

DS-6030 Homework Module 7

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8. In the lab, a classification tree was applied to the Carseats data set after converting Sales into a qualitative response variable.

Now we will seek to predict Sales using regression trees and related approaches, treating the response as a quantitative variable.

- (a) Split the data set into a training set and a test set.

```
set.seed(1)
library(ISLR2)
library(TomLeversRPackage)
training_and_testing_data <- split_data_set_into_training_and_testing_data(
  Carseats,
  proportion_of_training_data = 0.9
)
training_data <- training_and_testing_data$training_data
testing_data <- training_and_testing_data$testing_data
head(training_data, n = 2)
```

#	Sales	CompPrice	Income	Advertising	Population	Price	ShelveLoc	Age	Education
# 324	10.36	107	105	18	428	103	Medium	34	12
# 167	6.71	119	67	17	151	137	Medium	55	11
#	Urban	US							
# 324	Yes	Yes							
# 167	Yes	Yes							

```
head(testing_data, n = 2)
```

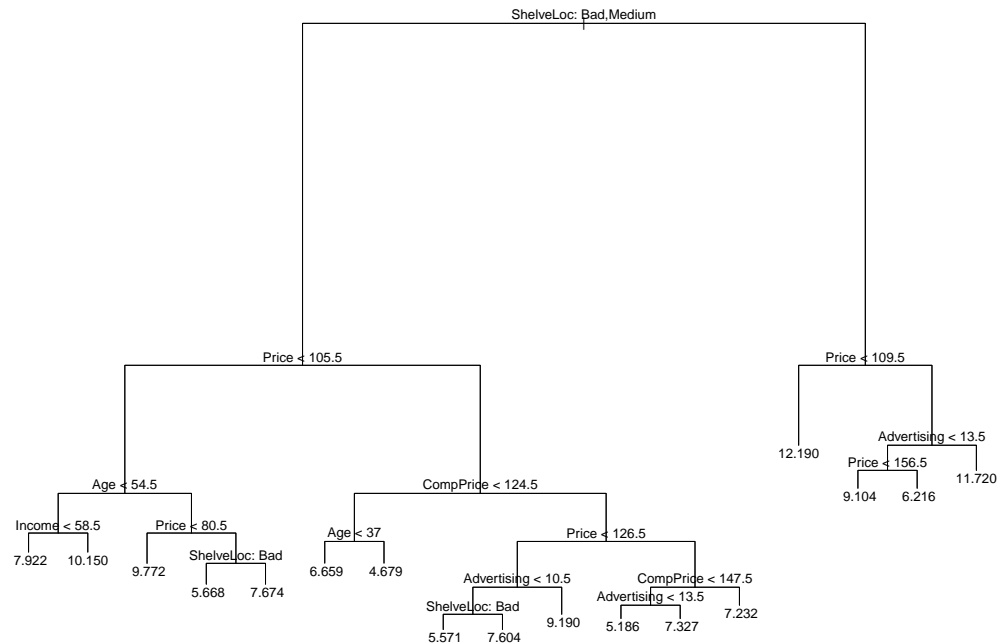
#	Sales	CompPrice	Income	Advertising	Population	Price	ShelveLoc	Age	Education
# 8	11.85	136	81	15	425	120	Good	67	10
# 123	6.88	119	100	5	45	108	Medium	75	10
#	Urban	US							
# 8	Yes	Yes							
# 123	Yes	Yes							

- (b) Fit a regression tree to the training set. Plot the tree, and interpret the results. What test MSE do you obtain?

```
library(tree)
full_tree <- tree(Sales ~ ., data = training_data)
summary(full_tree)
```

```
#
# Regression tree:
# tree(formula = Sales ~ ., data = training_data)
# Variables actually used in tree construction:
# [1] "ShelveLoc" "Price" "Age" "Income" "CompPrice"
# [6] "Advertising"
# Number of terminal nodes: 17
# Residual mean deviance: 2.653 = 910.1 / 343
# Distribution of residuals:
# Min. 1st Qu. Median Mean 3rd Qu. Max.
# -5.18600 -1.09000 0.05305 0.00000 1.08300 4.63100
```

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



```
vector_of_predicted_sales <- predict(full_tree, newdata = testing_data)
vector_of_actual_sales <- testing_data$Sales
calculate_mean_squared_error(vector_of_predicted_sales, vector_of_actual_sales)
```

```
# [1] 4.896065
```

When shelf location is good and price is less than 109.5 monetary units, our tree predicts that 12.190 thousand child car seats will be sold at each location in each time period.

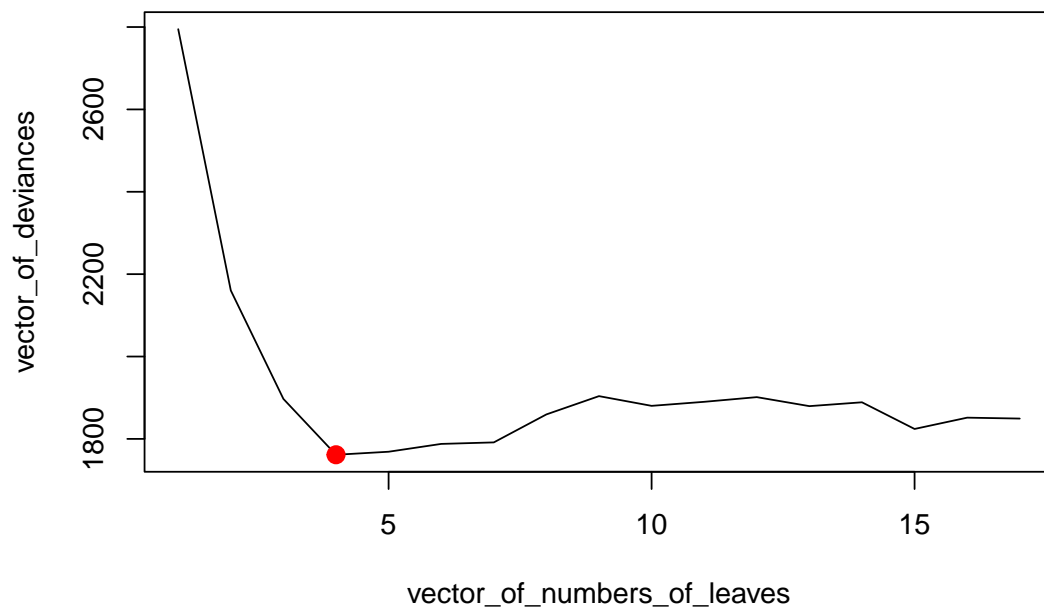
The test Mean Squared Error of our tree when predicting sales is 4.896 *thousand*².

- (c) Use cross-validation in order to determine the optimal level of tree complexity. Does pruning the tree improve the test MSE?

```

object_of_types_prune_and_tree_sequence <- cv.tree(full_tree)
vector_of_numbers_of_leaves <- object_of_types_prune_and_tree_sequence$size
vector_of_deviances <- object_of_types_prune_and_tree_sequence$dev
plot(vector_of_numbers_of_leaves, vector_of_deviances, type = "l")
index_of_minimum_deviance <- which.min(vector_of_deviances)
optimal_number_of_leaves <-
  vector_of_numbers_of_leaves[index_of_minimum_deviance]
minimum_deviance <- min(vector_of_deviances)
points(
  optimal_number_of_leaves,
  minimum_deviance,
  col = "red",
  cex = 2,
  pch = 20
)

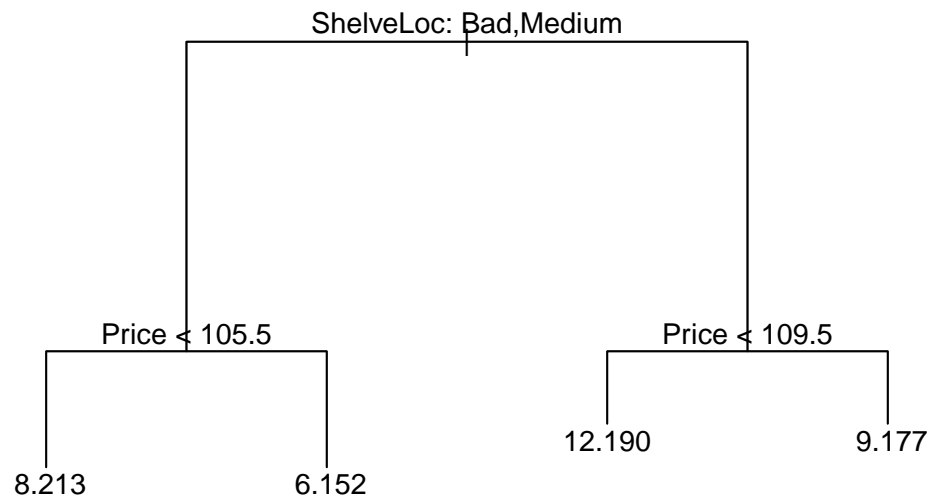
```



```

pruned_tree <- prune.tree(full_tree, best = optimal_number_of_leaves)
plot(pruned_tree)
text(pruned_tree, pretty = 0)

```



```
vector_of_predicted_sales <- predict(pruned_tree, newdata = testing_data)
calculate_mean_squared_error(vector_of_predicted_sales, vector_of_actual_sales)
```

```
# [1] 6.785063
```

The test Mean Squared Error for the pruned tree is greater and less desirable than the Mean Squared Error for the full tree.

- (d) Use the bagging approach in order to analyze this data. What test MSE do you obtain? Use the `importance()` function to determine which variables are most important.

Per *An Introduction to Statistical Learning* (Second Edition), bagging “is simply a special case of a random forest with [the number of variables randomly sampled as candidates at each split] $m = p$ the number of predictors.”

```
library(randomForest)
```

```
# randomForest 4.7-1.1
```

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

```
index_of_column_Sales <-
  get_index_of_column_of_data_frame(training_data, "Sales")
data_frame_of_predictors <- training_data[, -index_of_column_Sales]
data_frame_of_sales <- training_data[, index_of_column_Sales]
number_of_predictors <- ncol(data_frame_of_predictors)
get_test_MSE_and_vector_of_ordered_percent_increase_for_random_forest <-
  function(mtry) {
    the_randomForest <- randomForest(
      formula = Sales ~ .,
      data = training_data,
```

```

    mtry = mtry,
    importance = TRUE
  )
  vector_of_predicted_sales <-
    predict(the_randomForest, newdata = testing_data)
  test_MSE <- calculate_mean_squared_error(
    vector_of_predicted_sales,
    vector_of_actual_sales
  )
  matrix_of_importance_metrics <- importance(the_randomForest)
  vector_of_percents_increase_in_MSE <-
    matrix_of_importance_metrics[, "%IncMSE"]
  vector_of_indices_of_ordered_percents_increase_in_MSE <-
    order(vector_of_percents_increase_in_MSE, decreasing = TRUE)
  vector_of_ordered_percents_increase_in_MSE <-
    vector_of_percents_increase_in_MSE[
      vector_of_indices_of_ordered_percents_increase_in_MSE
    ]
  list_of_test_MSE_and_vector_of_ordered_percents_increase_for_random_forest <-
    list(
      test_MSE = test_MSE,
      vector_of_ordered_percents_increase_in_MSE =
        vector_of_ordered_percents_increase_in_MSE
    )
  return(
    list_of_test_MSE_and_vector_of_ordered_percents_increase_for_random_forest
  )
}
get_test_MSE_and_vector_of_ordered_percents_increase_for_random_forest(
  mtry = number_of_predictors
)

```

```

# $test_MSE
# [1] 2.912954
#
# $vector_of_ordered_percents_increase_in_MSE
#   ShelveLoc      Price  CompPrice Advertising      Age      Income
# 81.267672    79.323197  38.593171   25.822124  25.716498  14.313945
# Education      US      Urban  Population
# 2.885808     2.270115  -1.691179  -2.211183

```

The test Mean Squared Error for our bootstrap aggregation (BAG) is 2.974, which is 0.607 of the MSE for our full tree and 0.438 of the MSE for our pruned tree.

According to [In a random forest, is larger %IncMSE better or worse?](#), “%IncMSE is the most robust and informative measure. IT is the increase in mse of predictions(estimated with out-of-bag-CV) as a result of variable j being permuted(values randomly shuffled)... the higher the number, the more important.”

%IncMSE is highest for *ShelveLoc* followed by *Price*; *ShelveLoc* and *Price* are the two most important variables.

- (e) Use random forests to analyze this data. What test MSE do you obtain? Use the `importance()` function to determine which variables are most important. Describe the effect of `m`, the number of variables considered at each split, on the error rate obtained.
- (f) Now analyze the data using BART, and report your results. (skip this exercise)

9. This problem involves the OJ data set which is part of the ISLR package.

- (a) Create a training set containing a random sample of 800 observations, and a test set containing the remaining observations.
- (b) Fit a tree to the training data, with Purchase as the response and the other variables as predictors. Use the `summary()` function to produce summary statistics about the tree, and describe the results obtained. What is the training error rate? How many terminal nodes does the tree have?
- (c) Type in the name of the tree object in order to get a detailed text output. Pick one of the terminal nodes, and interpret the information displayed.
- (d) Create a plot of the tree, and interpret the results.
- (e) Predict the response on the test data, and produce a confusion matrix comparing the test labels to the predicted test labels. What is the test error rate?
- (f) Apply the `cv.tree()` function to the training set in order to determine the optimal tree size.
- (g) Produce a plot with tree size on the x-axis and cross-validated classification error rate on the y-axis.
- (h) Which tree size corresponds to the lowest cross-validated classification error rate?
- (i) Produce a pruned tree corresponding to the optimal tree size obtained using cross-validation. If cross-validation does not lead to selection of a pruned tree, then create a pruned tree with five terminal nodes.
- (j) Compare the training error rates between the pruned and unpruned trees. Which is higher?
- (k) Compare the test error rates between the pruned and unpruned trees. Which is higher?