ADM Assignment 2- Dhanush Myneni

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Q1.What is the key idea behind bagging? Can bagging deal both with high variance (overfitting) and high bias (underfitting)?

Ans. Bagging is also known as bootstap aggregation. When you train the classifiers on various subsets of samples by replacing them, then it is called as bootstap aggregation. Some observations may be repeated in each subset while others might never be included. The model is trained on each sample and the results are then combined.

Bagging is capable enough to deal with the problem of high variance (over-fitting) by intorducing the concept of diversity but not high bias (under-fitting). Since we deal with diverse data in training the model,there is diversity. The base learners are weak and are less liklier to overfit the training data. Even if they happen to overfit, it is done in a different way as compared to other base learners because they happen to be trained on a different dataset. Therefore, when these models are ensembled, the probability of overfitting will be low. However, this is not possible for high bias because when the individual models could not detect the underlying relationships, the overall ensembled model would also not be able to define them. Hence, bagging can deal with over fitting but not under-fitting.

Q2. Why bagging models are computationally more efficient when compared to boosting models with the same number of weak learners?

Ans. Bagging trains different models on different subsets of training data and merges them for a final prediction while in boosting models are trained sequentially. Bagging models are computationally more efficient when compared to boosting models with same number of weak learners due to multiple reasons such as parallel training of independent models, not too complex base learners and lesser sensitivity to hyperparameters. Every model in boosting is trained on the outcome or errors made by its before model. Therefore if an error is made by first model then it is rectified and again not committed by the second model. Additionally, bagging doesnt need plenty data as the models are trained parallelly resulting in a better computational efficiency than to boosting. Additionally, bagging needs lesser tuning of the hyperparameters as against boosting algorithms, increasing its efficiency in computational resources usage.

Q3. 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.

Ans. Two criterion for creating an ensemble model is that the base learner should be better than the random model implying better predictive power and the model should be independent of each other. The base learners considered by Mr. James lack diversity and will result in similar outcomes. Therefore, even if an ensemble model is created out of these base learners, since it lacks diversity, it wouldnt improve the overall performance efficiency

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Q4. Consider the following Table 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?

Ans. The formula for measuring the entropy between two classes is as follows: Entropy = sum_{i=1}^n- P(x=i).log__2.P(x=i) P(x=i) is the probability of class i.

With the help of information gain, the entropy is reduced and the best split for a decision tree is identified which can reduce the entropy.

Information gain =Entropy(parent)-[average entropy(children)].

Entropy(parent) = (-9/16 * log__2 9/16)-(7/16 * log__2 7/16)=0.988699 Entropy(children(large))[3-edible/5-non edible] = (-3/8*log__23/8)-(5/8*log__25/8) =0.954433 Entropy(children(small))[6-edible/2-non edible] = (-6/8*log__2 6/8)-(2/8*log2/8) =0.811277 Weighted[Average.Entropy](children =(8/16)*0.954433+(8/16)*0.811277=0.882854

Information Gain = (Parent Entropy - average[child Entropy])

Information.Gain = 0.988699-0.882854 = 0.105845

Q5.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.

Ans. A random forest model may consider the same attribute having the highest predictive power or information gain to split at the top order. The same will be continued by the child nodes which split based on the attribute with highest predicitive power resulting in similar nodes with no diversity included despite using bagging. To address this issue in random forest, out of all the p predictor variables, a set of random sampled predictors called m is used. This m represents the no. of attributes available for each split. Since all features are not available for split at each node, diversity will be improved which is a key characteristic of an ensemble model.

If m=p, it is just bagging since all the parameters are considered for splitting at each node of each tree. IF m is too small, underfitting could be the result as only few attributes are considered and might lack good predictive power. If m is large, we will be considering all attributes which might be similar leading to less diversity. In classification, the default value for m is square root of p and minimum value is 1. In regression the defaults are set at p/3 and the minimum node size is five. In reality, these values depend on the kind of problem we are dealing with and should be considered a tuning hyper parameter.

Part B

```r
#Loading needed libraries.
library(ISLR)
library(dplyr)
```

```
## Warning: package 'dplyr' was built under R version 4.3.2
```

```
##
## 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
```

```r
library(glmnet)
```

```
## Warning: package 'glmnet' was built under R version 4.3.3

## Loading required package: Matrix

## Warning: package 'Matrix' was built under R version 4.3.2

## Loaded glmnet 4.1-8
```

```r
library(caret)
```

```
## Loading required package: ggplot2

## Warning: package 'ggplot2' was built under R version 4.3.2

## Loading required package: lattice
```

```r
library(rpart)
library(rpart.plot)
```

```
## Warning: package 'rpart.plot' was built under R version 4.3.3
```

```r
library(rattle)
```

```
## Warning: package 'rattle' was built under R version 4.3.3

## Loading required package: tibble

## Loading required package: bitops

##
## Attaching package: 'bitops'

## The following object is masked from 'package:Matrix':
##
##     %&%

## Rattle: A free graphical interface for data science with R.
## Version 5.5.1 Copyright (c) 2006-2021 Togaware Pty Ltd.
## Type 'rattle()' to shake, rattle, and roll your data.
```

```r
#Filtering attributes needed for our analysis and making a new dataset.
New_data <- Carseats %>% select("Sales", "Price","Advertising","Population","Age","Income","Education")

head(New_data)
```

```
##   Sales Price Advertising Population Age Income Education
## 1  9.50   120          11        276  42     73        17
## 2 11.22    83          16        260  65     48        10
## 3 10.06    80          10        269  59     35        12
## 4  7.40    97           4        466  55    100        14
## 5  4.15   128           3        340  38     64        13
## 6 10.81    72          13        501  78    113        16
```

Q1.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?

Ans.

```r
reg_model<-rpart (Sales~.,data=New_data, method = 'anova')

summary(reg_model)
```

```
## Call:
## rpart(formula = Sales ~ ., data = New_data, method = "anova")
##   n= 400
##
##            CP nsplit rel error    xerror       xstd
## 1  0.14251535      0 1.0000000 1.0089516 0.06978271
## 2  0.08034146      1 0.8574847 0.9077180 0.06506291
## 3  0.06251702      2 0.7771432 0.9039805 0.06893417
## 4  0.02925241      3 0.7146262 0.7882700 0.05820865
## 5  0.02537341      4 0.6853738 0.8051609 0.05699878
## 6  0.02127094      5 0.6600003 0.7861381 0.05520631
## 7  0.02059174      6 0.6387294 0.7865273 0.05598899
## 8  0.01632010      7 0.6181377 0.7932480 0.05541973
## 9  0.01521801      8 0.6018176 0.8051312 0.05689324
## 10 0.01042023      9 0.5865996 0.8164039 0.05702480
## 11 0.01000559     10 0.5761793 0.8498288 0.05708375
## 12 0.01000000     12 0.5561681 0.8511865 0.05712347
##
## 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)
```

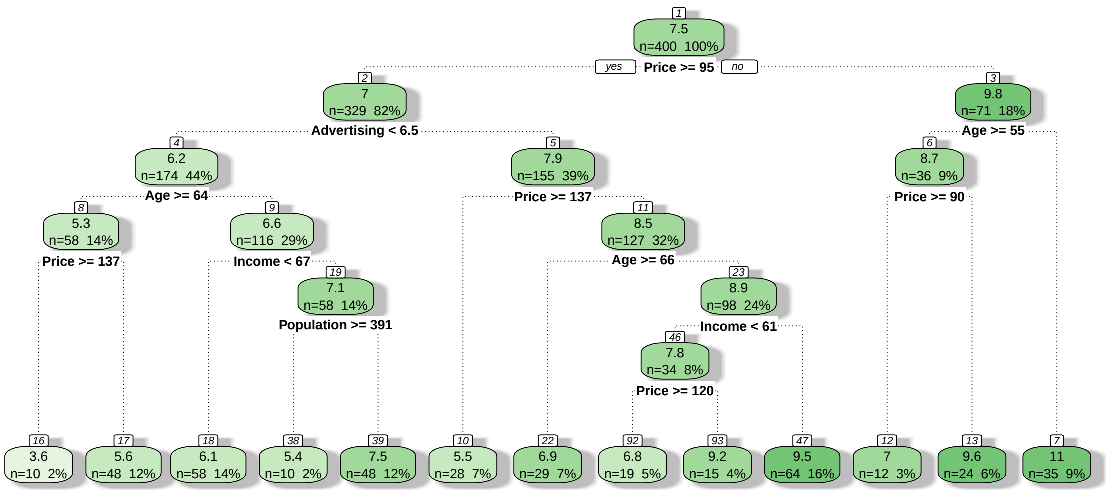
```
##       Age         < 61.5  to the right, improve=0.07120203, (0 missing)
##       Income      < 61.5  to the left,  improve=0.02840494, (0 missing)
##       Population  < 174.5 to the left,  improve=0.01077467, (0 missing)
##
## Node number 2: 329 observations,    complexity param=0.08034146
##   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
```

```r
fancyRpartPlot(reg_model)
```



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#From the above, we can say that the price attribute is at the top node for splitting.

Q2. 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?

Ans.

```
predicted_data<- data.frame(Sales=9,Price=6.54 ,Population=124,Advertising=0,Age=76,Income= 110, Educat

Anticipated_sales<- predict(reg_model,predicted_data)

Anticipated_sales
```

```
##       1
## 9.58625
```

#The predicted value of sales is 9.58625.

Q3.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?

Ans.

```r
#Training a random forest model

set.seed(123)


RF_model <- train(Sales~., data= New_data,method = "rf")

#printing the model

print(RF_model)
```

```
## Random Forest
##
## 400 samples
##   6 predictor
##
## No pre-processing
## Resampling: Bootstrapped (25 reps)
## Summary of sample sizes: 400, 400, 400, 400, 400, 400, ...
## Resampling results across tuning parameters:
##
##   mtry  RMSE      Rsquared   MAE
##   2     2.405819  0.2852547  1.926801
##   4     2.421577  0.2790266  1.934608
##   6     2.447373  0.2681323  1.953147
##
## RMSE was used to select the optimal model using the smallest value.
## The final value used for the model was mtry = 2.
```

```r
#mtry =2 has the least RMSE Value
```

#The best value for mtry=2 which has the least RMSE value

Q4. 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.

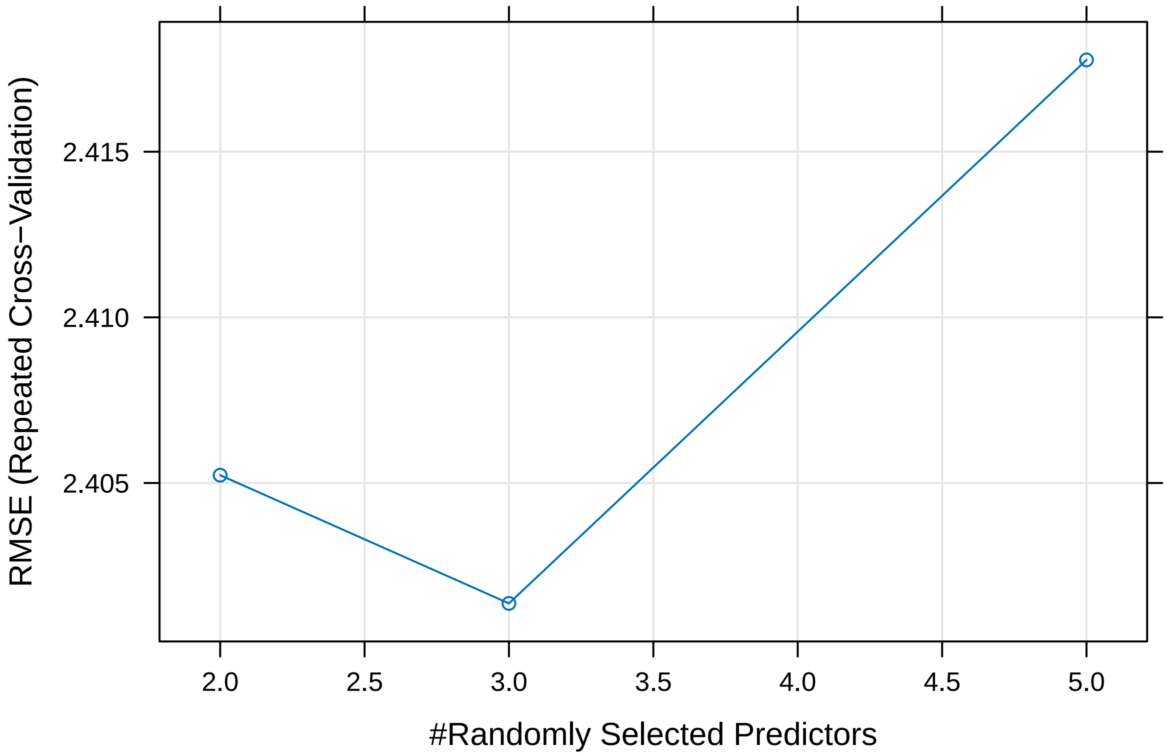
Ans.

```r
set.seed(123)

#Customizing  with mtry values of 2, 3 and 5 and  3 repeats of 5-fold cross validation.

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

#defining mtry values in search grid
```

```r
Search_grid <- expand.grid(mtry=c(2,3,5))

grid_search <- train(Sales~., data=New_data, method="rf",tuneGrid=Search_grid, trControl=customized)

print(grid_search)
```

```
## 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.
```

```r
#Plotting the search

plot(grid_search)
```



Mtry at 3 is the optimal value as the RMSE is the least.