ShootingProject

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NYC Shooting Dataset Background

This report covers an analysis of the NYC shooting dataset found at "https://data.cityofnewyork.us/api/views/833y-fsy8/rows.csv?accessType=DOWNLOAD". The dataset lists every shooting incident that occurred in NYC going back to 2006 through the end of the previous calendar year. This is a breakdown of every shooting incident that occurred in NYC going back to 2006 through the end of the previous calendar year. This data is manually extracted every quarter and reviewed by the Office of Management Analysis and Planning before being posted on the NYPD website. Each record represents a shooting incident in NYC and includes information about the event, the location and time of occurrence. In addition, information related to suspect and victim demographics is also included. This data can be used by the public to explore the nature of shooting/criminal activity.

Clear Statement of the Question of Interest

The question of interest I have from this dataset is: **Does a victim's age, race, and sex indicate who the perpetrator might be?**

Import Libraries

```
knitr::opts_chunk$set(echo = TRUE)
# Install necessary packages if they are not already installed
if (!requireNamespace("readr", quietly = TRUE)) {
  install.packages("readr")
}
if (!requireNamespace("dplyr", quietly = TRUE)) {
  install.packages("dplyr")
}
if (!requireNamespace("ggplot2", quietly = TRUE)) {
  install.packages("ggplot2")
}
if (!requireNamespace("VIM", quietly = TRUE)) {
  install.packages("VIM")
}
if (!requireNamespace("nnet", quietly = TRUE)) {
  install.packages("nnet")
}
# import libraries
```

```r
library(readr)
library(dplyr)
```

```
##
## Attaching package: 'dplyr'

## The following objects are masked from 'package:stats':
##
##     filter, lag

## The following objects are masked from 'package:base':
##
##     intersect, setdiff, setequal, union
```

```r
library(ggplot2)
library(VIM)
```

```
## Loading required package: colorspace

## Loading required package: grid

## VIM is ready to use.

## Suggestions and bug-reports can be submitted at: https://github.com/statistikat/VIM/issues

##
## Attaching package: 'VIM'

## The following object is masked from 'package:datasets':
##
##     sleep
```

```r
library(tidyr)
library(nnet)
```

Data Loading

Get Shooting Data

Using the link of where the data comes from is a much more **reproducible** form of loading the data.

```r
url_names <- c("https://data.cityofnewyork.us/api/views/833y-fsy8/rows.csv?accessType=DOWNLOAD")

shooting_data <- read_csv(url_names[1])
```

```
## Rows: 28562 Columns: 21
## -- Column specification --------------------------------------------------------
## Delimiter: ","
## chr  (12): OCCUR_DATE, BORO, LOC_OF_OCCUR_DESC, LOC_CLASSFCTN_DESC, LOCATION...
## dbl   (7): INCIDENT_KEY, PRECINCT, JURISDICTION_CODE, X_COORD_CD, Y_COORD_CD...
## lgl   (1): STATISTICAL_MURDER_FLAG
## time  (1): OCCUR_TIME
##
## i Use `spec()` to retrieve the full column specification for this data.
## i Specify the column types or set `show_col_types = FALSE` to quiet this message.
```

```
head(shooting_data)
```

```
## # A tibble: 6 x 21
##   INCIDENT_KEY OCCUR_DATE OCCUR_TIME BORO      LOC_OF_OCCUR_DESC PRECINCT
##          <dbl> <chr>      <time>     <chr>     <chr>                <dbl>
## 1    244608249 05/05/2022 00:10      MANHATTAN INSIDE                  14
## 2    247542571 07/04/2022 22:20      BRONX     OUTSIDE                 48
## 3     84967535 05/27/2012 19:35      QUEENS    <NA>                   103
## 4    202853370 09/24/2019 21:00      BRONX     <NA>                    42
## 5     27078636 02/25/2007 21:00      BROOKLYN  <NA>                    83
## 6    230311078 07/01/2021 23:07      MANHATTAN <NA>                    23
## # i 15 more variables: JURISDICTION_CODE <dbl>, LOC_CLASSFCTN_DESC <chr>,
## #   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>
```

Data Cleaning

Convert "(null)" strings to NA

```
shooting_data[shooting_data == "(null)"] <- NA
```

Remove unnecessary columns

```
columns_to_keep <- c("OCCUR_DATE", "BORO", "PRECINCT", "PERP_AGE_GROUP", "PERP_SEX", "PERP_RACE", "VIC_
shooting_data <- shooting_data %>%
  select(all_of(columns_to_keep))
head(shooting_data)
```

```
## # A tibble: 6 x 10
##   OCCUR_DATE BORO      PRECINCT PERP_AGE_GROUP PERP_SEX PERP_RACE VIC_AGE_GROUP
##   <chr>      <chr>        <dbl> <chr>          <chr>    <chr>     <chr>
## 1 05/05/2022 MANHATTAN       14 25-44          M        BLACK     25-44
## 2 07/04/2022 BRONX           48 <NA>           <NA>     <NA>      18-24
## 3 05/27/2012 QUEENS         103 <NA>           <NA>     <NA>      18-24
## 4 09/24/2019 BRONX           42 25-44          M        UNKNOWN   25-44
```

```
## 5 02/25/2007 BROOKLYN        83 25-44          M        BLACK     25-44
## 6 07/01/2021 MANHATTAN       23 <NA>           <NA>     <NA>      25-44
## # i 3 more variables: VIC_SEX <chr>, VIC_RACE <chr>,
## #   STATISTICAL_MURDER_FLAG <lgl>
```

Summary w/o cleaning

```
summary(shooting_data)
```

```
##   OCCUR_DATE            BORO              PRECINCT     PERP_AGE_GROUP
##  Length:28562       Length:28562       Min.   :  1.0   Length:28562
##  Class :character   Class :character   1st Qu.: 44.0   Class :character
##  Mode  :character   Mode  :character   Median : 67.0   Mode  :character
##                                        Mean   : 65.5
##                                        3rd Qu.: 81.0
##                                        Max.   :123.0
##    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         STATISTICAL_MURDER_FLAG
##  Length:28562       Mode :logical
##  Class :character   FALSE:23036
##  Mode  :character   TRUE :5526
##
##
##
```

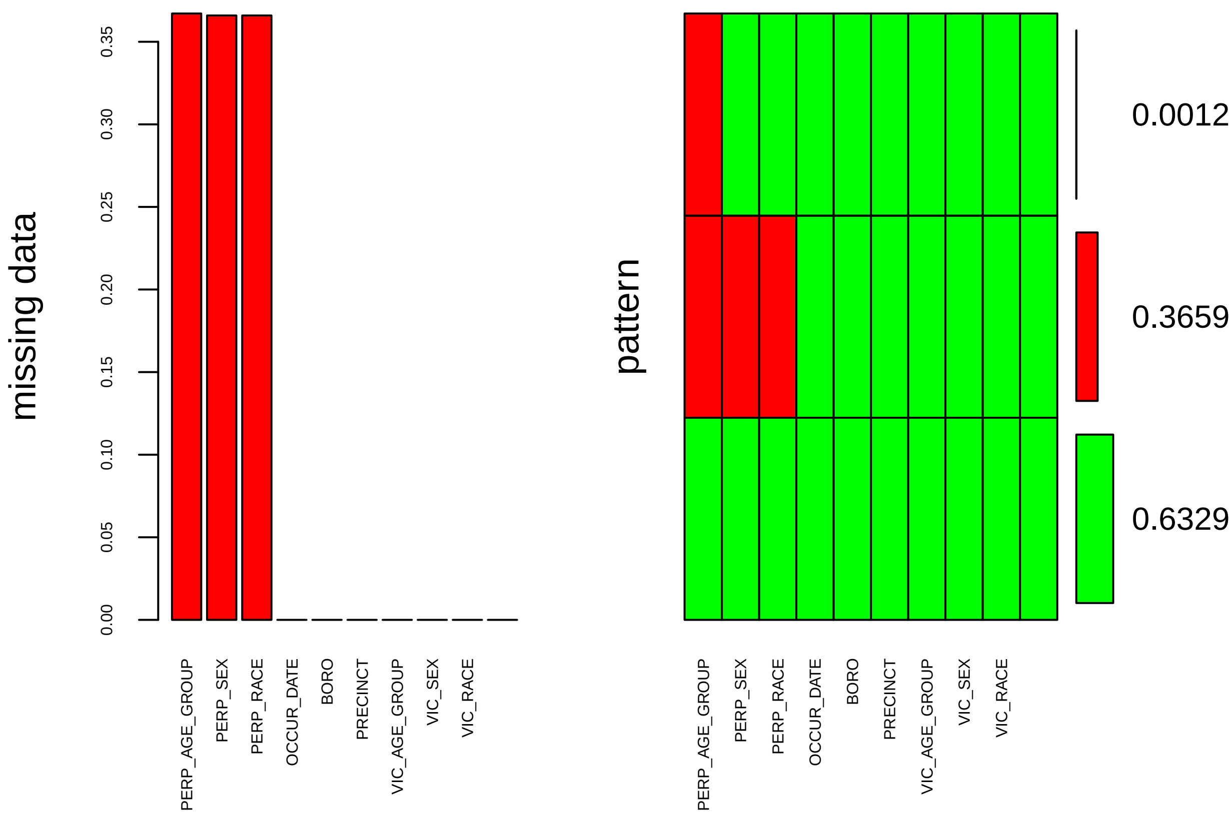
Total up missing data in each column

```
missing_counts <- colSums(is.na(shooting_data))
print(missing_counts)
```

```
##              OCCUR_DATE                    BORO                PRECINCT
##                       0                       0                       0
##          PERP_AGE_GROUP                PERP_SEX               PERP_RACE
##                   10485                   10451                   10451
##           VIC_AGE_GROUP                 VIC_SEX                VIC_RACE
##                       0                       0                       0
## STATISTICAL_MURDER_FLAG
##                       0
```

Visualize missing data

```r
library(VIM)
aggr(shooting_data, col=c('green','red'), numbers=TRUE, sortVars=TRUE, labels=names(shooting_data), cex
```




```
##
##  Variables sorted by number of missings:
##                Variable     Count
##          PERP_AGE_GROUP 0.3670961
##                PERP_SEX 0.3659057
##               PERP_RACE 0.3659057
##              OCCUR_DATE 0.0000000
##                    BORO 0.0000000
##                PRECINCT 0.0000000
##           VIC_AGE_GROUP 0.0000000
##                 VIC_SEX 0.0000000
##                VIC_RACE 0.0000000
##  STATISTICAL_MURDER_FLAG 0.0000000
```

Create an "UNKONWN" value for the missing data fields

It appears a significant amount of people might have gotten away with murder since over 30% of the missing data is from the perpetrator. Therefore, we don't want to omit this data. Instead, we want to just note that it is "UNKNOWN." This should help us have less bias in conclusions on shootings and murders since we would have to make some major assumptions otherwise.

```r
clean_data <- shooting_data %>%
  mutate(
    PERP_AGE_GROUP = replace_na(PERP_AGE_GROUP, "UNKNOWN"),
    PERP_SEX = replace_na(PERP_SEX, "UNKNOWN"),
    PERP_RACE = replace_na(PERP_RACE, "UNKNOWN"),
    VIC_AGE_GROUP = replace_na(VIC_AGE_GROUP, "UNKNOWN"),
    VIC_SEX = replace_na(VIC_SEX, "UNKNOWN"),
    VIC_RACE = replace_na(VIC_RACE, "UNKNOWN")
  )
```

Total up missing data in each column again

```r
missing_counts <- colSums(is.na(clean_data))
print(missing_counts)
```

```
##              OCCUR_DATE                    BORO                PRECINCT
##                       0                       0                       0
##          PERP_AGE_GROUP                PERP_SEX               PERP_RACE
##                       0                       0                       0
##           VIC_AGE_GROUP                 VIC_SEX                VIC_RACE
##                       0                       0                       0
## STATISTICAL_MURDER_FLAG
##                       0
```

Convert date to Date format

```r
clean_data <- clean_data %>%
  mutate(OCCUR_DATE = as.Date(OCCUR_DATE, format = "%m/%d/%Y"))
head(clean_data)
```

```
## # A tibble: 6 x 10
##   OCCUR_DATE BORO      PRECINCT PERP_AGE_GROUP PERP_SEX PERP_RACE VIC_AGE_GROUP
##   <date>     <chr>        <dbl> <chr>          <chr>    <chr>     <chr>
## 1 2022-05-05 MANHATTAN       14 25-44          M        BLACK     25-44
## 2 2022-07-04 BRONX           48 UNKNOWN        UNKNOWN  UNKNOWN   18-24
## 3 2012-05-27 QUEENS         103 UNKNOWN        UNKNOWN  UNKNOWN   18-24
## 4 2019-09-24 BRONX           42 25-44          M        UNKNOWN   25-44
## 5 2007-02-25 BROOKLYN        83 25-44          M        BLACK     25-44
## 6 2021-07-01 MANHATTAN       23 UNKNOWN        UNKNOWN  UNKNOWN   25-44
## # i 3 more variables: VIC_SEX <chr>, VIC_RACE <chr>,
## #   STATISTICAL_MURDER_FLAG <lgl>
```

Convert character columns to factors

```r
clean_data <- clean_data %>%
  mutate(across(where(is.character), as.factor))
head(clean_data)
```

```
## # A tibble: 6 x 10
##   OCCUR_DATE BORO      PRECINCT PERP_AGE_GROUP PERP_SEX PERP_RACE VIC_AGE_GROUP
##   <date>     <fct>        <dbl> <fct>          <fct>    <fct>     <fct>
## 1 2022-05-05 MANHATTAN       14 25-44          M        BLACK     25-44
## 2 2022-07-04 BRONX           48 UNKNOWN        UNKNOWN  UNKNOWN   18-24
## 3 2012-05-27 QUEENS         103 UNKNOWN        UNKNOWN  UNKNOWN   18-24
## 4 2019-09-24 BRONX           42 25-44          M        UNKNOWN   25-44
## 5 2007-02-25 BROOKLYN        83 25-44          M        BLACK     25-44
## 6 2021-07-01 MANHATTAN       23 UNKNOWN        UNKNOWN  UNKNOWN   25-44
## # i 3 more variables: VIC_SEX <fct>, VIC_RACE <fct>,
## #   STATISTICAL_MURDER_FLAG <lgl>
```

Summary w cleaning

```r
summary(clean_data)
```

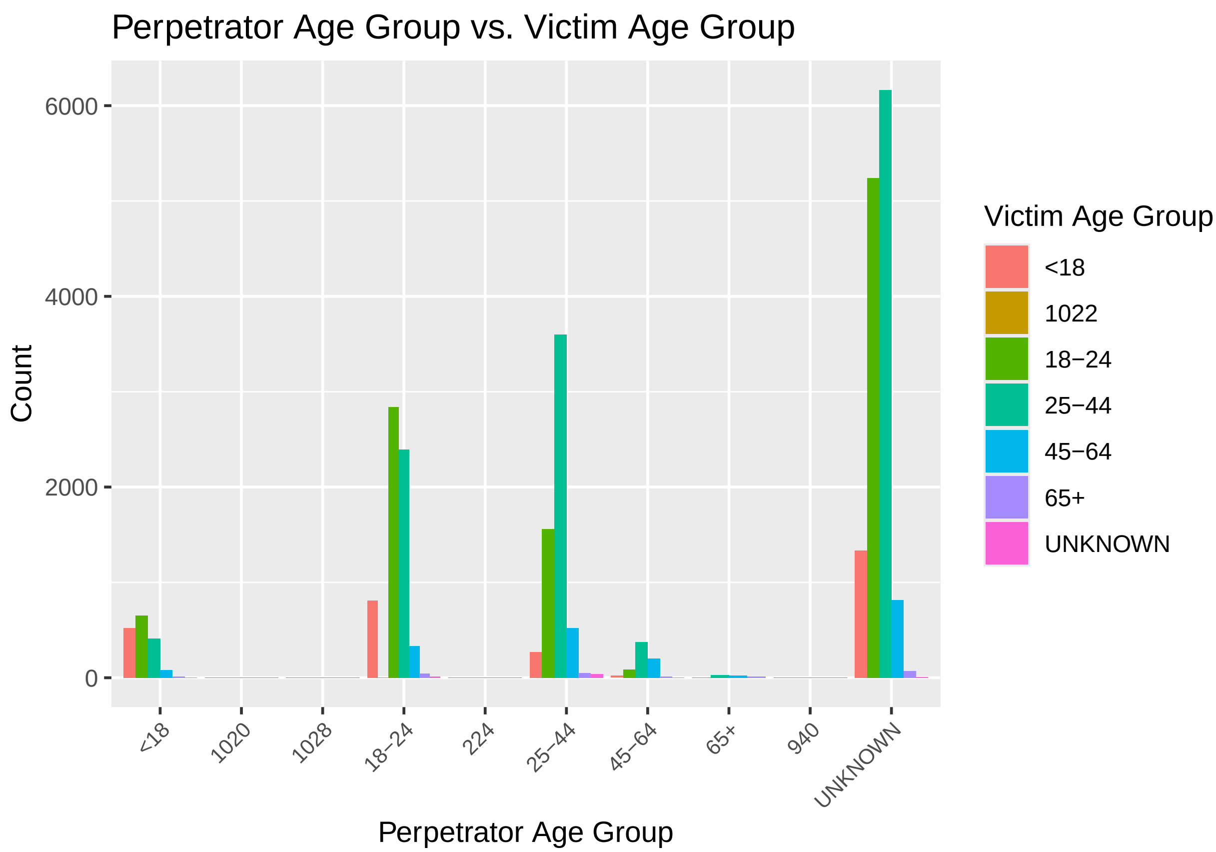
```
##    OCCUR_DATE                     BORO         PRECINCT     PERP_AGE_GROUP
##  Min.   :2006-01-01   BRONX        : 8376   Min.   :  1.0   UNKNOWN:13633
##  1st Qu.:2009-09-04   BROOKLYN     :11346   1st Qu.: 44.0   18-24  : 6438
##  Median :2013-09-20   MANHATTAN    : 3762   Median : 67.0   25-44  : 6041
##  Mean   :2014-06-07   QUEENS       : 4271   Mean   : 65.5   <18    : 1682
##  3rd Qu.:2019-09-29   STATEN ISLAND:  807   3rd Qu.: 81.0   45-64  :  699
##  Max.   :2023-12-29                         Max.   :123.0   65+    :   65
##                                                             (Other):    4
##     PERP_SEX                               PERP_RACE     VIC_AGE_GROUP
##  F      :  444   AMERICAN INDIAN/ALASKAN NATIVE:    2   <18    : 2954
##  M      :16168   ASIAN / PACIFIC ISLANDER      :  169   1022   :    1
##  U      : 1499   BLACK                         :11903   18-24  :10384
##  UNKNOWN:10451   BLACK HISPANIC                : 1392   25-44  :12973
##                  UNKNOWN                       :12288   45-64  : 1981
##                  WHITE                         :  298   65+    :  205
##                  WHITE HISPANIC                : 2510   UNKNOWN:   64
##  VIC_SEX                              VIC_RACE     STATISTICAL_MURDER_FLAG
##  F: 2760   AMERICAN INDIAN/ALASKAN NATIVE:   11   Mode :logical
##  M:25790   ASIAN / PACIFIC ISLANDER      :  440   FALSE:23036
##  U:   12   BLACK                         :20235   TRUE :5526
##            BLACK HISPANIC                : 2795
##            UNKNOWN                       :   70
##            WHITE                         :  728
##            WHITE HISPANIC                : 4283
```

Data Analysis

Bar plot of Perpetrator Age Group vs. Victim Age Group

```r
ggplot(clean_data, aes(x = PERP_AGE_GROUP, fill = VIC_AGE_GROUP)) +
  geom_bar(position = "dodge") +
  labs(title = "Perpetrator Age Group vs. Victim Age Group",
       x = "Perpetrator Age Group",
```

```
      y = "Count",
      fill = "Victim Age Group") +
  theme(axis.text.x = element_text(angle = 45, hjust = 1, size = 8))
```



Notice odd age groups

Odd Perpetrator Age groups: 1020, 940, 224, 1028 Odd Victim Age groups: 1022 Replace with UNKNOWN for specific odd age groups for perpetrators and victims

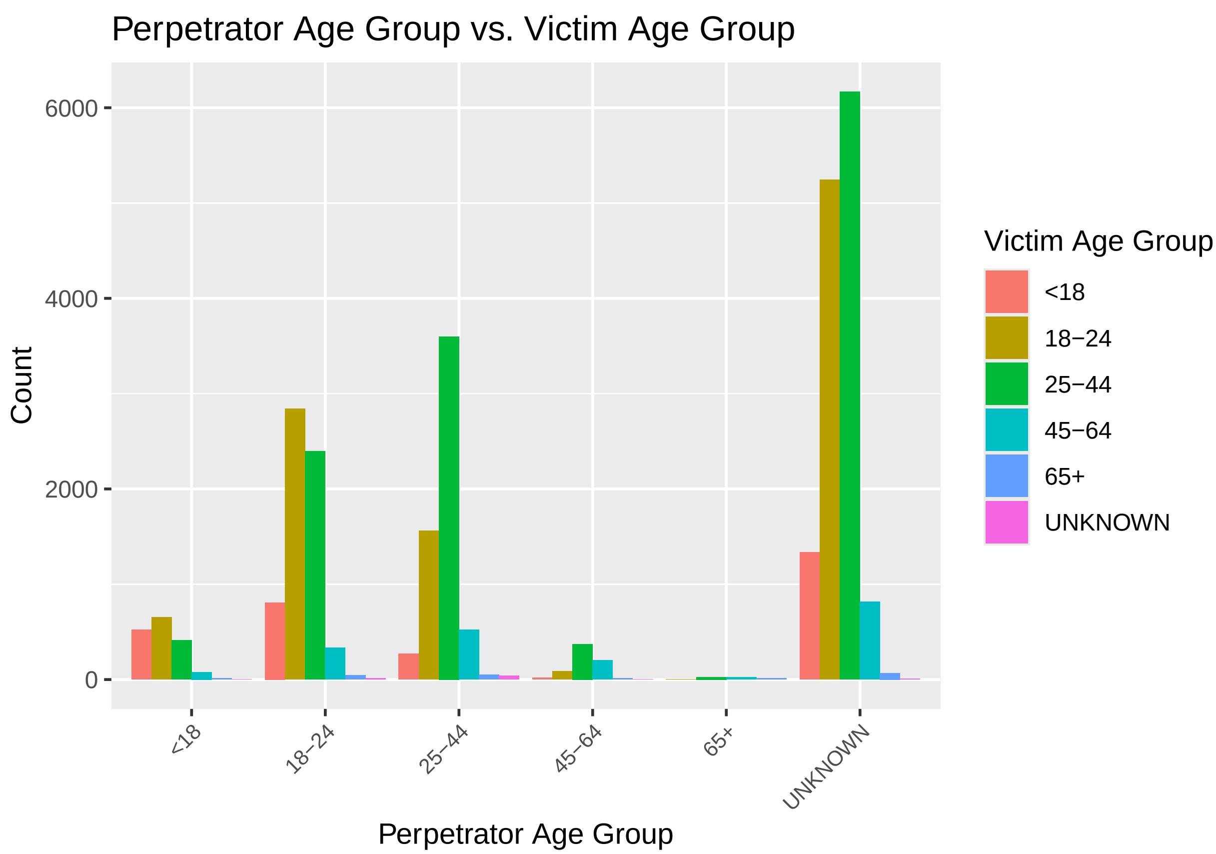
```
odd_perp_age_groups <- c("1020", "940", "224", "1028")
odd_vic_age_groups <- c("1022")

clean_data <- clean_data %>%
  mutate(
    PERP_AGE_GROUP = case_when(
      PERP_AGE_GROUP %in% odd_perp_age_groups ~ "UNKNOWN",
      TRUE ~ PERP_AGE_GROUP
    ),
    VIC_AGE_GROUP = case_when(
      VIC_AGE_GROUP %in% odd_vic_age_groups ~ "UNKNOWN",
      TRUE ~ VIC_AGE_GROUP
    )
  )
```

Bar plot of Perpetrator Age Group vs. Victim Age Group - Verify Age

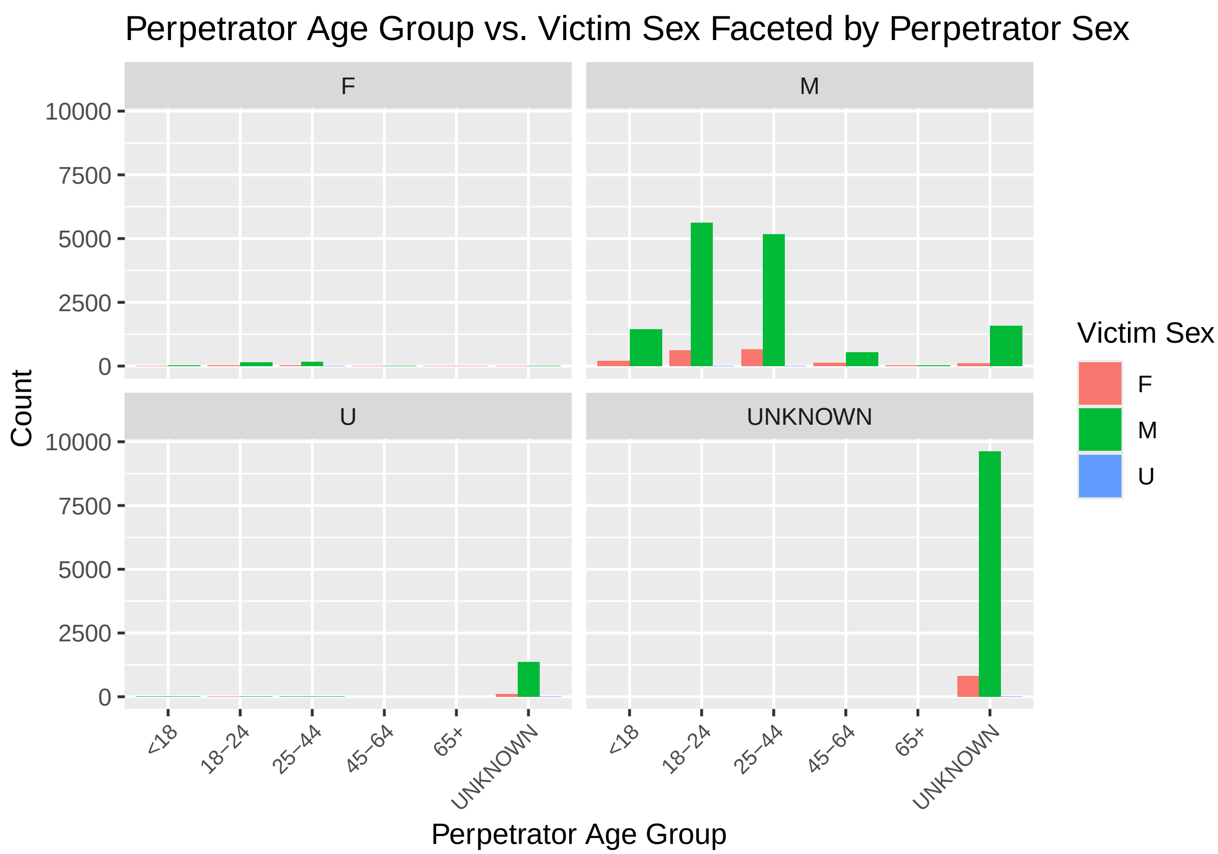
Notice the vicitim and perpetrator age groups of 18-24 & 25-44 are the highest in these shooting of all known age groups. Again, perpetrator's UNKNOWN is significant relative to the age, and it appears reasonable to assume the UNKNOWN age is similar to their victim's age from this chart.

```
ggplot(clean_data, aes(x = PERP_AGE_GROUP, fill = VIC_AGE_GROUP)) +
  geom_bar(position = "dodge") +
  labs(title = "Perpetrator Age Group vs. Victim Age Group",
       x = "Perpetrator Age Group",
       y = "Count",
       fill = "Victim Age Group") +
  theme(axis.text.x = element_text(angle = 45, hjust = 1, size = 8))
```



Bar plot by Perpetrator Sex

```
ggplot(clean_data, aes(x = PERP_AGE_GROUP, fill = VIC_SEX)) +
  geom_bar(position = "dodge") +
  facet_wrap(~ PERP_SEX) +
  labs(title = "Perpetrator Age Group vs. Victim Sex Faceted by Perpetrator Sex",
       x = "Perpetrator Age Group",
       y = "Count",
       fill = "Victim Sex") +
  theme(axis.text.x = element_text(angle = 45, hjust = 1, size = 8))
```



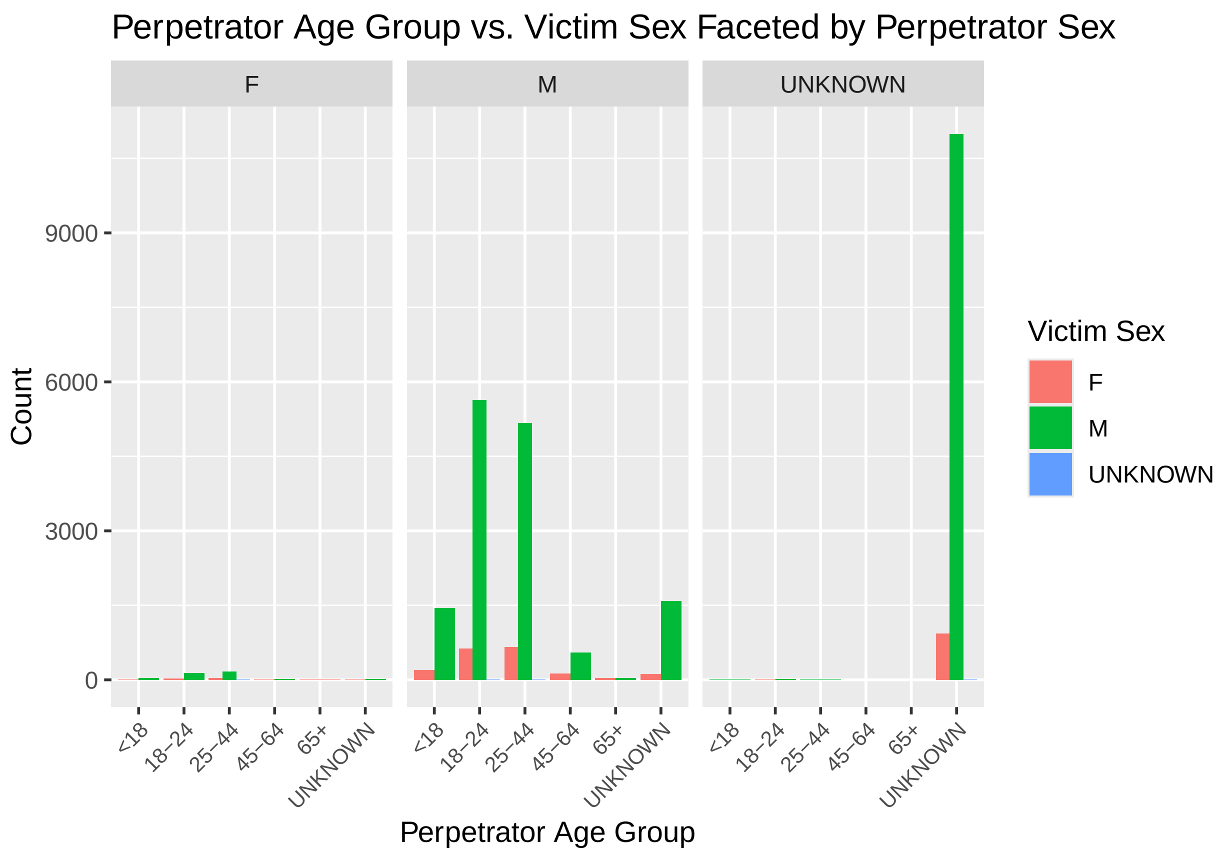
Replace sex "U" with "UNKNOWN"

```
# add levels to sex for UKNOWN if not in it
levels(clean_data$PERP_SEX) <- c(levels(clean_data$PERP_SEX), "UNKNOWN")
levels(clean_data$PERP_AGE_GROUP) <- c(levels(clean_data$PERP_AGE_GROUP), "UNKNOWN")
levels(clean_data$PERP_RACE) <- c(levels(clean_data$PERP_RACE), "UNKNOWN")
levels(clean_data$VIC_SEX) <- c(levels(clean_data$VIC_SEX), "UNKNOWN")
levels(clean_data$VIC_AGE_GROUP) <- c(levels(clean_data$VIC_AGE_GROUP), "UNKNOWN")
levels(clean_data$VIC_RACE) <- c(levels(clean_data$VIC_RACE), "UNKNOWN")
clean_data <- clean_data %>%
  mutate(
    PERP_SEX = replace(PERP_SEX, PERP_SEX == "U", "UNKNOWN"),
    VIC_SEX = replace(VIC_SEX, VIC_SEX == "U", "UNKNOWN")
  )
```

Bar plot by Perpetrator Sex Clean

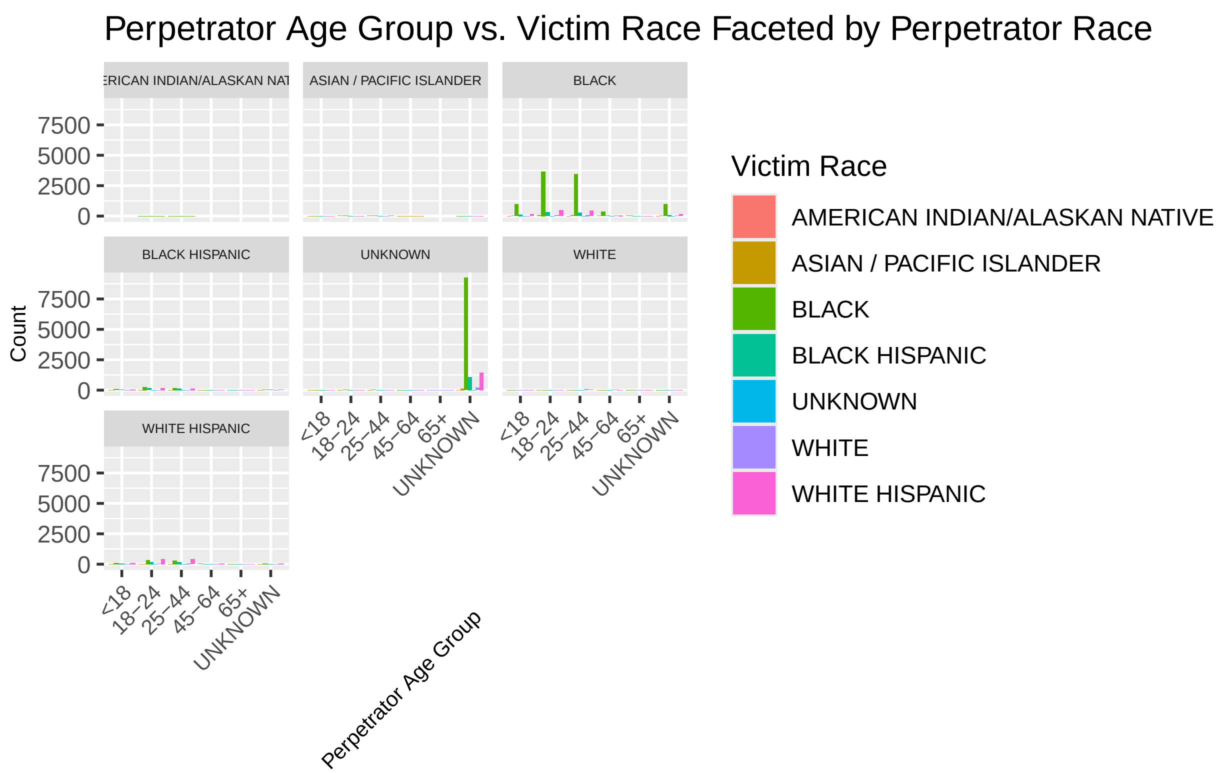
```
ggplot(clean_data, aes(x = PERP_AGE_GROUP, fill = VIC_SEX)) +
  geom_bar(position = "dodge") +
  facet_wrap(~ PERP_SEX) +
  labs(title = "Perpetrator Age Group vs. Victim Sex Faceted by Perpetrator Sex",
       x = "Perpetrator Age Group",
```

```
       y = "Count",
       fill = "Victim Sex") +
  theme(axis.text.x = element_text(angle = 45, hjust = 1, size = 8))
```



Bar plot by Perpetrator Race vs. Age Group

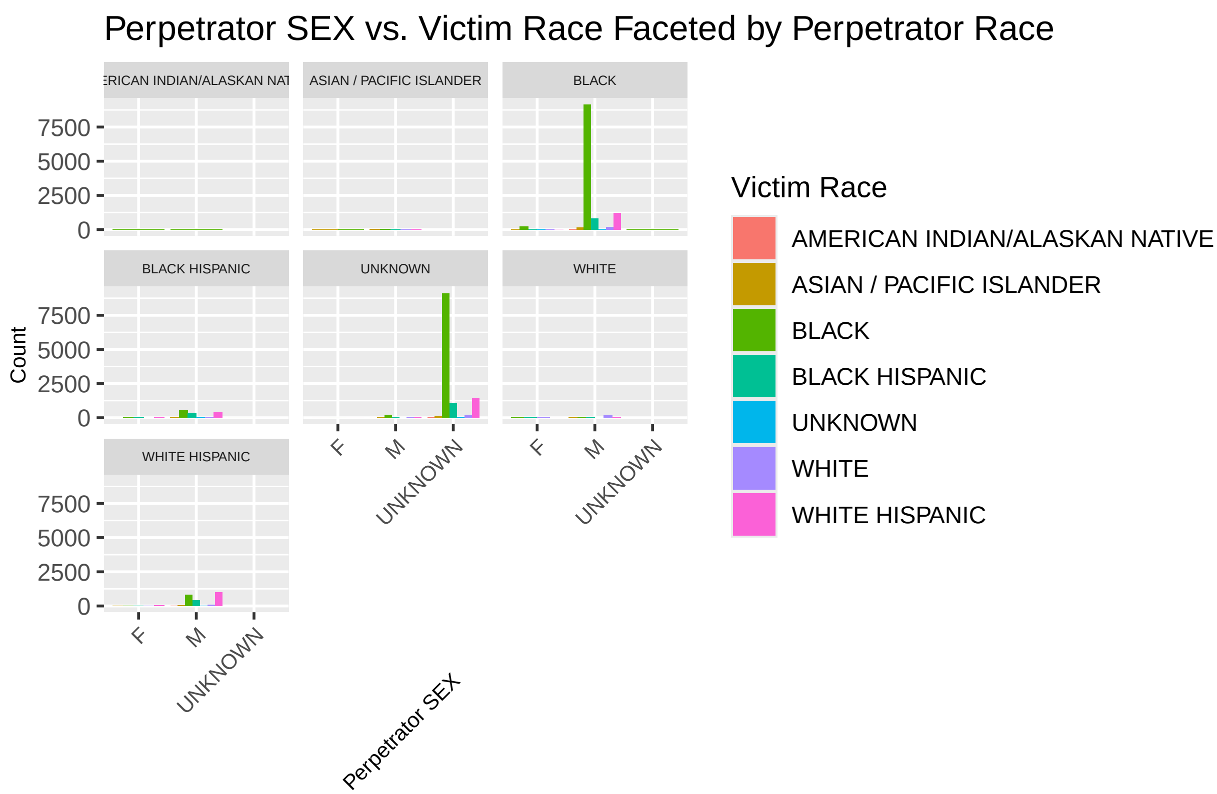
```
ggplot(clean_data, aes(x = PERP_AGE_GROUP, fill = VIC_RACE)) +
  geom_bar(position = "dodge") +
  facet_wrap(~ PERP_RACE) +
  labs(title = "Perpetrator Age Group vs. Victim Race Faceted by Perpetrator Race",
       x = "Perpetrator Age Group",
       y = "Count",
       fill = "Victim Race") +
  theme(axis.text.x = element_text(angle = 45, hjust = 1, size = 8),axis.title = element_text(angle=45,s
```



Bar plot by Perpetrator Race vs. Sex

It appears that Black Males are the majority of shooters among all races and genders.

```
ggplot(clean_data, aes(x = PERP_SEX, fill = VIC_RACE)) +
  geom_bar(position = "dodge") +
  facet_wrap(~ PERP_RACE) +
  labs(title = "Perpetrator SEX vs. Victim Race Faceted by Perpetrator Race",
       x = "Perpetrator SEX",
       y = "Count",
       fill = "Victim Race") +
  theme(axis.text.x = element_text(angle = 45, hjust = 1, size = 8),axis.title = element_text(angle=45,s
```



Model Selection/training

Multinomial logistic regression model

Remove unused levels

When training a model, we need to ensure that the levels are consistent.

```
clean_data <- droplevels(clean_data)
```

Model for PERP_AGE_GROUP

```
age_model <- multinom(PERP_AGE_GROUP ~ VIC_AGE_GROUP + VIC_RACE + VIC_SEX, data = clean_data)
```

```
## # weights:  90 (70 variable)
## initial  value 51176.233960
## iter  10 value 36943.478916
## iter  20 value 36639.281733
## iter  30 value 35831.734899
## iter  40 value 35553.028622
## iter  50 value 35402.069777
```

```
## iter  60 value 35346.495307
## iter  70 value 35332.548587
## iter  80 value 35331.933799
## iter  90 value 35331.795897
## final  value 35331.795071
## converged
```

```r
summary(age_model)
```

```
## Call:
## multinom(formula = PERP_AGE_GROUP ~ VIC_AGE_GROUP + VIC_RACE +
##     VIC_SEX, data = clean_data)
##
## Coefficients:
##         (Intercept) VIC_AGE_GROUP18-24 VIC_AGE_GROUP25-44 VIC_AGE_GROUP45-64
## 18-24    -0.9244584           1.024050           1.306704           0.988923
## 25-44    -0.9143144           1.531975           2.818131           2.504326
## 45-64   -11.2759284           1.194788           3.105194           3.989719
## 65+     -15.0471673           7.509251          10.517712          11.569059
## UNKNOWN   0.6008942           1.128902           1.750040           1.420436
##         VIC_AGE_GROUP65+ VIC_AGE_GROUPUNKNOWN VIC_RACEASIAN / PACIFIC ISLANDER
## 18-24          0.6784858            1.0650870                        1.2047114
## 25-44          1.7496282            3.2306905                        0.1443714
## 45-64          2.7314039            3.5097206                        8.9483958
## 65+           12.1302456            0.7876541                       -4.9339643
## UNKNOWN        0.6852055            0.0881566                       -0.4948816
##         VIC_RACEBLACK VIC_RACEBLACK HISPANIC VIC_RACEUNKNOWN VIC_RACEWHITE
## 18-24        1.292163              1.2136979       1.6787301     1.7660871
## 25-44        0.330123              0.1939993       1.1263704     1.2168681
## 45-64        8.389152              8.1608342       9.8183919    10.0328058
## 65+          2.844613              3.0128648      -5.9050866     5.5233798
## UNKNOWN      0.127846             -0.2545571       0.4384378     0.2076029
##         VIC_RACEWHITE HISPANIC    VIC_SEXM VIC_SEXUNKNOWN
## 18-24               1.3170331  0.08724731      8.3148833
## 25-44               0.3402653 -0.08289398      6.6417726
## 45-64               8.6060745 -0.47288053     -5.2671203
## 65+                 3.2299286 -1.63651798      0.2620697
## UNKNOWN            -0.2924216  0.36366174      8.0041405
##
## Std. Errors:
##         (Intercept) VIC_AGE_GROUP18-24 VIC_AGE_GROUP25-44 VIC_AGE_GROUP45-64
## 18-24     1.4241390         0.07134172         0.07781601          0.1376082
## 25-44     1.2555342         0.08863781         0.09161712          0.1426485
## 45-64     0.2520877         0.25120922         0.23442409          0.2603301
## 65+       6.4576772         2.63729741         2.58501416          2.5863620
## UNKNOWN   1.0744204         0.06671399         0.07294538          0.1292906
##         VIC_AGE_GROUP65+ VIC_AGE_GROUPUNKNOWN VIC_RACEASIAN / PACIFIC ISLANDER
## 18-24          0.3030489           0.78115897                        1.4373525
## 25-44          0.3061938           0.74178614                        1.2702315
## 45-64          0.4437977           0.89049296                        0.2748167
## 65+            2.5987392           0.05328585                       31.7160937
## UNKNOWN        0.2911826           0.81924368                        1.0911413
##         VIC_RACEBLACK VIC_RACEBLACK HISPANIC VIC_RACEUNKNOWN VIC_RACEWHITE
## 18-24       1.4217499              1.4236526      1.61915463     1.4409611
```

```
## 25-44       1.2520243             1.2543536      1.46597173     1.2729373
## 45-64       0.1548337             0.1951875      0.77822244     0.2588753
## 65+         9.0308545             9.0361375      0.06113658     9.0335795
## UNKNOWN     1.0715904             1.0739195      1.30765261     1.0958392
##         VIC_RACEWHITE HISPANIC   VIC_SEXM VIC_SEXUNKNOWN
## 18-24                1.4229745 0.08697427   4.307801e-01
## 25-44                1.2534835 0.08847244   5.310482e-01
## 45-64                0.1720977 0.12777076   7.895726e-07
## 65+                  9.0327763 0.27310627   1.150377e-05
## UNKNOWN              1.0731531 0.08344500   4.746731e-01
##
## Residual Deviance: 70663.59
## AIC: 70803.59
```

Model for PERP_RACE

```r
race_model <- multinom(PERP_RACE ~ VIC_AGE_GROUP + VIC_RACE + VIC_SEX, data = clean_data)
```

```
## # weights:  105 (84 variable)
## initial  value 55579.085677
## iter  10 value 34733.255277
## iter  20 value 33990.466735
## iter  30 value 32508.091332
## iter  40 value 31856.507428
## iter  50 value 31349.546100
## iter  60 value 31230.771414
## iter  70 value 31195.922943
## iter  80 value 31184.748810
## iter  90 value 31183.746796
## iter 100 value 31183.387797
## final  value 31183.387797
## stopped after 100 iterations
```

```r
summary(race_model)
```

```
## Call:
## multinom(formula = PERP_RACE ~ VIC_AGE_GROUP + VIC_RACE + VIC_SEX,
##     data = clean_data)
##
## Coefficients:
##                          (Intercept) VIC_AGE_GROUP18-24 VIC_AGE_GROUP25-44
## ASIAN / PACIFIC ISLANDER    12.86887           6.553150          -6.856668
## BLACK                       26.42123           6.454747          -7.307312
## BLACK HISPANIC              12.38022           6.383573          -7.454881
## UNKNOWN                     26.30540           6.655952          -7.149366
## WHITE                       13.95925           6.711761          -6.616384
## WHITE HISPANIC              24.80924           6.426062          -7.378855
##                          VIC_AGE_GROUP45-64 VIC_AGE_GROUP65+
## ASIAN / PACIFIC ISLANDER          -9.229065       -0.1419325
## BLACK                             -9.318187        0.7932155
## BLACK HISPANIC                    -9.471450        1.0538642
```

```
## UNKNOWN                        -9.328787       0.5152134
## WHITE                          -8.414135       2.0447737
## WHITE HISPANIC                 -9.368347       0.2644328
##                           VIC_AGE_GROUPUNKNOWN VIC_RACEASIAN / PACIFIC ISLANDER
## ASIAN / PACIFIC ISLANDER            -16.350507                        11.301148
## BLACK                                 2.542143                        -1.227556
## BLACK HISPANIC                        2.263549                        10.487086
## UNKNOWN                               0.766080                        -1.771431
## WHITE                                 1.346217                         8.060077
## WHITE HISPANIC                        2.614632                        -1.157053
##                           VIC_RACEBLACK VIC_RACEBLACK HISPANIC VIC_RACEUNKNOWN
## ASIAN / PACIFIC ISLANDER       3.614348              8.7437562      -13.873902
## BLACK                         -4.783889             -0.6884695       -1.428880
## BLACK HISPANIC                 6.205898             12.2874676       11.216835
## UNKNOWN                       -5.194031             -0.8016951       -1.389450
## WHITE                          1.731458              7.6471896        7.790332
## WHITE HISPANIC                -5.776722              0.0844545       -0.568337
##                           VIC_RACEWHITE VIC_RACEWHITE HISPANIC  VIC_SEXM
## ASIAN / PACIFIC ISLANDER     10.4972433              9.5281663 -6.329724
## BLACK                        -0.2047667             -0.1028563 -6.076347
## BLACK HISPANIC               11.9019990             12.5836231 -5.710140
## UNKNOWN                      -0.5069703             -0.3270288 -5.666423
## WHITE                        11.3829756              8.6630120 -6.055386
## WHITE HISPANIC                0.5584481              1.1635615 -5.807721
##                           VIC_SEXUNKNOWN
## ASIAN / PACIFIC ISLANDER       0.3506045
## BLACK                          5.3931481
## BLACK HISPANIC                -5.4662530
## UNKNOWN                        6.0191027
## WHITE                         -2.7668843
## WHITE HISPANIC                -6.5296137
##
## Std. Errors:
##                           (Intercept) VIC_AGE_GROUP18-24 VIC_AGE_GROUP25-44
## ASIAN / PACIFIC ISLANDER     2.979879         0.29002094           1.697546
## BLACK                        3.043836         0.08639871           1.676282
## BLACK HISPANIC               3.004487         0.11011950           1.677728
## UNKNOWN                      3.039321         0.08654538           1.676293
## WHITE                        3.013527         0.27688503           1.695363
## WHITE HISPANIC               3.086151         0.09968660           1.677056
##                           VIC_AGE_GROUP45-64 VIC_AGE_GROUP65+
## ASIAN / PACIFIC ISLANDER            1.702721        0.8892658
## BLACK                               1.666964        0.2240602
## BLACK HISPANIC                      1.670490        0.2895097
## UNKNOWN                             1.667015        0.2324469
## WHITE                               1.689797        0.4018563
## WHITE HISPANIC                      1.668729        0.2941476
##                           VIC_AGE_GROUPUNKNOWN VIC_RACEASIAN / PACIFIC ISLANDER
## ASIAN / PACIFIC ISLANDER          1.221622e-09                         2.040555
## BLACK                             2.980552e-01                         2.065101
## BLACK HISPANIC                    4.512807e-01                         2.011849
## UNKNOWN                           4.079231e-01                         2.058566
## WHITE                             8.647830e-01                         2.018330
## WHITE HISPANIC                    3.424749e-01                         2.128921
```

```
##                          VIC_RACEBLACK VIC_RACEBLACK HISPANIC VIC_RACEUNKNOWN
## ASIAN / PACIFIC ISLANDER      7.809175               4.506951    1.191130e-08
## BLACK                         7.856455               4.496737    5.961155e-01
## BLACK HISPANIC                7.840666               4.470714    4.003810e-01
## UNKNOWN                       7.854694               4.493640    5.682969e-01
## WHITE                         7.842514               4.474437    7.263888e-01
## WHITE HISPANIC                7.872817               4.525237    7.965141e-01
##                          VIC_RACEWHITE VIC_RACEWHITE HISPANIC VIC_SEXM
## ASIAN / PACIFIC ISLANDER     0.9400131               3.319119 3.314083
## BLACK                        1.0138113               3.319604 3.308721
## BLACK HISPANIC               0.8939856               3.284060 3.309558
## UNKNOWN                      1.0000588               3.315425 3.308748
## WHITE                        0.8954511               3.287120 3.311728
## WHITE HISPANIC               1.1346473               3.358018 3.309091
##                          VIC_SEXUNKNOWN
## ASIAN / PACIFIC ISLANDER   1.328690e-05
## BLACK                      3.403456e-01
## BLACK HISPANIC             1.566520e-06
## UNKNOWN                    3.403447e-01
## WHITE                      2.413741e-05
## WHITE HISPANIC             1.312090e-06
##
## Residual Deviance: 62366.78
## AIC: 62534.78
```

Model for PERP_SEX

```r
sex_model <- multinom(PERP_SEX ~ VIC_AGE_GROUP + VIC_RACE + VIC_SEX, data = clean_data)
```

```
## # weights:  45 (28 variable)
## initial  value 31378.564189
## iter  10 value 23641.499119
## iter  20 value 21774.618198
## iter  30 value 21189.615282
## iter  40 value 21188.756473
## final  value 21188.754411
## converged
```

```r
summary(sex_model)
```

```
## Call:
## multinom(formula = PERP_SEX ~ VIC_AGE_GROUP + VIC_RACE + VIC_SEX,
##     data = clean_data)
##
## Coefficients:
##         (Intercept) VIC_AGE_GROUP18-24 VIC_AGE_GROUP25-44 VIC_AGE_GROUP45-64
## M          1.963873         -0.6087350         -0.8920714          -1.059258
## UNKNOWN    1.093870         -0.3844589         -0.6952135          -1.029213
##         VIC_AGE_GROUP65+ VIC_AGE_GROUPUNKNOWN VIC_RACEASIAN / PACIFIC ISLANDER
## M             -0.5532355           -0.8277576                         1.496276
## UNKNOWN       -0.7750257           -2.5351516                         1.109400
```

```
##         VIC_RACEBLACK VIC_RACEBLACK HISPANIC VIC_RACEUNKNOWN VIC_RACEWHITE
## M           1.931508               2.112784        2.950059      1.551779
## UNKNOWN     2.167252               2.070459        3.042859      1.069760
##         VIC_RACEWHITE HISPANIC  VIC_SEXM VIC_SEXUNKNOWN
## M                     1.841210 0.5416342      -1.903586
## UNKNOWN               1.573242 0.8585556      -1.138234
##
## Std. Errors:
##         (Intercept) VIC_AGE_GROUP18-24 VIC_AGE_GROUP25-44 VIC_AGE_GROUP45-64
## M          1.108439          0.2238559          0.2169580          0.2529777
## UNKNOWN    1.146922          0.2248092          0.2179334          0.2549733
##         VIC_AGE_GROUP65+ VIC_AGE_GROUPUNKNOWN VIC_RACEASIAN / PACIFIC ISLANDER
## M              0.5510499            0.8419843                         1.124848
## UNKNOWN        0.5613373            0.9316651                         1.164241
##         VIC_RACEBLACK VIC_RACEBLACK HISPANIC VIC_RACEUNKNOWN VIC_RACEWHITE
## M           1.089591               1.100598        1.755197      1.110002
## UNKNOWN     1.128308               1.139088        1.785551      1.149461
##         VIC_RACEWHITE HISPANIC  VIC_SEXM VIC_SEXUNKNOWN
## M                     1.093701 0.1298153       1.386226
## UNKNOWN               1.132430 0.1319771       1.405314
##
## Residual Deviance: 42377.51
## AIC: 42433.51
```

Inference with Model on Sample Data Point

Define a single data point for victim characteristics

```r
# Define a single data point for victim characteristics
single_data_point <- clean_data[1, c("VIC_AGE_GROUP", "VIC_RACE", "VIC_SEX")]
single_data_point[1, ] <- list("25-44", "WHITE", "M")
```

Predict the perpetrator's age group

```r
predicted_age_group <- predict(age_model, newdata = single_data_point)
print(paste("Predicted Perpetrator Age Group:", predicted_age_group))
```

```
## [1] "Predicted Perpetrator Age Group: 25-44"
```

Predict the perpetrator's race

```r
predicted_race <- predict(race_model, newdata = single_data_point)
print(paste("Predicted Perpetrator Race:", predicted_race))
```

```
## [1] "Predicted Perpetrator Race: UNKNOWN"
```

Predict the perpetrator's sex

```
predicted_sex <- predict(sex_model, newdata = single_data_point)
print(paste("Predicted Perpetrator Sex:", predicted_sex))
```

```
## [1] "Predicted Perpetrator Sex: M"
```

Bias Identification/Conclusion

This dataset is strictly for New York City. So the data found here might not apply outside of this city in other parts of America or the world at large. Since I live in New York, but outside of New York City (source of this dataset), my **personal bias** might be that there isn't as many shootings. However, if I were to spend time in New York City, my **personal bias** might be more corrected by what I am able to observe, **mitigating** its overall effect on my analysis/conclusions.

From this dataset, it might appear that Black Males have the largest correlation with shooting. However, there is a significant amount of UNKNOWN data. Therefore, there could be bias built into this dataset to conclude UNKNOWN or Black Males are the number one perpetrators in shooting cases. It could be that another race has been getting away with shooting or murder much easier. This bias is observed by looking at the model's predictions given a single data point at random. The prediction appears to align very well with the visualization plots of the data, making it appear that the bias in the data is translated into the model's performance. Garbage in, garbage out might apply here to the model's prediction. By solving more of the UNKNOWN values, the model might have less bias and be more informative.

In conclusion, all we know is that there is a significant amount of UNKNOWN shooters out there, and from what we do know, a large number of them appear to be Black Males from this dataset. Using a model based on this dataset that predicts the perpertator given the victim's race, age, and gender might give very biased results as shown in this analysis.