# Case Study

*Load in the important libraries.*

```
library(tidyverse)
```

```
## -- Attaching core tidyverse packages ------------------------ tidyverse 2.0.0 --
## v dplyr     1.1.4     v readr     2.1.5
## v forcats   1.0.0     v stringr   1.5.1
## v ggplot2   3.5.1     v tibble    3.2.1
## v lubridate 1.9.3     v tidyr     1.3.1
## v purrr     1.0.2
## -- Conflicts ------------------------------------------ tidyverse_conflicts() --
## x dplyr::filter() masks stats::filter()
## x dplyr::lag()    masks stats::lag()
## i Use the conflicted package (<http://conflicted.r-lib.org/>) to force all conflicts to become errors
```

```
library(dplyr)
library(tidyr)
library(ggplot2)
library(lubridate)
```

## *Problem 1 – Data handling, analysis and plotting*

*The first problem of the case study builds on the data in the files p01-02_portfolio.csv and p01-02_rates.csv. One file contains membership information for a Group Life portfolio and one has information on the rates which should be charged.*

```
# Load the CSV file
portfolio_data <- read_delim(
  "Case Study/data/p01-02_portfolio.csv",
  delim = ";",
  show_col_types = FALSE
)

# View the data
head(portfolio_data)
```

```
## # A tibble: 6 x 5
##   SchemeName Date.of.Birth Gender DeathSI Industry
##   <chr>      <chr>         <chr>  <chr>   <chr>
## 1 Scheme2    29.05.1949    F      <NA>    Government & Public Administration
## 2 Scheme2    07.09.1950    F      <NA>    Government & Public Administration
## 3 Scheme2    27.09.1956    F      <NA>    Government & Public Administration
## 4 Scheme2    18.02.1942    F      <NA>    Government & Public Administration
## 5 Scheme2    31.07.1951    F      <NA>    Government & Public Administration
## 6 Scheme2    10.07.1960    F      <NA>    Government & Public Administration
```

```r
# Load the CSV file
rates_data <- read_delim("Case Study/data/p01-02_rates.csv",
                         delim = ";",
                         show_col_types = FALSE)

# View the data
head(rates_data)
```

```
## # A tibble: 6 x 3
##     Age Gender  Rate
##   <dbl> <chr>  <dbl>
## 1    18 M       0.32
## 2    19 M       0.32
## 3    20 M       0.32
## 4    21 M       0.31
## 5    22 M       0.31
## 6    23 M       0.31
```

*rates_data*

```r
# Count occurrences of each combination of Gender and Age
duplicates <- rates_data %>%
  group_by(Gender, Age) %>%
  summarise(count = n()) %>%
  filter(count > 1)
```

```
## `summarise()` has grouped output by 'Gender'. You can override using the
## `.groups` argument.
```

```r
# Check if any duplicates exist
if (nrow(duplicates) == 0) {
  message("Sanity Check Passed: 'Gender' and 'Age' form a unique key.")
} else {
  message("Sanity Check Failed: There are duplicate combinations of 'Gender' and 'Age'.")
  print(duplicates)
}
```

```
## Sanity Check Passed: 'Gender' and 'Age' form a unique key.
```

***Question a.***

*Read the data from the two files into R's memory. The rates are applicable to each individual in the portfolio, depending on that individual's age and gender. Combine the two datasets into a single table by looking up the rate for each line of the portfolio.*

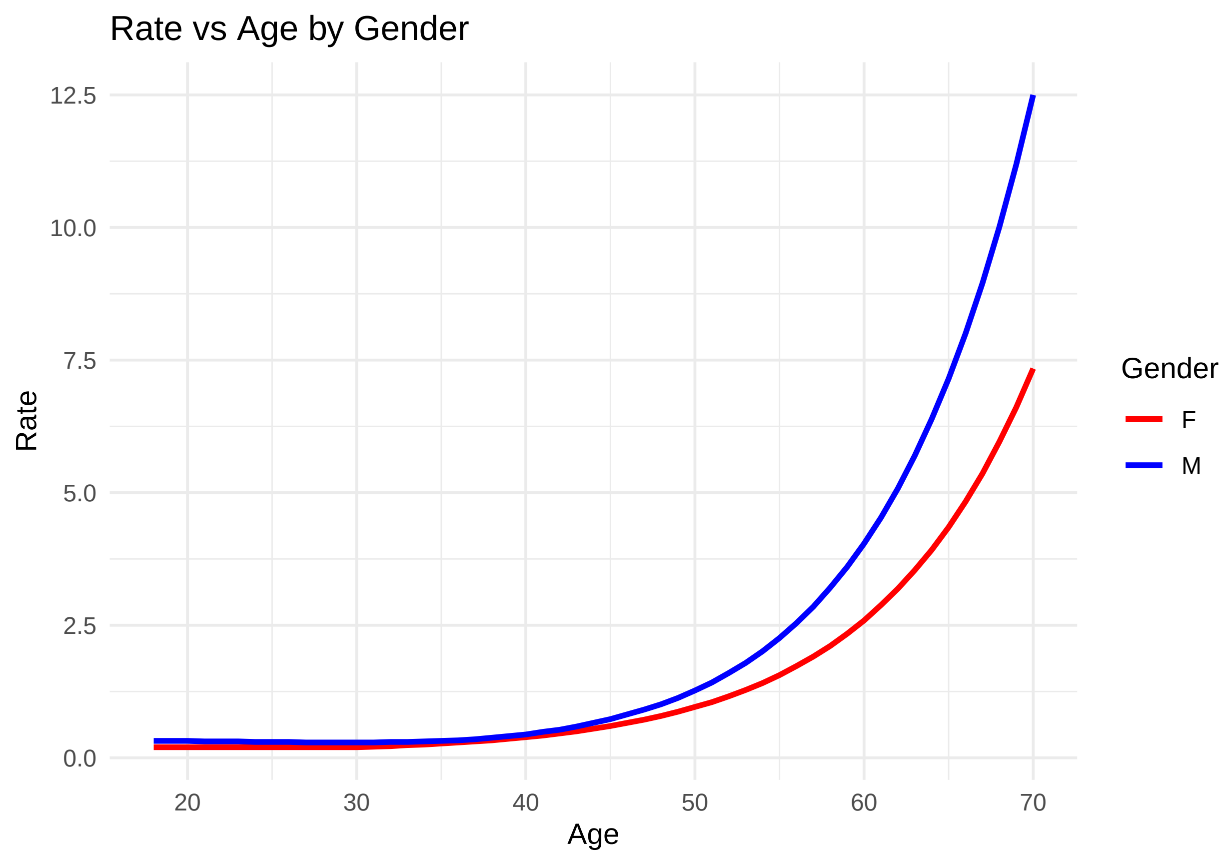
```r
# Step 1: Convert the Date.of.Birth column to Date format
# dmy is used for "day-month-year" format
portfolio_data$Date.of.Birth <- dmy(portfolio_data$Date.of.Birth)

# Step 2: Calculate the time difference in years
portfolio_data$age <- ceiling(interval(portfolio_data$Date.of.Birth, today()) / years(1))
```

```r
# Step 3: View the updated data with age column
head(portfolio_data)
```

```
## # A tibble: 6 x 6
##   SchemeName Date.of.Birth Gender DeathSI Industry                            age
##   <chr>      <date>        <chr>  <chr>   <chr>                             <dbl>
## 1 Scheme2    1949-05-29    F      <NA>    Government & Public Administrat~    76
## 2 Scheme2    1950-09-07    F      <NA>    Government & Public Administrat~    75
## 3 Scheme2    1956-09-27    F      <NA>    Government & Public Administrat~    68
## 4 Scheme2    1942-02-18    F      <NA>    Government & Public Administrat~    83
## 5 Scheme2    1951-07-31    F      <NA>    Government & Public Administrat~    74
## 6 Scheme2    1960-07-10    F      <NA>    Government & Public Administrat~    65
```

**Extrapolate Rates Data beyond 70 years**

```r
# Create the line plot with grouping by Gender
ggplot(rates_data, aes(
  x = Age,
  y = Rate,
  color = Gender,
  group = Gender
)) +
  geom_line(linewidth = 1) +  # Use linewidth instead of size
  scale_color_manual(values = c("F" = "red", "M" = "blue")) +  # Set colors for genders
  labs(title = "Rate vs Age by Gender", x = "Age", y = "Rate") +
  theme_minimal()  # Use a clean theme for the plot
```




**Fit an Exponential Model for Each Gender**

```r
# Fit an exponential model for each gender
exp_model_female <- nls(Rate ~ exp(a + b * Age), data = subset(rates_data, Gender == "F"), start = list
exp_model_male <- nls(Rate ~ exp(a + b * Age), data = subset(rates_data, Gender == "M"), start = list(a

# Summarize the models
summary(exp_model_female)
```

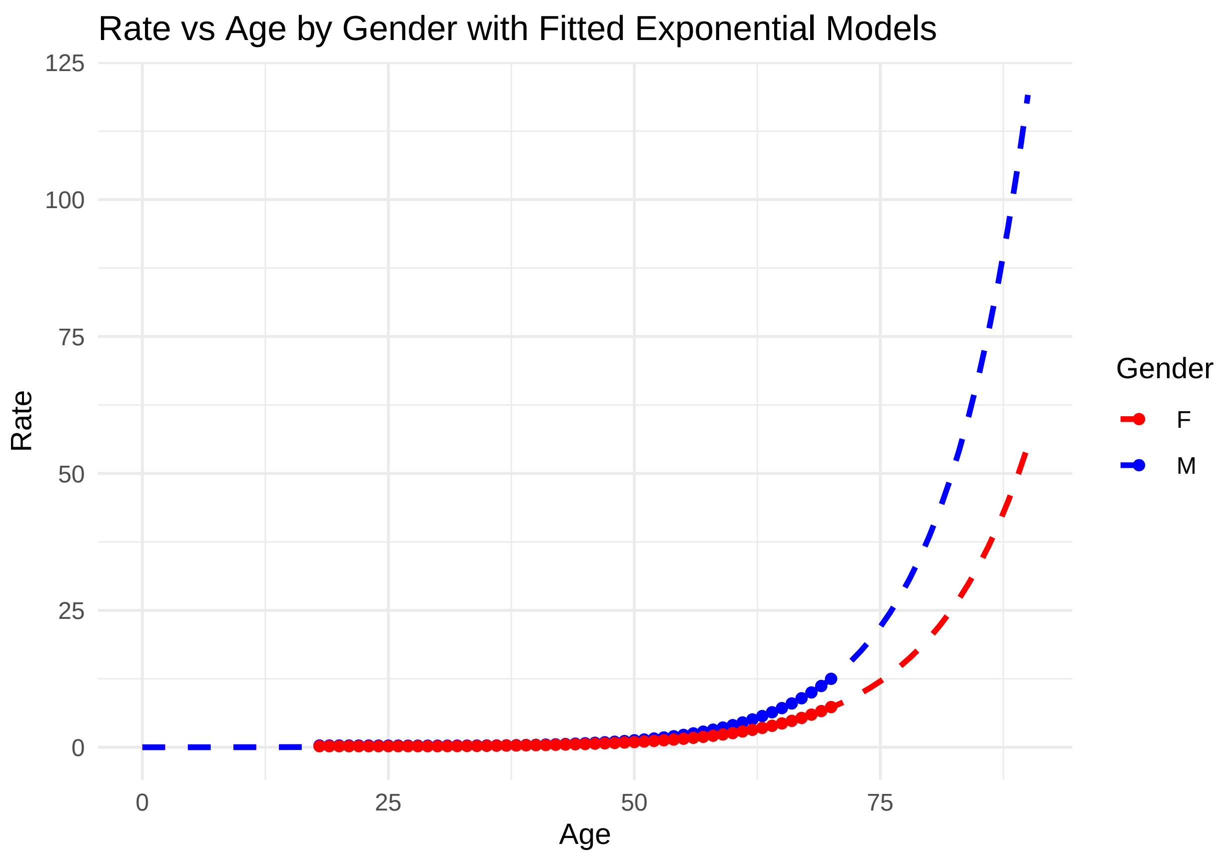
```
##
## Formula: Rate ~ exp(a + b * Age)
##
## Parameters:
##    Estimate Std. Error t value Pr(>|t|)
## a -5.1051905  0.0584289  -87.37   <2e-16 ***
## b  0.1012605  0.0008889  113.92   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.07425 on 51 degrees of freedom
##
## Number of iterations to convergence: 7
## Achieved convergence tolerance: 1.604e-06
```

```r
summary(exp_model_male)
```

```
##
## Formula: Rate ~ exp(a + b * Age)
##
## Parameters:
##   Estimate Std. Error t value Pr(>|t|)
## a -5.35891    0.06689  -80.12   <2e-16 ***
## b  0.11266    0.00101  111.49   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.1247 on 51 degrees of freedom
##
## Number of iterations to convergence: 6
## Achieved convergence tolerance: 4.649e-06
```

#### Plot the Data and the Fitted Exponential Curves

```r
# Generate new data for ages 0 to 90 for both genders
new_data <- data.frame(Age = rep(0:90, 2), Gender = rep(c("F", "M"), each = 91))

# Predict rates for the new data using the fitted models
new_data$Rate_pred <- ifelse(
  new_data$Gender == "F",
  predict(exp_model_female, newdata = subset(new_data, Gender == "F")),
  predict(exp_model_male, newdata = subset(new_data, Gender == "M"))
)

# Plot the original data along with the fitted exponential curves
ggplot() +
  geom_line(
    data = new_data,
    aes(x = Age, y = Rate_pred, color = Gender),
    linewidth = 1,
    linetype = "dashed"
  ) +  # Fitted lines for each gender
  geom_point(data = rates_data, aes(x = Age, y = Rate, color = Gender)) +  # Original data points
  scale_color_manual(values = c("F" = "red", "M" = "blue")) +  # Set colors for genders
  labs(title = "Rate vs Age by Gender with Fitted Exponential Models", x = "Age", y = "Rate") +
  theme_minimal()
```




### Add Extrapolated Values to Rates Data

```
# Get the unique values from the Gender column
unique_genders <- unique(rates_data$Gender)

# Print the unique values
unique_genders
```

```
## [1] "M" "F"
```

```
# Get the unique values from the Gender column
unique_genders <- unique(portfolio_data$Gender)

# Print the unique values
unique_genders
```

```
## [1] "F"      "M"      "Male"   "Female"
```

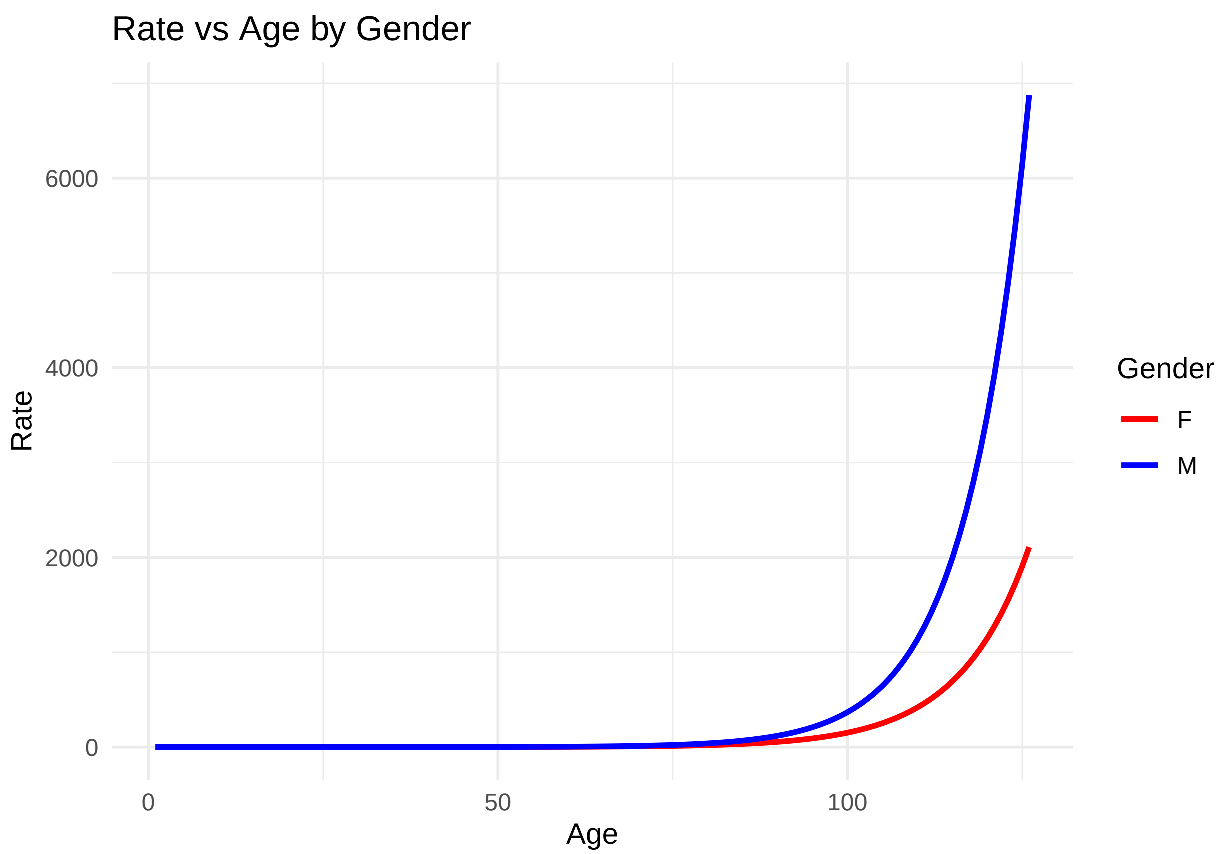
```
# Convert "Male" to "M" and "Female" to "F" using ifelse
portfolio_data$Gender <- ifelse(
  portfolio_data$Gender == "Male",
  "M",
  ifelse(portfolio_data$Gender == "Female", "F", portfolio_data$Gender)
```

```
)

# Get the unique values from the Gender column
unique_genders <- unique(portfolio_data$Gender)

# Print the unique values
unique_genders
```

```
## [1] "F" "M"
```

```
# Step 1: Create a complete sequence of ages from 1 to 110 for both genders
complete_ages <- expand.grid(Age = 1:126, Gender = c("F", "M"))

# Step 2: Identify missing "Age" and "Gender" combinations in the existing data
# Perform an anti-join to find missing combinations (from dplyr)
missing_ages <- anti_join(complete_ages, rates_data, by = c("Age", "Gender"))

# Step 3: Predict the rates for the missing combinations using the fitted models
missing_ages$Rate <- ifelse(
  missing_ages$Gender == "F",
  predict(exp_model_female, newdata = subset(missing_ages, Gender == "F")),
  predict(exp_model_male, newdata = subset(missing_ages, Gender == "M"))
)

# Step 4: Append the new data (with missing combinations filled) to the existing data
rates_data_extended <- rbind(rates_data, missing_ages)
```

```
# Create the line plot with grouping by Gender
ggplot(rates_data_extended,
       aes(
         x = Age,
         y = Rate,
         color = Gender,
         group = Gender
       )) +
  geom_line(linewidth = 1) +  # Use linewidth instead of size
  scale_color_manual(values = c("F" = "red", "M" = "blue")) +  # Set colors for genders
  labs(title = "Rate vs Age by Gender", x = "Age", y = "Rate") +
  theme_minimal()  # Use a clean theme for the plot
```




```r
# Inner join the two datasets
combined_data <- inner_join(portfolio_data,
                            rates_data_extended,
                            by = c("age" = "Age", "Gender" = "Gender"),
)

# Check if the row count of the joined data matches the original portfolio data
if (nrow(combined_data) == nrow(portfolio_data)) {
  message("Sanity Check Passed: The row count of combined_data matches portfolio_data.")
} else {
  message("Sanity Check Failed: The row count of combined_data does not match portfolio_data.")
  message("Rows in portfolio_data: ", nrow(portfolio_data))
  message("Rows in combined_data: ", nrow(combined_data))
}
```

```
## Sanity Check Passed: The row count of combined_data matches portfolio_data.
```

```r
# Get the unique values in the SchemeName column
unique_schemes <- unique(combined_data$SchemeName)
unique_schemes
```

```
## [1] "Scheme2" "Scheme1" "Scheme3" "Scheme5" "Scheme4"
```

*This sanity check is expected to fail because the rates data is cutoff at 70. Do not consider people over 70 in this analysis.*

```r
# Find rows in portfolio_data that do not have a match in rates_data
missing_matches <- anti_join(portfolio_data,
                             rates_data_extended,
                             by = c("age" = "Age", "Gender" = "Gender"))

# Check how many rows are missing
nrow(missing_matches)
```

***Investigate missing matches***

```
## [1] 0
```

***Question b.***

*Group the Industry field into common-sense based groupings and determine the mean, standard deviation and quantiles of DeathSI for each of your industry groups.*

```r
industry_counts <- combined_data %>%
  count(Industry) %>%
  arrange(desc(n))

# View the result
print(industry_counts)
```

```
## # A tibble: 33 x 2
##    Industry                              n
##    <chr>                             <int>
##  1 <NA>                             116769
##  2 Government & Public Administration  31304
##  3 Other                             14455
##  4 Sporting Club                      2243
##  5 Ex-Services Club                   1501
##  6 BSS-Business Services              1228
##  7 MAN-Manufacturing                  1147
##  8 EDN-Education                      1004
##  9 COM-Communication Serv.             878
## 10 FIN-Finance & Insurance             851
## # i 23 more rows
```

```r
combined_data <- combined_data %>%
  mutate(
    Industry_Group = case_when(
      Industry %in% c("Government & Public Administration", "Ex-Services Club") ~ "Government and Publi
      Industry %in% c(
        "Sporting Club",
        "Golf Club",
        "Bowls Club",
        "Registered Club",
        "Surf Life Saving Club",
        "Workers Club",
```

```r
        "Australian Rules Football Club",
        "Leagues Club",
        "Associated with Club Industry"
      ) ~ "Clubs and Associations",
      Industry %in% c(
        "BSS-Business Services",
        "FIN-Finance & Insurance",
        "Professional Services",
        "LAW-Solicitors/Barrister",
        "ENG-Engineers",
        "MGE-Medical Services Gen"
      ) ~ "Professional and Business Services",
      Industry %in% c(
        "MAN-Manufacturing",
        "CON-Construction",
        "ELE-Electricians",
        "VEH-Vehicle Industry",
        "WEO-Wholesale Trades"
      ) ~ "Manufacturing, Construction, and Trades",
      Industry %in% c(
        "EDN-Education",
        "HEA-Health Industry",
        "MGE-Medical Services Gen"
      ) ~ "Education and Health",
      Industry %in% c(
        "RTL-Retail Trade",
        "ACR-Accom. Cafes & Rests",
        "FOO-Food",
        "Hospitality"
      ) ~ "Retail, Hospitality, and Food",
      Industry %in% c("AGR-Farming/Agriculture", "EGW
-Electric/Gas/Water") ~ "Agriculture and Utilities",
Industry == "Other" ~ "Other",
TRUE ~ "Uncategorized"  # Catch any uncategorized industries
    )
  )


# View the newly grouped data
print(combined_data)
```

```
## # A tibble: 177,922 x 8
##    SchemeName Date.of.Birth Gender DeathSI Industry     age  Rate Industry_Group
##    <chr>      <date>        <chr>  <chr>   <chr>      <dbl> <dbl> <chr>
##  1 Scheme2    1949-05-29    F      <NA>    Governmen~    76 13.3  Government an~
##  2 Scheme2    1950-09-07    F      <NA>    Governmen~    75 12.1  Government an~
##  3 Scheme2    1956-09-27    F      <NA>    Governmen~    68  5.96 Government an~
##  4 Scheme2    1942-02-18    F      <NA>    Governmen~    83 27.1  Government an~
##  5 Scheme2    1951-07-31    F      <NA>    Governmen~    74 10.9  Government an~
##  6 Scheme2    1960-07-10    F      <NA>    Governmen~    65  4.35 Government an~
##  7 Scheme2    1954-12-24    F      <NA>    Governmen~    70  7.34 Government an~
##  8 Scheme2    1942-03-13    F      <NA>    Governmen~    83 27.1  Government an~
##  9 Scheme2    1958-02-28    F      <NA>    Governmen~    67  5.36 Government an~
```

```
## 10 Scheme2    1968-09-12    F       <NA>     Governmen~    57   1.91 Government an~
## # i 177,912 more rows
```

```r
industry_counts <- combined_data %>%
  count(Industry_Group) %>%
  arrange(desc(n))

# View the result
print(industry_counts)
```

```
## # A tibble: 9 x 2
##   Industry_Group                                n
##   <chr>                                     <int>
## 1 Uncategorized                            117899
## 2 Government and Public Services            32805
## 3 Other                                     14455
## 4 Clubs and Associations                     4944
## 5 Manufacturing, Construction, and Trades   2529
## 6 Professional and Business Services        2494
## 7 Education and Health                      1396
## 8 Retail, Hospitality, and Food             1008
## 9 Agriculture and Utilities                  392
```

1. ```r
   # Check the type of DeathSI
   typeof(combined_data$DeathSI)
   ```

   ```
   ## [1] "character"
   ```

   ```r
   # Count the number of NA values in DeathSI when it was character type
   na_count <- sum(is.na(combined_data$DeathSI))
   na_count
   ```

   ```
   ## [1] 21531
   ```

   ```r
   # Count the number of "NA" string values in DeathSI when it was character type
   na_string_count <- sum(combined_data$DeathSI == "NA", na.rm = TRUE)
   na_string_count
   ```

   ```
   ## [1] 0
   ```

   ```r
   # Remove apostrophes and convert the DeathSI column from character to numeric
   combined_data$DeathSI <- as.numeric(gsub("'", "", combined_data$DeathSI))

   # Check the type of DeathSI
   typeof(combined_data$DeathSI)
   ```

   ```
   ## [1] "double"
   ```
   ```

```r
# Count the number of NA values in DeathSI when it is the double type
na_count <- sum(is.na(combined_data$DeathSI))
na_count
```

```
## [1] 21531
```

```r
# Calculate mean, standard deviation, and quantiles for each industry group
summary_stats <- combined_data %>%
  group_by(Industry_Group) %>%
  summarize(
    mean_value = mean(DeathSI, na.rm = TRUE),
    sd_value = sd(DeathSI, na.rm = TRUE),
    q25 = quantile(DeathSI, 0.25, na.rm = TRUE),
    median_value = median(DeathSI, na.rm = TRUE),
    q75 = quantile(DeathSI, 0.75, na.rm = TRUE)
  )

# View the result
print(summary_stats)
```

```
## # A tibble: 9 x 6
##   Industry_Group                    mean_value sd_value    q25 median_value    q75
##   <chr>                                  <dbl>    <dbl>  <dbl>        <dbl>  <dbl>
## 1 Agriculture and Utilities            153992.  213974. 2.49e4      106412. 1.79e5
## 2 Clubs and Associations               275620.  183697. 1.98e5      219890. 2.96e5
## 3 Education and Health                 323269.  256159. 1.40e5      279255  4.69e5
## 4 Government and Public Services       215104.  104726. 1.5 e5      220000  3   e5
## 5 Manufacturing, Construction, a~      289155.  237042. 1.17e5      250380  3.96e5
## 6 Other                                259435.  115096. 2.05e5      244264  2.85e5
## 7 Professional and Business Serv~      438260.  332429. 2.40e5      368416  5.44e5
## 8 Retail, Hospitality, and Food        313829.  206804. 2.05e5      245601  3.78e5
## 9 Uncategorized                        217656.  220107. 7.15e4      162404  2.83e5
```

### Question c.

The following code performs a Monte Carlo simulation on the data you have loaded and combined in Question a.:

```r
set.seed(1234)
nsim <- 1000
res <- lapply(1:nsim, function(i,...) {
  x <- ifelse(
    runif(dim(combined_data)[1]) < combined_data$Rate / 1000,
    combined_data$DeathSI,
    0
  );
  list(cost = sum(x), count = length(x[x > 0]))
})
```

Apply this simulation to each scheme in the dataset you were provided, running 1000 simulations per scheme. Produce a plot of the simulated outcomes ("cost"). Your plot should show:

- a separate histogram per scheme;
- all 5 histograms below each other so that they can be easily compared;
- vertical lines in each graph indicating the median, mean and 99.5th percentile of each distribution.

**Remove rows where DeathSI is NA for Monte Carlo simulation.**

```
# Get the number of rows in the original dataset
original_row_count <- nrow(combined_data)

# Subset combined_data where DeathSI is not NA
combined_data_death_si_non_na <- subset(combined_data, !is.na(DeathSI))

# Get the number of rows in the filtered dataset
filtered_row_count <- nrow(combined_data_death_si_non_na)

# Print out the row counts to validate reduction
cat("Original row count:", original_row_count, "\n")
```

```
## Original row count: 177922
```

```
cat("Filtered row count (DeathSI not NA):", filtered_row_count, "\n")
```

```
## Filtered row count (DeathSI not NA): 156391
```

```
# Check if the row count was reduced
if (filtered_row_count < original_row_count) {
  cat("Row reduction validated: Rows were reduced after filtering.\n")
} else {
  cat("No row reduction: No NA values in DeathSI.\n")
}
```

```
## Row reduction validated: Rows were reduced after filtering.
```

```
monte_carlo_simulation <- function(data, nsim = 1000, seed = 1234) {
  # Set the seed for reproducibility
  set.seed(seed)

  # Perform the simulation
  res <- lapply(1:nsim, function(i, ...) {
    x <- ifelse(runif(dim(data)[1]) < data$Rate / 1000, data$DeathSI, 0)
    # Return the cost and count as a list
    list(cost = sum(x), count = length(x[x > 0]))
  })

  # Return the result of the simulation
  return(res)
}

# Get the unique values in the SchemeName column
```

```r
unique_schemes <- unique(combined_data$SchemeName)

# Print the unique values
unique_schemes
```

```
## [1] "Scheme2" "Scheme1" "Scheme3" "Scheme5" "Scheme4"
```

```r
# Filter rows where SchemeName is "Scheme_1", "Scheme_2", "Scheme_3", "Scheme_4", "Scheme_5"
combined_data_scheme_1 <- subset(combined_data_death_si_non_na, SchemeName == "Scheme1")
combined_data_scheme_2 <- subset(combined_data_death_si_non_na, SchemeName == "Scheme2")
combined_data_scheme_3 <- subset(combined_data_death_si_non_na, SchemeName == "Scheme3")
combined_data_scheme_4 <- subset(combined_data_death_si_non_na, SchemeName == "Scheme4")
combined_data_scheme_5 <- subset(combined_data_death_si_non_na, SchemeName == "Scheme5")

# Sanity check that each subset has more than 0 rows
check_scheme_1 <- nrow(combined_data_scheme_1) > 0
check_scheme_2 <- nrow(combined_data_scheme_2) > 0
check_scheme_3 <- nrow(combined_data_scheme_3) > 0
check_scheme_4 <- nrow(combined_data_scheme_4) > 0
check_scheme_5 <- nrow(combined_data_scheme_5) > 0

# Print the results
cat("Scheme 1 has more than 0 rows:", check_scheme_1, "\n")
```

```
## Scheme 1 has more than 0 rows: TRUE
```

```r
cat("Scheme 2 has more than 0 rows:", check_scheme_2, "\n")
```

```
## Scheme 2 has more than 0 rows: TRUE
```

```r
cat("Scheme 3 has more than 0 rows:", check_scheme_3, "\n")
```

```
## Scheme 3 has more than 0 rows: TRUE
```

```r
cat("Scheme 4 has more than 0 rows:", check_scheme_4, "\n")
```

```
## Scheme 4 has more than 0 rows: TRUE
```

```r
cat("Scheme 5 has more than 0 rows:", check_scheme_5, "\n")
```

```
## Scheme 5 has more than 0 rows: TRUE
```

```r
# Perform a monte carlo simulation for each scheme
monte_carlo_scheme_1_result <- monte_carlo_simulation(combined_data_scheme_1)
monte_carlo_scheme_2_result <- monte_carlo_simulation(combined_data_scheme_2)
monte_carlo_scheme_3_result <- monte_carlo_simulation(combined_data_scheme_3)
monte_carlo_scheme_4_result <- monte_carlo_simulation(combined_data_scheme_4)
monte_carlo_scheme_5_result <- monte_carlo_simulation(combined_data_scheme_5)
```