

Rworksheet_MAMINTA#4a

#1.

#a. Describe the data.

```
Respondent <- 1:8
Gender <- c("M", "F", "F", "M", "F", "M", "F", "M")
ShoeSize <- c(9, 7, 6, 10, 6.5, 9.5, 7, 11)
Height_cm <- c(175, 160, 158, 180, 162, 176, 159, 185)
shoe_height_df <- data.frame(Respondent, Gender, ShoeSize, Height_cm)
shoe_height_df
```

```
##   Respondent Gender ShoeSize Height_cm
## 1           1      M     9.0    175
## 2           2      F     7.0    160
## 3           3      F     6.0    158
## 4           4      M    10.0    180
## 5           5      F     6.5    162
## 6           6      M     9.5    176
## 7           7      F     7.0    159
## 8           8      M    11.0    185
```

#b. Create a subset by males and females with their corresponding shoe size and height.

```
males <- subset(shoe_height_df, Gender == "M", select = c(ShoeSize, Height_cm))
females <- subset(shoe_height_df, Gender == "F", select = c(ShoeSize, Height_cm))
males
```

```
##   ShoeSize Height_cm
## 1     9.0     175
## 4    10.0     180
## 6     9.5     176
## 8    11.0     185
```

```
females
```

```
##   ShoeSize Height_cm
## 2     7.0     160
## 3     6.0     158
## 5     6.5     162
## 7     7.0     159
```

#c. Find the mean of shoe size and height of the respondents.

```

mean_shoe_overall <- mean(shoe_height_df$ShoeSize)
mean_height_overall <- mean(shoe_height_df$Height_cm)
mean_shoe_by_gender <- tapply(shoe_height_df$ShoeSize, shoe_height_df$Gender, mean)
mean_height_by_gender <- tapply(shoe_height_df$Height_cm, shoe_height_df$Gender, mean)

mean_shoe_overall

## [1] 8.25

mean_height_overall

## [1] 169.375

mean_shoe_by_gender

##      F      M
## 6.625 9.875

mean_height_by_gender

##      F      M
## 159.75 179.00

```

#d. Is there a relationship between shoe size and height? Why?

*#The dataset shows that people with larger shoe sizes also tend to be taller.
#This makes sense, as shoe size is often linked to body proportions, and taller
#individuals usually have bigger feet. Although the pattern is visible in the
#data, using a statistical method like correlation analysis would provide a more
#precise measure of how strong this relationship is.*

*##2. Construct character vector months to a factor with factor() and assign the
#result to factor_months_vector. Print out factor_months_vector and assert that
#R prints out the factor levels below the actual values.*

```

Months <- c(
  "March", "April", "January", "November", "January",
  "September", "October", "September", "November", "August",
  "January", "November", "November", "February", "May", "August",
  "July", "December", "August", "August", "September", "November", "February",
  "April"
)

factor <- factor(Months)
factor

## [1] March     April     January   November  January   September October
## [8] September November August    January   November  November  February
## [15] May       August    July      December  August    August    September
## [22] November  February April
## 11 Levels: April August December February January July March May ... September

```

```
#3. Then check the summary() of the months_vector and factor_months_vector. Interpret the results of both vectors. Are they both equally useful in this case?
```

```
summary(Months)
```

```
##      Length     Class    Mode
##      24 character character
```

```
summary(factor)
```

```
##      April    August December February January July March May
##      2        4       1       2       3       1       1       1
##      November October September
##      5         1       3
```

```
#4. Create a vector and factor for the table below.
```

```
factor_data <- c("East", rep("West", 4), rep("North", 3))
factor_data
```

```
## [1] "East"   "West"   "West"   "West"   "West"   "North"  "North"  "North"
```

```
new_order_data <- factor(factor_data, levels = c("East", "West", "North"))
print(new_order_data)
```

```
## [1] East West West West North North North
## Levels: East West North
```

```
#5. Enter the data below in Excel with file name = import_march.csv
```

```
import_march <- read.table("import_march.csv", header = TRUE, sep = ",")
```

```
##   Students Strategy.1 Strategy.2 Strategy.3
## 1      Male        8        10        8
## 2                4        8        6
## 3                0        6        4
## 4    Female       14        4       15
## 5                10        2       12
## 6                6        0        9
```

```
#6. Full Search
```

```
#a. Create an R Program that allows the User to randomly select numbers from 1 to 50. Then display the chosen number. If the number is beyond the range of the selected choice, it will have to display a string "The number selected is beyond the range of 1 to 50". If number 20 is inputted by the User, it will have to display "TRUE", otherwise display the #input number.
```

```
num <- as.integer(readline("Choose a number (1 to 50): "))
```

```
## Choose a number (1 to 50):
```

```
cat("Chosen number:", num, "\n")
```

```
## Chosen number: NA
```

```
if (is.na(num)) {  
  cat("Invalid!\n")  
  
} else if (num < 1 || num > 50) {  
  cat("Choose only from 1-50!\n")  
  
} else if (num == 20) {  
  print(TRUE)  
  
} else {  
  print(num)  
}
```

```
## Invalid!
```

#7. Change

#At ISATU University's traditional cafeteria, snacks can only be purchased with bills. A long-standing rule at the concession stand is that snacks must be purchased with as few coins as possible. There are three types of bills: 50 pesos, 100 pesos, 200 pesos, 500 pesos, #1000 pesos.

#a. Write a function that prints the minimum number of bills that must be paid, given the #price of the snack.

#Input: Price of snack (a random number divisible by 50) Output: Minimum number of bills #needed to purchase a snack.

```
min_bills <- function(price) {  
  bills <- c(1000, 500, 200, 100, 50)  
  
  remaining <- price  
  count <- 0  
  
  for (b in bills) {  
    if (remaining >= b) {  
      count <- count + (remaining %/% b)  
      remaining <- remaining %% b  
    }  
  }  
  
  return(count)  
}
```