

DTSA 5301 - Project_1_NYPD

DTSA 5301 MSDS Student, Oct 2024

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Data Analysis Using NYPD Shooting Historic Data.

Loading NYPD Shooting Historic Data and Read.

The primary source of data for this project is publicly available from NYPD website.

A link for the same is here

Description of the data

From the description available on the website, data set contains list of every shooting incident that occurred in NYC going back to 2006 through the end of the previous calendar year, 2023. NYPD claims the data to be manually extracted every quarter and reviewed by the Office of Management Analysis and Planning before being posted on the NYPD website.

Lets read the data and inspect it ourselves.

```
#URL for the NYPD shooting data available in CSV
url_in <- "https://data.cityofnewyork.us/api/views/833y-fsy8/rows.csv?accessType=DOWNLOAD"

#Read in the csv
nypd_data <- read_csv(url_in, show_col_types = FALSE)
```

Inspect the data

```
#inspect the data to understand it better
dim(nypd_data)
```

```
## [1] 28562    21
```

```
colnames(nypd_data)
```

```
## [1] "INCIDENT_KEY"      "OCCUR_DATE"
## [3] "OCCUR_TIME"        "BORO"
## [5] "LOC_OF_OCCUR_DESC" "PRECINCT"
## [7] "JURISDICTION_CODE" "LOC_CLASSFCTN_DESC"
## [9] "LOCATION_DESC"      "STATISTICAL_MURDER_FLAG"
## [11] "PERP_AGE_GROUP"    "PERP_SEX"
## [13] "PERP_RACE"         "VIC_AGE_GROUP"
```

```
## [15] "VIC_SEX"          "VIC_RACE"
## [17] "X_COORD_CD"       "Y_COORD_CD"
## [19] "Latitude"         "Longitude"
## [21] "Lon_Lat"
```

```
summary(nypd_data)
```

```
## INCIDENT_KEY      OCCUR_DATE      OCCUR_TIME      BORO
## Min. : 9953245    Length:28562    Length:28562    Length:28562
## 1st Qu.: 65439914 Class :character Class1:hms      Class :character
## Median : 92711254 Mode  :character Class2:difftime Mode  :character
## Mean : 127405824      Mode :numeric
## 3rd Qu.: 203131993
## Max. : 279758069
##
## LOC_OF_OCCUR_DESC  PRECINCT      JURISDICTION_CODE LOC_CLASSFCTN_DESC
## Length:28562      Min. : 1.0    Min. :0.0000    Length:28562
## Class :character  1st Qu.: 44.0 1st Qu.:0.0000    Class :character
## Mode :character   Median : 67.0 Median :0.0000    Mode :character
##                  Mean : 65.5 Mean :0.3219
##                  3rd Qu.: 81.0 3rd Qu.:0.0000
##                  Max. :123.0 Max. :2.0000
##                  NA's :2
## LOCATION_DESC      STATISTICAL_MURDER_FLAG PERP_AGE_GROUP
## Length:28562      Mode :logical    Length:28562
## Class :character   FALSE:23036      Class :character
## Mode :character    TRUE :5526       Mode :character
##
##
##
## PERP_SEX          PERP_RACE          VIC_AGE_GROUP      VIC_SEX
## Length:28562      Length:28562      Length:28562      Length:28562
## Class :character   Class :character   Class :character   Class :character
## Mode :character    Mode :character    Mode :character    Mode :character
##
##
##
## VIC_RACE          X_COORD_CD      Y_COORD_CD      Latitude
## Length:28562      Min. : 914928    Min. :125757     Min. :40.51
## Class :character  1st Qu.:1000068  1st Qu.:182912    1st Qu.:40.67
## Mode :character   Median :1007772  Median :194901    Median :40.70
##                  Mean :1009424  Mean :208380      Mean :40.74
##                  3rd Qu.:1016807  3rd Qu.:239814    3rd Qu.:40.82
##                  Max. :1066815  Max. :271128      Max. :40.91
##                  NA's :59
## Longitude        Lon_Lat
## Min. : -74.25     Length:28562
## 1st Qu.: -73.94    Class :character
## Median : -73.92    Mode :character
## Mean : -73.91
## 3rd Qu.: -73.88
## Max. : -73.70
```

```
## NA's :59
```

```
#more inspection with results not included in report  
str(nypd_data)
```

Priliminary Observation of the data We can see data has 21 columns and 28562 rows of records that representing shooting incident including information about the event, location (longitude, latitude), date and time of occurrence along with information related to perpetrator's and victim's demographics, age, etc along with information about the precinct, jurisdiction, borough/counties.

Clean the data

Lets clean the data for analysis.

```
#from summary, we also see there are few NA's, esp for latitude and Longitude.  
#Lets drop those rows from the data set and also, drop 2 rows where jurisdiction code is NA.  
nypd_data_cleaned <- nypd_data %>%  
  filter(!is.na(Latitude) & !is.na(Longitude) & !is.na(JURISDICTION_CODE))  
  
#there are (null) values I see, lets get a count  
null_val_counts <- sapply(nypd_data_cleaned, function(x) sum(x == "(null)", na.rm = TRUE))  
null_val_counts
```

```
##          INCIDENT_KEY          OCCUR_DATE          OCCUR_TIME  
##              0              0              0  
##          BORO          LOC_OF_OCCUR_DESC          PRECINCT  
##              0              0              0  
## JURISDICTION_CODE          LOC_CLASSFCTN_DESC          LOCATION_DESC  
##              0              2          1668  
## STATISTICAL_MURDER_FLAG          PERP_AGE_GROUP          PERP_SEX  
##              0          1115          1115  
##          PERP_RACE          VIC_AGE_GROUP          VIC_SEX  
##          1115              0              0  
##          VIC_RACE          X_COORD_CD          Y_COORD_CD  
##              0              0              0  
##          Latitude          Longitude          Lon_Lat  
##              0              0              0
```

```
#there are NA values I see, lets get a count  
na_val_counts <- sapply(nypd_data_cleaned, function(x) sum(is.na(x)))  
na_val_counts
```

```
##          INCIDENT_KEY          OCCUR_DATE          OCCUR_TIME  
##              0              0              0  
##          BORO          LOC_OF_OCCUR_DESC          PRECINCT  
##              0          25594              0  
## JURISDICTION_CODE          LOC_CLASSFCTN_DESC          LOCATION_DESC  
##              0          25594          14976  
## STATISTICAL_MURDER_FLAG          PERP_AGE_GROUP          PERP_SEX  
##              0          9344          9310  
##          PERP_RACE          VIC_AGE_GROUP          VIC_SEX
```

```
##          9310          0          0
##          VIC_RACE          X_COORD_CD          Y_COORD_CD
##          0          0          0
##          Latitude          Longitude          Lon_Lat
##          0          0          0
```

*#there are a lot of NA values and NULL values esp for perp-age-group(1115),
#perp-race(1115) and perp-sex(1115). Set the values to "UNKNOWN" to use that
#category if needed, instead of dropping the rows as it significantly
#affects/introduces bias.*

```
nypd_data_cleaned$PERP_AGE_GROUP[is.na(nypd_data_cleaned$PERP_AGE_GROUP)] <- "Unknown"
nypd_data_cleaned$PERP_RACE[is.na(nypd_data_cleaned$PERP_RACE)] <- "Unknown"
nypd_data_cleaned$PERP_SEX[is.na(nypd_data_cleaned$PERP_SEX)] <- "Unknown"
```

#examine each columns as table

```
table(nypd_data_cleaned$PERP_AGE_GROUP)
```

```
##
## (null)      <18      1020      18-24      224      25-44      45-64      65+      940 Unknown
##      1115      1673          1      6425          1      6032          697          65          1      9344
## UNKNOWN
##      3147
```

```
table(nypd_data_cleaned$PERP_RACE)
```

```
##
##          (null) AMERICAN INDIAN/ALASKAN NATIVE
##          1115          2
##      ASIAN / PACIFIC ISLANDER          BLACK
##          169          11880
##          BLACK HISPANIC          Unknown
##          1388          9310
##          UNKNOWN          WHITE
##          1837          298
##          WHITE HISPANIC
##          2502
```

```
table(nypd_data_cleaned$PERP_SEX)
```

```
##
## (null)      F      M      U Unknown
##      1115      443      16134      1499      9310
```

#replace (null) values with "Unknown" and merge "UNKNOWN" with "Unknown"

```
nypd_data_cleaned$PERP_AGE_GROUP[nypd_data_cleaned$PERP_AGE_GROUP == "(null)"] <- "Unknown"
nypd_data_cleaned$PERP_RACE[nypd_data_cleaned$PERP_RACE == "(null)"] <- "Unknown"
nypd_data_cleaned$PERP_SEX[nypd_data_cleaned$PERP_SEX == "(null)"] <- "Unknown"
nypd_data_cleaned$PERP_AGE_GROUP[nypd_data_cleaned$PERP_AGE_GROUP == "UNKNOWN"] <- "Unknown"
nypd_data_cleaned$PERP_RACE[nypd_data_cleaned$PERP_RACE == "UNKNOWN"] <- "Unknown"
nypd_data_cleaned$PERP_SEX[nypd_data_cleaned$PERP_SEX == "UNKNOWN"] <- "Unknown"
```

```
#replace incorrect values in PERP_AGE_GROUP
nypd_data_cleaned$PERP_AGE_GROUP[nypd_data_cleaned$PERP_AGE_GROUP %in%
                                   c("1020", "224", "940")] <- "Unknown"

#replace incorrect values in VIC_AGE_GROUP
nypd_data_cleaned$VIC_AGE_GROUP[nypd_data_cleaned$VIC_AGE_GROUP %in% c("1022")] <- "Unknown"

#re-examine each columns as table
table(nypd_data_cleaned$PERP_AGE_GROUP)
```

```
##
##      <18   18-24   25-44   45-64   65+ Unknown
##      1673   6425   6032    697     65   13609
```

```
table(nypd_data_cleaned$PERP_RACE)
```

```
##
## AMERICAN INDIAN/ALASKAN NATIVE      ASIAN / PACIFIC ISLANDER
##                                   2                                   169
##                                   BLACK HISPANIC
##                                   11880                               1388
##                                   Unknown                               WHITE
##                                   12262                               298
##                                   WHITE HISPANIC
##                                   2502
```

```
table(nypd_data_cleaned$PERP_SEX)
```

```
##
##      F      M      U Unknown
##      443   16134  1499  10425
```

```
table(nypd_data_cleaned$VIC_AGE_GROUP)
```

```
##
##      <18   18-24   25-44   45-64   65+ Unknown UNKNOWN
##      2946  10362  12945   1978   205      1      64
```

Setting goals for analysis of the data

After getting a sense of the data from preliminary inspection and knowing what kind of data I have, I found that there are about 13606 incidents where perpetrator's age group information is not available, about 12262 incidents where perpetrators race information is not available and about 10425 incidents where perpetrators gender is not known. Such a large missing information will affect some type of analysis I was interested in doing, but will continue with that as bias from the data over any analysis.

What am I interested in with this data set ?

I am interested to explore the data and analyze it for the 4 of the below questions.

My questions, finding answers which will be the goal of this project for, are:

1. What is the profile/demographic relationship between perpetrators and victims in nyc shooting incidents ?
2. Could there be any seasonal trends/months of the year when shootings are more frequent ?
3. Which date of the year, every year since 2003, saw maximum shootings ?
4. What is the ratio/proportion of shootings that involve: a. female perpetrators and male victims. b. female perpetrators and female victims. c. male perpetrators and male victims. d. male perpetrators and female victims.

Lets analyze !

Analysis - Case 1:

What is the profile/demographic relationships between perpetrators and victims in nyc shooting incidents ?

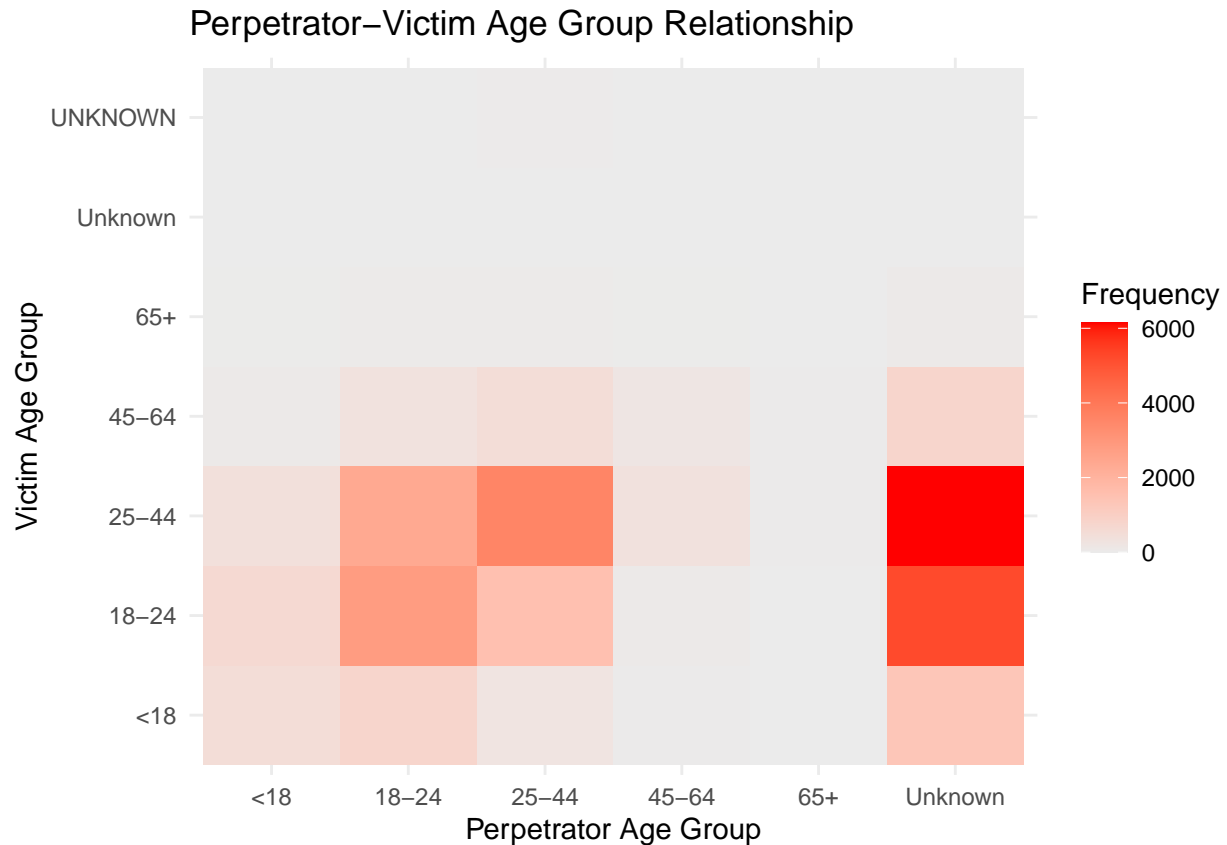
```
# make a table for perp-victim using age group
age_group_relationship <- table(nypd_data_cleaned$PERP_AGE_GROUP,
                                nypd_data_cleaned$VIC_AGE_GROUP)

# view the table
age_group_relationship
```

Perpetrator-Victim Age Group Relationship

```
##
##           <18 18-24 25-44 45-64 65+ Unknown UNKNOWN
## <18          517  648   412    79   15         0      2
## 18-24         808 2834  2388   335   47         1     12
## 25-44         270 1558  3594   523   49         0     38
## 45-64          21   85   371   202   13         0      5
## 65+            0    2    27    24   12         0      0
## Unknown 1330  5235  6153   815   69         0      7
```

```
# plot the relationship using a heatmap
library(ggplot2)
ggplot(as.data.frame(age_group_relationship), aes(Var1, Var2, fill = Freq)) +
  geom_tile() +
  #scale_fill_viridis_c(option = "plasma") +
  scale_fill_gradient(low = "grey92", high = "red") +
  labs(title = "Perpetrator-Victim Age Group Relationship",
       x = "Perpetrator Age Group",
       y = "Victim Age Group",
       fill = "Frequency") +
  theme_minimal()
```



Visual Observation/Inference:

- From the heat map, we can see majority of victims are in the age-group of 25-44 and majority of the perpetrator's (excluding those whose age-group is unknown) are also in the age group of 25-44 !

```
#clean/shorten long race names to see them better on the map
nypd_data_cleaned$PERP_RACE <- recode(nypd_data_cleaned$PERP_RACE,
  "AMERICAN INDIAN/ALASKAN NATIVE" = "Native",
  "ASIAN / PACIFIC ISLANDER" = "Asian/PI",
  "BLACK" = "Black",
  "BLACK HISPANIC" = "B-Hispanic",
  "WHITE" = "White",
  "WHITE HISPANIC" = "W-Hispanic",
  "Unknown" = "Unknown"
)

# Shorten the race names in VIC_RACE
nypd_data_cleaned$VIC_RACE <- recode(nypd_data_cleaned$VIC_RACE,
  "AMERICAN INDIAN/ALASKAN NATIVE" = "Native",
  "ASIAN / PACIFIC ISLANDER" = "Asian/PI",
  "BLACK" = "Black",
  "BLACK HISPANIC" = "B-Hispanic",
  "WHITE" = "White",
```

```

    "WHITE HISPANIC" = "W-Hispanic",
    "Unknown" = "Unknown"
)

#make a table for perpetrator-victim race
race_relationship <- table(nypd_data_cleaned$PERP_RACE,
                           nypd_data_cleaned$VIC_RACE)

# view the table
race_relationship

```

Perpetrator-Victim Race Relationship

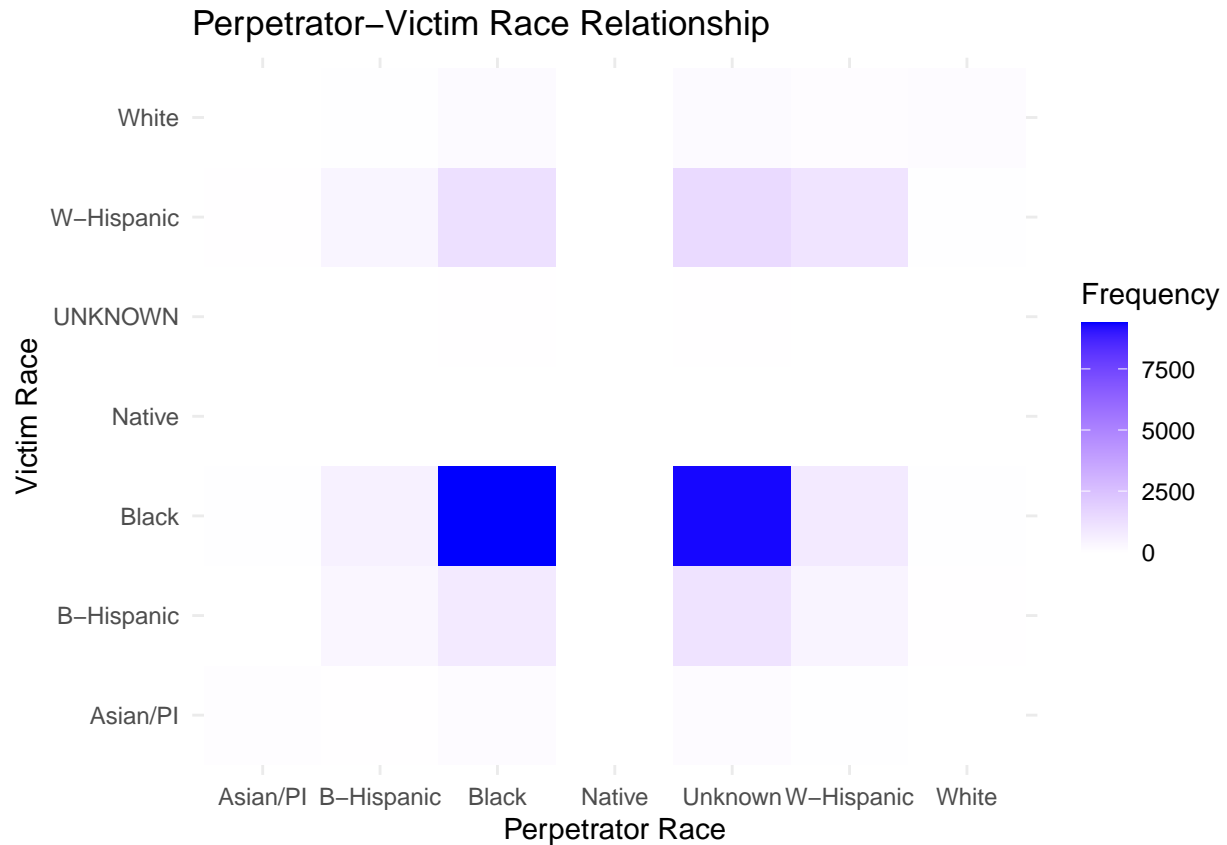
```
##
##           Asian/PI B-Hispanic Black Native UNKNOWN W-Hispanic White
## Asian/PI           61         14   56      0        0          26   12
## B-Hispanic         20        365  561      0        6         400   36
## Black            164        836 9396      4       25        1250  205
## Native              0          0    2      0        0          0    0
## Unknown          140       1109 9300      6       26        1474  207
## W-Hispanic         42        440  844      1       12        1060  103
## White             13         23   42      0        1          54  165

```

```

# Visualize the relationship using a heatmap
ggplot(as.data.frame(race_relationship), aes(Var1, Var2, fill = Freq)) +
  geom_tile() +
  scale_fill_gradient(low = "white", high = "blue") +
  labs(title = "Perpetrator-Victim Race Relationship",
       x = "Perpetrator Race",
       y = "Victim Race",
       fill = "Frequency") +
  theme_minimal()

```

Visual Observation/Inference:

- From the heat map, (excluding Unknown Race) we see a majority of perpetrators as well as majority of victims are both from the race identified as Black.

```
# make a table using Perpetrator-Victim identified sex/gender
gender_relationship <- table(nypd_data_cleaned$PERP_SEX, nypd_data_cleaned$VIC_SEX)

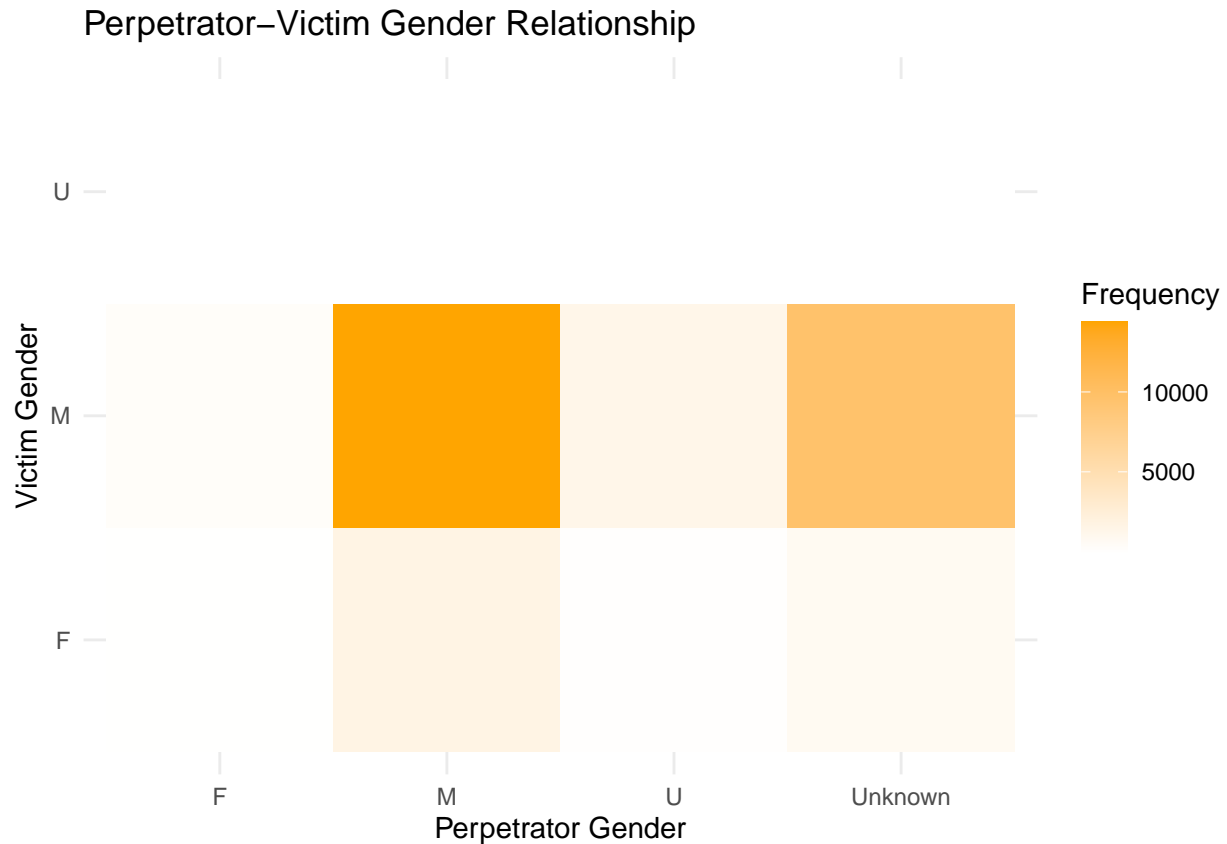
# View the table
gender_relationship
```

Perpetrator-Victim Gender Relationship

```
##
##           F      M      U
##  F          77   365    1
##  M       1752 14375    7
##  U         112  1386    1
##  Unknown   812  9610    3
```

```
# Visualize the relationship using a heatmap
ggplot(as.data.frame(gender_relationship), aes(Var1, Var2, fill = Freq)) +
  geom_tile() +
```

```
scale_fill_gradient(low = "white", high = "orange") +
labs(title = "Perpetrator-Victim Gender Relationship",
     x = "Perpetrator Gender",
     y = "Victim Gender",
     fill = "Frequency") +
theme_minimal()
```



Visual Observation/Inference:

- From the heat map, (excluding Unknown sex/gender) we see a majority of perpetrators as well as majority of victims are both Males.

Also, because from the data set we don't have sufficient data identified as female perpetrators or female victims, my 4th question - i.e., analysis for finding the ratio across combination of genders will not be meaningful at all to do on this data set.

Analysis - Case 2:

Could there be any seasonal trends/months of the year when shootings are more frequent ?

```
#check date format
nypd_data_cleaned$OCCUR_DATE <- as.Date(nypd_data_cleaned$OCCUR_DATE, format = "%m/%d/%Y")

#extract month and add it as a column to the data set. Using %B to get full month name.
```

```
nypd_data_cleaned$Month <- format(nypd_data_cleaned$OCCUR_DATE, "%B")

#create an additional 4-seasons column and add it to the data set
nypd_data_cleaned$Season <- cut(as.numeric(format(nypd_data_cleaned$OCCUR_DATE, "%m")),
                                breaks = c(0, 3, 6, 9, 12),
                                labels = c("Winter", "Spring", "Summer", "Fall"),
                                include.lowest = TRUE)

#check to see if we have new columns added
table(nypd_data_cleaned$Month)
```

```
##
##      April      August  December  February  January      July      June      March
##      2066      3261      2075      1435      1808      3383      2947      1793
##      May      November  October  September
##      2678      2009      2376      2670
```

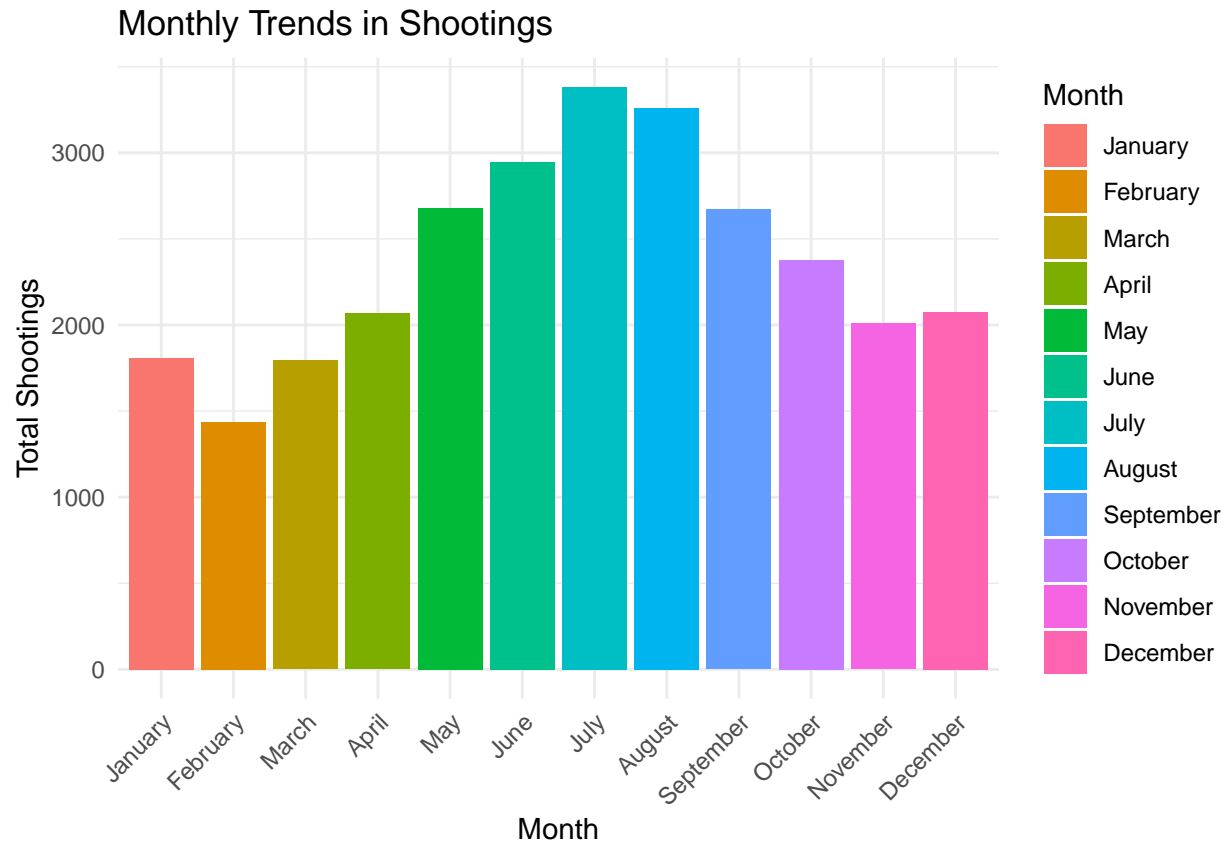
```
table(nypd_data_cleaned$Season)
```

```
##
## Winter Spring Summer  Fall
##  5036   7691   9314   6460
```

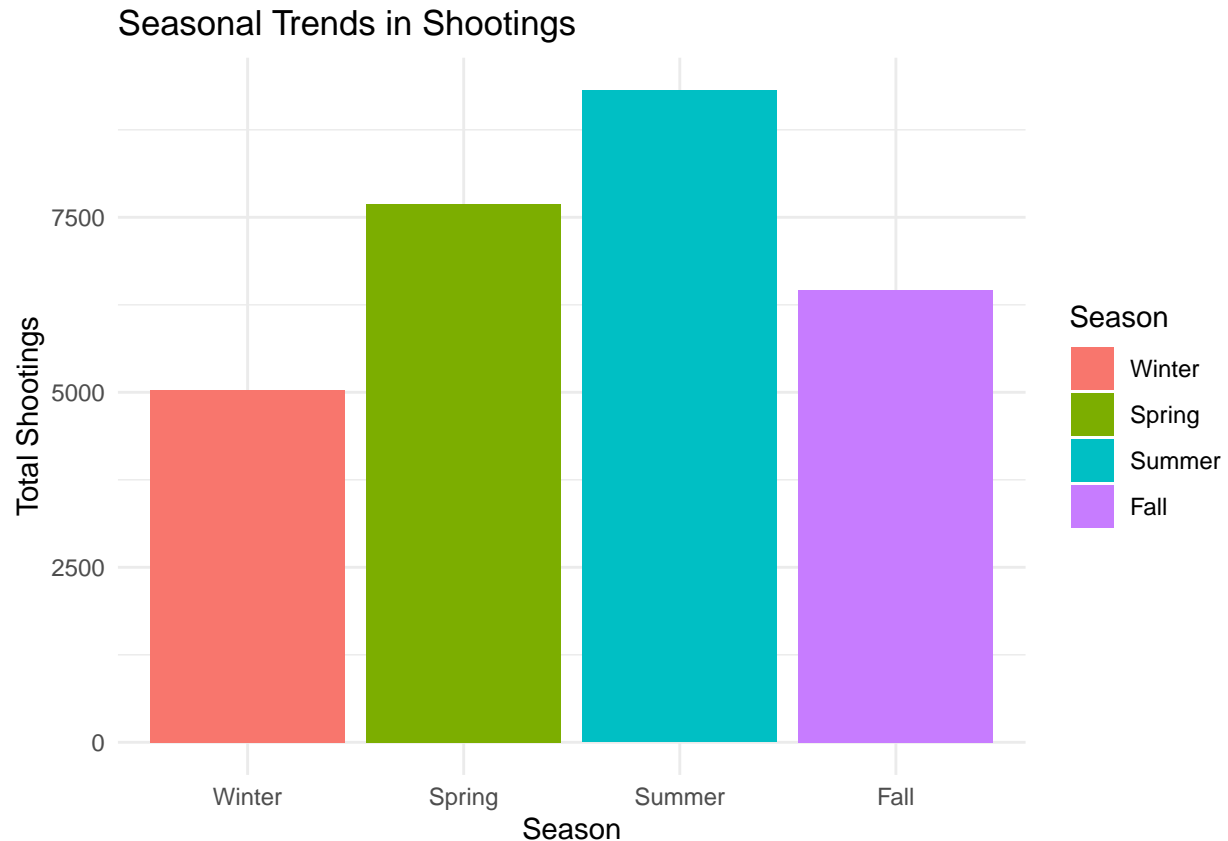
```
#group by month and count number of shootings in each month
nypd_data_cleaned$Month <- factor(nypd_data_cleaned$Month, levels = month.name)
monthly_trends <- nypd_data_cleaned %>%
  group_by(Month) %>%
  summarise(total_shootings = n()) %>%
  #arrange(match(month, month.name)) %>% #arrange by month
  ungroup()

#group by season and count number of shootings in each season
seasonal_trends <- nypd_data_cleaned %>%
  group_by(Season) %>%
  summarise(total_shootings = n()) %>%
  ungroup()
```

```
#plot monthly trends
ggplot(monthly_trends, aes(x = Month, y = total_shootings, fill = Month)) +
  geom_bar(stat = "identity") +
  labs(title = "Monthly Trends in Shootings",
       x = "Month",
       y = "Total Shootings") +
  theme_minimal() +
  theme(axis.text.x = element_text(angle = 45, hjust = 1))
```



```
#plot seasonal trends
ggplot(seasonal_trends, aes(x = Season, y = total_shootings, fill = Season)) +
  geom_bar(stat = "identity") +
  labs(title = "Seasonal Trends in Shootings",
       x = "Season",
       y = "Total Shootings") +
  theme_minimal()
```



Visual Observation/Inference:

- From the plots, we see february to be the month with least number of shootings (and I dont think its because it has less days !) and summer months, July and August are when there are a lot of shootings, which is surprising !

Analysis - Case 3:

Which date of the year, every year since 2003, saw maximum shootings ?

```
#extract the year and day-month (excluding the year) and add it as columns to use as group_by
nypd_data_cleaned$Year <- format(nypd_data_cleaned$OCCUR_DATE, "%Y")
nypd_data_cleaned$Day_Month <- format(nypd_data_cleaned$OCCUR_DATE, "%m-%d")

#group by year and day-month to get the number of shootings for each date
shootings_by_date <- nypd_data_cleaned %>%
  group_by(Year, Day_Month) %>%
  summarise(total_shootings = n()) %>%
  ungroup()
```

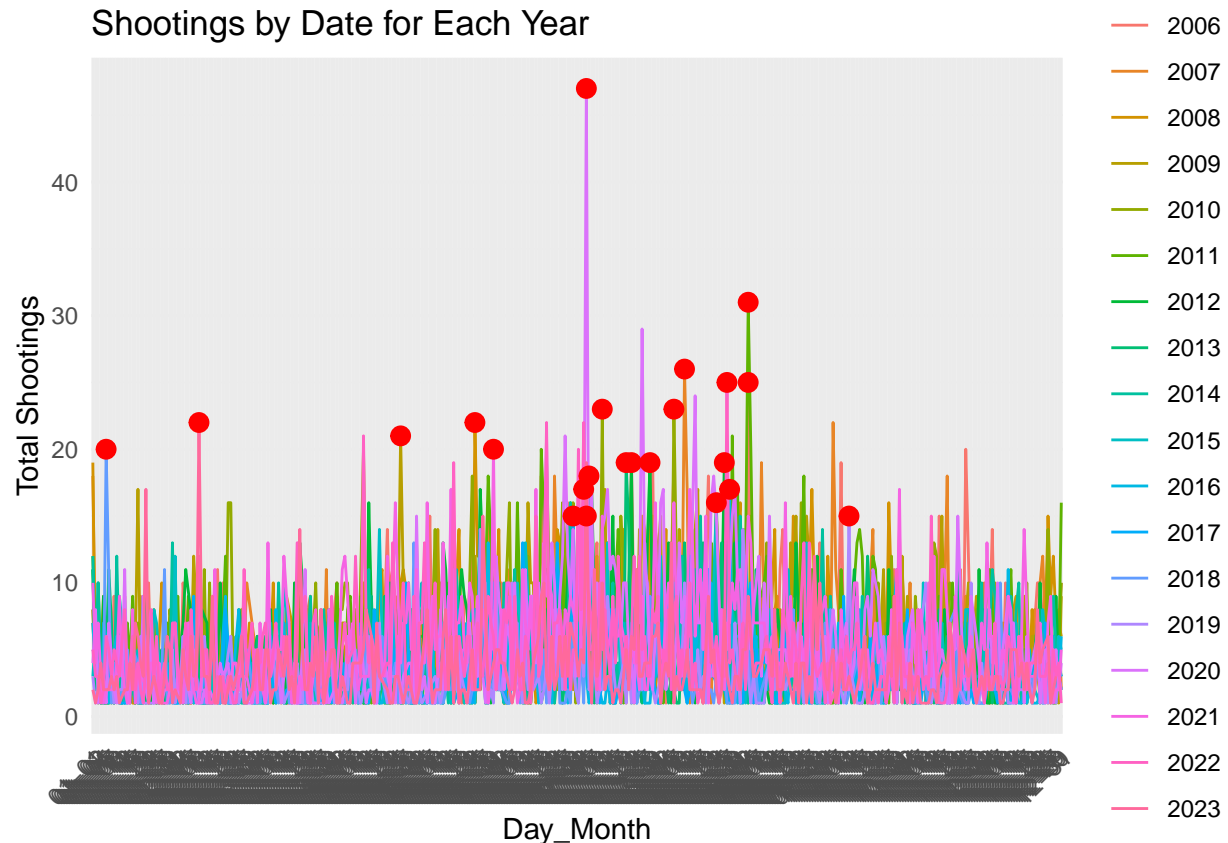
```
## 'summarise()' has grouped output by 'Year'. You can override using the
## '.groups' argument.
```

```
#find the date with the maximum number of shootings for each year
max_shootings_by_year <- shootings_by_date %>%
  group_by(Year) %>%
  filter(total_shootings == max(total_shootings)) %>%
  ungroup()
```

```
#check what we have in max_shootings_by_year
max_shootings_by_year
```

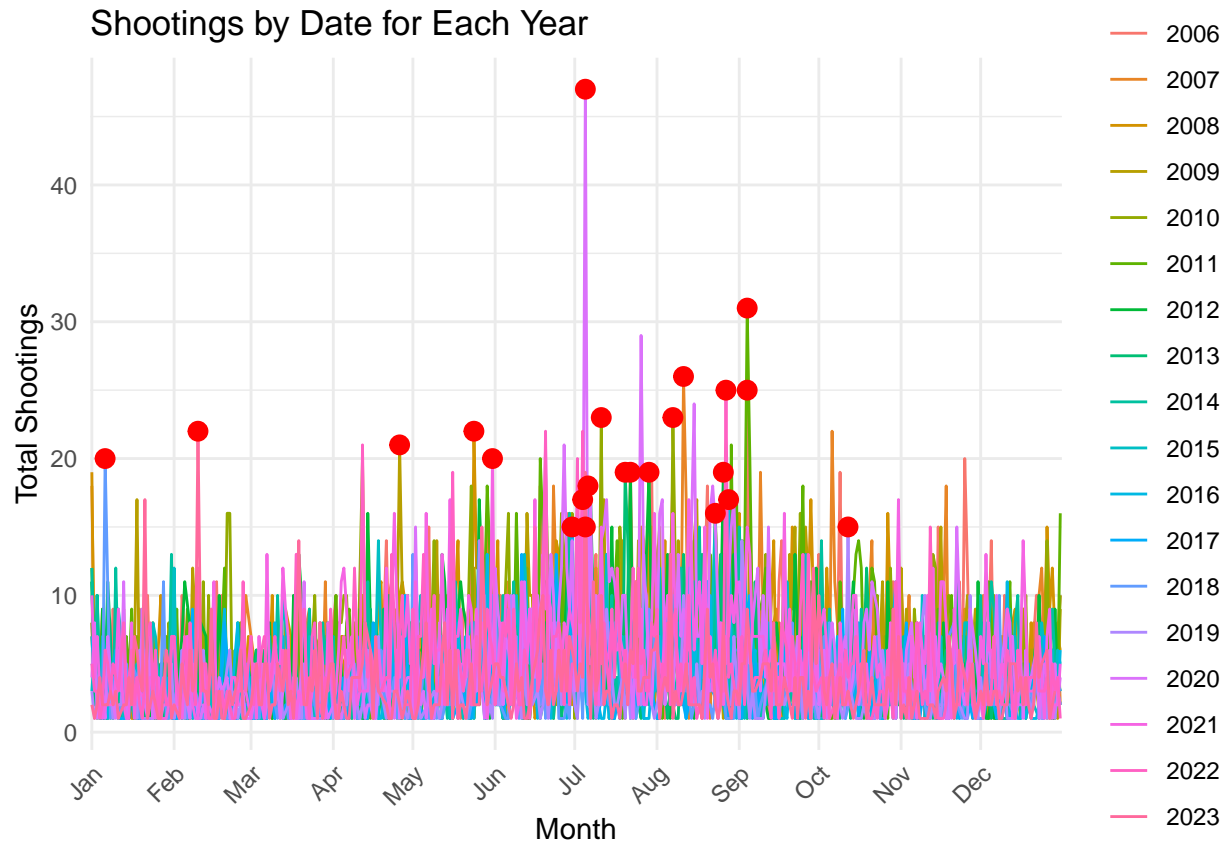
```
## # A tibble: 23 x 3
##   Year Day_Month total_shootings
##   <chr> <chr>          <int>
## 1 2006 09-04             25
## 2 2007 08-11             26
## 3 2008 05-24             22
## 4 2009 04-26             21
## 5 2010 07-11             23
## 6 2010 08-07             23
## 7 2011 09-04             31
## 8 2012 07-22             19
## 9 2012 07-29             19
## 10 2012 08-26            19
## # i 13 more rows
```

```
#plot shootings over the year and highlight the peak date for each year
ggplot(shootings_by_date, aes(x = Day_Month, y = total_shootings, group = Year, color = Year)) +
  geom_line() +
  geom_point(data = max_shootings_by_year, aes(x = Day_Month, y = total_shootings),
    color = "red", size = 3) +
  labs(title = "Shootings by Date for Each Year",
    x = "Day_Month",
    y = "Total Shootings",
    color = "Year") +
  theme_minimal() +
  theme(axis.text.x = element_text(angle = 45, hjust = 1))
```



```
#create levels from 1st jan to 31st dec and factor it to add back to same Day_month column
nypd_data_cleaned$Day_Month <- factor(nypd_data_cleaned$Day_Month,
                                       levels = format(seq(as.Date("2000-01-01"),
                                                           as.Date("2000-12-31"),
                                                           by = "1 day"), "%m-%d"))

#plot it with discrete scale with mapping from %d-%m% to actual names of the months as labels
ggplot(shootings_by_date, aes(x = Day_Month, y = total_shootings, group = Year, color = Year)) +
  geom_line() +
  geom_point(data = max_shootings_by_year, aes(x = Day_Month, y = total_shootings),
            color = "red", size = 3) +
  scale_x_discrete(breaks = c("01-01", "02-01", "03-01", "04-01", "05-01", "06-01",
                              "07-01", "08-01", "09-01", "10-01", "11-01", "12-01"),
                  labels = c("Jan", "Feb", "Mar", "Apr", "May", "Jun", "Jul", "Aug",
                              "Sep", "Oct", "Nov", "Dec")) +
  labs(title = "Shootings by Date for Each Year",
       x = "Month",
       y = "Total Shootings",
       color = "Year") +
  theme_minimal() +
  theme(axis.text.x = element_text(angle = 45, hjust = 1))
```



Visual Observation/Inference:

- This is a great and surprising insight ! I never thought to see, year over year (at least many years), the maximum shootings for that entire year have happened right around the 4th of July !!!

Analysis - Case 4:

What is the ratio/proportion of shootings across gender combinations of perpetrators to victims ? - female perpetrators and male victims. - female perpetrators and female victims. - male perpetrators and male victims. - male perpetrators and female victims.

Skipping this analysis:

- From the data set we don't have sufficient data identified as female perpetrators or female victims, hence, analysis for finding the ratio across combination of genders will not be meaningful at all to do on this data set.
- Heat map in Analysis 1, part 3 confirms this as well.

Modelling from the Data

Goal: The goal is to create a model applying logistic regression to predict whether the victim belongs to the 25-44 age group (a binary outcome) based on the attributes like perpetrator's age, race, gender and time of the year (month/season).

Once the model is created, then to check the model's performance, co-efficients and statistical significance of the model can be done.

```
#set a binary variable (as column) for whether the victim is in the age group 25-44
nypd_data_cleaned$VIC_AGE_25_44 <- ifelse(nypd_data_cleaned$VIC_AGE_GROUP == "25-44", 1, 0)

#get a model_data to work on and select predictors, remove rows with NA values
model_data <- nypd_data_cleaned %>%
  select(VIC_AGE_25_44, PERP_AGE_GROUP, PERP_RACE, PERP_SEX, Month, Season) %>%
  filter(!is.na(PERP_AGE_GROUP) & !is.na(PERP_RACE) & !is.na(PERP_SEX))

#apply logistic regression model using glm()
model <- glm(VIC_AGE_25_44 ~ PERP_AGE_GROUP + PERP_RACE + PERP_SEX + Month + Season,
             data = model_data, family = binomial)

#dump a summary to see the coefficients and significance levels
summary(model)
```

```
##
## Call:
## glm(formula = VIC_AGE_25_44 ~ PERP_AGE_GROUP + PERP_RACE + PERP_SEX +
##      Month + Season, family = binomial, data = model_data)
##
## Coefficients: (3 not defined because of singularities)
##              Estimate Std. Error z value Pr(>|z|)
## (Intercept)   -0.5316620  0.2010134  -2.645  0.00817 **
## PERP_AGE_GROUP18-24  0.5928721  0.0624014   9.501 < 2e-16 ***
## PERP_AGE_GROUP25-44  1.5025086  0.0626103  23.998 < 2e-16 ***
## PERP_AGE_GROUP45-64  1.2506929  0.0953930  13.111 < 2e-16 ***
## PERP_AGE_GROUP65+    0.8035103  0.2603000   3.087  0.00202 **
## PERP_AGE_GROUPUnknown 0.6621196  0.0765486   8.650 < 2e-16 ***
## PERP_RACEB-Hispanic -0.3732378  0.1698128  -2.198  0.02795 *
## PERP_RACEBlack      -0.3208928  0.1614574  -1.987  0.04687 *
## PERP_RACENative     -0.3621831  1.4403137  -0.251  0.80146
## PERP_RACEUnknown    -0.2343000  0.1943898  -1.205  0.22808
## PERP_RACEW-Hispanic -0.3632886  0.1656112  -2.194  0.02826 *
## PERP_RACEWhite      -0.3828016  0.2002479  -1.912  0.05592 .
## PERP_SEXM          -0.1923855  0.0998817  -1.926  0.05409 .
## PERP_SEXU          -0.3618266  0.1544946  -2.342  0.01918 *
## PERP_SEXUnknown     0.0649826  0.1473083   0.441  0.65912
## MonthFebruary      -0.1392321  0.0726404  -1.917  0.05527 .
## MonthMarch         -0.0614096  0.0683192  -0.899  0.36873
## MonthApril         -0.1255318  0.0660899  -1.899  0.05751 .
## MonthMay           -0.1146007  0.0624116  -1.836  0.06633 .
## MonthJune          -0.0570069  0.0611206  -0.933  0.35098
## MonthJuly          -0.0663039  0.0596640  -1.111  0.26644
## MonthAugust        -0.0477960  0.0600049  -0.797  0.42572
## MonthSeptember     -0.0674357  0.0623299  -1.082  0.27929
## MonthOctober       -0.0946224  0.0639421  -1.480  0.13892
## MonthNovember      -0.0514722  0.0663686  -0.776  0.43801
## MonthDecember      -0.0007044  0.0657759  -0.011  0.99146
## SeasonSpring        NA          NA          NA          NA
## SeasonSummer        NA          NA          NA          NA
## SeasonFall          NA          NA          NA          NA
```

```
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##      Null deviance: 39271  on 28500  degrees of freedom
## Residual deviance: 38172  on 28475  degrees of freedom
## AIC: 38224
##
## Number of Fisher Scoring iterations: 4
```

Final Summary

In this set of analysis of the historical NYPD shooting incident data, several important insights were uncovered.

- **Demographic Relationship Between Perpetrators and Victims:**

- **Based on Age Group:** The majority of both perpetrators and victims was found to fall within the 25-44 age group.
- **Based on Race:** Excluding unknown values, both perpetrators and victims are predominantly identified as Black.
- **Based on Gender:** A significant majority of both perpetrators and victims are identified as male.

- **Seasonal Trends in NYPD Shootings:**

- **Monthly Trends:** February consistently showed the fewest shootings, while the summer months, particularly July and August, saw the highest number of incidents. This spike in shootings during the summer months may be tied to various social or environmental factors.

- **Date With Maximum Shootings Each Year:**

- **A surprising trend was uncovered:** Year over year, the highest number of shootings within a given year tends to occur around the 4th of July. This pattern suggests that Independence Day or the activities surrounding it may be linked to an increase in shooting incidents, making it a period of heightened concern for public safety.

- **Bias in analysis:**

- While the analysis provides meaningful insights into patterns of shooting incidents, some of the results, especially demographic and seasonal conclusions may be affected by missing or inaccurate data.
- Perpetrator demographics related analysis could be influenced by incomplete or missing information and as we see in the analysis, there were a lot of NA/("null") values which were considered as Unknown in our analysis and excluded in inference.
- Thus, inference doesn't capture the full essence of analysis that would have taken into account of every shooting incident. There can as well be a selection bias at the source of data itself since we only considered data reported by NYPD.
- Any unreported or mis-classified incidents are not included, which might cause towards under-representation, over-representation or mis-representation.

Summary of Logistic Regression Results

Using logistic regression model, I aimed to predict whether a shooting victim belongs to the 25-44 age group based on factors like the perpetrator's age, race, gender, and the time of year (month and season).

My Key findings:

- **Perpetrator Age Group:**
 - Age is the most significant predictor. Perpetrators in the 18-24, 25-44, and 45-64 age groups are strongly associated with victims also being in the 25-44 age group, with the 25-44 age group having the strongest effect.
- **Perpetrator Race:**
 - Perpetrators identified as **Black Hispanic**, **Black**, and **White Hispanic** have slightly lower odds of the victim being in the 25-44 age group, though the effect sizes are relatively small.
- **Perpetrator Gender:**
 - Gender has a marginally significant effect, with male perpetrators being associated with slightly lower odds of the victim being in the 25-44 age group.
- **Months:**
 - The month of the year shows weak effects. February has marginally lower odds of the victim being in the 25-44 age group, but other months are not significant.
- **Seasons:**
 - The season variable was excluded due to overlap with the month variable, suggesting that month alone captures most of the temporal variation.

Conclusion:

The model applied shows that the **perpetrator's age** is the strongest factor in predicting whether the victim is in the 25-44 age group, while race and gender play smaller roles. Month and season have limited influence on the outcome.

Bias in the model:

The logistic regression model is likely influenced by several biases, including selection bias, missing data bias, and omitted variable bias. These biases can lead to over or underestimation of the influence of specific predictors like age, race, and gender. Thus, biases would affect the the model's accuracy.