Final_R_Code

Zoe Lu

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Reading Data

```r
raw <- read.csv("/Users/zoelu/Downloads/Crime_Data_from_2010_to_2019_20241126.csv")
```

At glance view of the data

```r
summary(raw)
```

```
##      DR_NO             Date.Rptd           DATE.OCC            TIME.OCC   
##  Min.   :  1208575   Length:2093455     Length:2093455     Min.   :   1  
##  1st Qu.:121815922   Class :character   Class :character   1st Qu.: 930  
##  Median :161113993   Mode  :character   Mode  :character   Median :1430  
##  Mean   :154145763                                         Mean   :1360  
##  3rd Qu.:180907498                                         3rd Qu.:1900  
##  Max.   :910220366                                         Max.   :2359  
##                                                                           
##       AREA        AREA.NAME          Rpt.Dist.No      Part.1.2    
##  Min.   : 1.00   Length:2093455     Min.   : 100   Min.   :1.000  
##  1st Qu.: 6.00   Class :character   1st Qu.: 636   1st Qu.:1.000  
##  Median :11.00   Mode  :character   Median :1152   Median :1.000  
##  Mean   :10.88                      Mean   :1134   Mean   :1.441  
##  3rd Qu.:16.00                      3rd Qu.:1622   3rd Qu.:2.000  
##  Max.   :21.00                      Max.   :2199   Max.   :2.000  
##                                                                   
##      Crm.Cd    Crm.Cd.Desc          Mocodes             Vict.Age     
##  Min.   :110   Length:2093455     Length:2093455     Min.   :-12.00  
##  1st Qu.:330   Class :character   Class :character   1st Qu.: 19.00  
##  Median :442   Mode  :character   Mode  :character   Median : 32.00  
##  Mean   :507                                         Mean   : 31.71  
##  3rd Qu.:626                                         3rd Qu.: 46.00  
##  Max.   :956                                         Max.   :118.00  
##                                                                      
##    Vict.Sex         Vict.Descent         Premis.Cd      Premis.Desc       
##  Length:2093455     Length:2093455     Min.   :101.0   Length:2093455    
##  Class :character   Class :character   1st Qu.:102.0   Class :character  
##  Mode  :character   Mode  :character   Median :210.0   Mode  :character  
```

```
##                                          Mean   :309.4
##                                          3rd Qu.:501.0
##                                          Max.   :971.0
##                                          NA's   :40
##  Weapon.Used.Cd    Weapon.Desc          Status           Status.Desc
##  Min.   :101.0     Length:2093455     Length:2093455     Length:2093455
##  1st Qu.:400.0     Class :character   Class :character   Class :character
##  Median :400.0     Mode  :character   Mode  :character   Mode  :character
##  Mean   :370.7
##  3rd Qu.:400.0
##  Max.   :516.0
##  NA's   :1383033
##     Crm.Cd.1        Crm.Cd.2         Crm.Cd.3         Crm.Cd.4
##  Min.   :110.0   Min.   :210.0    Min.   : 93.0    Min.   :421.0
##  1st Qu.:330.0   1st Qu.:998.0    1st Qu.:998.0    1st Qu.:998.0
##  Median :442.0   Median :998.0    Median :998.0    Median :998.0
##  Mean   :506.8   Mean   :947.8    Mean   :973.2    Mean   :966.5
##  3rd Qu.:626.0   3rd Qu.:998.0    3rd Qu.:998.0    3rd Qu.:998.0
##  Max.   :999.0   Max.   :999.0    Max.   :999.0    Max.   :999.0
##  NA's   :10      NA's   :1951889  NA's   :2089623  NA's   :2093349
##    LOCATION         Cross.Street            LAT              LON
##  Length:2093455     Length:2093455     Min.   : 0.00   Min.   :-118.8
##  Class :character   Class :character   1st Qu.:34.01   1st Qu.:-118.4
##  Mode  :character   Mode  :character   Median :34.06   Median :-118.3
##                                          Mean   :34.06   Mean   :-118.3
##                                          3rd Qu.:34.17   3rd Qu.:-118.3
##                                          Max.   :34.71   Max.   :   0.0
##
```

Subsetting data and changing variable types

```r
# Getting rid of Records Number, Location(Street Address of Crime),
# Cross Street(Cross Street of Rounded Address), Latitude, Longitude
raw_subset <- raw[2:24]

# setting variable types
raw_subset$AREA <- as.factor(raw_subset$AREA)
raw_subset$AREA.NAME <- as.factor(raw_subset$AREA.NAME)
raw_subset$Part.1.2 <- as.factor(raw_subset$Part.1.2)
raw_subset$Vict.Sex <- as.factor(raw_subset$Vict.Sex)
raw_subset$Vict.Descent <- as.factor(raw_subset$Vict.Descent)
raw_subset$Status <- as.factor(raw_subset$Status)
raw_subset$Status.Desc <- as.factor(raw_subset$Status.Desc)

# at glance view of categorical data
table(raw$Status.Desc)
```

```
##
## Adult Arrest  Adult Other  Invest Cont   Juv Arrest    Juv Other          UNK
##       218880       255425      1598598        15229         5291           32
```

Re-Coding Response:Status of Case

```r
# Setting rows marked as UNK(unclear) to NA
raw_subset$Status.Desc[raw_subset$Status.Desc == "UNK"] <- NA

# Creating new Variable with our proposed Binary Outcome Legal Actions vs. No Legal Action(Status Case)
raw_subset$Legal_Action <- raw_subset$Status.Desc
raw_subset$Legal_Action <- as.character(raw_subset$Legal_Action)
raw_subset$Legal_Action <- ifelse(raw_subset$Legal_Action == "Invest Cont", 0, 1)

# counts of response variable
table(raw_subset$Legal_Action)
```

```
##
##       0       1
## 1598598  494825
```

ReCoding Date & Coding Difference in Report Time

```r
raw_subset$date_report <- raw_subset$Date.Rptd
raw_subset$date_report <- as.POSIXct(raw_subset$date_report, format = "%m/%d/%Y %I:%M:%S %p")
raw_subset$date_report <- as.Date(raw_subset$date_report)

# Occurence Date
raw_subset$date_occur <- raw_subset$DATE.OCC
raw_subset$date_occur <- as.POSIXct(raw_subset$date_occur, format = "%m/%d/%Y %I:%M:%S %p")
raw_subset$date_occur <- as.Date(raw_subset$date_occur)

#Creating New Column: Difference Between Report vs Occurence
raw_subset$date_occur_report_difference <- as.numeric(difftime(raw_subset$date_report,
                                                               raw_subset$date_occur,
                                                               units = "days"))
```

Categorizing Time Occurred

```r
# Convert military time to string
raw_subset$military_time <- raw_subset$TIME.OCC

#Time Ranges:
# Morning 5 am to 12 pm (noon)
# Afternoon 12 pm to 5 pm.
# Evening 5 pm to 9 pm.
# Night 9 pm to 4 am.
military_times_str <- sprintf("%04d", raw_subset$military_time)

hours <- as.integer(substr(military_times_str, 1, 2))
```

```r
categories <- ifelse(hours >= 5 & hours < 12, "Morning",
                     ifelse(hours >= 12 & hours < 17, "Afternoon",
                            ifelse(hours >= 17 & hours < 21, "Evening", "Night")))

raw_subset$time_occur_cat <- categories
```

Creating dictionaries to store descriptions of unique values and frequencies of each category

```r
summary_tables_top20 <- function(key_input,value_input) {
  dict <- setNames(key_input,value_input)
  df <- data.frame(
    key = names(dict),
    value = unname(dict)
  ) %>%
    dplyr::group_by(key, value) %>%
    dplyr::summarize(frequency = n(), .groups = "drop") %>%
    arrange(desc(frequency))
  df_name <- paste0(gsub(".*\\$", "",deparse(substitute(value_input))))
  assign(df_name, df, envir = .GlobalEnv)

  #Frequency Counts
  row_counts <- c(10,15, 20, 25, 50)
  total_rows <- nrow(df)

  # printing out top cateogries
  cat("Cumulative sums of frequencies for the top categories:\n")
  for (n in row_counts) {
      if (n <= total_rows) {
          cat(paste0("Top ", n, " categories: ", sum(df$frequency[1:n]), "\n"))
      } else {
          cat(paste0("Top ", n, " categories: Not enough categories (only ", total_rows, " categories a
      }
  }
  return(head(df,20))
}

# view summaries of top categories
summary_tables_top20(raw_subset$AREA.NAME, raw_subset$AREA)
```

```
## Cumulative sums of frequencies for the top categories:
## Top 10 categories: 1123992
## Top 15 categories: 1583968
## Top 20 categories: 2019153
## Top 25 categories: Not enough categories (only 21 categories available).
## Top 50 categories: Not enough categories (only 21 categories available).
```

```
## # A tibble: 20 x 3
##    key   value      frequency
```

```
##    <chr> <fct>          <int>
##  1 12    77th Street    146824
##  2 3     Southwest      141044
##  3 14    Pacific        113389
##  4 15    N Hollywood    110365
##  5 18    Southeast      108188
##  6 13    Newton         104064
##  7 6     Hollywood      101551
##  8 11    Northeast       99985
##  9 9     Van Nuys        99669
## 10 1     Central         98913
## 11 19    Mission         94188
## 12 5     Harbor          92650
## 13 10    West Valley     91437
## 14 8     West LA         91171
## 15 7     Wilshire        90530
## 16 2     Rampart         89524
## 17 21    Topanga         89389
## 18 17    Devonshire      87873
## 19 20    Olympic         87398
## 20 4     Hollenbeck      81001
```

```r
summary_tables_top20(raw_subset$Crm.Cd.Desc,raw_subset$Crm.Cd)
```

```
## Cumulative sums of frequencies for the top categories:
## Top 10 categories: 1325082
## Top 15 categories: 1671296
## Top 20 categories: 1786035
## Top 25 categories: 1875445
## Top 50 categories: 2037624
```

```
## # A tibble: 20 x 3
##    key   value                                                    frequency
##    <chr> <chr>                                                        <int>
##  1 624   BATTERY - SIMPLE ASSAULT                                    185209
##  2 330   BURGLARY FROM VEHICLE                                       161295
##  3 510   VEHICLE - STOLEN                                            160481
##  4 440   THEFT PLAIN - PETTY ($950 & UNDER)                          148064
##  5 310   BURGLARY                                                    142573
##  6 354   THEFT OF IDENTITY                                           121517
##  7 626   INTIMATE PARTNER - SIMPLE ASSAULT                           112375
##  8 740   VANDALISM - FELONY ($400 & OVER, ALL CHURCH VANDALISMS)     109646
##  9 230   ASSAULT WITH DEADLY WEAPON, AGGRAVATED ASSAULT               93679
## 10 420   THEFT FROM MOTOR VEHICLE - PETTY ($950 & UNDER)              90243
## 11 745   VANDALISM - MISDEAMEANOR ($399 OR UNDER)                     87833
## 12 210   ROBBERY                                                      84186
## 13 341   THEFT-GRAND ($950.01 & OVER)EXCPT,GUNS,FOWL,LIVESTK,PROD     70565
## 14 930   CRIMINAL THREATS - NO WEAPON DISPLAYED                       54645
## 15 442   SHOPLIFTING - PETTY THEFT ($950 & UNDER)                     48985
## 16 331   THEFT FROM MOTOR VEHICLE - GRAND ($950.01 AND OVER)          31103
## 17 888   TRESPASSING                                                  22526
## 18 649   DOCUMENT FORGERY / STOLEN FELONY                             21357
## 19 956   LETTERS, LEWD  -  TELEPHONE CALLS, LEWD                      20264
## 20 946   OTHER MISCELLANEOUS CRIME                                    19489
```

```r
summary_tables_top20(raw_subset$Premis.Desc, raw_subset$Premis.Cd)
```

```
## Cumulative sums of frequencies for the top categories:
## Top 10 categories: 1684905
## Top 15 categories: 1781415
## Top 20 categories: 1845674
## Top 25 categories: 1890018
## Top 50 categories: 2008647

## # A tibble: 20 x 3
##    key   value                                         frequency
##    <chr> <chr>                                             <int>
##  1 101   STREET                                           473543
##  2 501   SINGLE FAMILY DWELLING                           416635
##  3 502   MULTI-UNIT DWELLING (APARTMENT, DUPLEX, ETC)    256929
##  4 108   PARKING LOT                                      150225
##  5 102   SIDEWALK                                         104771
##  6 203   OTHER BUSINESS                                    95144
##  7 122   VEHICLE, PASSENGER/TRUCK                          78105
##  8 104   DRIVEWAY                                          42445
##  9 707   GARAGE/CARPORT                                    37700
## 10 210   RESTAURANT/FAST FOOD                              29408
## 11 404   DEPARTMENT STORE                                  27105
## 12 402   MARKET                                            21727
## 13 123   PARKING UNDERGROUND/BUILDING                      16573
## 14 406   OTHER STORE                                       16406
## 15 109   PARK/PLAYGROUND                                   14699
## 16 103   ALLEY                                             14173
## 17 121   YARD (RESIDENTIAL/BUSINESS)                       14104
## 18 710   OTHER PREMISE                                     12927
## 19 721   HIGH SCHOOL                                       12370
## 20 403   DRUG STORE                                        10685
```

```r
summary_tables_top20(raw_subset$Weapon.Desc, raw_subset$Weapon.Used.Cd)
```

```
## Cumulative sums of frequencies for the top categories:
## Top 10 categories: 2014130
## Top 15 categories: 2038301
## Top 20 categories: 2058118
## Top 25 categories: 2071307
## Top 50 categories: 2091121

## # A tibble: 20 x 3
##    key   value                                               frequency
##    <chr> <chr>                                                   <int>
##  1 <NA>  ""                                                    1383033
##  2 400   "STRONG-ARM (HANDS, FIST, FEET OR BODILY FORCE)"    428182
##  3 511   "VERBAL THREAT"                                         58308
##  4 500   "UNKNOWN WEAPON/OTHER WEAPON"                           58003
##  5 102   "HAND GUN"                                              34857
##  6 109   "SEMI-AUTOMATIC PISTOL"                                 13405
##  7 200   "KNIFE WITH BLADE 6INCHES OR LESS"                      13250
```

```
##   8 207   "OTHER KNIFE"                                          9799
##   9 106   "UNKNOWN FIREARM"                                      7978
##  10 307   "VEHICLE"                                              7315
##  11 101   "REVOLVER"                                             5409
##  12 212   "BOTTLE"                                               5113
##  13 306   "ROCK/THROWN OBJECT"                                   4658
##  14 308   "STICK"                                                4639
##  15 204   "FOLDING KNIFE"                                        4352
##  16 304   "CLUB/BAT"                                             4337
##  17 512   "MACE/PEPPER SPRAY"                                    4225
##  18 302   "BLUNT INSTRUMENT"                                     4044
##  19 205   "KITCHEN KNIFE"                                        3845
##  20 113   "SIMULATED GUN"                                        3366
```

Weapons NA Recode

```
#Creating new category None instead of NA for no weapon used
raw_subset$Weapon.Used.Cd <- as.character(raw_subset$Weapon.Used.Cd)
raw_subset$Weapon.Used.Cd[is.na(raw_subset$Weapon.Used.Cd) == T] <- "None"
```

Subsetting Columns needed readying data for cleaning

```
columns_to_subset <- c("AREA", "Rpt.Dist.No", "Part.1.2", "Crm.Cd", "Mocodes",
                       "Vict.Age", "Vict.Sex", "Vict.Descent", "Premis.Cd",
                       "Weapon.Used.Cd", "Status", "Legal_Action",
                       "date_occur_report_difference", "time_occur_cat")

subset1 <- raw_subset[, columns_to_subset]

#Only including rows whose Crm.Cd is in top 50
crime_top_50_string_vec <- Crm.Cd$key[1:50]
filtered_subset2 <- subset1[subset1$Crm.Cd %in% crime_top_50_string_vec, ]

#Only including rows whose crime took place in Premise in top 50
premise_top_50_string_vec <- Premis.Cd$key[1:50]
filtered_subset3 <- filtered_subset2[filtered_subset2$Premis.Cd %in% premise_top_50_string_vec, ]

#Only including rows if weapon Used in top 10
summary_tables_top20(raw_subset$Weapon.Desc, raw_subset$Weapon.Used.Cd)
```

```
## Cumulative sums of frequencies for the top categories:
## Top 10 categories: 2014130
## Top 15 categories: 2038301
## Top 20 categories: 2058118
## Top 25 categories: 2071307
## Top 50 categories: 2091121
```

```
## # A tibble: 20 x 3
```

```
##    key   value                                             frequency
##    <chr> <chr>                                                 <int>
##  1 None  ""                                                  1383033
##  2 400   "STRONG-ARM (HANDS, FIST, FEET OR BODILY FORCE)"     428182
##  3 511   "VERBAL THREAT"                                       58308
##  4 500   "UNKNOWN WEAPON/OTHER WEAPON"                         58003
##  5 102   "HAND GUN"                                            34857
##  6 109   "SEMI-AUTOMATIC PISTOL"                               13405
##  7 200   "KNIFE WITH BLADE 6INCHES OR LESS"                    13250
##  8 207   "OTHER KNIFE"                                          9799
##  9 106   "UNKNOWN FIREARM"                                      7978
## 10 307   "VEHICLE"                                              7315
## 11 101   "REVOLVER"                                             5409
## 12 212   "BOTTLE"                                               5113
## 13 306   "ROCK/THROWN OBJECT"                                   4658
## 14 308   "STICK"                                                4639
## 15 204   "FOLDING KNIFE"                                        4352
## 16 304   "CLUB/BAT"                                             4337
## 17 512   "MACE/PEPPER SPRAY"                                    4225
## 18 302   "BLUNT INSTRUMENT"                                     4044
## 19 205   "KITCHEN KNIFE"                                        3845
## 20 113   "SIMULATED GUN"                                        3366
```

```
weapon_top_10_string_vec <- Weapon.Used.Cd$key[1:10]
filtered_subset4 <- filtered_subset3[filtered_subset3$Weapon.Used.Cd %in% weapon_top_10_string_vec, ]

#Dropping Mocodes
filtered_subset5 <- filtered_subset4[, !(colnames(filtered_subset4) %in% "Mocodes")]

#Changing Column types
filtered_subset5$Rpt.Dist.No <- as.factor(filtered_subset5$Rpt.Dist.No)
filtered_subset5$Crm.Cd <- as.factor(filtered_subset5$Crm.Cd)
filtered_subset5$Premis.Cd <- as.factor(filtered_subset5$Premis.Cd)
filtered_subset5$Weapon.Used.Cd <- as.factor(filtered_subset5$Weapon.Used.Cd)
filtered_subset5$Legal_Action <- as.factor(filtered_subset5$Legal_Action)
filtered_subset5$time_occur_cat <- as.factor(filtered_subset5$time_occur_cat)
```

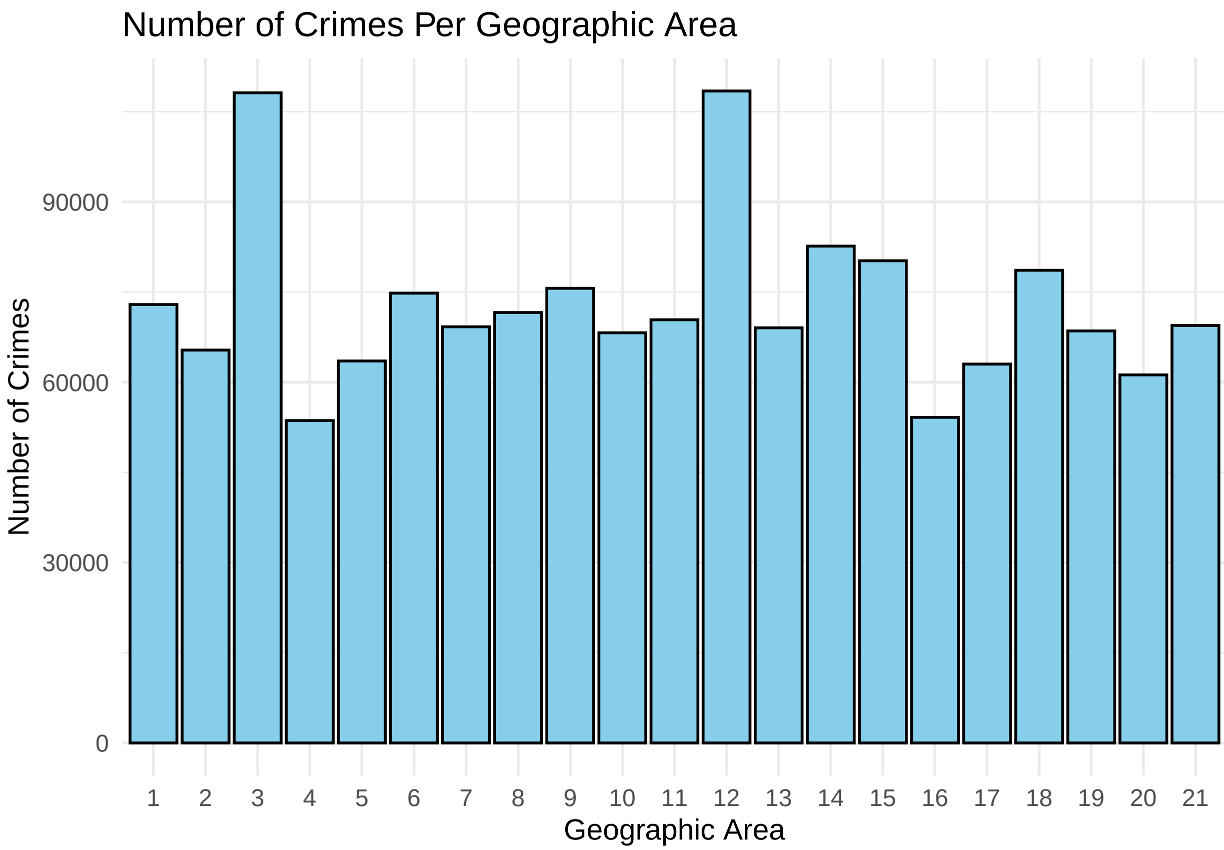
Cleaning Data: Changing Columns

```
# Identified and cleaning Negative Ages, one age of 118, and sex:X
filtered_subset6 <- filtered_subset5[filtered_subset5$Vict.Age > 0,]
filtered_subset7 <- filtered_subset6[filtered_subset6$Vict.Age <= 100, ]
filtered_subset8 <- filtered_subset7[filtered_subset7$Vict.Sex == "F" | filtered_subset7$Vict.Sex == "M

#Identified and cleaning Null Race and "-" Race entering Race
filtered_subset9 <- filtered_subset8[filtered_subset8$Vict.Descent != "-", ]
filtered_subset9$Vict.Descent.Description <- ifelse(
    filtered_subset9$Vict.Descent == "A",
    "Other Asian",ifelse(filtered_subset9$Vict.Descent == "B",
    "Black", ifelse(filtered_subset9$Vict.Descent == "C",
    "Chinese",ifelse(filtered_subset9$Vict.Descent == "D",
```

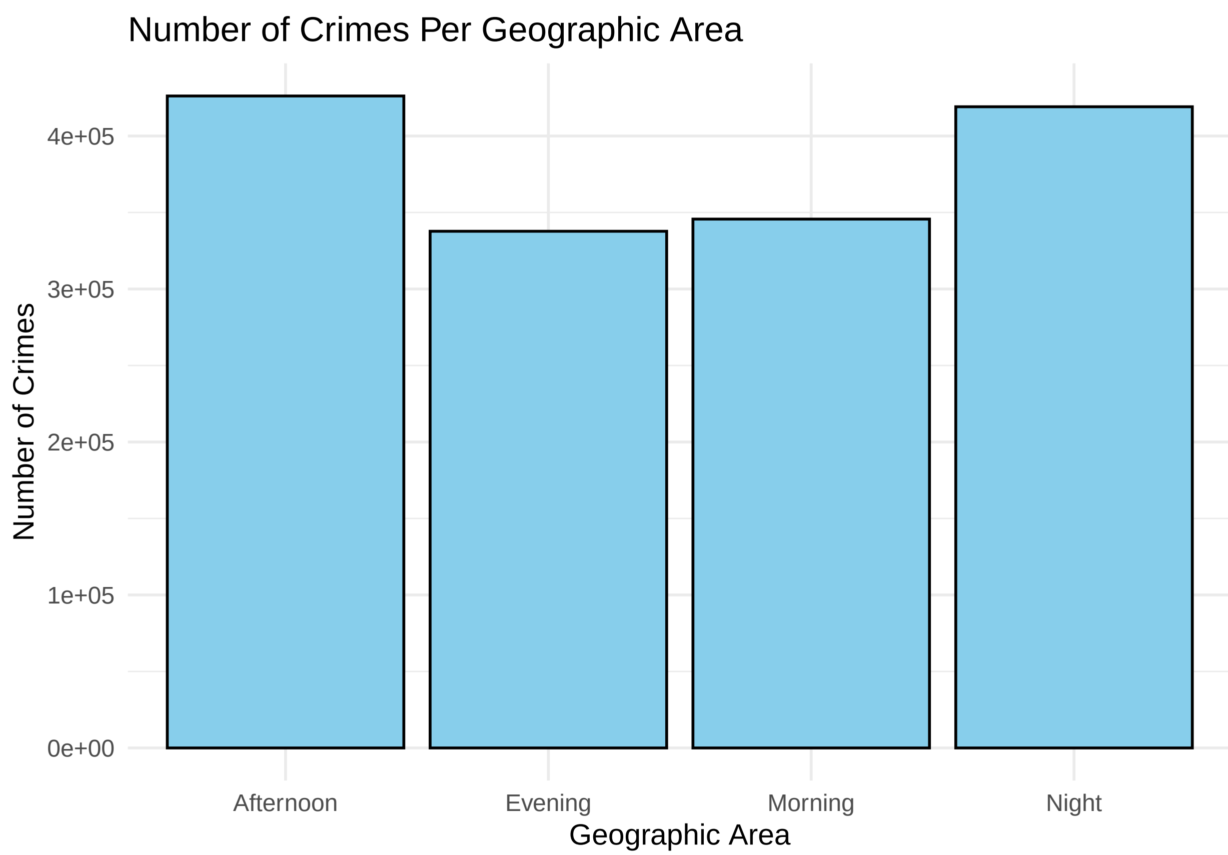
```
    "Cambodian",ifelse(filtered_subset9$Vict.Descent == "F",
     "Filipino",ifelse(filtered_subset9$Vict.Descent == "G",
      "Guamanian",ifelse(filtered_subset9$Vict.Descent == "H",
       "Hispanic/Latin/Mexican",
       ifelse(filtered_subset9$Vict.Descent == "I",
       "American Indian/Alaskan Native",
       ifelse(filtered_subset9$Vict.Descent == "J","Japanese",
        ifelse(filtered_subset9$Vict.Descent == "K","Korean",
        ifelse(filtered_subset9$Vict.Descent == "L","Laotian",
        ifelse(filtered_subset9$Vict.Descent == "O","Other",
        ifelse(filtered_subset9$Vict.Descent == "P",
        "Pacific Islander",
        ifelse(filtered_subset9$Vict.Descent == "S","Samoan",
        ifelse(filtered_subset9$Vict.Descent == "U",
        "Hawaiian",ifelse(filtered_subset9$Vict.Descent == "V",
        "Vietnamese",ifelse(filtered_subset9$Vict.Descent == "W",
         "White",ifelse(filtered_subset9$Vict.Descent == "X",NA,
         ifelse(filtered_subset9$Vict.Descent == "Z", "Asian Indian", NA))))))))))))))))))

filtered_subset10 <- filtered_subset9[, !(colnames(filtered_subset9) %in% "Vict.Descent")]
filtered_subset10$Vict.Descent.Description <- as.factor(filtered_subset10$Vict.Descent.Description)

#Only Including those with sex M or F
filtered_subset11 <- filtered_subset10[filtered_subset10$Vict.Sex == "M" | filtered_subset10$Vict.Sex ==

#Removing Sub-Areas as redundant to Geopgraphic Areas
filtered_subset12 <- filtered_subset11[, !(colnames(filtered_subset11) %in% "Rpt.Dist.No")]

#Removing Status as outcome coded into Legal Action
filtered_subset13 <- filtered_subset12[, !(colnames(filtered_subset12) %in% "Status")]

#Omitting Nulls
filtered_subset14 <- na.omit(filtered_subset13)

clean_data <- filtered_subset14
```

EDA: Count Plots for Some Categorical

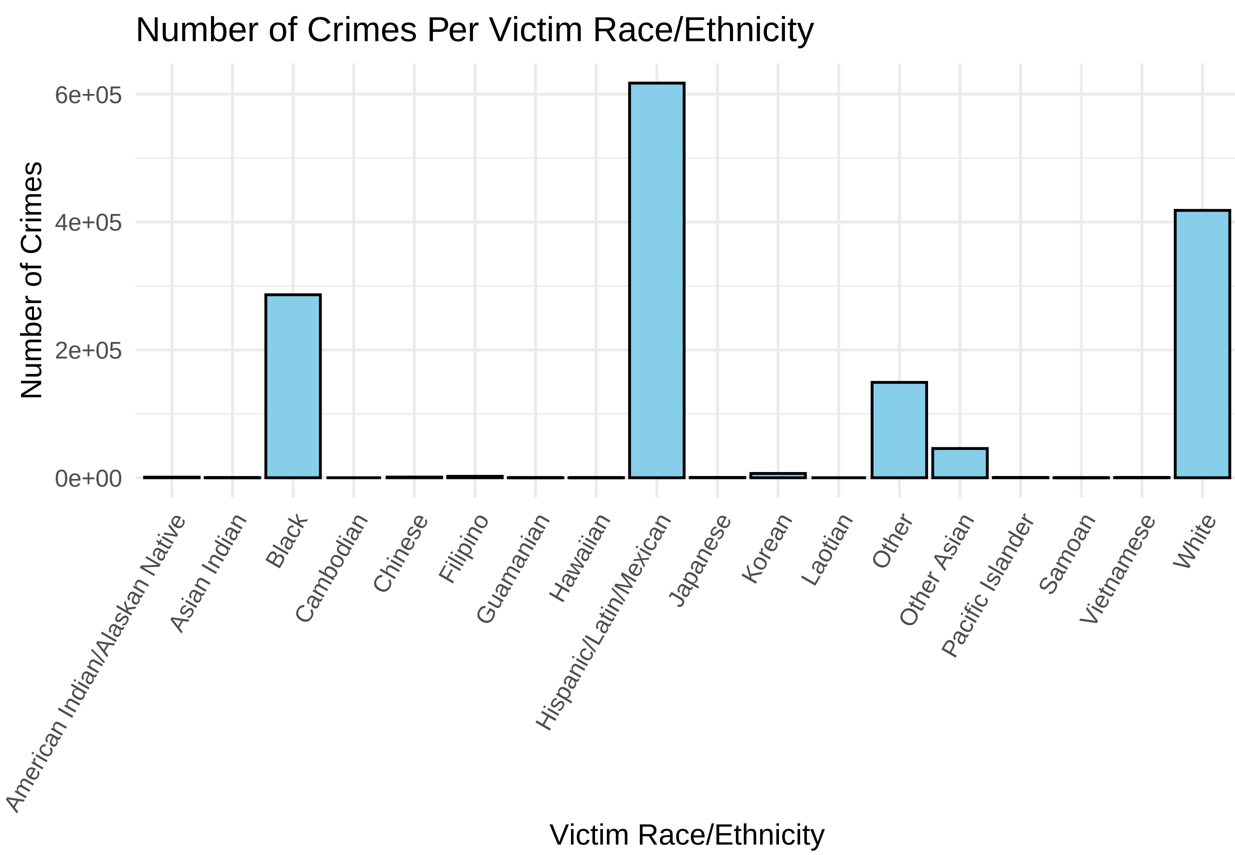
```
# function to create plots
barchart_fcn <- function(variable, title, x, y) {
    ggplot(clean_data, aes(x = .data[[variable]]), title, x, y) +
        geom_bar(color = "black", fill = "skyblue") +
        labs(title = title, x = x, y = y) +
        theme_minimal()
}

# area barchart
barchart_fcn("AREA",
             title = "Number of Crimes Per Geographic Area",
             x = "Geographic Area", y = "Number of Crimes")
```



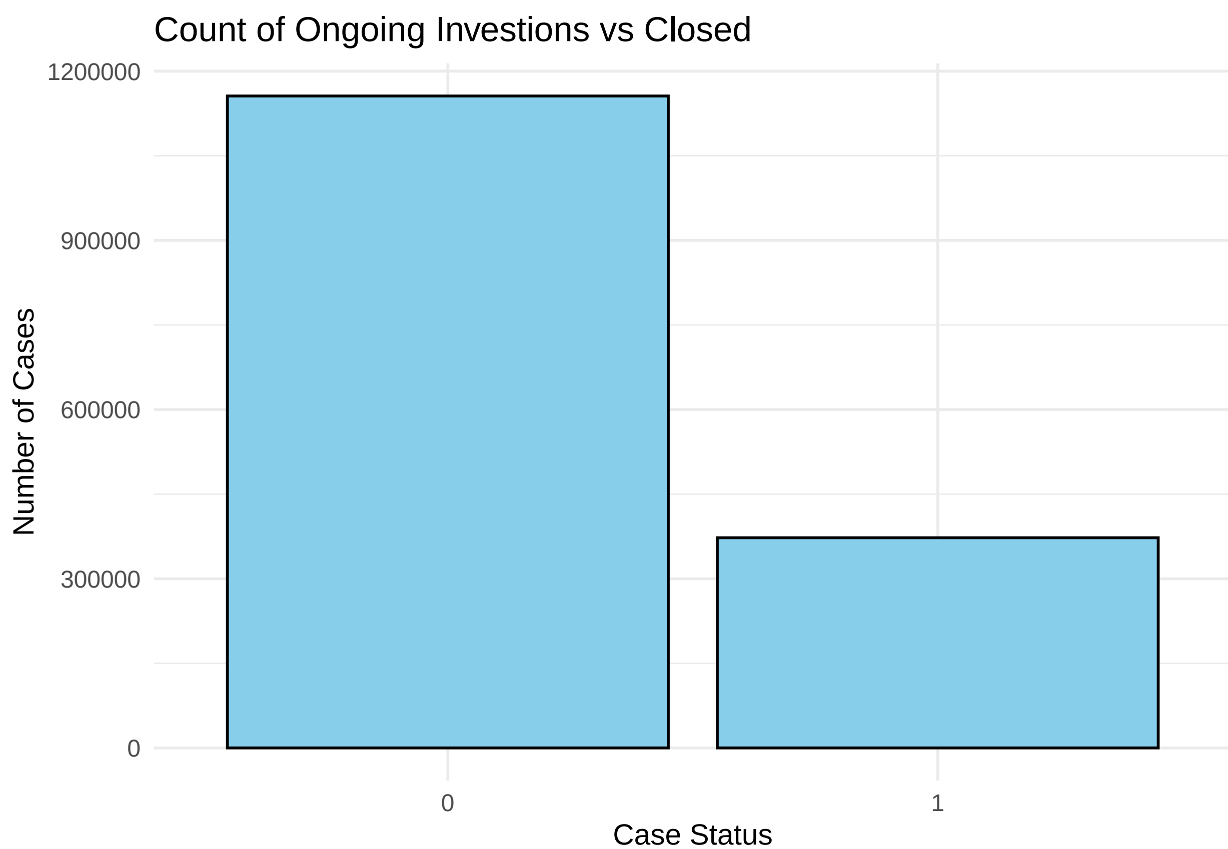

```r
#Number of Crimes Per time_occur_cat
barchart_fcn("time_occur_cat",
             title = "Number of Crimes Per Geographic Area",
             x = "Geographic Area", y = "Number of Crimes")
```



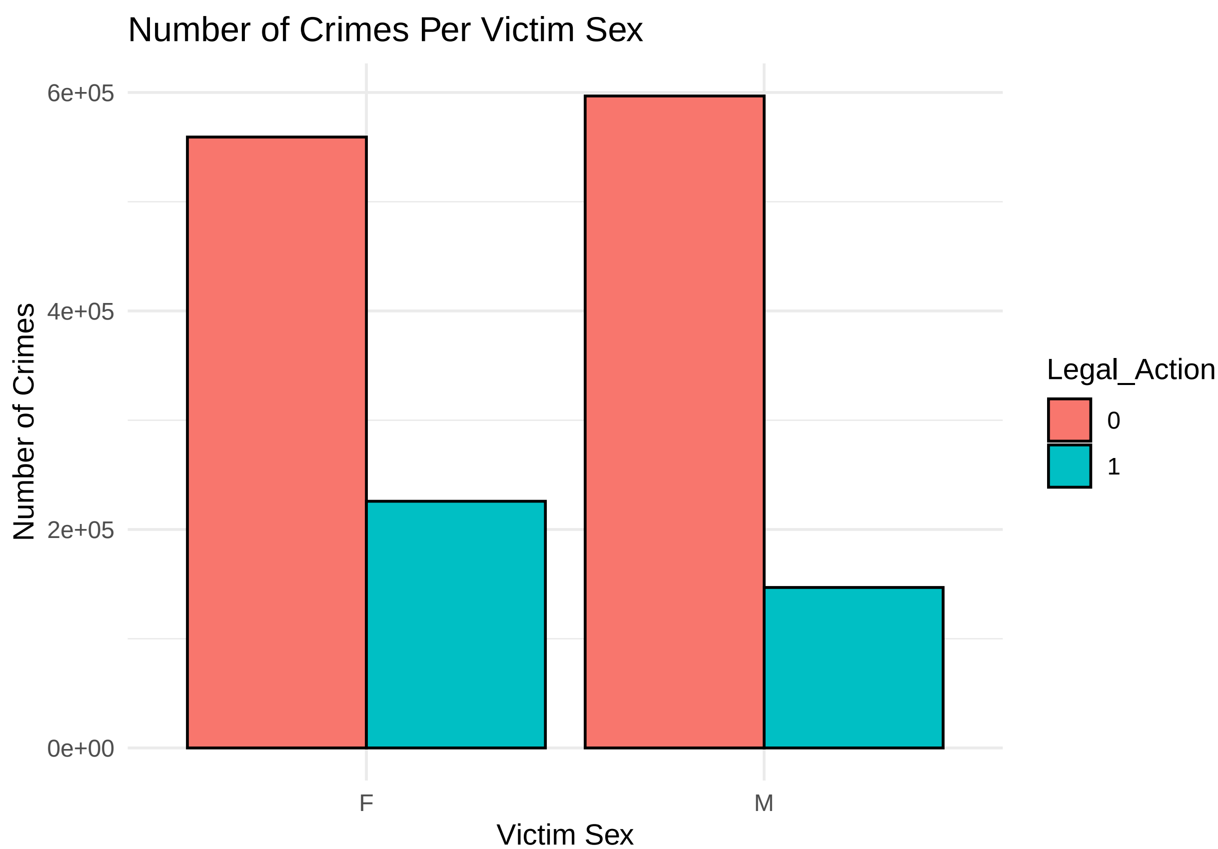

```r
#Number of Crimes Per Vict.Descent.Description
ggplot(clean_data, aes(x = Vict.Descent.Description)) +
    geom_bar(color = "black", fill = "skyblue") +
    theme_minimal() +
    theme(axis.text.x = element_text(angle = 60, hjust = 1)) +
    labs(title = "Number of Crimes Per Victim Race/Ethnicity", x = "Victim Race/Ethnicity", y = "Number
```




```r
# legal action barchart
barchart_fcn("Legal_Action",
             title = "Count of Ongoing Investions vs Closed",
             x = "Case Status", y = "Number of Cases")
```

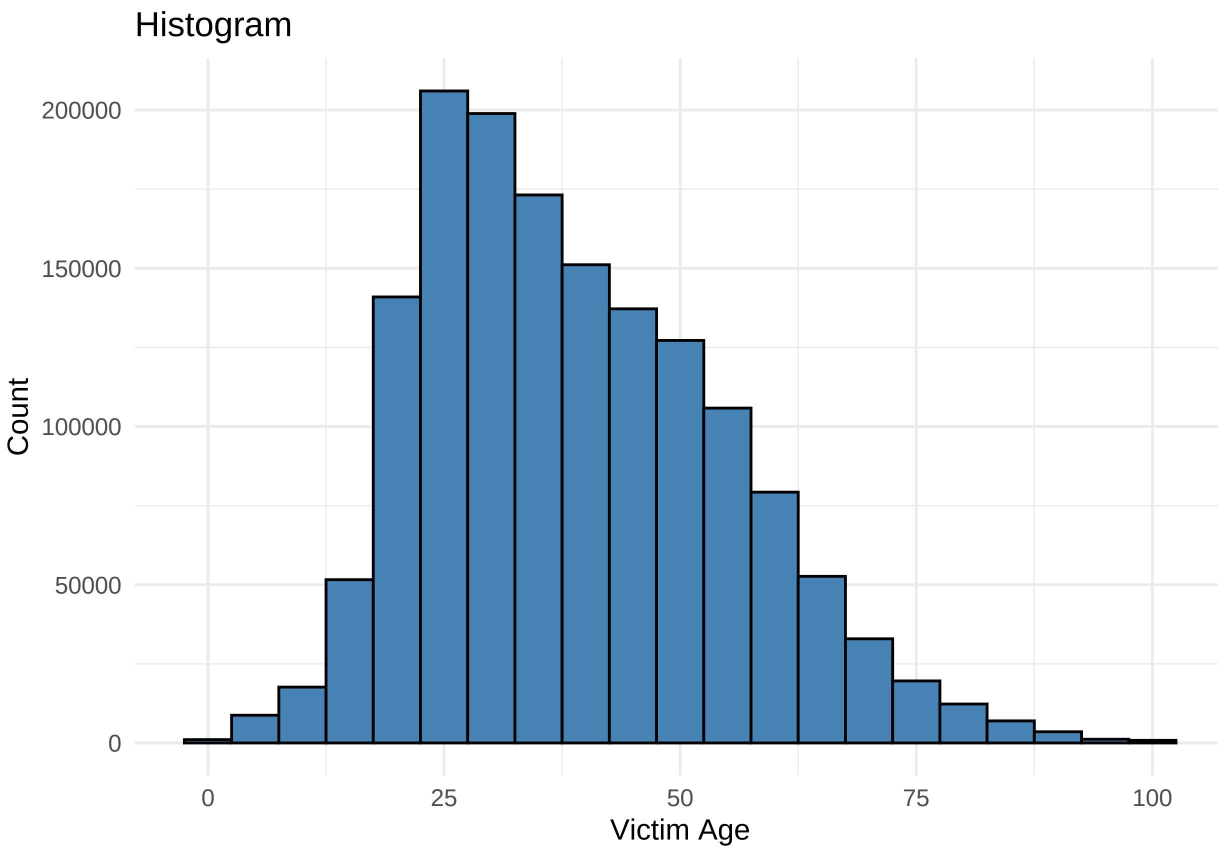



```
# Number of Crimes Per Victim Sex by Case Status
ggplot(clean_data, aes(x = Vict.Sex, fill = Legal_Action)) +
    geom_bar(color = "black", position = "dodge") +
    labs(title = "Number of Crimes Per Victim Sex", x = "Victim Sex", y = "Number of Crimes") +
    theme_minimal()
```

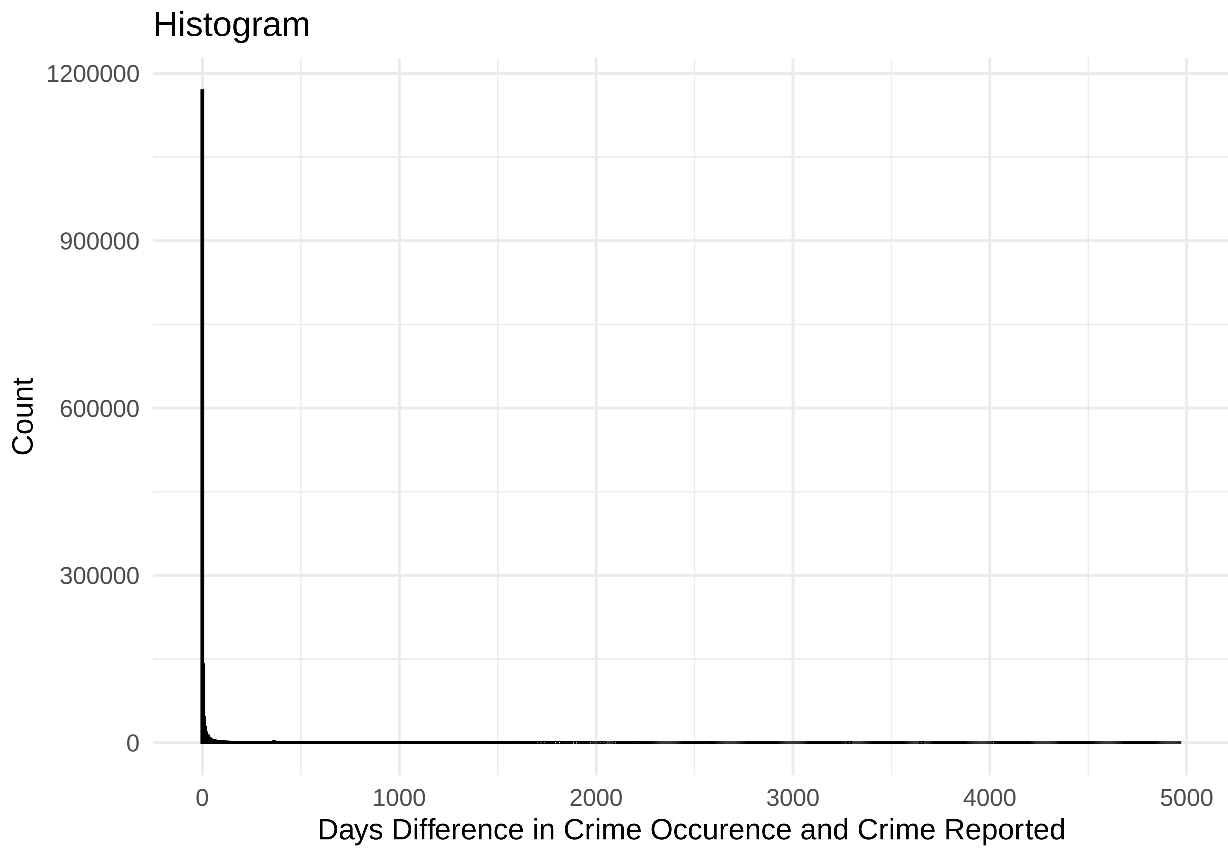


EDA: Box Plots/Histograms for Continuous

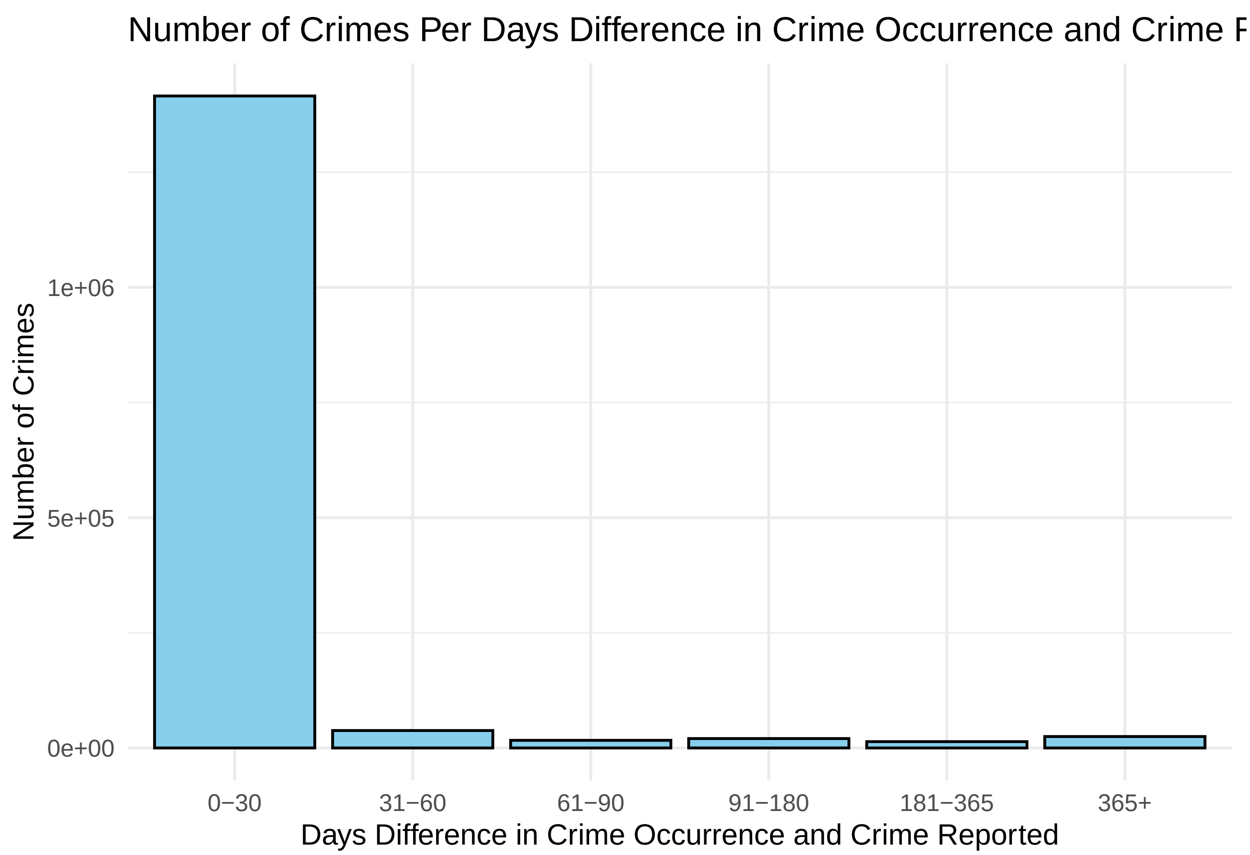
```
# Victim Age histogram
ggplot(clean_data, aes(x = Vict.Age)) +
    geom_histogram(binwidth = 5, fill = "steelblue", color = "black") +
    labs(title = "Histogram", x = "Victim Age", y = "Count") +
    theme_minimal()
```




```
# Days Difference in Crime Occurrence and Crime Reported histogram
ggplot(clean_data, aes(x = date_occur_report_difference)) +
    geom_histogram(binwidth = 5, fill = "steelblue", color = "black") +
    labs(title = "Histogram", x = "Days Difference in Crime Occurence and Crime Reported", y = "Count")
    theme_minimal()
```




```r
#EDA Reveals date_occur_report_difference should be categorized
clean_data$date_occur_report_difference <- cut(clean_data$date_occur_report_difference,
                             breaks = c(0, 30, 60, 90, 180, 365, Inf),
                             labels = c("0-30", "31-60", "61-90", "91-180", "181-365", "365+"),
                             right = FALSE)

#Number of Crimes Per Days Difference in Crime Occurrence and Crime Reported Count Plot
ggplot(clean_data, aes(x = date_occur_report_difference)) +
    geom_bar(position = position_dodge(width = 0.4),color = "black", fill = "skyblue") +
    theme_minimal() +
    labs(title = "Number of Crimes Per Days Difference in Crime Occurrence and Crime Reported Count Plo
         x = "Days Difference in Crime Occurrence and Crime Reported", y = "Number of Crimes")
```



Subsetting bootstraps defining bootstrap function

```
set.seed(123)
# Randomly shuffling the data and dividing into train/test
clean_data <- clean_data[sample(nrow(clean_data)), ]


clean_data_indexes <- sample(2, nrow(clean_data),
                             replace = TRUE, prob = c(0.8,0.2))
clean_data_train <- clean_data[clean_data_indexes==1,]
clean_data_test <- clean_data[clean_data_indexes==2,]


#Subsetting Train into 31 datasets
clean_data_train$Group <- sample(1:31, size = nrow(clean_data_train), replace = T)
df_subsets_train <- split(clean_data_train, clean_data_train$Group)

#Subsetting Test into 31 datasets
clean_data_test$Group <- sample(1:31, size = nrow(clean_data_test), replace = T)
clean_data_test_list <- split(clean_data_test, clean_data_test$Group)

# Define oversampling function
oversample_data <- function(data) {
```

```
    return(ovun.sample(Legal_Action ~ ., data = data, p=0.5)$data)
}
```

Intializing Parallel and Bootstrapping

```
unregister_dopar <- function() {
    env <- foreach:::.foreachGlobals
    rm(list=ls(name=env), pos=env)
}
unregister_dopar()

#initializing parallel processing
num_cores <- detectCores() - 1
cl <- makePSOCKcluster(num_cores)
registerDoParallel(cl)

oversampled_data_list <- foreach(data = df_subsets_train, .packages = c("ROSE")) %dopar% {
    oversample_data(data)
}

#Calling 31st dataset
extra_clean_train <- oversampled_data_list[[31]]
```

Running Logistic Regression

```
library(pROC)
```

```
## Type 'citation("pROC")' for a citation.
```

```
##
## Attaching package: 'pROC'
```

```
## The following objects are masked from 'package:stats':
##
##     cov, smooth, var
```

```
trControl_log <- trainControl(method = 'repeatedcv',
                          number = 5,
                          repeats =  5,
                          search = 'random')

logit_gridsearch <- caret::train( Legal_Action ~ AREA + Part.1.2 + Crm.Cd + Vict.Age +
                               Vict.Sex + Premis.Cd + Weapon.Used.Cd +
                               date_occur_report_difference + time_occur_cat + Vict.Descent.Description
                           data = extra_clean_train,
                           method = 'glmnet',
```

```r
                              trControl = trControl_log,
                              family = 'binomial',
                              metric = 'Accuracy')
#Optimal Parameters
logit_gridsearch$bestTune
```

```
##        alpha   lambda
## 1 0.00126282 6.382388
```

```r
#Creating empty lists
accuracy_vector_logit <- numeric(length(1:30))
conf_mat_list_logit <- vector("list",length(1:30))
auc_list_logit <- numeric(length(1:30))

results_logit <- foreach (i = 1:30,
                         .packages = c("caret", "dplyr", "pROC")) %dopar% {
                             logit_alpha <- logit_gridsearch$bestTune$alpha
                             logit_lambda<- logit_gridsearch$bestTune$lambda

                             # Training the Random Forest model 30 times w/optimal parameters
                             logit_model <- caret::train(
                                 Legal_Action ~ AREA + Part.1.2 + Crm.Cd + Vict.Age + Vict.Sex + Premis.C
                                 data = oversampled_data_list[[i]],
                                 method = "glmnet",
                                 trControl = trainControl(method = "none"),
                                 tuneGrid = expand.grid(alpha = logit_alpha, lambda = logit_lambda))

                             #Confusion Matrix of final model predicting Resolved Case
                             predictions_logit <- predict(logit_model, newdata = clean_data_test_list[[i]]
                             confusion_mat_logit <- confusionMatrix(predictions_logit, clean_data_test_li

                             accuracy_vector_logit[i] <- confusion_mat_logit$overall['Accuracy']

                             #Predictions with probabilities
                             logit_auc_pred <- predict(logit_model, clean_data_test_list[[i]], 'prob')
                             logit_auc_pred <- cbind(logit_auc_pred[,1],as.character(clean_data_test_list
                             logit_auc_pred <- as.data.frame(logit_auc_pred)
                             logit_auc_pred$V2 <- as.factor(logit_auc_pred$V2)
                             logit_auc_pred$V1 <- as.numeric(logit_auc_pred$V1)

                             #AUC
                             logit_auc_roc <- roc(logit_auc_pred$V2, logit_auc_pred$V1)
                             auc_list_logit <- logit_auc_roc$auc[1]

                             list(
                                 confusion_matrix = confusion_mat_logit,
                                 accuracy = confusion_mat_logit$overall['Accuracy'],
                                 auc = auc_list_logit
                             )
                         }

for (i in 1:length(results_logit)){
    conf_mat_list_logit[[i]] <- results_logit[[i]]$confusion_matrix
```

```r
    accuracy_vector_logit[i] <- results_logit[[i]]$accuracy
    auc_list_logit[[i]] <- results_logit[[i]]$auc

}

accuracy_vector_logit <- unlist(accuracy_vector_logit)

cat("Creating 95% Confidence Interval for Accuracy of Model
    predicting if case was resolved\n")
```

```
## Creating 95% Confidence Interval for Accuracy of Model
##     predicting if case was resolved
```

```r
mean_logit_vec  <- mean(accuracy_vector_logit)

#standard error
std_error_logit <- sd(accuracy_vector_logit) / sqrt(30)

#critical t value for 95% CI
critical_value_logit <- qt(0.975, df = 30 - 1)

#confidence interval
lower_ci_logit <- mean_logit_vec - (critical_value_logit * std_error_logit)
upper_ci_logit <- mean_logit_vec + (critical_value_logit * std_error_logit)

# 95% CI
cat("95% Confidence Interval Predicting if Case Resolved: [", lower_ci_logit, ", ", upper_ci_logit, "]\r
```

```
## 95% Confidence Interval Predicting if Case Resolved: [ 0.7505613 ,  0.7552972 ]
```

```r
#Finding Index of accuracy value closest to mean
closest_index_logit <- which.min(abs(accuracy_vector_logit - mean_logit_vec))

#Confusion Matrix of Model closest to mean accuracy
print(conf_mat_list_logit[closest_index_logit])
```

```
## [[1]]
## Confusion Matrix and Statistics
##
##           Reference
## Prediction    0    1
##          0 5570  547
##          1 1879 1813
##
##                Accuracy : 0.7527
##                  95% CI : (0.744, 0.7612)
##     No Information Rate : 0.7594
##     P-Value [Acc > NIR] : 0.9415
##
##                   Kappa : 0.4326
##
##  Mcnemar's Test P-Value : <2e-16
```

```
##
##             Sensitivity : 0.7478
##             Specificity : 0.7682
##          Pos Pred Value : 0.9106
##          Neg Pred Value : 0.4911
##              Prevalence : 0.7594
##          Detection Rate : 0.5678
##    Detection Prevalence : 0.6236
##       Balanced Accuracy : 0.7580
##
##        'Positive' Class : 0
##
```

```
#AUC of Model closest to mean
print(auc_list_logit[closest_index_logit])
```

```
## [1] 0.8133538
```

Running Neural Network

```
library(NeuralNetTools)
library(nnet)
library(NeuralSens)
###          ###
###Neural Net###
###          ###

tr_control_nnet <- trainControl(
    method = "cv",
    number = 5,
    allowParallel = TRUE)

#Neural Net
fit.nnet <- caret::train(Legal_Action ~ AREA + Part.1.2 + Crm.Cd + Vict.Age + Vict.Sex + Premis.Cd + Wea
                         data = extra_clean_train,
                         method = "nnet",
                         trControl = tr_control_nnet,
                         tuneGrid = expand.grid(size=c(1:5),
                                                decay=c(0,0.1,0.01)),
                         skip = TRUE)
```

```
## # weights:  804
## initial  value 2510809.457301
## iter  10 value 25156.622107
## iter  20 value 21960.221473
## iter  30 value 20907.672412
## iter  40 value 20249.584303
## iter  50 value 19794.467096
## iter  60 value 19599.178388
## iter  70 value 19470.260566
```

```
## iter  80 value 19376.159436
## iter  90 value 19288.971679
## iter 100 value 19223.880345
## final  value 19223.880345
## stopped after 100 iterations
```

```
pred.nnet <- predict(fit.nnet,clean_data_test_list[[31]])
confusionMatrix(table(clean_data_test_list[[31]]$Legal_Action, pred.nnet))
```

```
## Confusion Matrix and Statistics
##
##    pred.nnet
##        0    1
##   0 5530 1814
##   1  560 1840
##
##                Accuracy : 0.7564
##                  95% CI : (0.7477, 0.7649)
##     No Information Rate : 0.625
##     P-Value [Acc > NIR] : < 2.2e-16
##
##                   Kappa : 0.4419
##
##  Mcnemar's Test P-Value : < 2.2e-16
##
##             Sensitivity : 0.9080
##             Specificity : 0.5036
##          Pos Pred Value : 0.7530
##          Neg Pred Value : 0.7667
##              Prevalence : 0.6250
##          Detection Rate : 0.5675
##    Detection Prevalence : 0.7537
##       Balanced Accuracy : 0.7058
##
##        'Positive' Class : 0
##
```

```
#Optimal Parameters
fit.nnet$bestTune
```

```
##    size decay
## 12    4   0.1
```

```
#Creating empty lists
accuracy_vector_nnet <- numeric(length(1:30))
conf_mat_list_nnet <- vector("list",length(1:30))
variable_importance_list_nnet <- vector("list",length(1:30))


tr_control2_nnet <- trainControl(
    method = "none",
    allowParallel = TRUE)
```

```r
results_nnet <- foreach (i = 1:30,
                        .packages = c("caret", "dplyr", "nnet")) %dopar% {
                            num_neurons <- fit.nnet$bestTune$size
                            decay_rate <- fit.nnet$bestTune$decay

                            # Training the neural net model 30 times w/1 neuron
                            nnet_model <- caret::train(
                                Legal_Action ~ AREA + Part.1.2 + Crm.Cd + Vict.Age + Vict.Sex + Premis.Cd
                                data = oversampled_data_list[[i]],
                                method = "nnet",
                                tuneGrid = expand.grid(size=num_neurons,decay=decay_rate),
                                trControl = tr_control2_nnet,
                                skip = TRUE
                            )

                            #Confusion Matrix of final model predicting Resolved Case
                            predictions_nnet <- predict(nnet_model, newdata = clean_data_test_list[[i]])
                            confusion_mat_nnet <- confusionMatrix(predictions_nnet, clean_data_test_list

                            accuracy_vector_nnet[i] <- confusion_mat_nnet$overall['Accuracy']

                            var_importance_nnet <- varImp(nnet_model)
                            variable_importance_list_nnet[[i]] <- var_importance_nnet

                            list(
                                confusion_matrix = confusion_mat_nnet,
                                accuracy = confusion_mat_nnet$overall['Accuracy'],
                                variable_importance = var_importance_nnet
                            )
                        }

for (i in 1:length(results_nnet)){
    conf_mat_list_nnet[[i]] <- results_nnet[[i]]$confusion_matrix
    accuracy_vector_nnet[i] <- results_nnet[[i]]$accuracy
    variable_importance_list_nnet[[i]] <- results_nnet[[i]]$variable_importance

}
accuracy_vector_nnet <- unlist(accuracy_vector_nnet)

cat("Creating 95% Confidence Interval for Accuracy of Model
    predicting if case was resolved")
```

```
## Creating 95% Confidence Interval for Accuracy of Model
##     predicting if case was resolved
```

```r
mean_nnet_vec  <- mean(accuracy_vector_nnet)

#standard error
std_error_nnet <- sd(accuracy_vector_nnet) / sqrt(30)

#critical t value for 95% CI
critical_value_nnet <- qt(0.975, df = 30 - 1)
```

```r
#confidence interval
lower_ci_nnet <- mean_nnet_vec - (critical_value_nnet * std_error_nnet)
upper_ci_nnet <- mean_nnet_vec + (critical_value_nnet * std_error_nnet)

# 95% CI
cat("95% Confidence Interval Predicting if Case Resolved: [", lower_ci_nnet, ", ", upper_ci_nnet, "]\n")
```

```
## 95% Confidence Interval Predicting if Case Resolved: [ 0.7602532 ,  0.7647787 ]
```

```r
#Finding Index of accuracy value closest to mean
closest_index_nnet <- which.min(abs(accuracy_vector_nnet - mean_nnet_vec))


#Confusion Matrix of Model closest to mean accuracy
print(conf_mat_list_nnet[closest_index_nnet])
```

```
## [[1]]
## Confusion Matrix and Statistics
##
##           Reference
## Prediction    0    1
##          0 5637  562
##          1 1752 1806
##
##                Accuracy : 0.7628
##                  95% CI : (0.7543, 0.7712)
##     No Information Rate : 0.7573
##     P-Value [Acc > NIR] : 0.103
##
##                   Kappa : 0.4489
##
##  Mcnemar's Test P-Value : <2e-16
##
##             Sensitivity : 0.7629
##             Specificity : 0.7627
##          Pos Pred Value : 0.9093
##          Neg Pred Value : 0.5076
##              Prevalence : 0.7573
##          Detection Rate : 0.5777
##    Detection Prevalence : 0.6353
##       Balanced Accuracy : 0.7628
##
##        'Positive' Class : 0
##
```

Running Naive Bayes

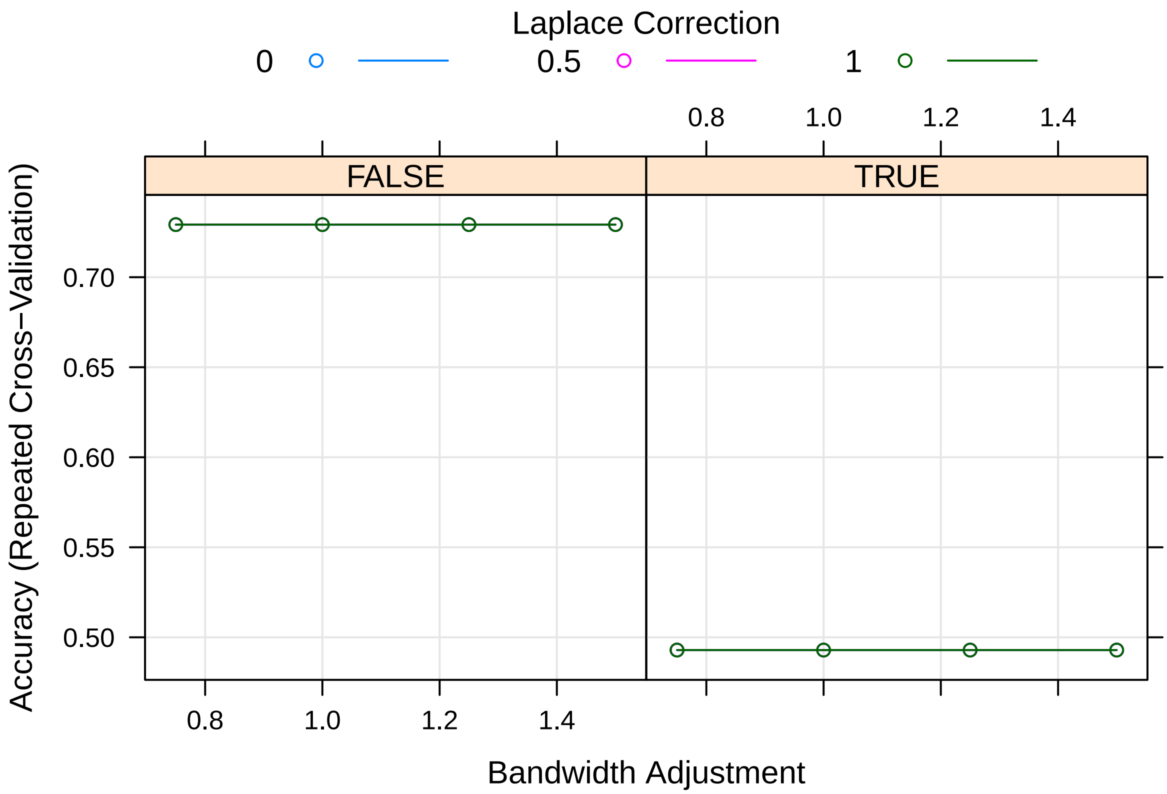
```r
library(naivebayes)
```

```
## naivebayes 1.0.0 loaded

## For more information please visit:

## https://majkamichal.github.io/naivebayes/
```

```r
extra_clean_train_nb <- extra_clean_train
extra_clean_train_nb <- extra_clean_train_nb[,-12]

nb_grid <- expand.grid(usekernel = c(TRUE, FALSE),
                       laplace = c(0, 0.5, 1),
                       adjust = c(0.75, 1, 1.25, 1.5))

tr_control_nb <- trainControl(
    method = "repeatedcv",
    number = 10,
    repeats = 3,
    allowParallel = TRUE
)

nb_fit <- caret::train(
    Legal_Action ~ .,
    data = extra_clean_train_nb,
    method = "naive_bayes",
    trControl = tr_control_nb,
    tuneGrid = nb_grid
)

#Checking model optimal parameters
nb_fit$finalModel$tuneValue
```

```
##   laplace usekernel adjust
## 1       0     FALSE   0.75
```

```r
#Visualizing tuning process
nb_fit_plot <- plot(nb_fit)
nb_fit_plot
```




```r
# Performing classification
predictions_nb1 <- predict(nb_fit, newdata = clean_data_test_list[[31]])
confusion_mat_nb1 <- confusionMatrix(predictions_nb1, clean_data_test_list[[31]]$Legal_Action)

#Creating accuracy and confusion matrices vectors
accuracy_vector_nb <- numeric(length(1:30))
conf_mat_list_nb <- vector("list",length(1:30))

results_nb <- foreach (i = 1:30,
                        .packages = c("caret", "dplyr", "naivebayes")) %dopar% {
                            #Optimal Parameters
                            laplace_param <- nb_fit$finalModel$tuneValue$laplace
                            usekernel_param <- nb_fit$finalModel$tuneValue$usekernel
                            adjust_param <- nb_fit$finalModel$tuneValue$adjust

                            # Training the Naive Bayes model 30 times w/optimal parameters
                            nb_model <- caret::train(
                                Legal_Action ~ AREA + Part.1.2 + Crm.Cd + Vict.Age + Vict.Sex + Premis.C
                                data = oversampled_data_list[[i]],
                                method = "naive_bayes",
                                trControl = trainControl(method = "none"),
                                tuneGrid = expand.grid(.laplace = laplace_param, .usekernel = usekernel_
                            )

                            #Confusion Matrix of final model predicting Resolved Case
                            predictions_nb <- predict(nb_model, newdata = clean_data_test_list[[i]])
                            confusion_mat_nb <- confusionMatrix(predictions_nb, clean_data_test_list[[i
```

```r
                            accuracy_vector_nb[i] <- confusion_mat_nb$overall['Accuracy']

                            list(confusion_matrix = confusion_mat_nb,
                                 accuracy = confusion_mat_nb$overall['Accuracy']
                            )
                        }

for (i in 1:length(results_nb)){
    conf_mat_list_nb[[i]] <- results_nb[[i]]$confusion_matrix
    accuracy_vector_nb[i] <- results_nb[[i]]$accuracy
}
accuracy_vector_nb <- unlist(accuracy_vector_nb)


cat("Creating 95% Confidence Interval for Accuracy of Model
    predicting if case was resolved\n")
```

```
## Creating 95% Confidence Interval for Accuracy of Model
##     predicting if case was resolved
```

```r
mean_nb_vec  <- mean(accuracy_vector_nb)

#standard error
std_error_nb <- sd(accuracy_vector_nb) / sqrt(30)

#critical t value for 95% CI
critical_value_nb <- qt(0.975, df = 30 - 1)

#confidence interval
lower_ci_nb <- mean_nb_vec - (critical_value_nb * std_error_nb)
upper_ci_nb <- mean_nb_vec + (critical_value_nb * std_error_nb)

# 95% CI
cat("95% Confidence Interval Predicting if Case Resolved: [", lower_ci_nb, ", ", upper_ci_nb, "]\n")
```

```
## 95% Confidence Interval Predicting if Case Resolved: [ 0.6616566 ,  0.6898714 ]
```

```r
#Finding Index of accuracy value closest to mean
closest_index_nb <- which.min(abs(accuracy_vector_nb - mean_nb_vec))


#Confusion Matrix of Model closest to mean accuracy
print(conf_mat_list_nb[closest_index_nb])
```

```
## [[1]]
## Confusion Matrix and Statistics
##
##           Reference
## Prediction    0    1
##          0 4798  428
##          1 2764 1983
##
```

```
##                Accuracy : 0.6799
##                  95% CI : (0.6707, 0.6891)
##     No Information Rate : 0.7582
##     P-Value [Acc > NIR] : 1
##
##                   Kappa : 0.3436
##
##  Mcnemar's Test P-Value : <2e-16
##
##             Sensitivity : 0.6345
##             Specificity : 0.8225
##          Pos Pred Value : 0.9181
##          Neg Pred Value : 0.4177
##              Prevalence : 0.7582
##          Detection Rate : 0.4811
##    Detection Prevalence : 0.5240
##       Balanced Accuracy : 0.7285
##
##        'Positive' Class : 0
##
```