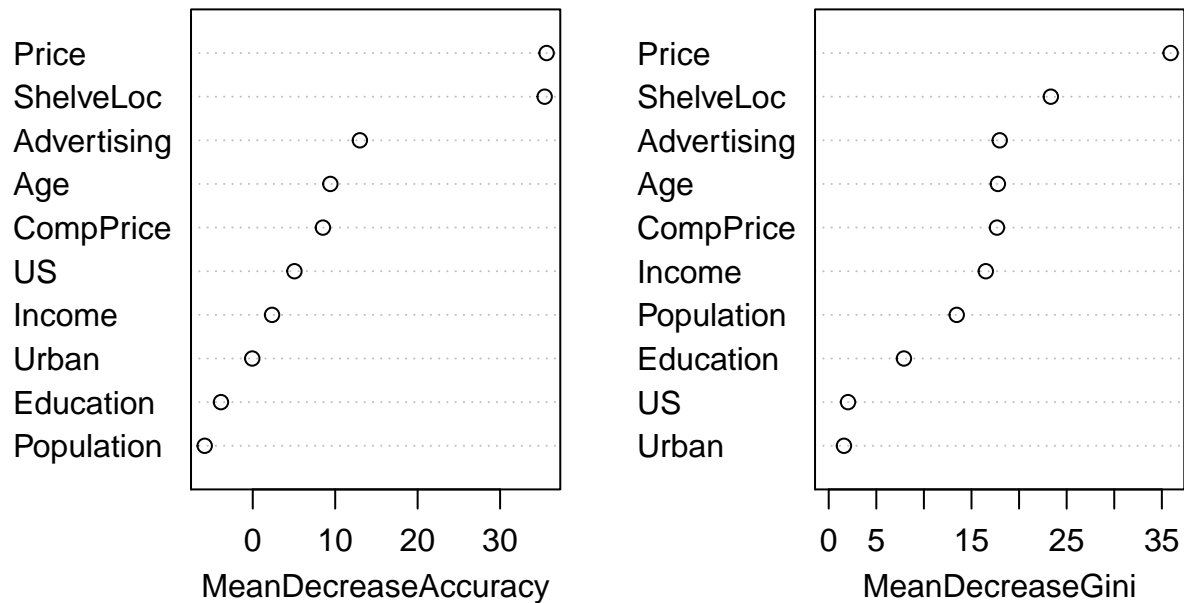
```
## [1] 0.175
```

```
randomForest::importance(rf)
```

	No	Yes	MeanDecreaseAccuracy	MeanDecreaseGini
## CompPrice	8.36916959	2.91117011	8.50864854	17.678930
## Income	0.39579991	3.25532567	2.34027456	16.503003
## Advertising	6.65805187	12.05615582	12.99366314	17.967101
## Population	-2.88848674	-5.07534885	-5.82995892	13.449605
## Price	27.19897167	25.90688901	35.64189722	35.922717
## ShelveLoc	29.48850638	28.53645200	35.40435451	23.335803
## Age	6.07907833	6.68942744	9.41109449	17.773115
## Education	-3.00970397	-2.61744796	-3.85681059	7.902363
## Urban	-0.09313098	0.08359962	-0.05974897	1.598495
## US	0.27545841	5.78679251	5.05518967	2.028199

```
varImpPlot(rf)
```

rf



Boosted Trees

Q. What does it mean by “The idea of boosting is to iteratively fit a small tree to the residuals from the current model”???

Q. Dont we have to say “distribution = bernoulli” as this is classification problem...??

Q. How to set 0.5 as the cutoff for the predicted probabilities??

Q. So, what is the difference between boosted trees and random forest...? I still dont understand when they important variables....

Q. When I do predict to get test error rate, do I include gbm inside of for-loop as well???

Q. How do I understand shrinkage parameter conceptually here in tree???

Q. Why my plot shows monotonically increasing? Am I supposed to have a diagram looks quadratic??? I found that if I split data into training and testing like “as.vector(createDataPartition(1:nrow(carseats), p = 0.8))[[1]]” for data partition, then I get monotonically increasing, but if I do “as.vector(createDataPartition(carseats[,1], p = 0.8))[[1]]”, then I got quadratic... So, I guess data partion makes some difference. What is wrong...??? (please refer to the codes below for evidence....)

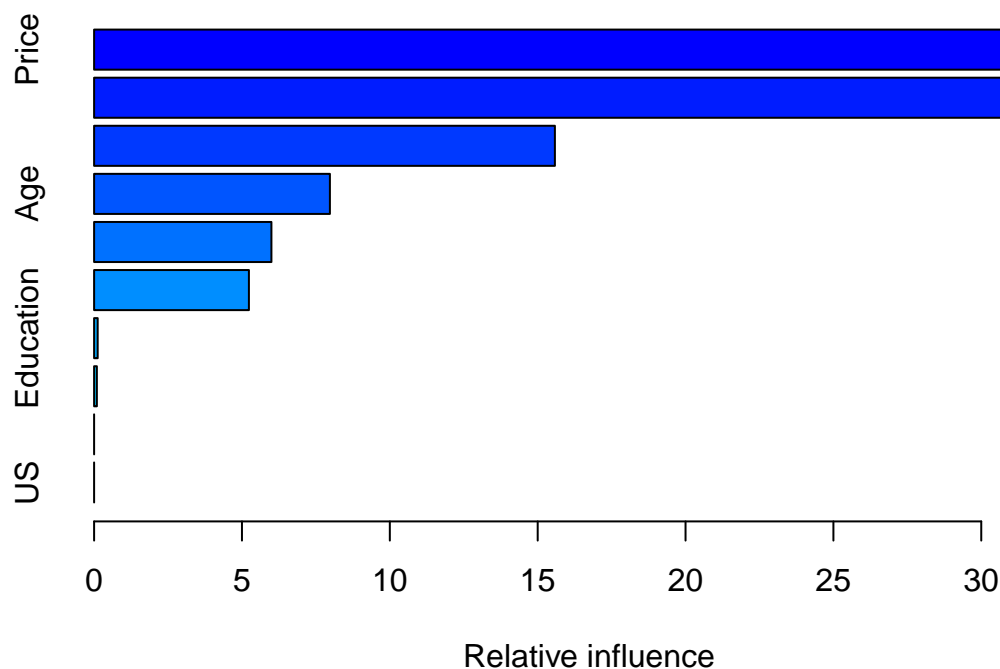
Q. Why do I have high test errorr as I increase interaction? Intuively saying, am I supposed to get small mse if the variable is more flexible??

You do not do MSE for classification, but you are doing comparing actual and prediction to get error rates....

```
carseats$High <- as.numeric(carseats$High) - 1  
  
#1  
  
boosting <- gbm(High~.-Sales, data = carseats[train, ], distribution = "bernoulli", n.trees = 5000,  
                interaction.depth = 1)  
boosting
```

```
## gbm(formula = High ~ . - Sales, distribution = "bernoulli", data = carseats[train,  
##      ], n.trees = 5000, interaction.depth = 1)  
## A gradient boosted model with bernoulli loss function.  
## 5000 iterations were performed.  
## There were 10 predictors of which 8 had non-zero influence.
```

```
summary(boosting)
```



```
##          var      rel.inf  
## Price      Price 33.81445486  
## ShelveLoc  ShelveLoc 31.18481213  
## Advertising Advertising 15.58206140  
## Age         Age 7.97407974  
## Income      Income 5.99578098  
## CompPrice   CompPrice 5.23490756  
## Education   Education 0.12080515  
## Population  Population 0.09309819  
## Urban       Urban 0.00000000  
## US          US 0.00000000
```

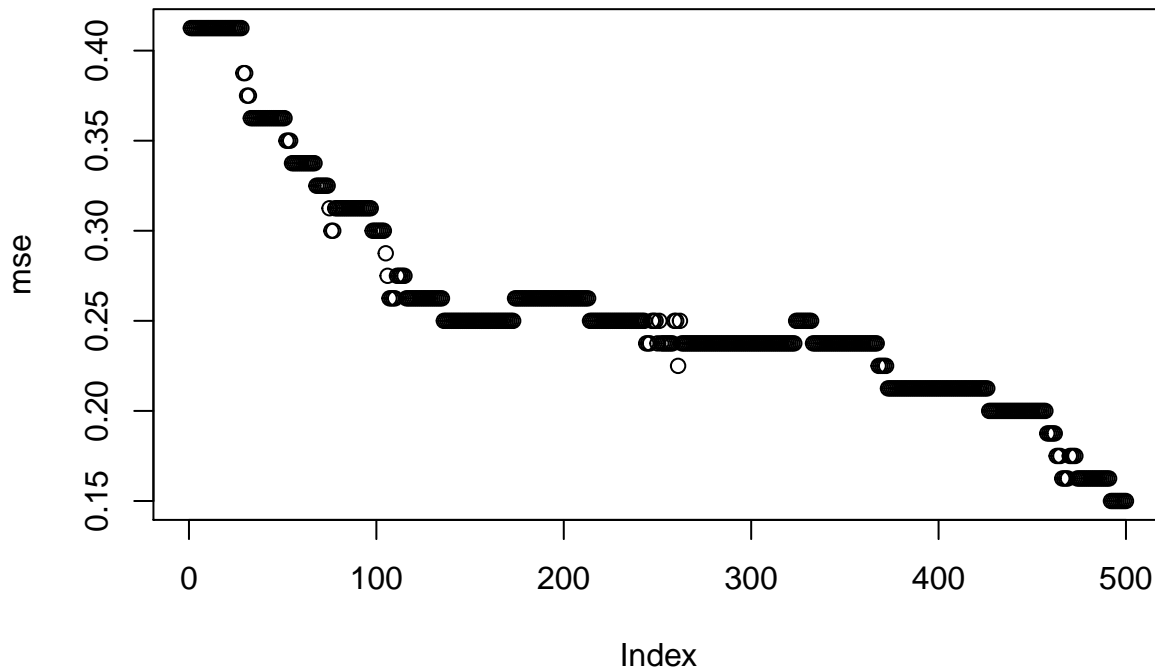
```
mse <- c()  
thresh <- 0.5
```

```

for(i in 1:500){
  #If I do not type = "response", they will give you logit output.
  yhat <- predict(boosting, newdata = carseats[-train, ], n.trees = (10 * i), type = "response")
  yhat <- (yhat > thresh)
  mse[i] <- mean(yhat != carseats$High[-train])
}

```

```
plot(mse)
```



#2

```

boosting2 <- gbm(High~.-Sales, data = carseats[train, ], distribution = "bernoulli",
  n.trees = 5000, interaction.depth = 2)
boosting2

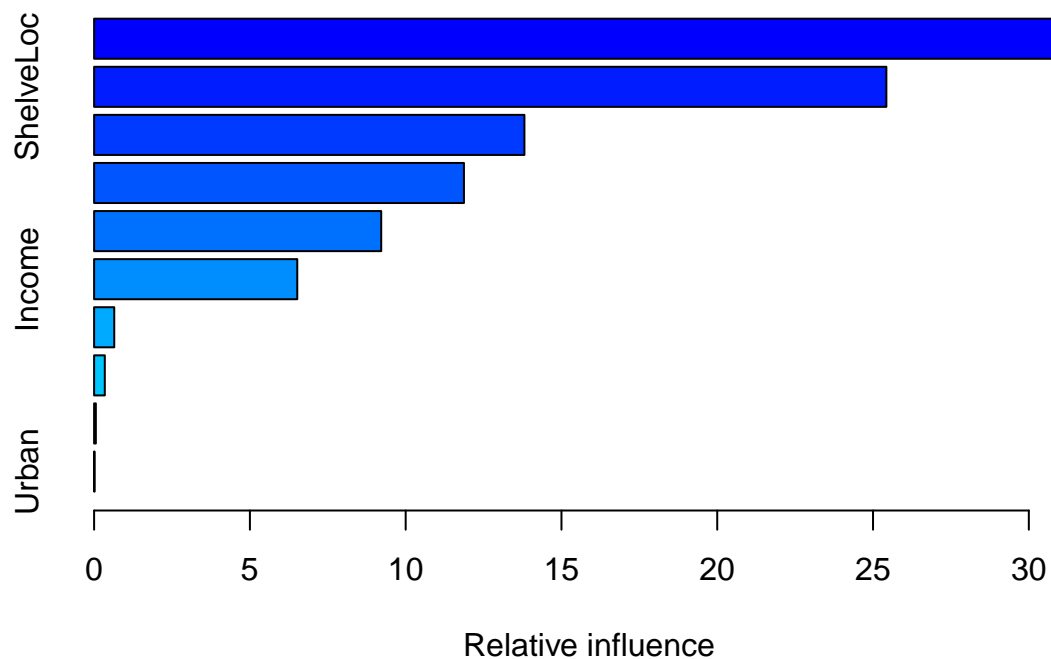
```

```

## gbm(formula = High ~ . - Sales, distribution = "bernoulli", data = carseats[train,
##      ], n.trees = 5000, interaction.depth = 2)
## A gradient boosted model with bernoulli loss function.
## 5000 iterations were performed.
## There were 10 predictors of which 10 had non-zero influence.

```

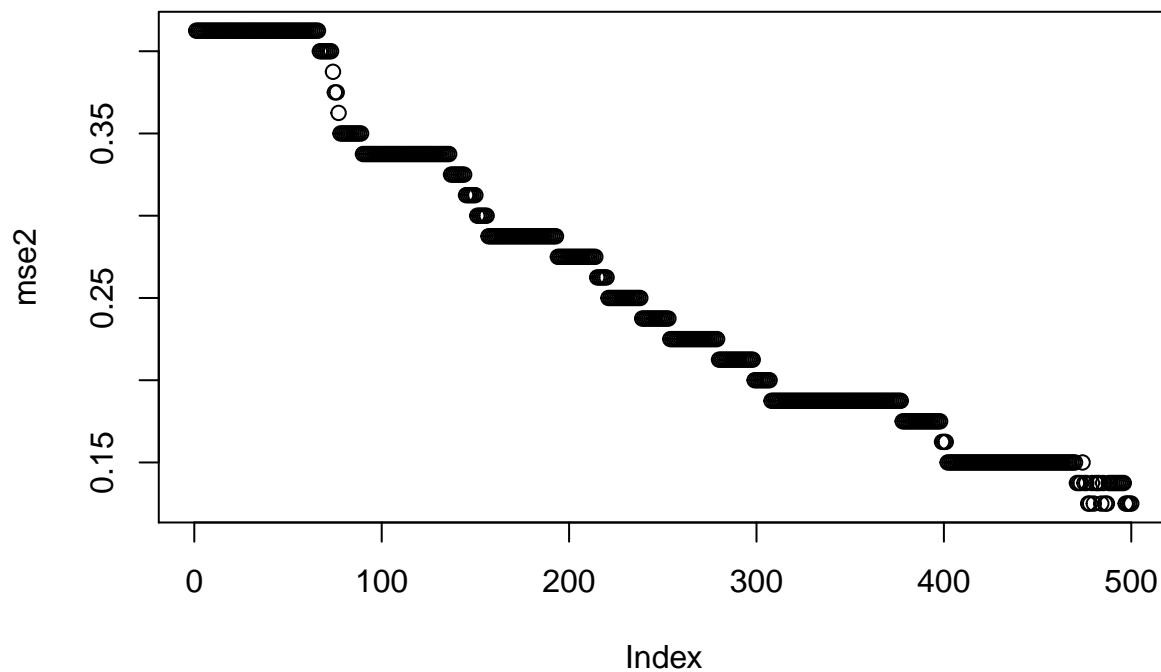
```
summary(boosting2)
```

```
##           var      rel.inf
## Price      Price 32.09476062
## ShelfLoc    ShelfLoc 25.42750999
## Advertising Advertising 13.81159526
## CompPrice   CompPrice 11.87025883
## Age         Age 9.21481597
## Income      Income 6.52005165
## Population  Population 0.64664477
## Education   Education 0.34302613
## US          US 0.05578035
## Urban       Urban 0.01555645
```

```
mse2 <- c()
for(i in 1:500){
  yhat <- predict(boosting2, newdata = carseats[-train, ], n.trees = (10 * i))
  yhat <- (yhat > thresh)
  mse2[i] <- mean(yhat != carseats$High[-train])
}

plot(mse2)
```



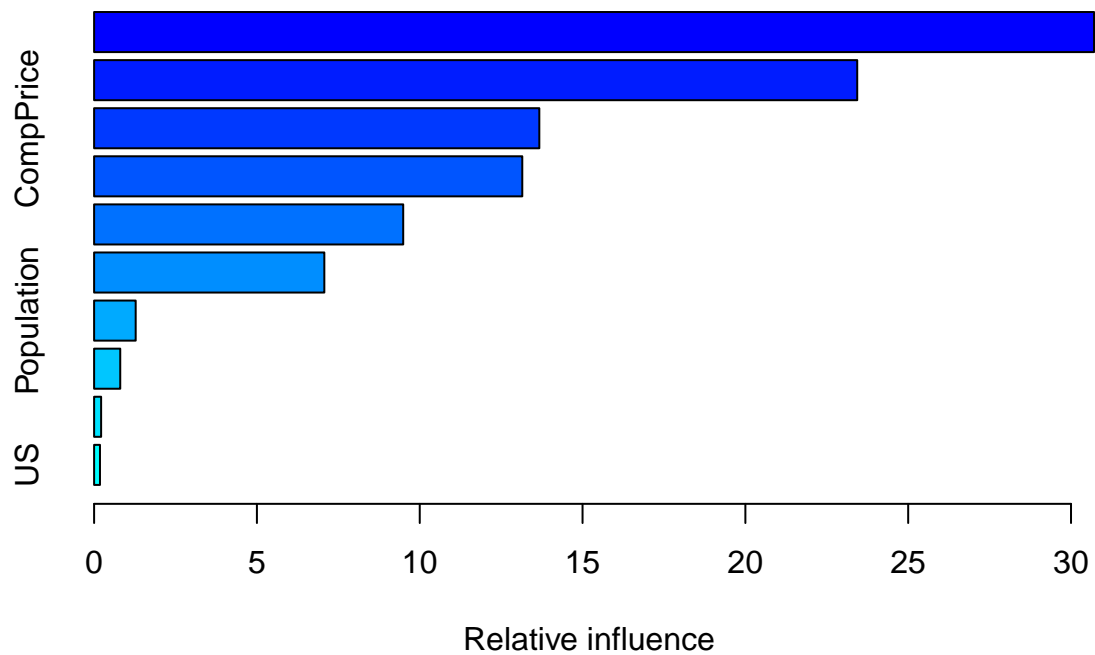
#3

```
boosting3 <- gbm(High ~ . - Sales, data = carseats[train, ], distribution = "bernoulli",
  n.trees = 5000, interaction.depth = 3)
```

boosting3

```
## gbm(formula = High ~ . - Sales, distribution = "bernoulli", data = carseats[train,
##      ], n.trees = 5000, interaction.depth = 3)
## A gradient boosted model with bernoulli loss function.
## 5000 iterations were performed.
## There were 10 predictors of which 10 had non-zero influence.
```

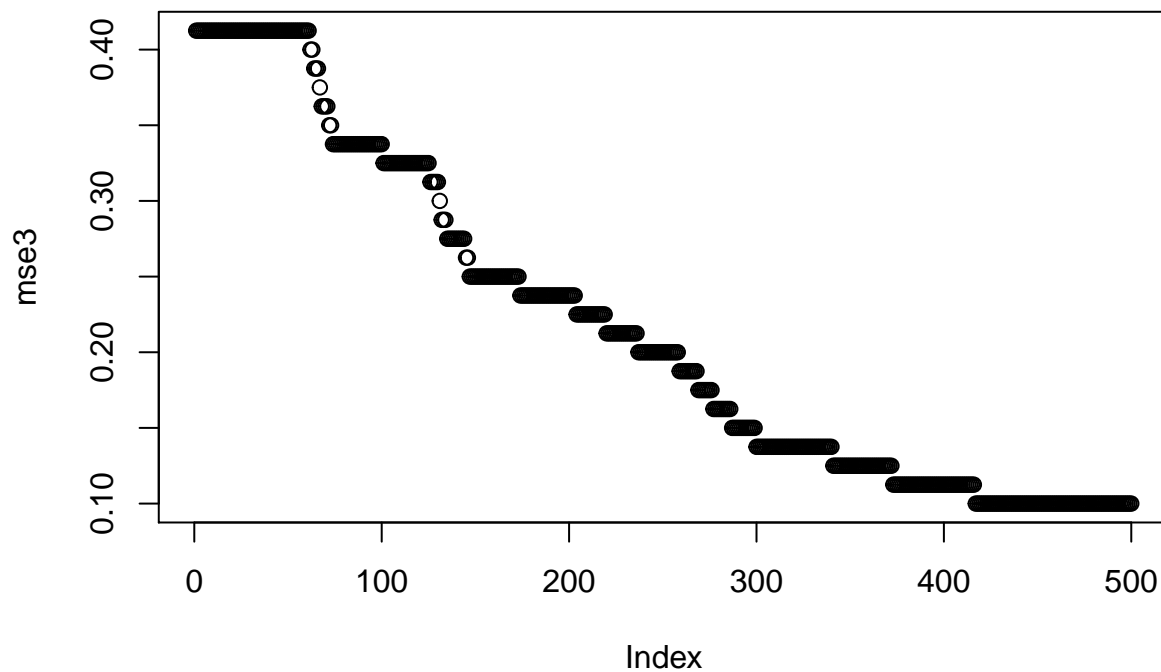
```
summary(boosting3)
```



```
##           var    rel.inf
## Price           Price 30.7075820
## ShelveLoc      ShelveLoc 23.4348672
## CompPrice      CompPrice 13.6720242
## Advertising Advertising 13.1490970
## Age            Age    9.4924069
## Income          Income  7.0694535
## Population      Population 1.2763808
## Education       Education 0.8026839
## Urban           Urban   0.2155784
## US              US     0.1799260
```

```
mse3 <- c()
for(i in 1:500){
  yhat <- predict(boosting3, newdata = carseats[-train, ], n.trees = (10 * i))
  yhat <- (yhat > thresh)
  mse3[i] <- mean(yhat != carseats$High[-train])
}
```

```
plot(mse3)
```



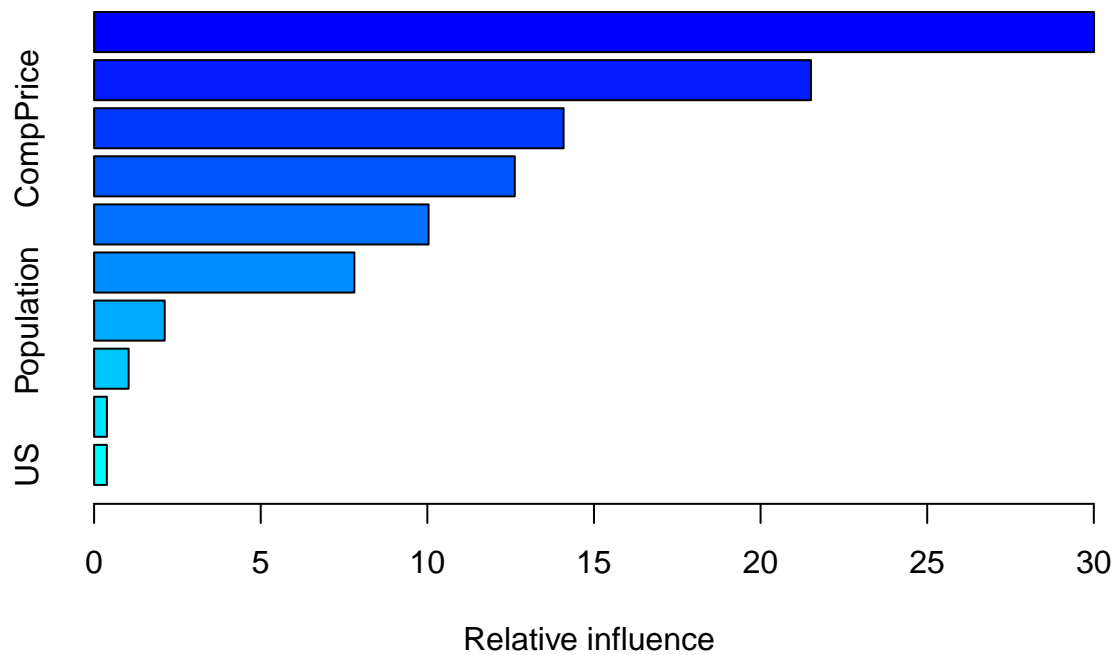
#4

```
boosting4 <- gbm(High ~ . - Sales, data = carseats[train, ], distribution = "bernoulli",
  n.trees = 5000, interaction.depth = 4)
```

boosting4

```
## gbm(formula = High ~ . - Sales, distribution = "bernoulli", data = carseats[train,
##      ], n.trees = 5000, interaction.depth = 4)
## A gradient boosted model with bernoulli loss function.
## 5000 iterations were performed.
## There were 10 predictors of which 10 had non-zero influence.
```

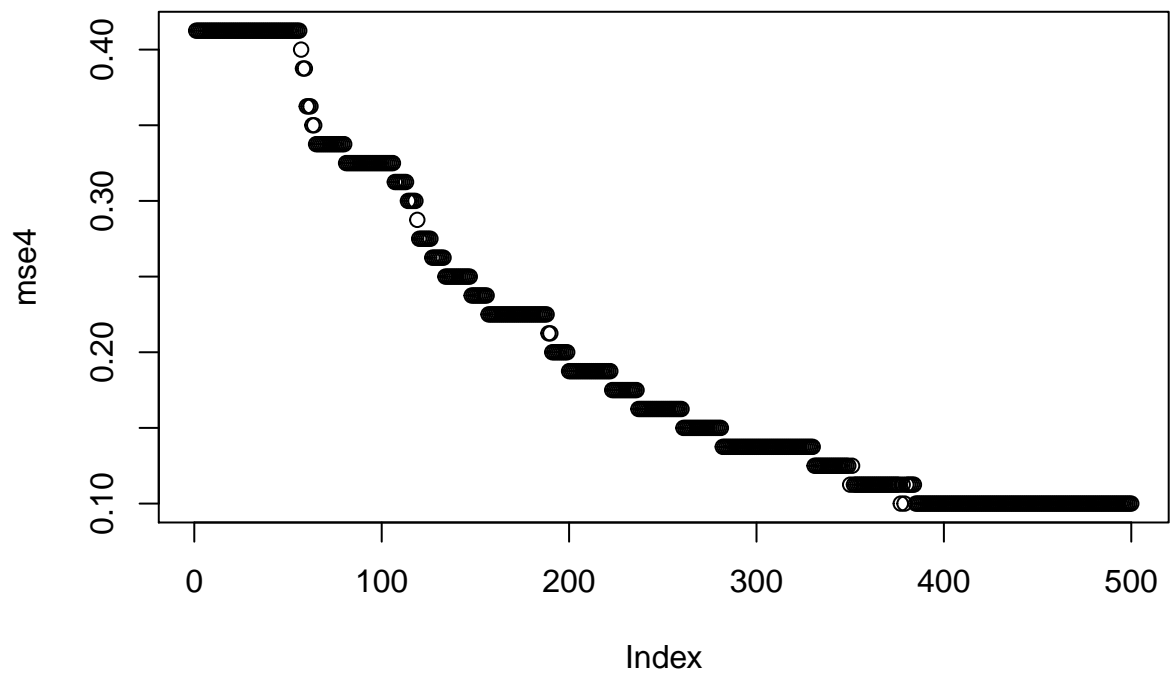
```
summary(boosting4)
```



```
##           var    rel.inf
## Price      Price 30.0071879
## ShelfLoc   ShelfLoc 21.5113706
## CompPrice  CompPrice 14.0894052
## Advertising Advertising 12.6240706
## Age        Age 10.0364719
## Income     Income  7.8108277
## Population Population  2.1178988
## Education  Education  1.0363377
## Urban      Urban  0.3837958
## US         US    0.3826339
```

```
mse4 <- c()
for(i in 1:500){
  yhat <- predict(boosting4, newdata = carseats[-train, ], n.trees = (10 * i))
  yhat <- (yhat > thresh)
  mse4[i] <- mean(yhat != carseats$High[-train])
}

plot(mse4)
```



ShelveLoc and Price are the top two important variables...