NYPD Shooting Incident Data Report

4/3/2024

A list of all the shooting incidents that took place in New York City between 2006 and the end of the preceding year.
This is a summary of every gunshot that happened in New York City between the end of the preceding year and 2006. Every quarter, this data is manually removed and sent to the Office of Management Analysis and Planning for evaluation before being made available on the NYPD website. Every record depicts a shooting incident that happened in New York City and contains details on the incident, including its date, time, and location. Furthermore, the demographics of the suspect and victim are also mentioned. The public can utilize this data to investigate the nature of shootings and criminal behavior.

Step 0: Import Library

```
#install.packages("tidyverse")
library(tidyverse) library(lubridate)
```

Step 1: Load Data

- read_csv() reads comma delimited files, read_csv2() reads semicolon separated files (common in countries where , is used as the decimal place), read_tsv() reads tab delimited files, and read_delim() reads in files with any delimiter.

```
df = read_csv("https://data.cityofnewyork.us/api/views/833y-fsy8/rows.csv?accessType=DOWNLOAD")
```

```
##
## --· Column specification ##     --------------------------------------------------------------
cols(
##      INCIDENT_KEY = col_double(), ##
       OCCUR_DATE = col_character(),
##      OCCUR_TIME = col_time(format = ""), ##
       BORO = col_character(),
##      PRECINCT = col_double(),
##      JURISDICTION_CODE = col_double(), ##
       LOCATION_DESC = col_character(),
##      STATISTICAL_MURDER_FLAG = col_logical(), ##
       PERP_AGE_GROUP = col_character(),
##      PERP_SEX = col_character(), ##
       PERP_RACE = col_character(),
##      VIC_AGE_GROUP = col_character(), ##
       VIC_SEX = col_character(),
```

```
##      VIC_RACE = col_character(), ##
        X_COORD_CD = col_number(), ##
        Y_COORD_CD = col_number(), ##
        Latitude = col_double(),
##    Longitude   =   col_double(),    ##
Lon_Lat = col_character() ## )
```

```
head(df)
```

```
## # A tibble: 6 x 19
##   INCIDENT_KEY OCCUR_DATE OCCUR_TIME BORO          PRECINCT JURISDICTION_CODE
##          <dbl> <chr>      <time>     <chr>            <dbl>             <dbl>
## 1    201575314 08/23/2019 22:10      QUEENS             103                 0
## 2    205748546 11/27/2019 15:54      BRONX               40                 0
## 3    193118596 02/02/2019 19:40      MANHATTAN           23                 0
## 4    204192600 10/24/2019 00:52      STATEN ISLAND      121                 0
## 5    201483468 08/22/2019 18:03      BRONX               46                 0
## 6    198255460 06/07/2019 17:50      BROOKLYN            73                 0
## # ... with 13 more variables: LOCATION_DESC <chr>,
## #     STATISTICAL_MURDER_FLAG <lgl>, PERP_AGE_GROUP <chr>, PERP_SEX <chr>, ## #
          PERP_RACE <chr>, VIC_AGE_GROUP <chr>, VIC_SEX <chr>, VIC_RACE <chr>,
## #     X_COORD_CD <dbl>, Y_COORD_CD <dbl>, Latitude <dbl>, Longitude <dbl>, ## #
          Lon_Lat <chr>
```

Step 2: Tidy and Transform Data

Let's first eliminate the columns I do not need for this assignment, which are: **PRECINCT**,**JURISDICTION_CODE**,**LO X_COORD_CD**, **Y_COORD_CD**, and **Lon_Lat**.

```
df_2 = df %>% select(INCIDENT_KEY,
                     OCCUR_DATE,
                     OCCUR_TIME,
                     BORO,
                     STATISTICAL_MURDER_FLAG,
                     PERP_AGE_GROUP, PERP_SEX,
                     PERP_RACE,
                     VIC_AGE_GROUP,
                     VIC_SEX, VIC_RACE,
                     Latitude,
                     Longitude)

# Return the column name along with the missing values
lapply(df_2, function(x) sum(is.na(x)))
```

```
## $INCIDENT_KEY ##
[1] 0
##
## $OCCUR_DATE
## [1] 0
```

```
##
##$OCCUR_TIME
## [1] 0
##
## $BORO
##[1] 0 ##
##$STATISTICAL_MURDER_FLAG
## [1] 0
##
##$PERP_AGE_GROUP
## [1] 8459
##
##$PERP_SEX
## [1] 8425 ##
##$PERP_RACE
## [1] 8425 ##
##$VIC_AGE_GROUP
## [1] 0
##
##$VIC_SEX ##
[1] 0
##
##$VIC_RACE
## [1] 0
##
##$Latitude ##
[1] 0
##
##$Longitude ##
[1] 0
```

Understanding the reasons why data are missing is important for handling the remaining data correctly. There's a fair amount of unidentifiable data on perpetrators (age, race, or sex.) Those cases are possibly still active and ongoing investigation. In fear of missing meaningful information, I handle this group of missing data by calling them as another group of "Unknown".

Key observations on data type conversion are:

- **INCIDENT_KEY** should be treated as a string.
- **BORO** should be treated as a factor.
- **PERP_AGE_GROUP** should be treated as a factor.
- **PERP_SEX** should be treated as a factor.
- **PERP_RACE** should be treated as a factor.
- **VIC_AGE_GROUP** should be treated as a factor.
- **VIC_SEX** should be treated as a factor.
- **VIC_RACE** should be treated as a factor.

```
# Tidy and transform data
df_2 = df_2 %>%
  replace_na(list(PERP_AGE_GROUP = "Unknown", PERP_SEX = "Unknown", PERP_RACE = "Unknown"))
```

```
# Remove extreme values in data
df_2 = subset(df_2, PERP_AGE_GROUP!="1020" & PERP_AGE_GROUP!="224" & PERP_AGE_GROUP!="940")

df_2$PERP_AGE_GROUP = recode(df_2$PERP_AGE_GROUP, UNKNOWN = "Unknown") df_2$PERP_SEX =
recode(df_2$PERP_SEX, U = "Unknown")
df_2$PERP_RACE = recode(df_2$PERP_RACE, UNKNOWN = "Unknown")
df_2$VIC_SEX        = recode(df_2$VIC_SEX, U = "Unknown") df_2$VIC_RACE
                    = recode(df_2$VIC_RACE, UNKNOWN = "Unknown")
df_2$INCIDENT_KEY = as.character(df_2$INCIDENT_KEY) df_2$BORO =
as.factor(df_2$BORO)
df_2$PERP_AGE_GROUP = as.factor(df_2$PERP_AGE_GROUP)
df_2$PERP_SEX = as.factor(df_2$PERP_SEX) df_2$PERP_RACE =
as.factor(df_2$PERP_RACE) df_2$VIC_AGE_GROUP =
as.factor(df_2$VIC_AGE_GROUP) df_2$VIC_SEX =
as.factor(df_2$VIC_SEX)
df_2$VIC_RACE = as.factor(df_2$VIC_RACE)

# Return summary statistics
summary(df_2)
```

```
##  INCIDENT_KEY        OCCUR_DATE          OCCUR_TIME                        BORO
## Length:23565      Length:23565      Length:23565     BRONX                  6698
## Class :character  Class :character  Class1:hms       BROOKLYN               9721
##   Mode   :character    Mode   :character    Class2:difftime    MANHATTAN      2921  ##
                                                       Mode  :numeric    QUEENS         3527
##                                                                     STATEN ISLAND: 698
##
##
## STATISTICAL_MURDER_FLAG PERP_AGE_GROUP        PERP_SEX
##  Mode :logical             <18      : 1354      F        :  334
##  FALSE:19077               18-24  : 5448        M          13302
##  TRUE :4488                25-44  : 4613        Unknown: 9929
##                            45-64  :  481
##                            65+      :    54
##                            Unknown:11615
##
##                              PERP_RACE        VIC_AGE_GROUP        VIC_SEX
##   AMERICAN INDIAN/ALASKAN  NATIVE:       2    <18       : 2525      F          : 2195
##   ASIAN / PACIFIC ISLANDER             :  120    18-24  : 8999      M         :21350
##   BLACK                                : 9854    25-44     :10285   Unknown:      20
##   BLACK HISPANIC                       : 1081    45-64      : 1536
##   Unknown                              :10294    65+        :  155
##   WHITE                                :  255    UNKNOWN:    65
##   WHITE HISPANIC                       : 1959
##                               VIC_RACE           Latitude            Longitude
##   AMERICAN INDIAN/ALASKAN  NATIVE:       9    Min.      :40.51      Min.      :-74.25
##   ASIAN / PACIFIC ISLANDER             :  320    1st Qu.:40.67      1st Qu.:-73.94
##   BLACK                                :16845    Median :40.70      Median :-73.92
##   BLACK HISPANIC                       : 2244    Mean      :40.74      Mean      :-73.91
##   Unknown                              :  102    3rd Qu.:40.82      3rd Qu.:-73.88
##   WHITE                                :  615    Max.      :40.91      Max.      :-73.70
##   WHITE HISPANIC                       : 3430
```

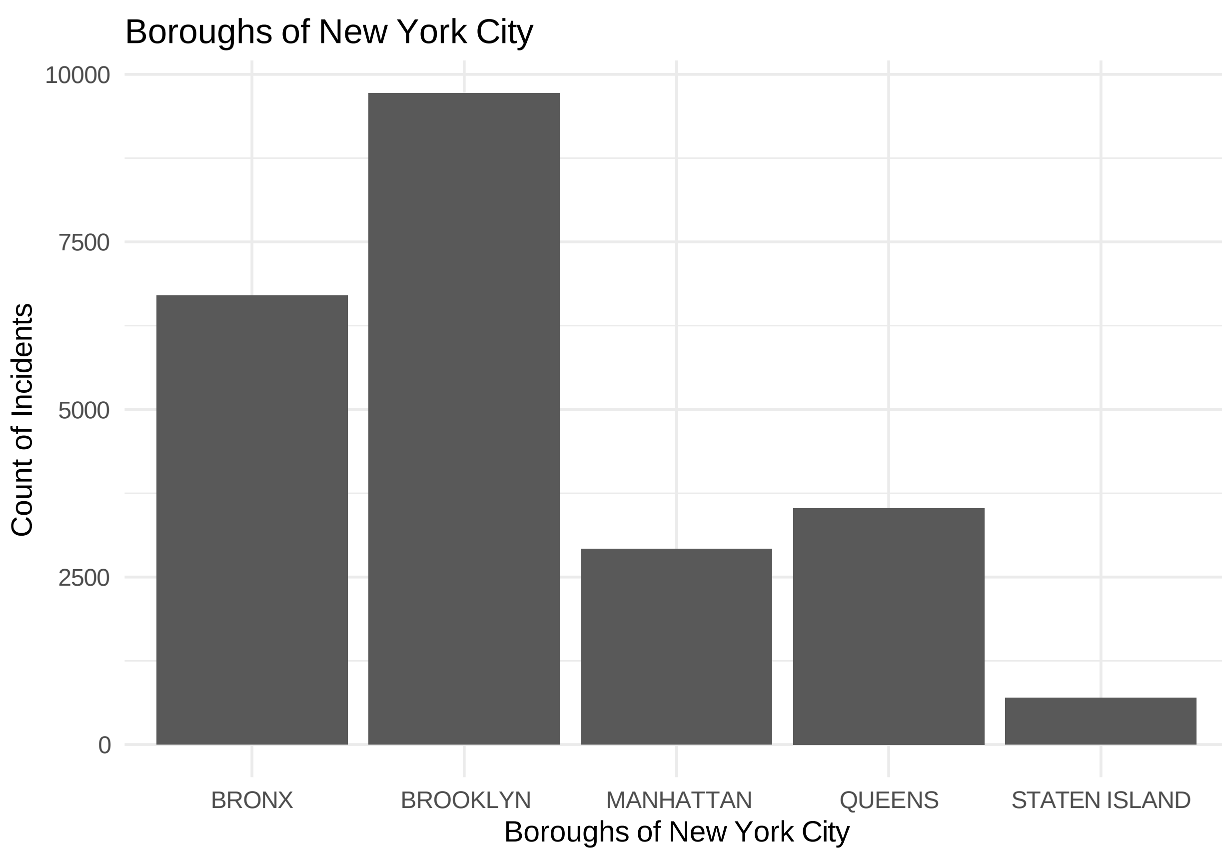
Step 3: Add Visualizations and Analysis

Research Question

1. Which part of New York has the most number of incidents? Of those incidents, how many are murder cases?

Brooklyn is the 1st in terms of the number of incidents, followed by Bronx and Queens respectively. Likewise, the number of murder cases follows the same pattern as that of incidents.

```
g <- ggplot(df_2, aes(x = BORO)) + geom_bar()
  +
  labs(title = "Boroughs of New York City", x =
         "Boroughs of New York City",
         y = "Count of Incidents") +
  theme_minimal()
g
```




```
table(df_2$BORO, df_2$STATISTICAL_MURDER_FLAG)
```

```
##
##                 FALSE TRUE
##   BRONX          5454 1244
##   BROOKLYN       7829 1892
```

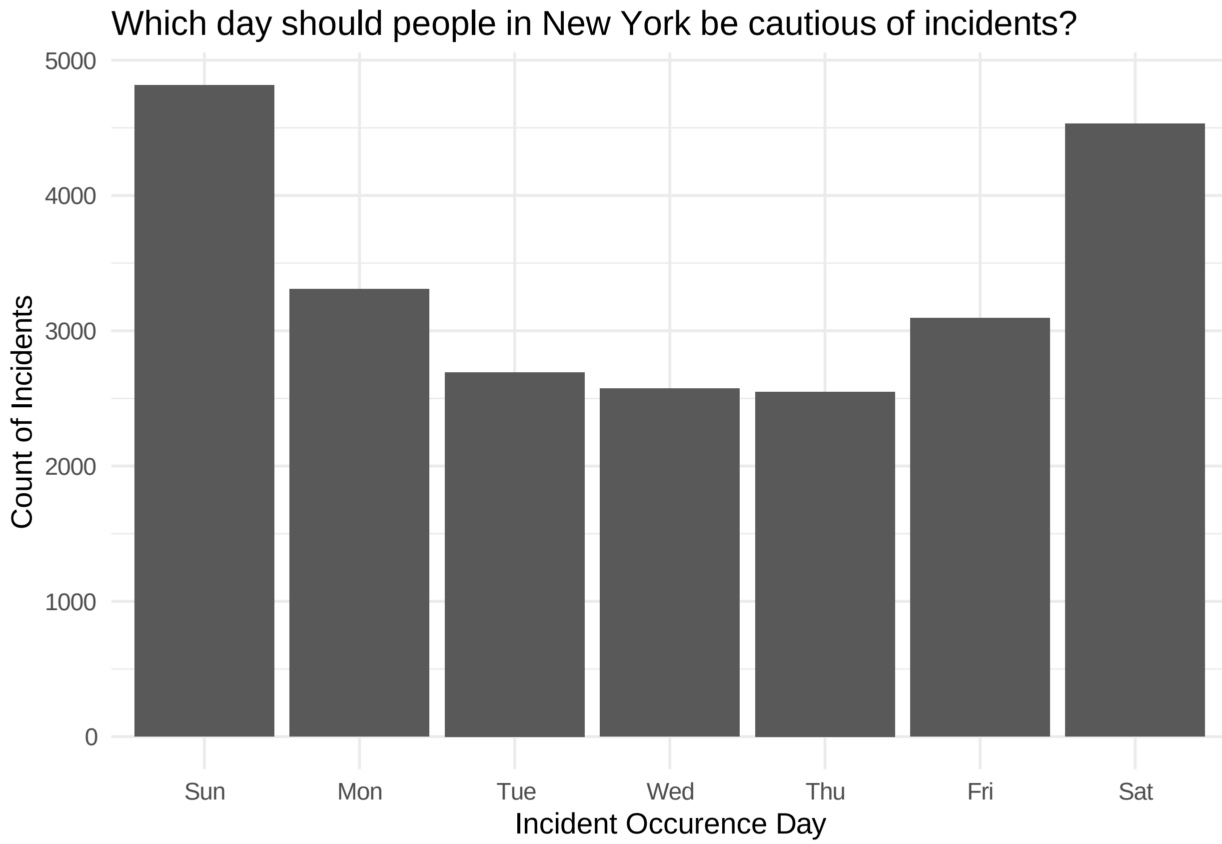
```
##      MANHATTAN        2409   512
##      QUEENS           2830   697
##      STATEN ISLAND     555   143
```

2. Which day and time should people in New York be cautious of falling into victims of crime?

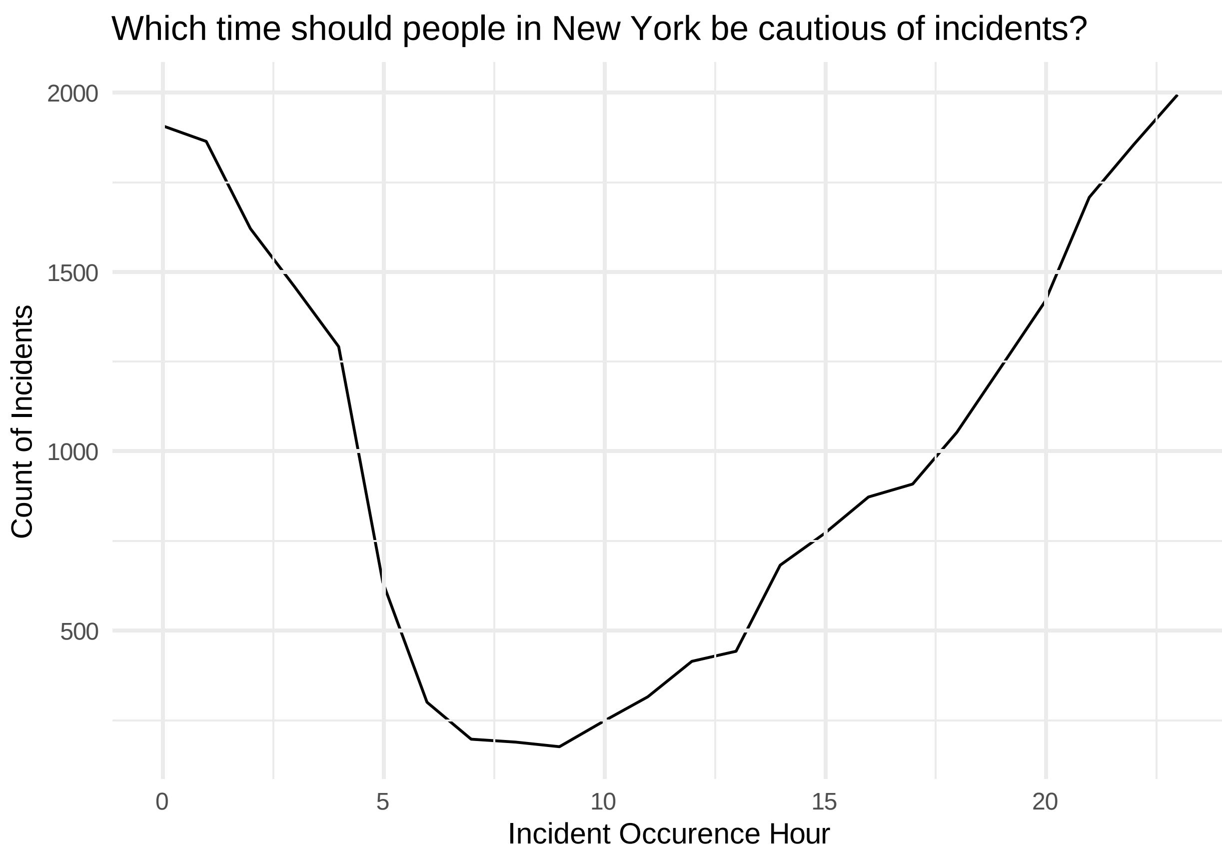
- Weekends in NYC have the most chances of incidents. Be cautious!
- Incidents historically happen in the evening and night time. If there's nothing urgent, recommend people staying at home!

```
df_2$OCCUR_DAY = mdy(df_2$OCCUR_DATE) df_2$OCCUR_DAY
= wday(df_2$OCCUR_DAY, label = TRUE)
df_2$OCCUR_HOUR = hour(hms(as.character(df_2$OCCUR_TIME)))

df_3 = df_2 %>%
  group_by(OCCUR_DAY) %>% count()

df_4 = df_2 %>%
  group_by(OCCUR_HOUR) %>%
  count()
```

```
g <- ggplot(df_3, aes(x = OCCUR_DAY, y = n)) + geom_col() +
  labs(title = "Which day should people in New York be cautious of incidents?", x = "Incident
        Occurence Day",
        y = "Count of Incidents") +
  theme_minimal()
g
```




```
g <- ggplot(df_4, aes(x = OCCUR_HOUR, y = n)) + geom_line() +
  labs(title = "Which time should people in New York be cautious of incidents?", x = "Incident
        Occurence Hour",
        y = "Count of Incidents") +
  theme_minimal()
g
```



3. The Profile of Perpetrators and Victims

- There's a striking number of incidents in the age group of 25-44 and 18-24.
- Black and White Hispanic stood out in the number of incidents in Boroughs of New York City.
- There are significantly more incidents with Male than those of Female.

```
table(df_2$PERP_AGE_GROUP, df_2$VIC_AGE_GROUP)
```

```
##
##              <18 18-24 25-44 45-64  65+ UNKNOWN
##   <18        410   548   324    62    8       2
##   18-24      712  2447  1959   283   34      13
##   25-44      232  1291  2632   386   39      33
##   45-64       18    58   255   133   10       7
##   65+          0     1    22    21   10       0
##   Unknown   1153  4654  5093   651   54      10
```

```
table(df_2$PERP_SEX, df_2$VIC_SEX)
```

```
##
##                F     M Unknown
##   F           49   284       1
##   M         1414 11878      10
##   Unknown    732  9188       9
```

```
table(df_2$PERP_RACE, df_2$VIC_RACE)
```

```
##
##                                  AMERICAN INDIAN/ALASKAN NATIVE
##   AMERICAN INDIAN/ALASKAN NATIVE                              0
##   ASIAN / PACIFIC ISLANDER                                    0
##   BLACK                                                       4
##   BLACK HISPANIC                                              0
##   Unknown                                                     5
##   WHITE                                                       0
##   WHITE HISPANIC                                              0
##
##                                  ASIAN / PACIFIC ISLANDER BLACK BLACK HISPANIC
##   AMERICAN INDIAN/ALASKAN NATIVE                        0     2              0
##   ASIAN / PACIFIC ISLANDER                             38    37             12
##   BLACK                                               124  7825            676
##   BLACK HISPANIC                                       17   444            276
##   Unknown                                              99  7878            912
##   WHITE                                                11    29             18
##   WHITE HISPANIC                                       31   630            350
##
##                                  Unknown WHITE WHITE HISPANIC
##   AMERICAN INDIAN/ALASKAN NATIVE       0     0              0
##   ASIAN / PACIFIC ISLANDER             2    11             20
##   BLACK                               34   160           1031
##   BLACK HISPANIC                       6    31            307
##   Unknown                             46   179           1175
##   WHITE                                1   151             45
##   WHITE HISPANIC                      13    83            852
```

4. Building logistic regression model to predict if the incident is likely a murder case or not?

Logistic regression is an instance of classification technique that you can use to predict a qualitative response. I will use logistic regression models to estimate the probability that a murder case belongs to a particular profile, location, or date & time.

The output shows the coefficients, their standard errors, the z-statistic (sometimes called a Wald z-statistic), and the associated p-values. **PERP_SEXUnknown**, **PERP_AGE_GROUP45-64**, **PERP_AGE_GROUP65+**, **PERP_AGE_GROUPUnknown**, and **PERP_AGE_GROUP25-44** are statistically significant, as are the **latitude** and **longitude**. The logistic regression coefficients give the change in the log odds of the outcome for a one unit increase in the predictor variable.

- The person in the age group of 65+, versus a person whose age < 18, changes the log odds of murder by 1.03.

```
# Logistics Regression
glm.fit <- glm(STATISTICAL_MURDER_FLAG ~ PERP_RACE + PERP_SEX + PERP_AGE_GROUP + OCCUR_HOUR + OCCUR_DAY
summary(glm.fit)
```

```
##
## Call:
## glm(formula = STATISTICAL_MURDER_FLAG ~ PERP_RACE + PERP_SEX +
```

```
##          PERP_AGE_GROUP + OCCUR_HOUR + OCCUR_DAY + Latitude + Longitude, ##
            family = binomial, data = df_2)
##
## Deviance Residuals:
##      Min       1Q    Median       3Q       Max ## -1.9895   -
0.6692   -0.6156   -0.2267   2.9730 ##
## Coefficients:
##                                              Estimate  Std.  Error  z  value  Pr(>|z|)  ##
(Intercept)                                 46.6487856 86.8848399   0.537   0.5913
##   PERP_RACEASIAN  /  PACIFIC   ISLANDER     9.9583265   84.2371629     0.118     0.9059
##   PERP_RACEBLACK                            9.4739726   84.2369224     0.112     0.9105
## PERP_RACEBLACK HISPANIC                     9.3665415 84.2369569       0.111     0.9115
##  PERP_RACEUnknown                           8.8306675 84.2371713       0.105     0.9165
##  PERP_RACEWHITE                            10.1798523 84.2370262       0.121     0.9038
##  PERP_RACEWHITE HISPANIC                    9.6533960 84.2369353       0.115     0.9088
##  PERP_SEXM                                 -0.1624763  0.1294760  -1.255         0.2095
##  PERP_SEXUnknown                            2.6324936  0.2724963       9.661     < 2e-16  ***
##  PERP_AGE_GROUP18-24                        0.1507956  0.0788415       1.913     0.0558  .
##  PERP_AGE_GROUP25-44                        0.4889669  0.0788390       6.202     5.57e-10 ***
##  PERP_AGE_GROUP45-64                        0.8269393  0.1207340       6.849     7.42e-12 ***
##  PERP_AGE_GROUP65+                          1.0304833  0.2910766       3.540     0.0004  ***
##  PERP_AGE_GROUPUnknown                     -2.1879192  0.1705836 -12.826         < 2e-16  ***
##  OCCUR_HOUR                                -0.0028675  0.0020679  -1.387         0.1655
##  OCCUR_DAY.L                               -0.0501244  0.0415798  -1.205         0.2280
##  OCCUR_DAY.Q                               -0.1178332  0.0449146  -2.623         0.0087  **
##  OCCUR_DAY.C                               -0.0459558  0.0449878  -1.022         0.3070
##  OCCUR_DAY^4                               -0.0466743  0.0459089  -1.017         0.3093
##  OCCUR_DAY^5                               -0.0008623  0.0481348  -0.018         0.9857
##  OCCUR_DAY^6                               -0.0410963  0.0497679  -0.826         0.4089
##  Latitude                                  -0.4202647  0.1988285  -2.114         0.0345  *
##  Longitude                                  0.5459242  0.2506784       2.178     0.0294  *
##  ---
##  Signif. codes:   0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##  (Dispersion parameter for binomial family taken to be 1)
##
##      Null deviance: 22947   on 23564   degrees of freedom ## Residual
deviance: 22095  on 23542  degrees of freedom ## AIC: 22141
##
## Number of Fisher Scoring iterations: 9
```

Step 4: Identify Bias

In this discussion, the potential for fostering discrimination and implicit bias among individuals is evident. Drawing from my personal experience living near New York City, I might assume that the Bronx has the highest number of incidents and that they are more likely to involve women than men. However, it's imperative to substantiate these beliefs with data to ensure informed decision-making. It's fascinating to discover that Brooklyn tops the list in terms of incident numbers, followed by the Bronx and Queens, aligning with the pattern observed in murder cases. Additionally, there is a notable disparity in incidents between males and females. Relying solely on personal experience can lead to biased judgments, emphasizing the importance of data-driven validation. These findings resonate with CNN's report on the surge in hate crimes and shooting incidents in New York City, notably the 73% increase in shooting incidents for May 2021 compared to May 2020"

Additional Resources

- NYPD Shooting Incident Data (Historic) - CKAN
- NYC, Chicago see another wave of weekend gun violence
- Hate crimes, shooting incidents in New York City have surged since last year, NYPD data show - CNN