ADMPL- Assignment 2

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QA1. What is the key idea behind bagging? Can bagging deal both with high variance (overfitting) and high bias (underfitting)? (10% of total points)

Bagging essentially involves creating different classifiers on different random samples of training data, using replacement. The predictions are then aggregated to ultimately make a final prediction. As for reducing overfitting, bagging is effective as it averages multiple different samples of the data which can ultimately reduce the risk of overfitting. As for underfitting however, it is unlikely that incorporating bagging will improve underfitting that would otherwise be present.

QA2. Why bagging models are computationally more efficient when compared to boosting models with the same number of weak learners? (5% of total points)

Bagging models are more efficient because there is no interdependency training the weak learners. Each can be trained independently, whereas boosting models are trained in succession to each other.

QA3. James is thinking of creating an ensemble mode to predict whether a given stock will go up or down in the next week. He has trained several decision tree models but each model is not performing any better than a random model. The models are also very similar to each other. Do you think creating an ensemble model by combining these tree models can boost the performance? Discuss your answer. (5% of total points)

No. Ensemble models tend to perform better with more diversity. Since all the models are similar to each other, it makes sense that incorporating an ensemble model would yield little benefit.

QA4. Consider the following Table (not shown) that classifies some objects into two classes of edible (+) and non- edible (-), based on some characteristics such as the object color, size and shape. What would be the Information gain for splitting the dataset based on the “Size” attribute? (15% of total points)

Entropy(full) = ((-9/16)(log2)(9/16)) – ((7/16)(log2)(7/16)) = 0.988

Entropy(small) = ((-0.75)(log2)(0.75)) – ((0.25)(log2)(0.25)) = 0.811

Entropy(large) = ((-3/8)(log2)(3/8)) – ((5/8)(log2)(5/8)) = 0.955

Entropy(weighted) = (0.5(0.811)) + (0.5(0.955)) = 0.883

Information gain = 0.988 – 0.883 = 0.105

QA5. Why is it important that the m parameter (number of attributes available at each split) to be optimally set in random forest models? Discuss the implications of setting this parameter too small or too large. (5% of total points)

M is important in random forests primarily to keep things random. If all parameters were available, there runs the risk of overfitting. Keeping m at a higher value may improve individual performance but when averaged together, the risk of overfitting is increased. The opposite is true for reducing m- each split may have more diversity but the risk of underfitting can start to appear.

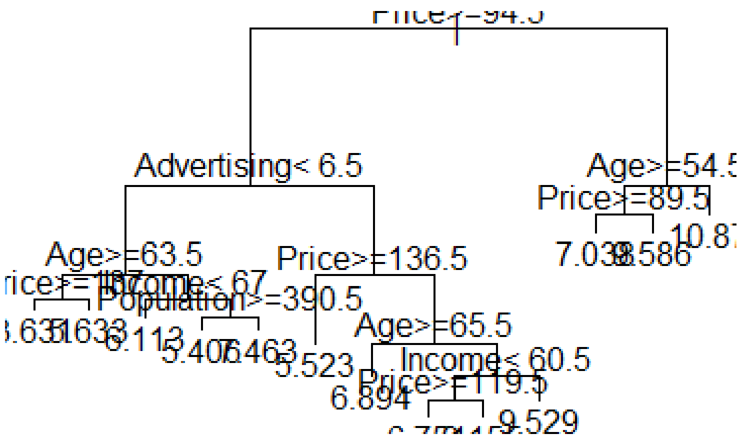
QB1. Build a decision tree regression model to predict Sales based on all other attributes (“Price”, “Advertising”, “Population”, “Age”, “Income” and “Education”). Which attribute is used at the top of the tree (the root node) for splitting? Hint: you can either plot () and text() functions or use the summary() function to see the decision tree rules. (15% of total points)

```
library(dplyr)

##
## Attaching package: 'dplyr'

## The following objects are masked from 'package:stats':
##
##     filter, lag

## The following objects are masked from 'package:base':
##
##     intersect, setdiff, setequal, union

library(ISLR)
library(glmnet)

## Warning: package 'glmnet' was built under R version 4.4.2

## Loading required package: Matrix

## Loaded glmnet 4.1-8

library(caret)

## Loading required package: ggplot2

## Loading required package: lattice

library(rpart)
library(rpart.plot)

## Warning: package 'rpart.plot' was built under R version 4.4.2

Carseats_Filtered <- Carseats %>% select("Sales", "Price",
"Advertising","Population","Age","Income","Education")
```

```r
DecTreeModel <- rpart(Sales ~ ., data = Carseats_Filtered, method = "anova")

summary(DecTreeModel)

## Call:
## rpart(formula = Sales ~ ., data = Carseats_Filtered, method = "anova")
##   n= 400
##
##            CP nsplit rel error    xerror       xstd
## 1  0.14251535      0 1.0000000 1.0046778 0.06918322
## 2  0.08034146      1 0.8574847 0.8903885 0.06362915
## 3  0.06251702      2 0.7771432 0.8227573 0.06147349
## 4  0.02925241      3 0.7146262 0.7787417 0.05757265
## 5  0.02537341      4 0.6853738 0.7816321 0.05425116
## 6  0.02127094      5 0.6600003 0.7936380 0.05400941
## 7  0.02059174      6 0.6387294 0.7751826 0.05365339
## 8  0.01632010      7 0.6181377 0.7675471 0.05271083
## 9  0.01521801      8 0.6018176 0.7888364 0.05338734
## 10 0.01042023      9 0.5865996 0.8426002 0.05740581
## 11 0.01000559     10 0.5761793 0.8581249 0.05855373
## 12 0.01000000     12 0.5561681 0.8668632 0.06026142
##
## Variable importance
##       Price Advertising         Age      Income  Population   Education
##          49          18          16           8           6           3
##
## Node number 1: 400 observations,    complexity param=0.1425153
##   mean=7.496325, MSE=7.955687
##   left son=2 (329 obs) right son=3 (71 obs)
##   Primary splits:
##       Price       < 94.5  to the right, improve=0.14251530, (0 missing)
##       Advertising < 7.5   to the left,  improve=0.07303226, (0 missing)
##       Age         < 61.5  to the right, improve=0.07120203, (0 missing)
##       Income      < 61.5  to the left,  improve=0.02840494, (0 missing)
##       Population  < 174.5 to the left,  improve=0.01077467, (0 missing)
##
## Node number 2: 329 observations,    complexity param=0.08034146
##   mean=7.001672, MSE=6.815199
##   left son=4 (174 obs) right son=5 (155 obs)
##   Primary splits:
##       Advertising < 6.5   to the left,  improve=0.11402580, (0 missing)
##       Price       < 136.5 to the right, improve=0.08411056, (0 missing)
##       Age         < 63.5  to the right, improve=0.08091745, (0 missing)
##       Income      < 60.5  to the left,  improve=0.03394126, (0 missing)
##       Population  < 23    to the left,  improve=0.01831455, (0 missing)
##   Surrogate splits:
##       Population < 223   to the left,  agree=0.599, adj=0.148, (0 split)
##       Education  < 10.5  to the right, agree=0.565, adj=0.077, (0 split)
##       Age        < 53.5  to the right, agree=0.547, adj=0.039, (0 split)
##       Income     < 114.5 to the left,  agree=0.547, adj=0.039, (0 split)
##       Price      < 106.5 to the right, agree=0.544, adj=0.032, (0 split)
## 
## Node number 3: 71 observations,    complexity param=0.02537341
##   mean=9.788451, MSE=6.852836 
##   left son=6 (36 obs) right son=7 (35 obs)
##   Primary splits:
##       Age        < 54.5  to the right, improve=0.16595410, (0 missing)
##       Price      < 75.5  to the right, improve=0.08365773, (0 missing)
##       Income     < 30.5  to the left,  improve=0.03322169, (0 missing)
##       Education  < 10.5  to the right, improve=0.03019634, (0 missing)
##       Population < 268.5 to the left,  improve=0.02383306, (0 missing)
##   Surrogate splits:
##       Advertising < 4.5   to the right, agree=0.606, adj=0.200, (0 split)
##       Price       < 73    to the right, agree=0.592, adj=0.171, (0 split)
##       Population  < 272.5 to the left,  agree=0.592, adj=0.171, (0 split)
##       Income      < 79.5  to the right, agree=0.592, adj=0.171, (0 split)
##       Education   < 11.5  to the left,  agree=0.577, adj=0.143, (0 split)
## 
## Node number 4: 174 observations,    complexity param=0.02127094
##   mean=6.169655, MSE=4.942347 
##   left son=8 (58 obs) right son=9 (116 obs)
##   Primary splits:
##       Age         < 63.5  to the right, improve=0.078712160, (0 missing)
##       Price       < 130.5 to the right, improve=0.048919280, (0 missing)
##       Population  < 26.5  to the left,  improve=0.030421540, (0 missing)
##       Income      < 67.5  to the left,  improve=0.027749670, (0 missing)
##       Advertising < 0.5   to the left,  improve=0.006795377, (0 missing)
##   Surrogate splits:
##       Income     < 22.5  to the left,  agree=0.678, adj=0.034, (0 split)
##       Price      < 96.5  to the left,  agree=0.672, adj=0.017, (0 split)
##       Population < 26.5  to the left,  agree=0.672, adj=0.017, (0 split)
## 
## Node number 5: 155 observations,    complexity param=0.06251702
##   mean=7.935677, MSE=7.268151 
##   left son=10 (28 obs) right son=11 (127 obs)
##   Primary splits:
##       Price       < 136.5 to the right, improve=0.17659580, (0 missing)
##       Age         < 73.5  to the right, improve=0.08000201, (0 missing)
##       Income      < 60.5  to the left,  improve=0.05360755, (0 missing)
##       Advertising < 13.5  to the left,  improve=0.03920507, (0 missing)
##       Population  < 399   to the left,  improve=0.01037956, (0 missing)
##   Surrogate splits:
##       Advertising < 24.5  to the right, agree=0.826, adj=0.036, (0 split)
## 
## Node number 6: 36 observations,    complexity param=0.0163201
##   mean=8.736944, MSE=4.961043 
##   left son=12 (12 obs) right son=13 (24 obs)
##   Primary splits:
##       Price       < 89.5  to the right, improve=0.29079360, (0 missing)
##       Income      < 39.5  to the left,  improve=0.19043350, (0 missing)
##       Advertising < 11.5  to the left,  improve=0.17891930, (0 missing)
##       Age         < 75.5  to the right, improve=0.04316067, (0 missing)
##       Education   < 14.5  to the left,  improve=0.03411396, (0 missing)
##   Surrogate splits:
##       Advertising < 16.5  to the right, agree=0.722, adj=0.167, (0 split)
##       Income      < 37.5  to the left,  agree=0.722, adj=0.167, (0 split)
##       Age         < 56.5  to the left,  agree=0.694, adj=0.083, (0 split)
##
## Node number 7: 35 observations
##   mean=10.87, MSE=6.491674
##
## Node number 8: 58 observations,    complexity param=0.01042023
##   mean=5.287586, MSE=3.93708
##   left son=16 (10 obs) right son=17 (48 obs)
##   Primary splits:
##       Price      < 137   to the right, improve=0.14521540, (0 missing)
##       Education  < 15.5  to the right, improve=0.07995394, (0 missing)
##       Income     < 35.5  to the left,  improve=0.04206708, (0 missing)
##       Age        < 79.5  to the left,  improve=0.02799057, (0 missing)
##       Population < 52.5  to the left,  improve=0.01914342, (0 missing)
##
## Node number 9: 116 observations,    complexity param=0.01000559
##   mean=6.61069, MSE=4.861446
##   left son=18 (58 obs) right son=19 (58 obs)
##   Primary splits:
##       Income     < 67    to the left,  improve=0.05085914, (0 missing)
##       Population < 392   to the right, improve=0.04476721, (0 missing)
##       Price      < 127   to the right, improve=0.04210762, (0 missing)
##       Age        < 37.5  to the right, improve=0.02858424, (0 missing)
##       Education  < 14.5  to the left,  improve=0.01187387, (0 missing)
##   Surrogate splits:
##       Education   < 12.5  to the right, agree=0.586, adj=0.172, (0 split)
##       Age         < 58.5  to the left,  agree=0.578, adj=0.155, (0 split)
##       Price       < 144.5 to the left,  agree=0.569, adj=0.138, (0 split)
##       Population  < 479   to the right, agree=0.560, adj=0.121, (0 split)
##       Advertising < 2.5   to the right, agree=0.543, adj=0.086, (0 split)
##
## Node number 10: 28 observations
##   mean=5.522857, MSE=5.084213
##
## Node number 11: 127 observations,    complexity param=0.02925241
##   mean=8.467638, MSE=6.183142
##   left son=22 (29 obs) right son=23 (98 obs)
##   Primary splits:
##       Age         < 65.5  to the right, improve=0.11854590, (0 missing)
##       Income      < 51.5  to the left,  improve=0.08076060, (0 missing)
##       Advertising < 13.5  to the left,  improve=0.04801701, (0 missing)
##       Education   < 11.5  to the right, improve=0.02471512, (0 missing)
##       Population  < 479   to the left,  improve=0.01908657, (0 missing)
##
```

```
## Node number 12: 12 observations
##   mean=7.038333, MSE=2.886964
##
## Node number 13: 24 observations
##   mean=9.58625, MSE=3.834123
##
## Node number 16: 10 observations
##   mean=3.631, MSE=5.690169
##
## Node number 17: 48 observations
##   mean=5.632708, MSE=2.88102
##
## Node number 18: 58 observations
##   mean=6.113448, MSE=3.739109
##
## Node number 19: 58 observations,    complexity param=0.01000559
##   mean=7.107931, MSE=5.489285
##   left son=38 (10 obs) right son=39 (48 obs)
##   Primary splits:
##       Population  < 390.5 to the right, improve=0.10993270, (0 missing)
##       Price       < 124.5 to the right, improve=0.07534567, (0 missing)
##       Advertising < 0.5   to the left,  improve=0.07060488, (0 missing)
##       Age         < 45.5  to the right, improve=0.04611510, (0 missing)
##       Education   < 11.5  to the right, improve=0.03722944, (0 missing)
##
## Node number 22: 29 observations
##   mean=6.893793, MSE=6.08343
##
## Node number 23: 98 observations,    complexity param=0.02059174
##   mean=8.933367, MSE=5.262759
##   left son=46 (34 obs) right son=47 (64 obs)
##   Primary splits:
##       Income      < 60.5  to the left,  improve=0.12705480, (0 missing)
##       Advertising < 13.5  to the left,  improve=0.07114001, (0 missing)
##       Price       < 118.5 to the right, improve=0.06932216, (0 missing)
##       Education   < 11.5  to the right, improve=0.03377416, (0 missing)
##       Age         < 49.5  to the right, improve=0.02289004, (0 missing)
##   Surrogate splits:
##       Education < 17.5  to the right, agree=0.663, adj=0.029, (0 split)
##
## Node number 38: 10 observations
##   mean=5.406, MSE=2.508524
##
## Node number 39: 48 observations
##   mean=7.4625, MSE=5.381106
##
## Node number 46: 34 observations,    complexity param=0.01521801
##   mean=7.811471, MSE=4.756548
##   left son=92 (19 obs) right son=93 (15 obs)
##   Primary splits:
```

```
##       Price       < 119.5 to the right, improve=0.29945020, (0 missing)
##       Advertising < 11.5  to the left,  improve=0.14268440, (0 missing)
##       Income      < 40.5  to the right, improve=0.12781140, (0 missing)
##       Population  < 152   to the left,  improve=0.03601768, (0 missing)
##       Age         < 49.5  to the right, improve=0.02748814, (0 missing)
##   Surrogate splits:
##       Education   < 12.5  to the right, agree=0.676, adj=0.267, (0 split)
##       Advertising < 7.5   to the right, agree=0.647, adj=0.200, (0 split)
##       Age         < 53.5  to the left,  agree=0.647, adj=0.200, (0 split)
##       Population  < 240   to the right, agree=0.618, adj=0.133, (0 split)
##       Income      < 41.5  to the right, agree=0.618, adj=0.133, (0 split)
##
## Node number 47: 64 observations
##   mean=9.529375, MSE=4.5078
##
## Node number 92: 19 observations
##   mean=6.751053, MSE=3.378915
##
## Node number 93: 15 observations
##   mean=9.154667, MSE=3.273025

plot(DecTreeModel)
text(DecTreeModel)
```



Price is the root node.

QB2. Consider the following input:

• Sales=9

• Price=6.54

• Population=124

• Advertising=0

• Age=76

• Income= 110

• Education=10

What will be the estimated Sales for this record using the decision tree model? (15% of total points)

```
Q2Data <- data.frame(
  Price = 6.54,
  Advertising = 0,
  Population = 124,
  Age = 76,
  Income = 110,
  Education = 10
)

Q2Prediction <- predict(DecTreeModel, newdata = Q2Data)
print(Q2Prediction)

##       1
## 9.58625
```

QB3. Use the caret function to train a random forest (method='rf') for the same dataset. Use the caret default settings. By default, caret will examine the "mtry" values of 2,4, and 6. Recall that mtry is the number of attributes available for splitting at each splitting node. Which mtry value gives the best performance? (Make sure to set the random number generator seed to 123) (15% of total points)

```
library(randomForest)

## Warning: package 'randomForest' was built under R version 4.4.2

## randomForest 4.7-1.2

## Type rfNews() to see new features/changes/bug fixes.

##
## Attaching package: 'randomForest'

## The following object is masked from 'package:ggplot2':
##
##     margin
## The following object is masked from 'package:dplyr':
##
##     combine

set.seed(123)

TrainRF <- trainControl(method = "cv", number = 10)

RandomForestCaret <- train(
  Sales ~ .,
  data = Carseats_Filtered,
  method = "rf",
  trControl = TrainRF,
  tuneGrid = data.frame(mtry = c(2, 4, 6))
)

print(RandomForestCaret)

## Random Forest
##
## 400 samples
##   6 predictor
##
## No pre-processing
## Resampling: Cross-Validated (10 fold)
## Summary of sample sizes: 359, 360, 360, 360, 361, 360, ...
## Resampling results across tuning parameters:
##
##   mtry  RMSE      Rsquared   MAE
##   2     2.364895  0.3007628  1.899022
##   4     2.374320  0.2977478  1.895662
##   6     2.394879  0.2875968  1.914578
##
## RMSE was used to select the optimal model using the smallest value.
## The final value used for the model was mtry = 2.
```

An mtry of 4 appears to give the lowest MAE, however an mtry of 2 has the lowest RMSE and highest Rsquared. Though both are comparable, an mtry of 2 is nominally better.

QB4. Customize the search grid by checking the model's performance for mtry values of 2, 3 and 5 using 3 repeats of 5-fold cross validation. (15% of total points

```
TrainRF2 <- trainControl(method = "repeatedcv", number = 5, repeats = 3)

set.seed(123)

RandomForest2 <- train(
  Sales ~ .,
  data = Carseats_Filtered,
  method = "rf",
  trControl = TrainRF2,
  tuneGrid = data.frame(mtry = c(2, 3, 5))
)

print(RandomForest2)

## Random Forest
##
## 400 samples
##   6 predictor
##
## No pre-processing
## Resampling: Cross-Validated (5 fold, repeated 3 times)
## Summary of sample sizes: 320, 321, 319, 320, 320, 319, ...
## Resampling results across tuning parameters:
##
##   mtry  RMSE      Rsquared   MAE
##   2     2.405235  0.2813795  1.930855
##   3     2.401365  0.2858295  1.920612
##   5     2.417771  0.2821938  1.934886
##
## RMSE was used to select the optimal model using the smallest value.
## The final value used for the model was mtry = 3.
```

An mtry of 3 gives the best performance across all 3 metrics.