Lab 2

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11:59PM February 20

Basic Modeling

• In class we considered a variable x_3 which measured "criminality". We imagined L = 4 levels "none", "infraction", "misdemeanor" and "felony". Create a variable x_3 here with 100 random elements (equally probable). Create it as a nominal (i.e. unordered) factor.

```
#TO-DO
n = 100 # number of elements
x_3 = as.factor(
   sample(
        c( "none", "infraction", "misdemeanor", "felony"),
        size=100,
        replace=TRUE)
   )
x_3
```

```
##
     [1] none
                                 infraction infraction none
                     none
                                                                      none
##
     [7] infraction felony
                                 misdemeanor infraction misdemeanor felony
##
    [13] misdemeanor felony
                                              infraction infraction none
                                 none
##
    [19] none
                                 none
                                              felony
                                                          felony
                                                                      infraction
##
    [25] misdemeanor none
                                 felony
                                             felony
                                                          misdemeanor infraction
    [31] infraction felony
                                 felony
                                              infraction misdemeanor infraction
    [37] misdemeanor felony
                                              infraction none
                                                                      misdemeanor
##
                                 none
    [43] infraction infraction
                                 felony
                                                                      misdemeanor
                                             none
                                                          none
##
   [49] infraction misdemeanor felony
                                              infraction infraction none
   [55] misdemeanor infraction
                                 misdemeanor infraction misdemeanor infraction
##
   [61] none
                     none
                                 felony
                                              felony
                                                          infraction none
    [67] infraction felony
                                 felony
                                             none
                                                          none
                                                                      felony
##
   [73] none
                                                          misdemeanor felony
                     none
                                 felony
                                              felony
    [79] felony
                     infraction
                                 none
                                                          misdemeanor none
                                             none
##
    [85] infraction misdemeanor none
                                              none
    [91] none
                     infraction infraction
                                             none
                                                          misdemeanor none
   [97] infraction infraction infraction
## Levels: felony infraction misdemeanor none
```

```
# measure criminality
# Replace = True allows duplicates to fulfill size
```

• Use x_3 to create x_3_bin, a binary feature where 0 is no crime and 1 is any crime.

• Use x_3 to create x_3_ord, an ordered factor variable. Ensure the proper ordinal ordering.

```
#TO-DO
crime_level = c("none", "infraction", "misdemeanor", "felony")
x_3_ord = factor(x_3, ordered=TRUE, levels=crime_level)
x_3_ord
```

```
##
                                 infraction infraction none
     [1] none
                    none
                                                                    none
##
     [7] infraction felony
                                misdemeanor infraction misdemeanor felony
##
    [13] misdemeanor felony
                                none
                                            infraction infraction none
##
  [19] none
                    none
                                none
                                            felony
                                                        felony
                                                                    infraction
##
  [25] misdemeanor none
                                felony
                                            felony
                                                        misdemeanor infraction
##
   [31] infraction felony
                                 felony
                                            infraction misdemeanor infraction
                                            infraction none
   [37] misdemeanor felony
                                                                    misdemeanor
                                none
##
  [43] infraction infraction
                                felony
                                            none
                                                        none
                                                                    misdemeanor
  [49] infraction misdemeanor felony
##
                                            infraction infraction none
##
   [55] misdemeanor infraction misdemeanor infraction
                                                        misdemeanor infraction
##
  [61] none
                                 felony
                    none
                                            felony
                                                        infraction none
  [67] infraction felony
                                 felony
                                            none
                                                        none
                                                                    felony
  [73] none
##
                    none
                                 felony
                                            felony
                                                        misdemeanor felony
   [79] felony
                     infraction
                                none
                                            none
                                                        misdemeanor none
## [85] infraction misdemeanor none
                                                                    none
                                            none
                                                        none
                     infraction infraction
                                            none
                                                        misdemeanor none
## [97] infraction infraction infraction felony
## Levels: none < infraction < misdemeanor < felony
```

• Convert this variable into three binary variables without any information loss and put them into a data matrix.

```
#TO-DO
bin_vector1 = ifelse(x_3_ord == "infraction", 1, 0)
bin_vector2 = ifelse(x_3_ord == "misdemeanor", 1, 0)
bin_vector3 = ifelse(x_3_ord == "felony", 1, 0)
crime_bin_vectors = cbind(bin_vector1, bin_vector2, bin_vector3)

colnames(crime_bin_vectors) = c(
    "[,1]",
    "[,2]",
    "[,3]"
)

#crime_bin_vectors
```

• What should the sum of each row be (in English)?

#TO-DO

Verify that.

• How should the column sum look (in English)?

#TO-DO Column sums should be counts of number of each crime level in the data Verify that.

```
#TO-DO
colSums(crime_bin_vectors)

## [,1] [,2] [,3]
## 29 17 22
```

• Generate a matrix with 100 rows where the first column is realization from a normal with mean 17 and variance 38, the second column is uniform between -10 and 10, the third column is poisson with mean 6, the fourth column in exponential with lambda of 9, the fifth column is binomial with n = 20 and p = 0.12 and the sixth column is a binary variable with exactly 24% 1's dispersed randomly. Name the rows the entries of the fake_first_names vector.

```
# cbind == concatenate arrays to make a matrix
X = cbind(
  rnorm(n, mean=17, sd=sqrt(38)), # realization from a normal with mean 17 and variance 38
  runif(n, -10, 10),
                                    # uniform between -10 and 10
  rpois(n, 6),
                                    # poisson with mean 6
  rexp(n, 9),
                                    # fourth column in exponential with lambda of 9
  rbinom(n, 20, .12),
                                    # binomial with n = 20 and p = 0.12
  sample(c(rep(1, round(n*.24)), rep(0, round(n*.76)))) # binary variable with exactly 24%
  # random 1's dispersed
fake_first_names = c(
  "Sophia", "Emma", "Olivia", "Ava", "Mia", "Isabella", "Riley",
  "Aria", "Zoe", "Charlotte", "Lily", "Layla", "Amelia", "Emily",
  "Madelyn", "Aubrey", "Adalyn", "Madison", "Chloe", "Harper",
  "Abigail", "Aaliyah", "Avery", "Evelyn", "Kaylee", "Ella", "Ellie",
  "Scarlett", "Arianna", "Hailey", "Nora", "Addison", "Brooklyn",
  "Hannah", "Mila", "Leah", "Elizabeth", "Sarah", "Eliana", "Mackenzie",
  "Peyton", "Maria", "Grace", "Adeline", "Elena", "Anna", "Victoria",
  "Camilla", "Lillian", "Natalie", "Jackson", "Aiden", "Lucas",
  "Liam", "Noah", "Ethan", "Mason", "Caden", "Oliver", "Elijah",
```

```
"Grayson", "Jacob", "Michael", "Benjamin", "Carter", "James",
"Jayden", "Logan", "Alexander", "Caleb", "Ryan", "Luke", "Daniel",
"Jack", "William", "Owen", "Gabriel", "Matthew", "Connor", "Jayce",
"Isaac", "Sebastian", "Henry", "Muhammad", "Cameron", "Wyatt",
"Dylan", "Nathan", "Nicholas", "Julian", "Eli", "Levi", "Isaiah",
"Landon", "David", "Christian", "Andrew", "Brayden", "John",
"Lincoln"
)

#TO-DO
#rownames(X) = fake_first_names
# X
# removed output for pdf conversion
```

• Create a data frame of the same data as above except make the binary variable a factor "DOMESTIC" vs "FOREIGN" for 0 and 1 respectively. Use RStudio's View function to ensure this worked as desired.

• Print out a table of the binary variable. Then print out the proportions of "DOMESTIC" vs "FOREIGN".

```
#TO-DO
# X_df$origin -> Returns count for values within
manual_props_table = table(X_df$origin)/nrow(X_df)
manual_props_table

##
## DOMESTIC FOREIGN
## 0.76 0.24

prop.table(table(X_df$origin))

##
## DOMESTIC FOREIGN
## 0.76 0.24
```

Print out a summary of the whole dataframe.

```
#TO-DO
summary(X_df)
```

```
##
        normie
                            eunice
                                                fish
                                                                 expy
##
    Min.
           :-0.9224
                               :-9.6660
                                          Min.
                                                  : 1.00
                                                            Min.
                                                                   :0.002796
##
    1st Qu.:11.4780
                       1st Qu.:-4.8685
                                           1st Qu.: 4.00
                                                            1st Qu.:0.024227
##
    Median :16.7780
                       Median :-0.8305
                                          Median: 6.00
                                                            Median :0.077206
##
            :16.0953
                               :-0.1110
                                                  : 6.18
    Mean
                       Mean
                                          Mean
                                                            Mean
                                                                   :0.104276
##
    3rd Qu.:20.7960
                       3rd Qu.: 5.5705
                                          3rd Qu.: 8.00
                                                            3rd Qu.:0.141978
##
    Max.
           :32.0573
                              : 9.9584
                                                  :13.00
                                                                   :0.487444
                                          Max.
                                                            Max.
##
        nomie
                         origin
##
                    DOMESTIC:76
    Min.
            :0.00
##
    1st Qu.:1.00
                    FOREIGN:24
##
    Median:2.00
##
    Mean
            :2.35
##
    3rd Qu.:3.00
    Max.
            :7.00
```

Dataframe creation

Imagine you are running an experiment with many manipulations. You have 14 levels in the variable "treatment" with levels a, b, c, etc. For each of those manipulations you have 3 submanipulations in a variable named "variation" with levels A, B, C. Then you have "gender" with levels M / F. Then you have "generation" with levels Boomer, GenX, Millenial. Then you will have 6 runs per each of these groups. In each set of 6 you will need to select a name without duplication from the appropriate set of names (from the last question). Create a data frame with columns treatment, variation, gender, generation, name and y that will store all the unique unit information in this experiment. Leave y empty because it will be measured as the experiment is executed. Hint, we've been using the rep function using the times argument. Look at the each argument using ?rep.

```
names = list(
   Boomer = list(
        M = strsplit("Theodore, Bernard, Gene, Herbert, Ray, Tom, Lee, Alfred, Leroy, Eddie", ", ")[[1]
        F = strsplit("Gloria, Joan, Dorothy, Shirley, Betty, Dianne, Kay, Marjorie, Lorraine, Mildred",
   ),
    GenX = list(
        M = strsplit("Marc, Jamie, Greg, Darryl, Tim, Dean, Jon, Chris, Troy, Jeff", ", ")[[1]],
        F = strsplit("Tracy, Dawn, Tina, Tammy, Melinda, Tamara, Tracey, Colleen, Sherri, Heidi",
   ),
   Millenial = list(
        M = strsplit("Zachary, Dylan, Christian, Wesley, Seth, Austin, Gabriel, Evan, Casey, Luis", ",
        F = strsplit("Samantha, Alexis, Brittany, Lauren, Taylor, Bethany, Latoya, Candice, Brittney, C.
   )
)
#names
n = 14 * 3 * 2 * 3 * 6
X = data.frame(
  treatment=rep(letters[1:14], each=3 * 2 * 3 * 6),
```

variation=rep(LETTERS[1:3], each=2 * 3 * 6, times=14),

```
gender=rep(c('M', 'F'), each=3 * 6, times=14 * 3),
  generation=rep(c("Boomer", "GenX", "Millenial"), each=6, times=14 * 3 * 2),
  name=0
)
X2 = data.frame(expand.grid(
  name=rep(NA,6),
  generation=c("Boomer", "GenX", "Millenial"),
  gender=rep(c('M', 'F')),
      variation=rep(LETTERS[1:3]),
          treatment=rep(letters[1:14])
  ))
#X2
for (i in seq(from=1, to=n, by=6)) {
  X$names[i:(i+5)] = sample(names[[X$generation[i]]][[X$gender[i]]], 6)
}
for (i in seq(from=1, to=n, by=6)) {
  X2$names[i:(i+5)] = sample(names[[X2$generation[i]]][[X2$gender[i]]], 6)
}
#X
#X2
```

Basic Binary Classification Modeling

• Load the famous iris data frame into the namespace. Provide a summary of the columns using the skim function in package skimr and write a few descriptive sentences about the distributions using the code below in English.

```
#TO-DO
data("iris")

pacman::p_load(skimr)

skim(iris)
```

Table 1: Data summary

Name	iris
Number of rows	150
Number of columns	5
Column type frequency:	
factor	1
numeric	4

Group variables	None
-----------------	------

Variable type: factor

skim_variable	n_missing	complete_rate	ordered	n_unique	top_counts
Species	0	1	FALSE	3	set: 50, ver: 50, vir: 50

Variable type: numeric

skim_variable	n_missing	complete_rate	mean	sd	p0	p25	p50	p75	p100	hist
Sepal.Length	0	1	5.84	0.83	4.3	5.1	5.80	6.4	7.9	
Sepal.Width	0	1	3.06	0.44	2.0	2.8	3.00	3.3	4.4	
Petal.Length	0	1	3.76	1.77	1.0	1.6	4.35	5.1	6.9	
Petal.Width	0	1	1.20	0.76	0.1	0.3	1.30	1.8	2.5	

TO-DO: We have dataset that has plant information. Based on the skim there are no missing values in each category/feature and has a complete rate of 100%. It also shows the mean values in each feature as well as the standard deviation and percentile values.

The outcome / label / response is Species. This is what we will be trying to predict. However, we only care about binary classification between "setosa" and "versicolor" for the purposes of this exercise. Thus the first order of business is to drop one class. Let's drop the data for the level "virginica" from the data frame.

```
#TO-DO
# We Want to make it a binary classification problem between
# setosa, versicolor hence we drop the extra column 'virginica'
iris_binary = subset(iris, subset=Species != "virginica")
#iris
#iris_binary
#temp = sum(iris_binary$Species == "virginica")
#temp
```

Now create a vector **y** that is length the number of remaining rows in the data frame whose entries are 0 if "setosa" and 1 if "versicolor".

```
## [1] 50
```

```
versicolor_count = sum(y == 0)
versicolor_count
```

[1] 50

 Write a function mode returning the sample mode of a vector of numeric values. Try not to look in the class notes.

```
#T0-D0
# we're trying the mode for g0
mode_function = function(x) {
    # Gets unique values
   uniq_x = unique(x)
   # match : Each element of the original vector is matched to its index in the unique elements.
    # Tabulate : Tabulates counts the occurences of the matched values
    # return the index of the max
   return(uniq_x[which.max(tabulate(match(x, uniq_x)))])
}
multiple_mode_function <- function(x) {</pre>
   uniq_x = unique(x)
   freq = tabulate(match(x, uniq_x))
   max\_freq = max(freq)
   # Returns all the indices if multiple modes
   modes = uniq_x[freq == max_freq]
   return(modes)
}
# Example usage
single_mode = mode_function(y)
mult_mode = multiple_mode_function(y)
single_mode
## [1] 0
mult_mode
```

[1] 0 1

• Fit a threshold model to y using the feature Sepal.Length. Write your own code to do this. What is the estimated value of the threshold parameter? Save the threshold value as threshold.

```
#TO-DO
best_threshold = NULL
best_accuracy = 0
for (threshold in iris_binary$Sepal.Length) {
```

```
# Classify based on the threshold
    # we compare threshold (or each sepal length)
    # predictions return a vector of size of sepal.length
    # creates a vector of predictions based on the current threshold
   predictions = ifelse(iris_binary$Sepal.Length <= threshold, 0, 1)</pre>
    # accuracy of predictions
    # sum(predictions == y) counts how many times we predicted right
   accuracy = sum(predictions == y) / length(y)
    # Update the best threshold if we get a better accuracy
   if (accuracy > best_accuracy) {
        best_accuracy = accuracy
        best_threshold = threshold
   }
}
print(best_threshold)
## [1] 5.4
threshold = best_threshold
What is the total number of errors this model makes?
#T0-D0
best_predictions = ifelse(iris_binary$Sepal.Length <= best_threshold, 0, 1)</pre>
count_correct_preds = sum(best_predictions == y)
error = 1 - (count_correct_preds / length(y))
cat("Error:",error,"%")
## Error: 0.11 %
Does the threshold model's performance make sense given the following summaries:
threshold
## [1] 5.4
summary(iris[iris$Species == "setosa", "Sepal.Length"])
##
     Min. 1st Qu. Median Mean 3rd Qu.
                                              Max.
           4.800 5.000 5.006 5.200
                                             5.800
summary(iris[iris$Species == "versicolor", "Sepal.Length"])
     Min. 1st Qu. Median Mean 3rd Qu.
##
                                              Max.
     4.900 5.600 5.900 5.936 6.300 7.000
##
```

TO-DO: Write your answer here in English. Answer: It makes sense. The threshold is the cutoff point or the point where separates the two binary classes. The mean sepal length of setosa's are 5.006 which is below the thresh hold. The mean length of versicolors is 5.9 which is above the mean. Our thresold makes a split in the middle. There may be some interlaps or edge cases on both where a setosa could be above the threshold and a versicolor could be below the threshold.

Create the function g explicitly that can predict y from x being a new Sepal.Length.

```
g = function(x){
  return(ifelse(x <= threshold, "Setosa", "Versicolor"))
}

test_x = sample(iris_binary$Sepal.Length, size=1)
cat("Sepal Length:", test_x, "is a", g(test_x))</pre>
```

Sepal Length: 5.5 is a Versicolor