ADS502-Assignment-2.1-R.R

DDY

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```
# Assignment 2.1 [R]

# University of San Diego

# ADS 502

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# For Exercises 21-30, continue working with the
bank_marketing_training
# data set. Use either Python or R to solve each problem.

# 21. Produce the following graphs. What is the strength of each graph?
Weakness?

# a. Bar graph of marital.

library(ggplot2)

bank_train <- read.csv(file = "C:/Users/DDY/Desktop/2021-Spring-
textbooks/ADS-502/Module2/Website Data
Sets/bank_marketing_training.csv")

ggplot(bank_train, aes(marital)) + geom_bar() + coord_flip()
```
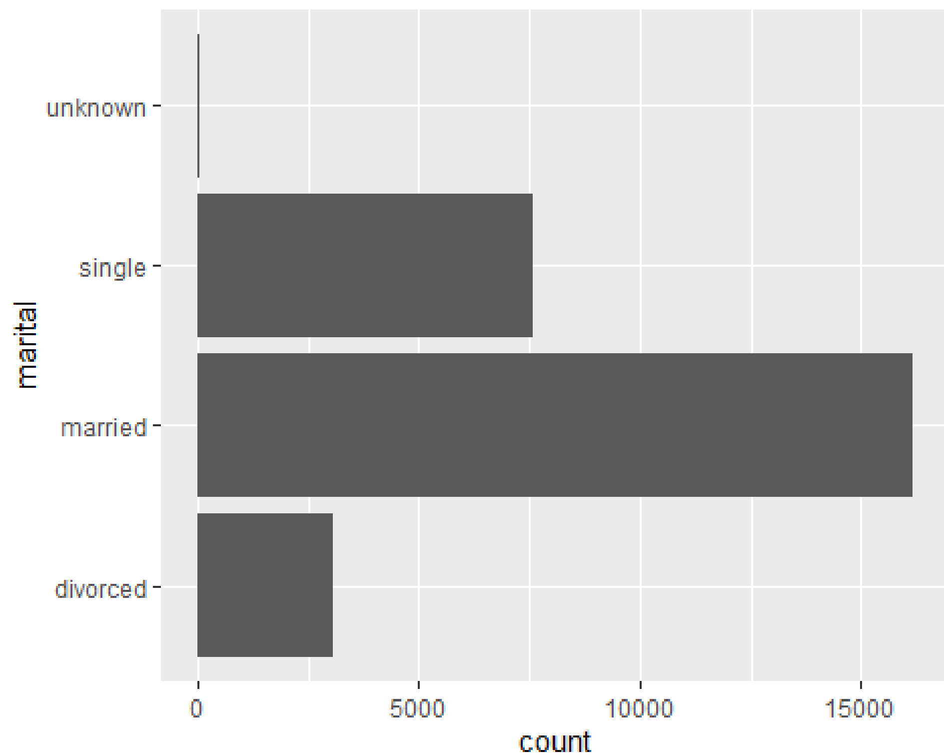
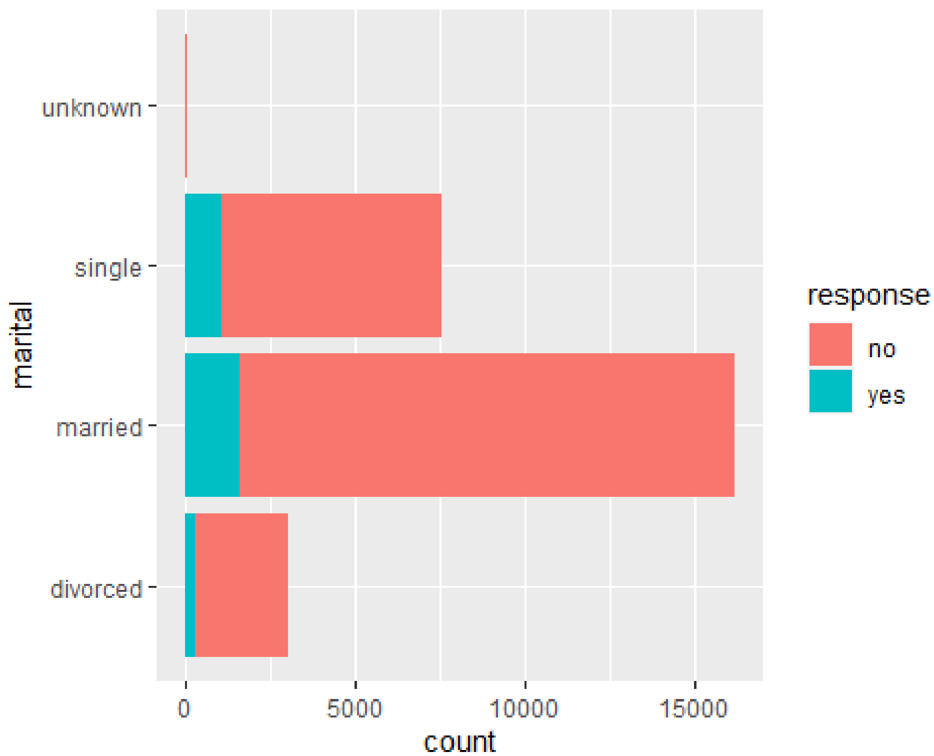
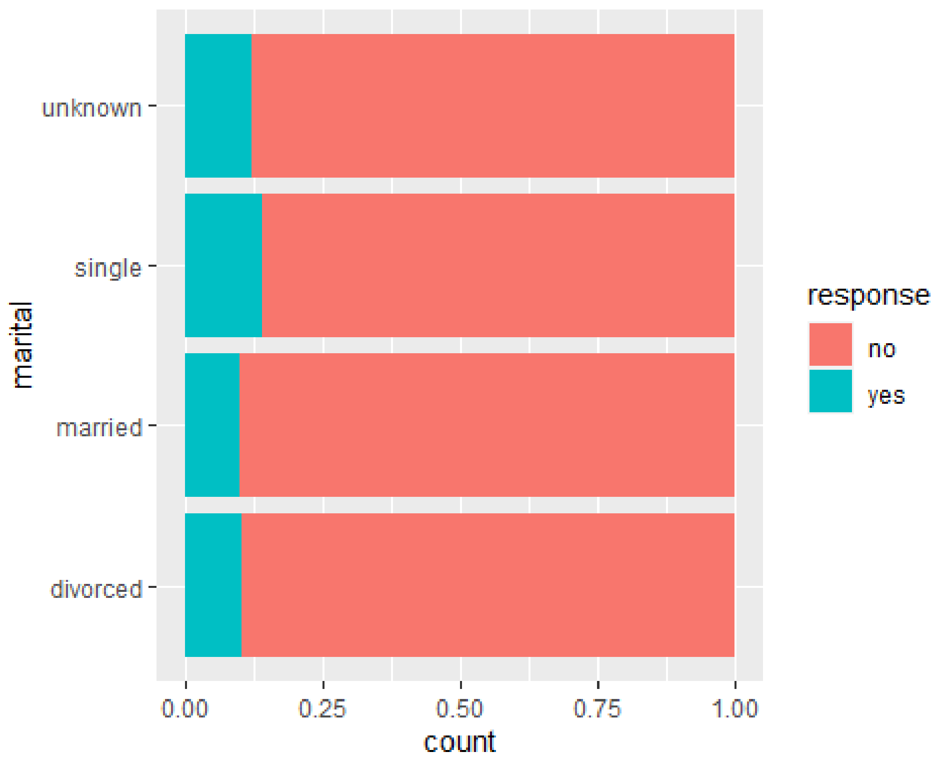




```
# b. Bar graph of marital, with overlay of response.

ggplot(bank_train, aes(marital)) + geom_bar(aes(fill = response)) +
coord_flip()
```



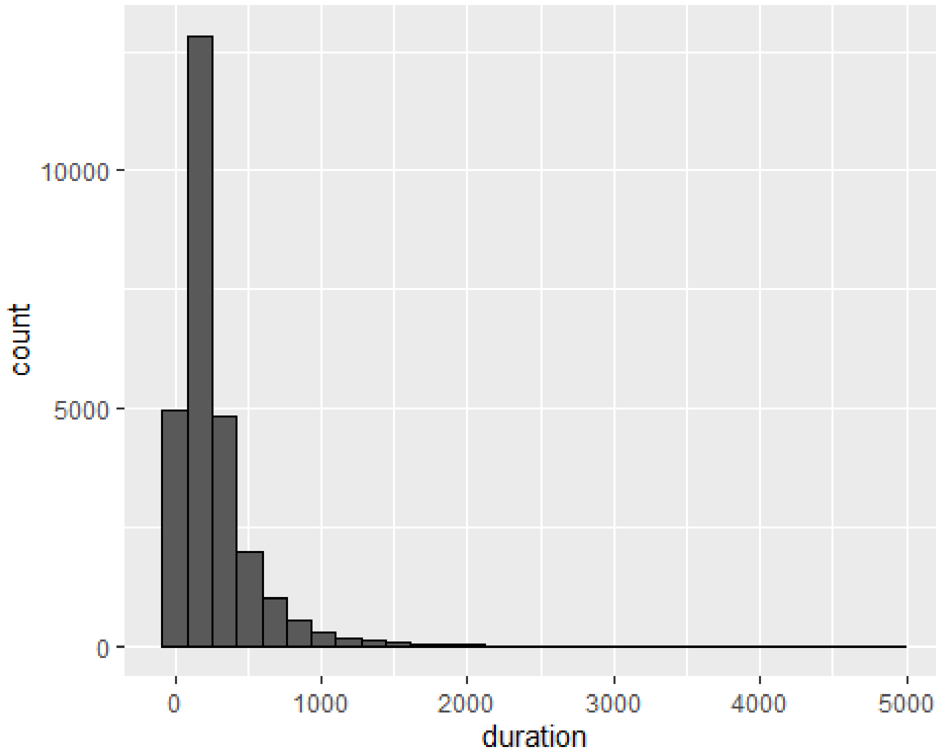

```
# c. Normalized bar graph of marital, with overlay of response.

ggplot(bank_train, aes(marital)) + geom_bar(aes(fill = response),
                                              position = "fill") +
coord_flip()
```



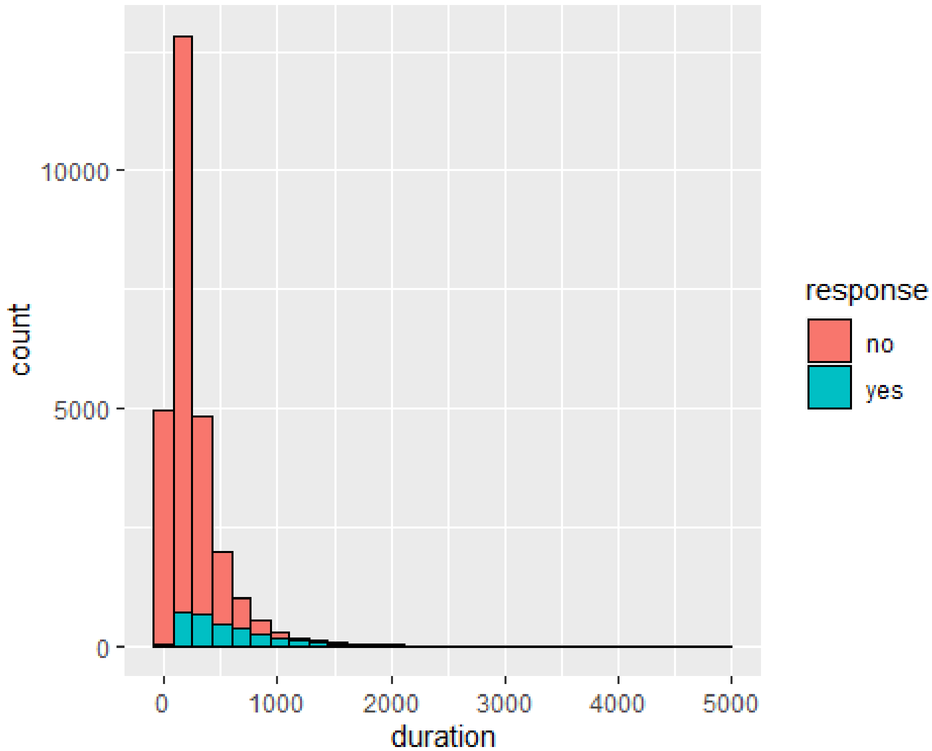

```
# 22. Using the graph from Exercise 21c, describe the relationship
between marital and response.
# In divorced and married status, the response of "yes" rate is the
same and the lowest among all;
# For unknown status, the response of "yes" rate is in between single
and divorced/married;
# Response rate of "yes" is the highest for single marital status


## 23. Do the following with the variables marital and response.

# a. Build a contingency table, being careful to have the correct
variables
# representing the rows and columns. Report the counts and the column
percentages.

t.v1 <- table(bank_train$response, bank_train$marital)
t.v2 <- addmargins(A = t.v1, FUN = list(total = sum),quiet = TRUE)

# table without total
t.v1

##
##         divorced married single unknown
##    no       2743   14579   6514      50
##    yes       312    1608   1061       7
```

```r
# table with total
t.v2

##
##          divorced married single unknown total
##   no         2743   14579   6514      50 23886
##   yes         312    1608   1061       7  2988
##   total      3055   16187   7575      57 26874

t.v1_pct <- round(prop.table(t.v1, margin = 2)*100, 1)
t.v2_pct <- addmargins(A = t.v1_pct, FUN = list(total = sum),quiet =
TRUE)

# percentage table
t.v1_pct

##
##        divorced married single unknown
##   no       89.8    90.1   86.0    87.7
##   yes      10.2     9.9   14.0    12.3

# b. Describe what the contingency table is telling you.
# For response of "no", 'married' has the most percentage;
# For response of "yes", 'single' has the most percentage.

# 24. Repeat the previous exercise, this time reporting the row
percentages. Explain the
# difference between the interpretation of this table and the previous
contingency table.

# swap cols and rows
t.v1_r <- table(bank_train$marital, bank_train$response)
t.v2_r <- addmargins(A = t.v1_r, FUN = list(total = sum),quiet = TRUE)

t.v1_r

##
##                 no   yes
##   divorced  2743   312
##   married  14579  1608
##   single    6514  1061
##   unknown     50     7

t.v2_r

##
##                 no   yes total
##   divorced  2743   312  3055
##   married  14579  1608 16187
##   single    6514  1061  7575
```

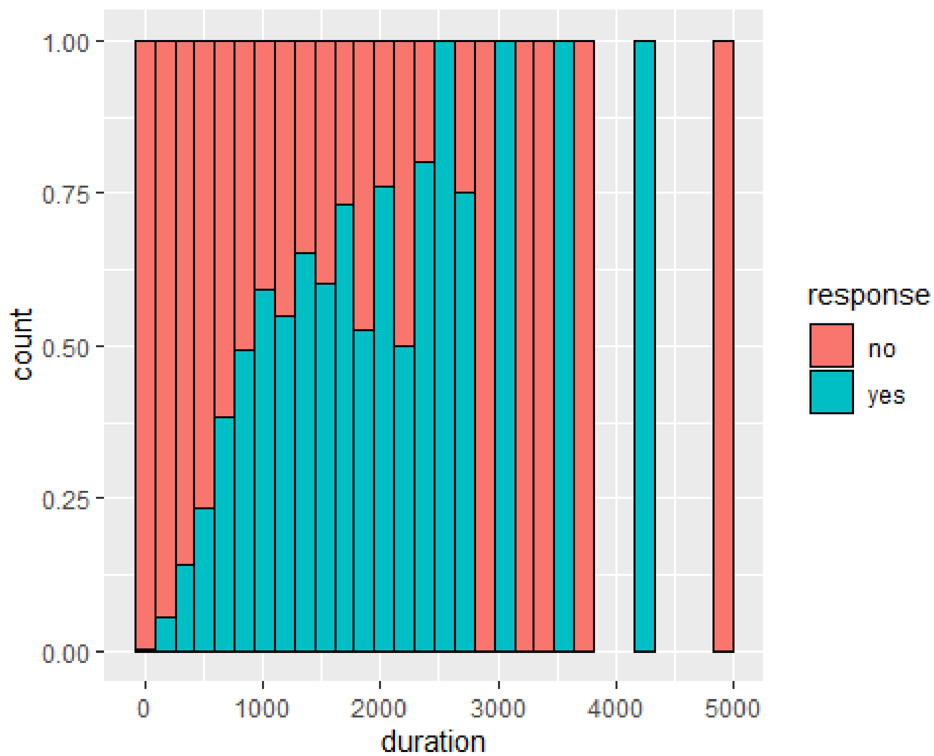
```
##   unknown      50     7    57
##   total     23886  2988 26874

t.v1_r_pct <- round(prop.table(t.v1_r, margin = 1)*100, 1)
t.v2_r_pct <- addmargins(A = t.v1_r_pct, FUN = list(total = sum),quiet
= TRUE)

t.v1_r_pct

##
##               no  yes
##   divorced 89.8 10.2
##   married  90.1  9.9
##   single   86.0 14.0
##   unknown  87.7 12.3

# This time the row percentage shows the ratio in each marital status
of response of "yes" and "no";
# In "divorced", 89.79% responded "no" and 10.21% responded "yes";
# In "married", 90.07% responded "no" and 9.93% responded "yes";
# In "single", 85.99% responded "no" and 14.01% responded "yes";
# In "unknown", 87.72% responded "no" and 12.38% responded "yes";
# Overall, more people recompensed "no" than "yes".

# The difference between this two tables is one is from the perspective
of
# response while the other is
# from the perspective of marital status.


### 25. Produce the following graphs. What is the strength of each
graph? Weakness?

# a. Histogram of duration.

ggplot(bank_train, aes(duration)) + geom_histogram(color="black")

## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
```



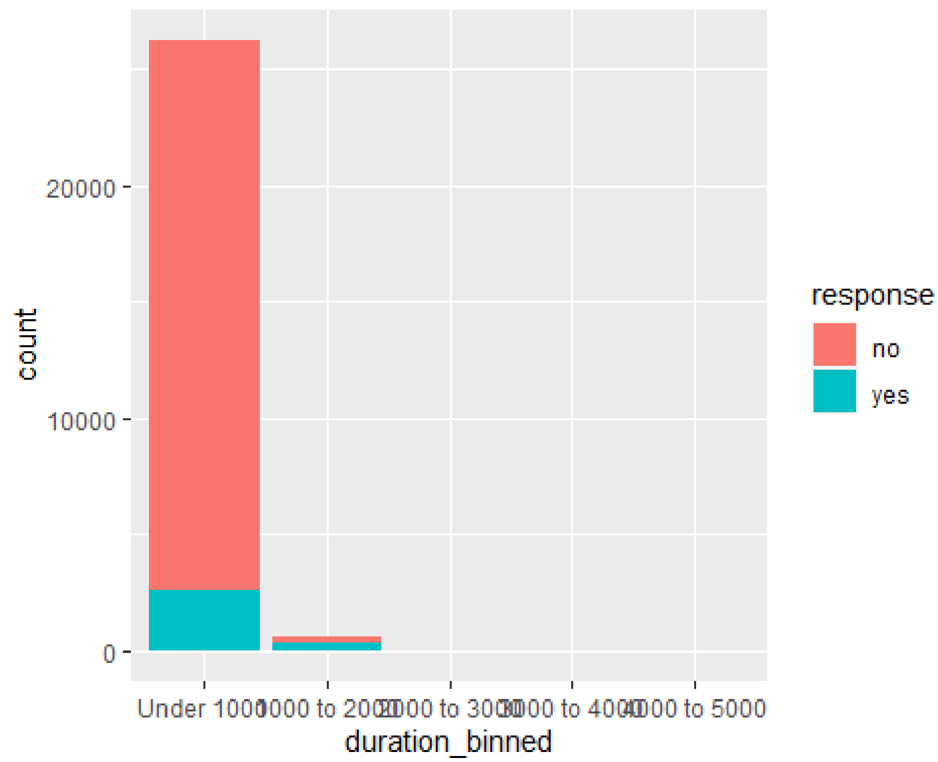

```
# b. Histogram of duration, with overlay of response.

ggplot(bank_train, aes(duration)) + geom_histogram(aes(fill =
response), color="black")

## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
```



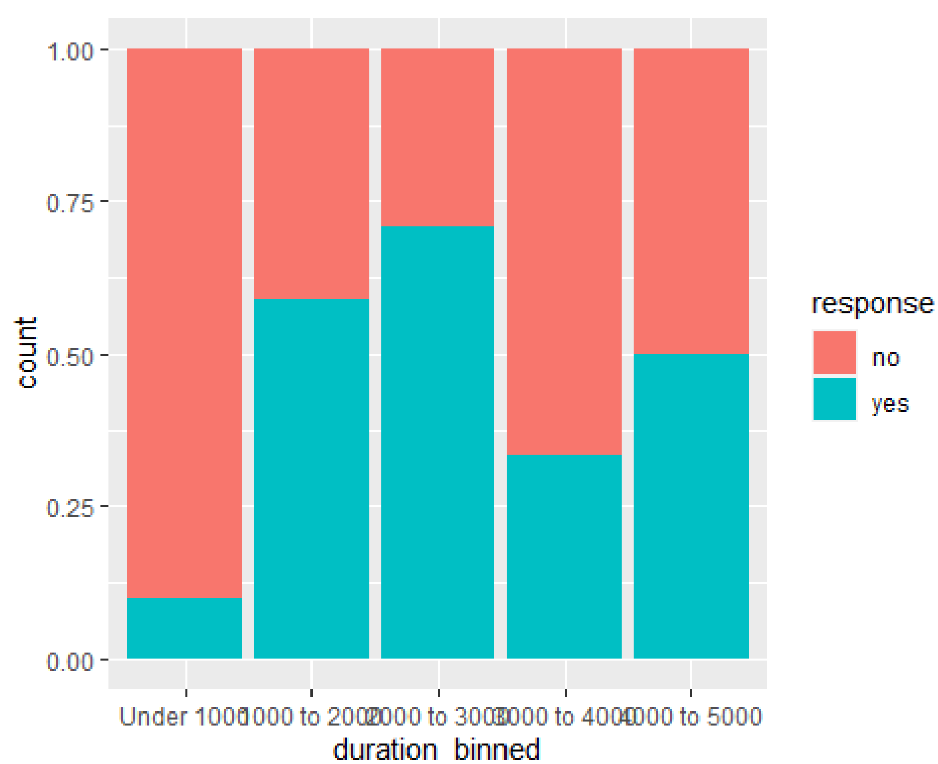

```
# c. Normalized histogram of duration, with overlay of response.

ggplot(bank_train, aes(duration)) + geom_histogram(aes(fill =
response), color="black",
                 position = "fill")

## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.

## Warning: Removed 10 rows containing missing values (geom_bar).
```



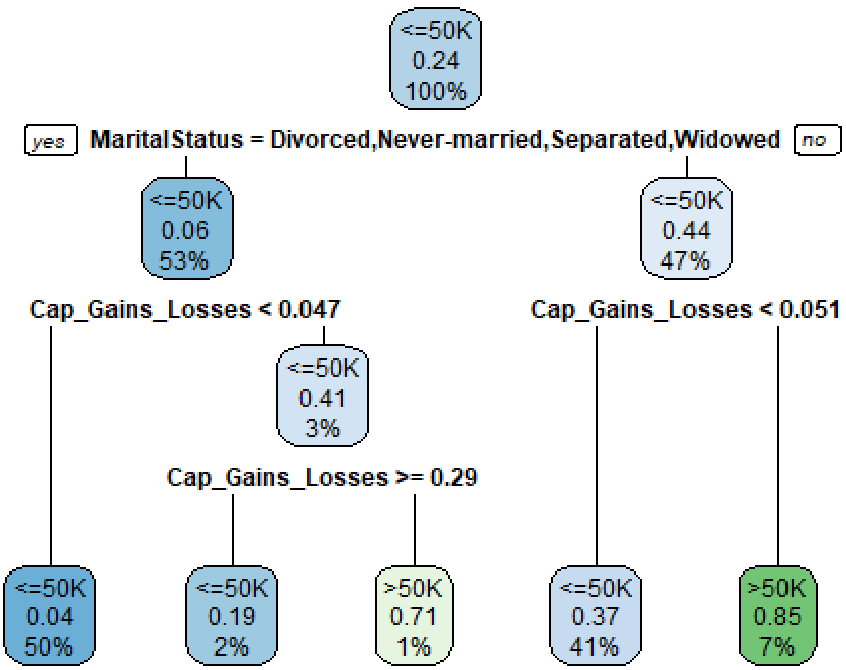

```
# binned barchart

bank_train$duration_binned <- cut(x = bank_train$duration, breaks =
c(0, 1000, 2000, 3000,4000,5000),
                              right = FALSE,
                              labels = c("Under 1000", "1000 to 2000",
"2000 to 3000",
                                         "3000 to 4000", "4000 to
5000"))
ggplot(bank_train, aes(duration_binned)) + geom_bar(aes(fill =
response))
```



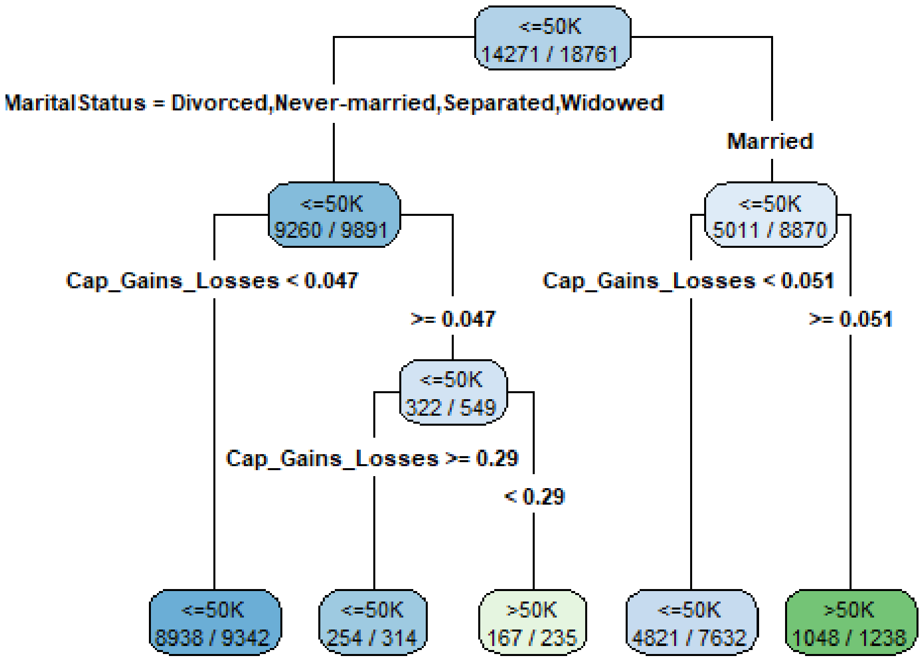

```
ggplot(bank_train, aes(duration_binned)) + geom_bar(aes(fill =
response), position = 'fill')
```



```r
# For Exercises 14-20, work with the adult_ch6_training and
adult_ch6_test data
# sets. Use either Python or R to solve each problem.

# 14. Create a CART model using the training data set that predicts
income using
# marital status and capital  gains and losses. Visualize the decision
tree
# (that is, provide the decision tree output). Describe the first few
splits in the decision tree.

adult_training <- read.csv(file = "C:/Users/DDY/Desktop/2021-Spring-
textbooks/ADS-502/Module2/Website Data Sets/adult_ch6_training")

colnames(adult_training)[1] <- "MaritalStatus"

# change income and marital status to factors
adult_training$Income <- factor(adult_training$Income)
adult_training$MaritalStatus <- factor(adult_training$MaritalStatus)


library(rpart); library(rpart.plot)

# build decision tree
DT_CART <- rpart(formula = Income ~ MaritalStatus +
Cap_Gains_Losses,data =
                   adult_training, method = "class")

rpart.plot(DT_CART)
```

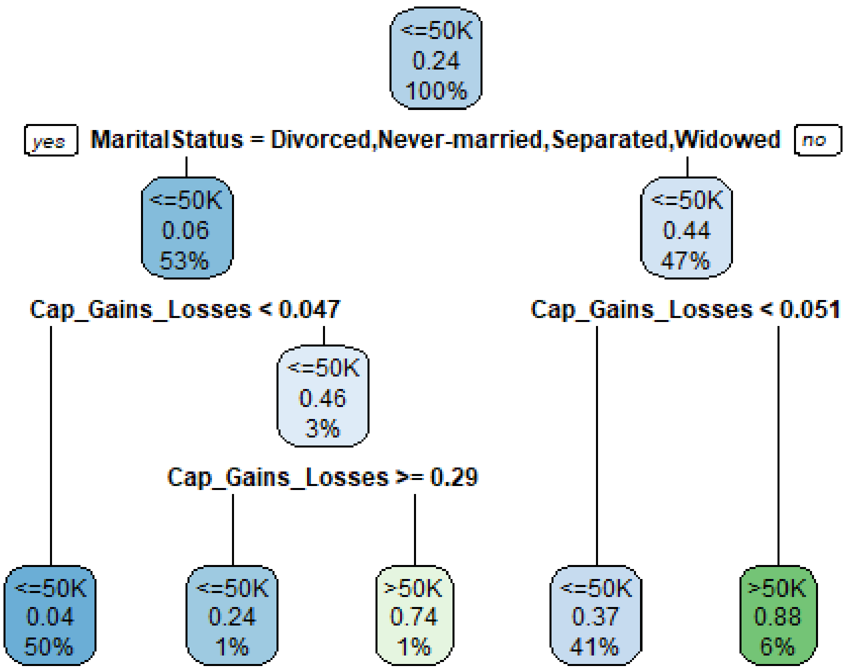



```
?rpart.plot

## starting httpd help server ...

##   done

# using type = 4 to label each branch with its specific value, instead
of a
# yes/no at the top of the split

#extra = 2 to add the correct classification proportion to each node.

rpart.plot(DT_CART, type = 4, extra = 2)
```

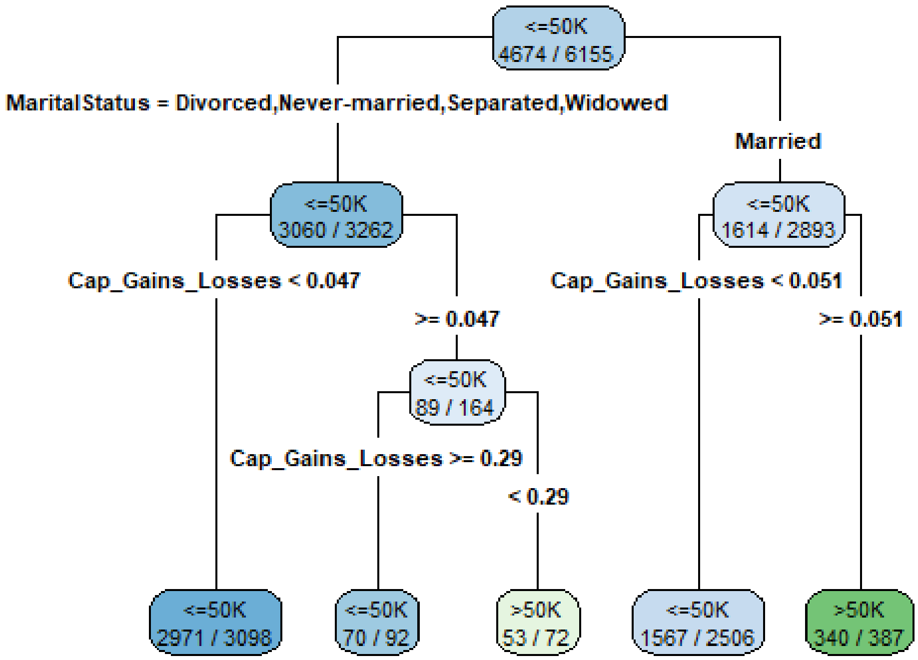



```
# create a data frame that includes the predictor variables of the
records you
# wish to classify
X = data.frame(MaritalStatus = adult_training$MaritalStatus,
               Cap_Gains_Losses =
                 adult_training$Cap_Gains_Losses)

# Once you have the predictor variables you wish to classify, use the
predict()
# command.
predIncomeCART = predict(object = DT_CART, newdata = X,type = "class")


# 15. Develop a CART model using the test data set that utilizes the
same target
# and predictor variables. Visualize the decision tree. Compare the
decision trees.
# Does the test data result match the training data result?

adult_test <- read.csv(file = "C:/Users/DDY/Desktop/2021-Spring-
textbooks/ADS-502/Module2/Website Data Sets/adult_ch6_test")

# run through the same process using test dataset
colnames(adult_test)[1] <- "MaritalStatus"
adult_test$Income <- factor(adult_test$Income)
adult_test$MaritalStatus <- factor(adult_test$MaritalStatus)
```

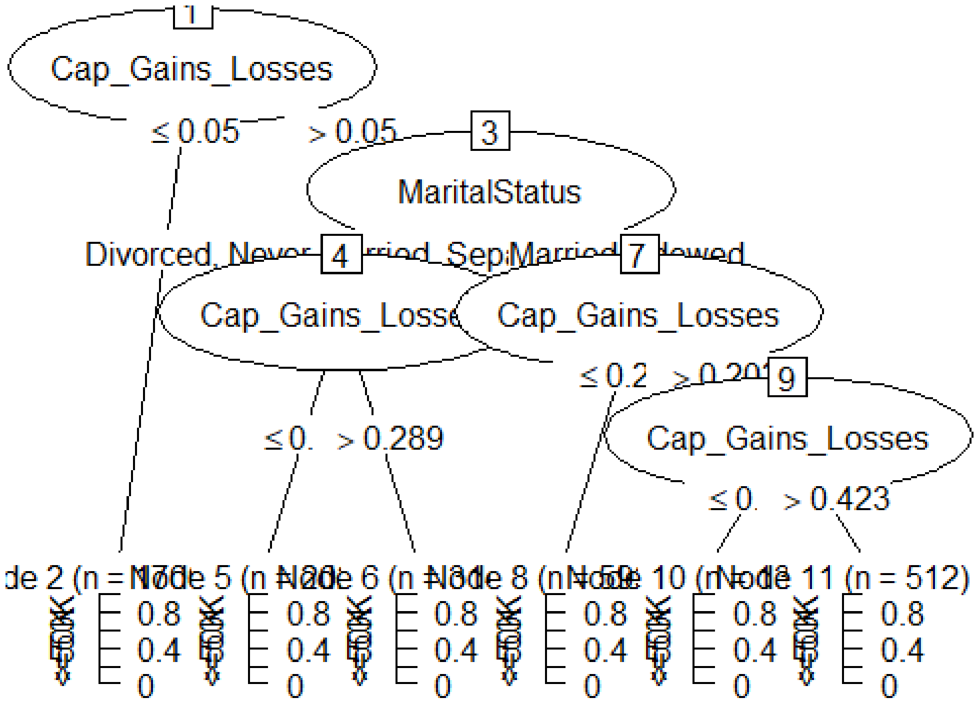
```r
DT_CART_test <- rpart(formula = Income ~ MaritalStatus +
Cap_Gains_Losses,data =
                   adult_test, method = "class")

rpart.plot(DT_CART_test)
```




```r
rpart.plot(DT_CART_test, type = 4, extra = 2)
```




```
X_test = data.frame(MaritalStatus = adult_test$MaritalStatus,
               Cap_Gains_Losses =
                 adult_test$Cap_Gains_Losses)

predIncomeCART_test = predict(object = DT_CART_test, newdata = X_test,
                         type = "class")

# The decision tree of test dataset matches the one with training
dataset.


# 16. Use the training data set to build a C5.0 model to predict income
using
# marital status and capital gains and losses. Specify a minimum of 75
cases per
# terminal node. Visualize the decision tree. Describe the first few
splits in the decision tree.

library(C50)

# run c5.0 algo
C5 <- C5.0(formula = Income ~ MaritalStatus + Cap_Gains_Losses,
           data = adult_training, control = C5.0Control(minCases=75))
plot(C5)
```




```
#predict(object = C5, newdata = X)

# 17. How does your C5.0 model compare to the CART model? Describe the
similarities and differences.

# Similarities: Both CART and C50 follow the similar logic of test
conditions;
# Differences: CART starts the split with marital status and goes on
with Cap_Gains_Losses
# while c50 starts with Cap_Gains_Losses and goes on with marital
status; Different
# number of nodes and different ways of displaying classes for the leaf
nodes.


# For the following exercises, work with the bank_reg_training and the
# bank_reg_test data sets. Use either Python or R to solve each
problem.

# 34. Use the training set to run a regression predicting Credit Score,
# based on Debt-to-Income Ratio and Request Amount. Obtain a summary of
the model.
# Do both predictors belong in the model?

bank_reg_train = read.csv(file ='C:/Users/DDY/Desktop/2021-Spring-
textbooks/ADS-502/Module2/Website Data Sets/bank_reg_training')
```

```r
bank_reg_test = read.csv(file ='C:/Users/DDY/Desktop/2021-Spring-textbooks/ADS-502/Module2/Website Data Sets/bank_reg_test')

# run the model
model01 <- lm(formula = Credit.Score ~ Debt.to.Income.Ratio +Request.Amount,
              data = bank_reg_train)

# display the summary table
summary(model01)

## 
## Call:
## lm(formula = Credit.Score ~ Debt.to.Income.Ratio + Request.Amount, 
##     data = bank_reg_train)
## 
## Residuals:
##     Min      1Q  Median      3Q     Max 
## -279.13  -25.11   10.87   39.93  175.32 
## 
## Coefficients:
##                       Estimate Std. Error t value Pr(>|t|)    
## (Intercept)          6.685e+02  1.336e+00  500.27   <2e-16 ***
## Debt.to.Income.Ratio -4.813e+01  4.785e+00  -10.06   <2e-16 ***
## Request.Amount        1.075e-03  6.838e-05   15.73   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
## 
## Residual standard error: 66 on 10690 degrees of freedom
## Multiple R-squared:  0.02839,	Adjusted R-squared:  0.02821 
## F-statistic: 156.2 on 2 and 10690 DF,  p-value: < 2.2e-16

# 35. Validate the model from the previous exercise.

model02 <- lm(formula = Credit.Score ~ Debt.to.Income.Ratio + Request.Amount,
              data = bank_reg_test)

summary(model02)

## 
## Call:
## lm(formula = Credit.Score ~ Debt.to.Income.Ratio + Request.Amount, 
##     data = bank_reg_test)
## 
## Residuals:
##     Min      1Q  Median      3Q     Max 
## -288.16  -24.49   11.08   39.47  199.84 
## 
## Coefficients:
```

```
##                          Estimate Std. Error t value Pr(>|t|)
## (Intercept)            6.655e+02  1.328e+00  501.26   <2e-16 ***
## Debt.to.Income.Ratio -5.214e+01  4.826e+00  -10.80   <2e-16 ***
## Request.Amount         1.302e-03  6.849e-05   19.01   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 65.78 on 10772 degrees of freedom
## Multiple R-squared:  0.03845,    Adjusted R-squared:  0.03827
## F-statistic: 215.4 on 2 and 10772 DF,  p-value: < 2.2e-16

# Validation complete.

# 36. Use the regression equation to complete this sentence: "The
estimated Credit Score equals.."
# The estimated Credit Score equals y = 668.4562 - 48.1262* Debt-to-
Income Ratio + 0.0011* Request Amount

# 37. Interpret the coefficient for Debt-to-Income Ratio.
# The coefficient for Debt-to-Income Ratio is negative which means the
lower the
# Debt-to-Income Ratio, the higher the credit score.

# 38. Interpret the coefficient for Request Amount.
# The coefficient for Request Amount is positive which means the higher
the
# Request Amount, the higher the credit score.

# 39. Find and interpret the value of s.
# Residual standard error: 65.78 on 10772 degrees of freedom. The size
of model
# prediction error is 65.8 (66), that is the difference between the
actual
# credit score and of which predicated from the model.

# 40. Find and interpret Radj2 . Comment.
# The adjusted R squared value is modified version of R-squared that
has been
# adjusted for the number of predictors in the model. It increases when
the new
# term improves the model more than would be expected by chance. It
decreases
# when a predictor improves the model by less than expected. The R-
adj^2 is 0.028
# from the model. This means that 2.8% of the variability in Credit
Score is
# accounted for by the predictors Debt-to-Income Ratio and Request
Amount.
```

```r
# 41. Find MAE_Baseline and MAE_Regression, and determine whether the regression
# model outperformed its baseline model.

# use the predicators from the test dataset to predict
X_test <- data.frame(Debt.to.Income.Ratio =
bank_reg_test$Debt.to.Income.Ratio,
                     Request.Amount = bank_reg_test$Request.Amount)

# y predicated using the model from the test dataset
ypred <- predict(object = model02, newdata = X_test)

# compare to the actual targets from the test dataset
ytrue <- bank_reg_test$Credit.Score

library(MLmetrics)

##
## Attaching package: 'MLmetrics'

## The following object is masked from 'package:base':
##
##     Recall

# mean absolute error for regression
MAE_Regression = MAE(y_pred = ypred, y_true = ytrue)

# mean absolute error for baseline using the formula
```

Compute the MAE for the baseline model, as follows:

$$MAE_{Baseline} = \frac{\sum |y - \overline{y}|}{n}$$

```r
y_y_bar = abs(bank_reg_test$Credit.Score -
mean(bank_reg_test$Credit.Score))
MAE_Baseline = sum(y_y_bar)/length(y_y_bar)

MAE_Regression

## [1] 48.01625

MAE_Baseline

## [1] 48.60024

# So the MAE_Regression is 48.02 and the MAE_Baseline is 48.60.
# Since MAE_Regression < MAE_Baseline, thus, our regression model
outperformed its baseline model.
```