NYPD Shooting Incident Analysis

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Intro: As concerns around gun violence escalate, we're delving into the NYPD Shooting Incident data to crunch the numbers and uncover patterns. The goal here is to get a grip on what's happening, without getting bogged down in the larger societal debate. By sifting through the data, our aim is to spotlight trends and relationships that can be useful for law enforcement strategies. This report cuts to the chase, focusing on the nitty-gritty of the NYPD Shooting Incident data to provide insights that can help shape practical policies and tactics.

Step 1 Install `tidyverse` and `lubridate` which are the packages I'll need to preform my analysis

```
library(tidyverse)
library(lubridate)
```

Step 2 Read the data

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

Step 3 Check out first 6 rows

```
head(shooting_incident)
```

```
## # A tibble: 6 x 21
##   INCIDE~1 OCCUR~2 OCCUR~3 BORO  LOC_O~4 PRECI~5 JURIS~6 LOC_C~7 LOCAT~8 STATI~9
##      <dbl> <chr>   <time>  <chr> <chr>     <dbl>   <dbl> <chr>   <chr>   <lgl>
## 1   2.29e8 05/27/~ 21:30   QUEE~ <NA>        105       0 <NA>    <NA>    FALSE
## 2   1.37e8 06/27/~ 17:40   BRONX <NA>         40       0 <NA>    <NA>    FALSE
## 3   1.48e8 11/21/~ 03:56   QUEE~ <NA>        108       0 <NA>    <NA>    TRUE
## 4   1.47e8 10/09/~ 18:30   BRONX <NA>         44       0 <NA>    <NA>    FALSE
## 5   5.89e7 02/19/~ 22:58   BRONX <NA>         47       0 <NA>    <NA>    TRUE
## 6   2.20e8 10/21/~ 21:36   BROO~ <NA>         81       0 <NA>    <NA>    TRUE
## # ... with 11 more variables: 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>, and abbreviated variable names 1: INCIDENT_KEY,
## #   2: OCCUR_DATE, 3: OCCUR_TIME, 4: LOC_OF_OCCUR_DESC, 5: PRECINCT,
## #   6: JURISDICTION_CODE, 7: LOC_CLASSFCTN_DESC, 8: LOCATION_DESC,
## #   9: STATISTICAL_MURDER_FLAG
```

Step 4 Lets take a look at the summary of the dataframe

```
summary(shooting_incident)
```

```
##   INCIDENT_KEY        OCCUR_DATE         OCCUR_TIME           BORO
##  Min.   :  9953245   Length:27312       Length:27312       Length:27312
##  1st Qu.: 63860880   Class :character   Class1:hms         Class :character
##  Median : 90372218   Mode  :character   Class2:difftime    Mode  :character
##  Mean   :120860536                      Mode  :numeric
##  3rd Qu.:188810230
##  Max.   :261190187
##
##  LOC_OF_OCCUR_DESC     PRECINCT      JURISDICTION_CODE LOC_CLASSFCTN_DESC
##  Length:27312       Min.   :  1.00   Min.   :0.0000    Length:27312
##  Class :character   1st Qu.: 44.00   1st Qu.:0.0000    Class :character
##  Mode  :character   Median : 68.00   Median :0.0000    Mode  :character
##                     Mean   : 65.64   Mean   :0.3269
##                     3rd Qu.: 81.00   3rd Qu.:0.0000
##                     Max.   :123.00   Max.   :2.0000
##                                      NA's   :2
##  LOCATION_DESC      STATISTICAL_MURDER_FLAG PERP_AGE_GROUP
##  Length:27312       Mode :logical           Length:27312
##  Class :character   FALSE:22046             Class :character
##  Mode  :character   TRUE :5266              Mode  :character
##
##
##
##
##    PERP_SEX           PERP_RACE          VIC_AGE_GROUP        VIC_SEX
##  Length:27312       Length:27312       Length:27312       Length:27312
##  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:27312       Min.   : 914928   Min.   :125757   Min.   :40.51
##  Class :character   1st Qu.:1000029   1st Qu.:182834   1st Qu.:40.67
##  Mode  :character   Median :1007731   Median :194487   Median :40.70
##                     Mean   :1009449   Mean   :208127   Mean   :40.74
##                     3rd Qu.:1016838   3rd Qu.:239518   3rd Qu.:40.82
##                     Max.   :1066815   Max.   :271128   Max.   :40.91
##                                                        NA's   :10
##    Longitude         Lon_Lat
##  Min.   :-74.25   Length:27312
##  1st Qu.:-73.94   Class :character
##  Median :-73.92   Mode  :character
##  Mean   :-73.91
##  3rd Qu.:-73.88
##  Max.   :-73.70
##  NA's   :10
```

Step 5 Looks like the `OCCUR_DATE` is a character, lets try to change it to a date in a new column called `OCCUR_DATE_LUBRIDATE`

```
shooting_incident <- shooting_incident %>%
  mutate(OCCUR_DATE_LUBRIDATE = mdy(OCCUR_DATE))
```

Step 6 Confirm the date changes worked

```
summary(shooting_incident$OCCUR_DATE)
```

```
##    Length     Class      Mode
##     27312 character character
```

```
summary(shooting_incident$OCCUR_DATE_LUBRIDATE)
```

```
##         Min.      1st Qu.       Median         Mean      3rd Qu.         Max.
## "2006-01-01" "2009-07-18" "2013-04-29" "2014-01-06" "2018-10-15" "2022-12-31"
```

Step 7 It worked! Lets remove the old `OCCUR_DATE` and rename `OCCUR_DATE_LUBRIDATE` to `OCCUR_DATE`

```
shooting_incident <- shooting_incident %>%
  select(-c(OCCUR_DATE)) %>%
  rename(OCCUR_DATE = OCCUR_DATE_LUBRIDATE)
```

Step 8 Now we can take a look to see how the `VIC_AGE_GROUP`s are allocated

```
shooting_incident %>%
  group_by(VIC_AGE_GROUP) %>%
  summarise(Total = n()) %>%
  arrange(desc(Total))
```

```
## # A tibble: 7 x 2
##   VIC_AGE_GROUP Total
##   <chr>         <int>
## 1 25-44         12281
## 2 18-24         10086
## 3 <18            2839
## 4 45-64          1863
## 5 65+             181
## 6 UNKNOWN          61
## 7 1022              1
```

Step 9 There could be some funky values (1022 is obviously an error) so lets only include the values that are good. (I could exclude 1022, but I want to make sure I also exclude other "fat-fingered" values in the future, so I'll make it an include rather than exclude function)

```
shooting_incident <- shooting_incident %>%
  filter(VIC_AGE_GROUP %in% c("25-44", "18-24", "<18", "45-64", "65+", "UNKNOWN"))
```

Step 10 Check to make sure that looks better

```
shooting_incident %>%
  group_by(VIC_AGE_GROUP) %>%
  summarise(Total = n()) %>%
  arrange(desc(Total))
```

```
## # A tibble: 6 x 2
##   VIC_AGE_GROUP Total
##   <chr>         <int>
## 1 25-44         12281
## 2 18-24         10086
## 3 <18            2839
## 4 45-64          1863
## 5 65+             181
## 6 UNKNOWN          61
```

Step 11 I think I'll want to sort them as well, so lets rename them

```
shooting_incident <- shooting_incident %>%
  mutate(
    VIC_AGE_GROUP = case_when(
      VIC_AGE_GROUP == "<18" ~ "1. <18",
      VIC_AGE_GROUP == "18-24" ~ "2. 18-24",
      VIC_AGE_GROUP == "25-44" ~ "3. 25-44",
      VIC_AGE_GROUP == "45-64" ~ "4. 45-64",
      VIC_AGE_GROUP == "65+" ~ "5. 65+"
    )
  )
```

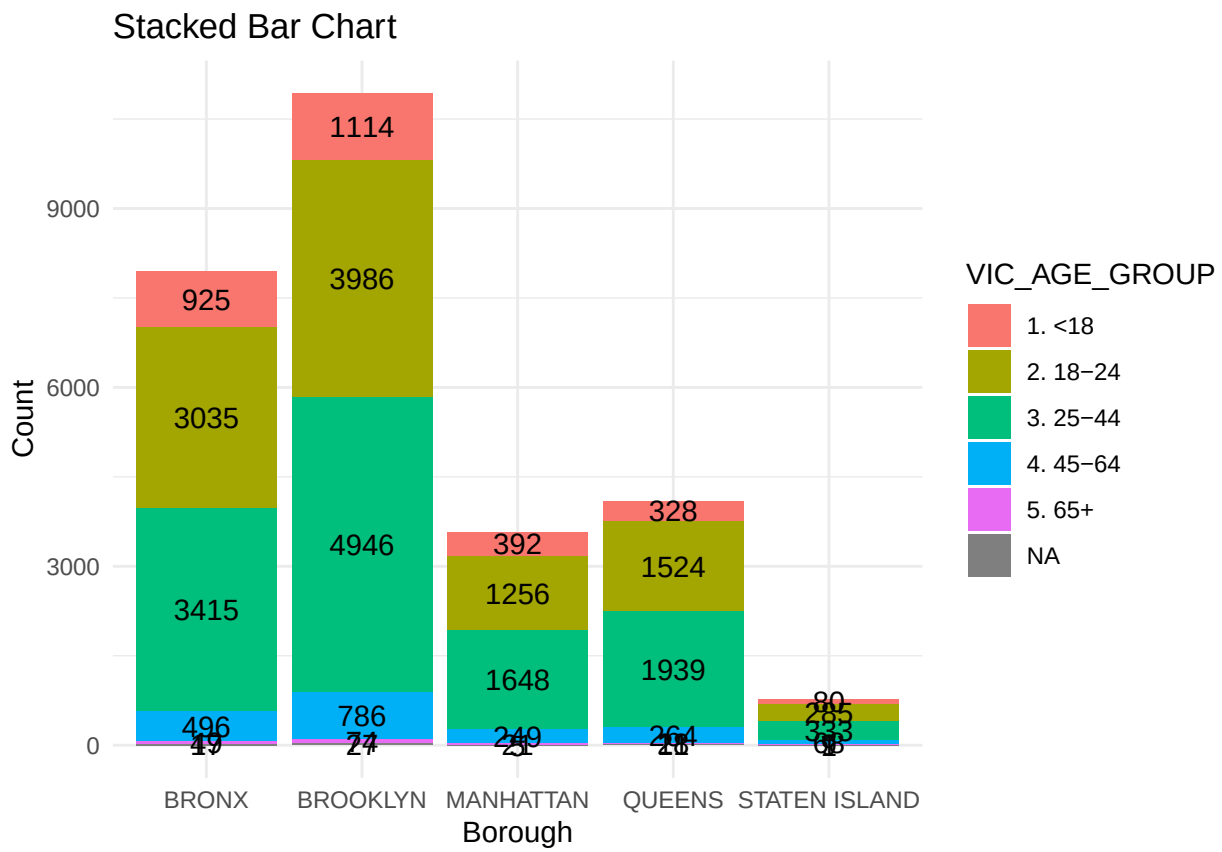
Step 12 Check to make sure that looks better

```
shooting_incident %>%
  group_by(VIC_AGE_GROUP) %>%
  summarise(Total = n()) %>%
  arrange(VIC_AGE_GROUP)
```

```
## # A tibble: 6 x 2
##   VIC_AGE_GROUP Total
##   <chr>         <int>
## 1 1. <18         2839
## 2 2. 18-24      10086
## 3 3. 25-44      12281
## 4 4. 45-64       1863
## 5 5. 65+          181
## 6 <NA>             61
```

Step 13 Create a stacked bar chart

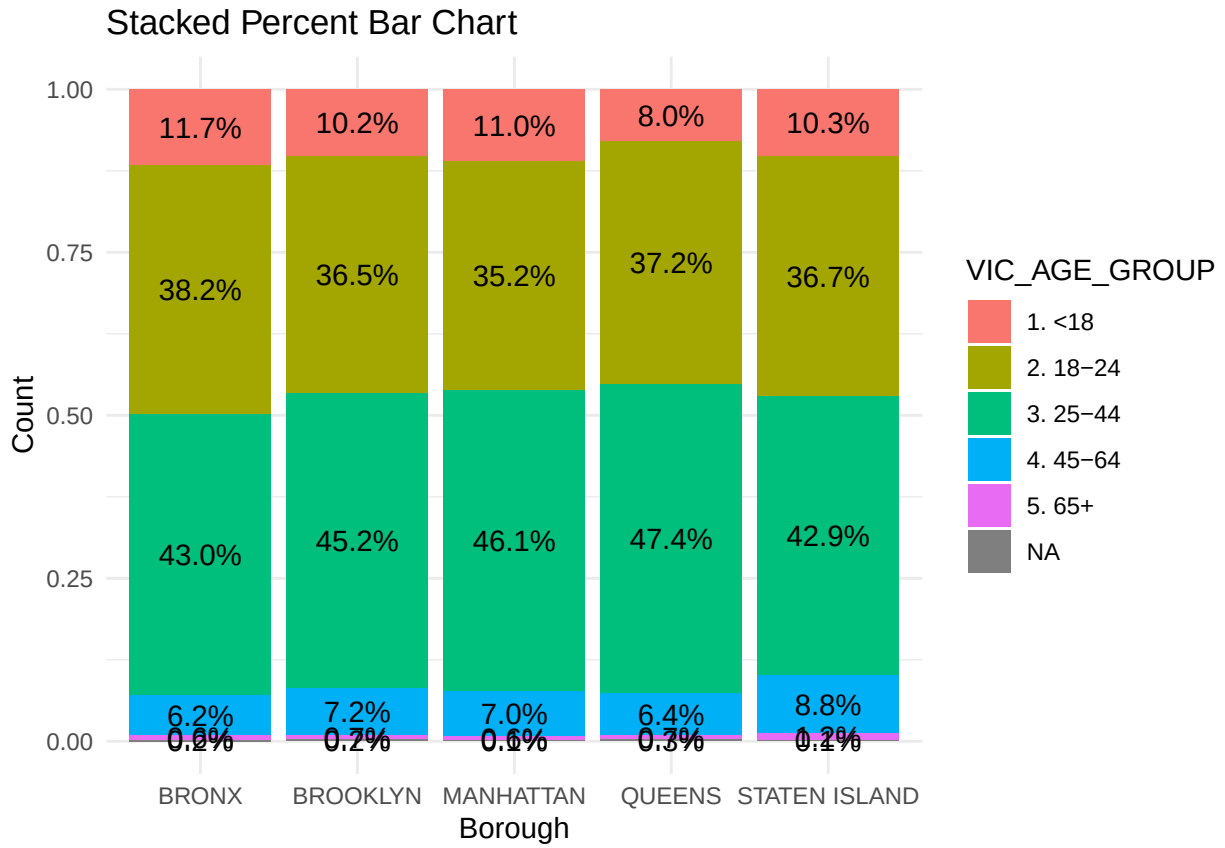
```
ggplot(shooting_incident, aes(fill = VIC_AGE_GROUP, x = BORO)) +
  geom_bar(position = "stack", stat = "count") +
  geom_text(
    stat = 'count',
    aes(label = after_stat(count), group = VIC_AGE_GROUP),
    position = position_stack(vjust = 0.5)
  ) +
  labs(title = "Stacked Bar Chart",
       x = "Borough",
       y = "Count") +
  theme_minimal()
```



Step 14 That's a little hard to understand since the populations of the borough are pretty varied. lets make a stacked percent bar char to see if that helps

```
shooting_incident %>%
  count(BORO, VIC_AGE_GROUP) %>%
  group_by(BORO) %>%
  mutate(pct = prop.table(n) * 100) %>%
  ggplot(aes(fill = VIC_AGE_GROUP, x = BORO, y = pct)) +
  geom_col(position = "fill") +
  labs(title = "Stacked Percent Bar Chart",
       x = "Borough",
       y = "Count") +
```

```
  geom_text(aes(label = paste0(sprintf("%1.1f", pct), "%")), position = position_fill(vjust = 0.5)) +
  theme_minimal()
```



Step 15 We can see that as a % of all victims in the boroughs, 18-24 year olds make up a smaller % in Manhattan than the other boroughs, and 25-44 year-olds make up a smaller % in the Bronx, but I want to create a model to see if that is statistically significant. In order to do that, I want to preform a chi-squared test of homogeneity. To start, I need to create a contingency table

```
contingency_table <-
  table(shooting_incident$BORO, shooting_incident$VIC_AGE_GROUP)
print(contingency_table)
```

```
##
##                1. <18 2. 18-24 3. 25-44 4. 45-64 5. 65+
##   BRONX            925     3035     3415      496     49
##   BROOKLYN        1114     3986     4946      786     74
##   MANHATTAN        392     1256     1648      249     21
##   QUEENS           328     1524     1939      264     28
##   STATEN ISLAND     80      285      333       68      9
```

Step 16 Now I can run the chi-squared test using `chisq.test`

```r
chi_squared_test <- chisq.test(contingency_table)
print(chi_squared_test)
```

```
##
##  Pearson's Chi-squared test
##
## data:  contingency_table
## X-squared = 72.13, df = 16, p-value = 4.215e-09
```

Step 17 The P value is super low! Lets dig into standardized residuals see where the biggest offenders are.

```r
chi_squared_test$stdres
```

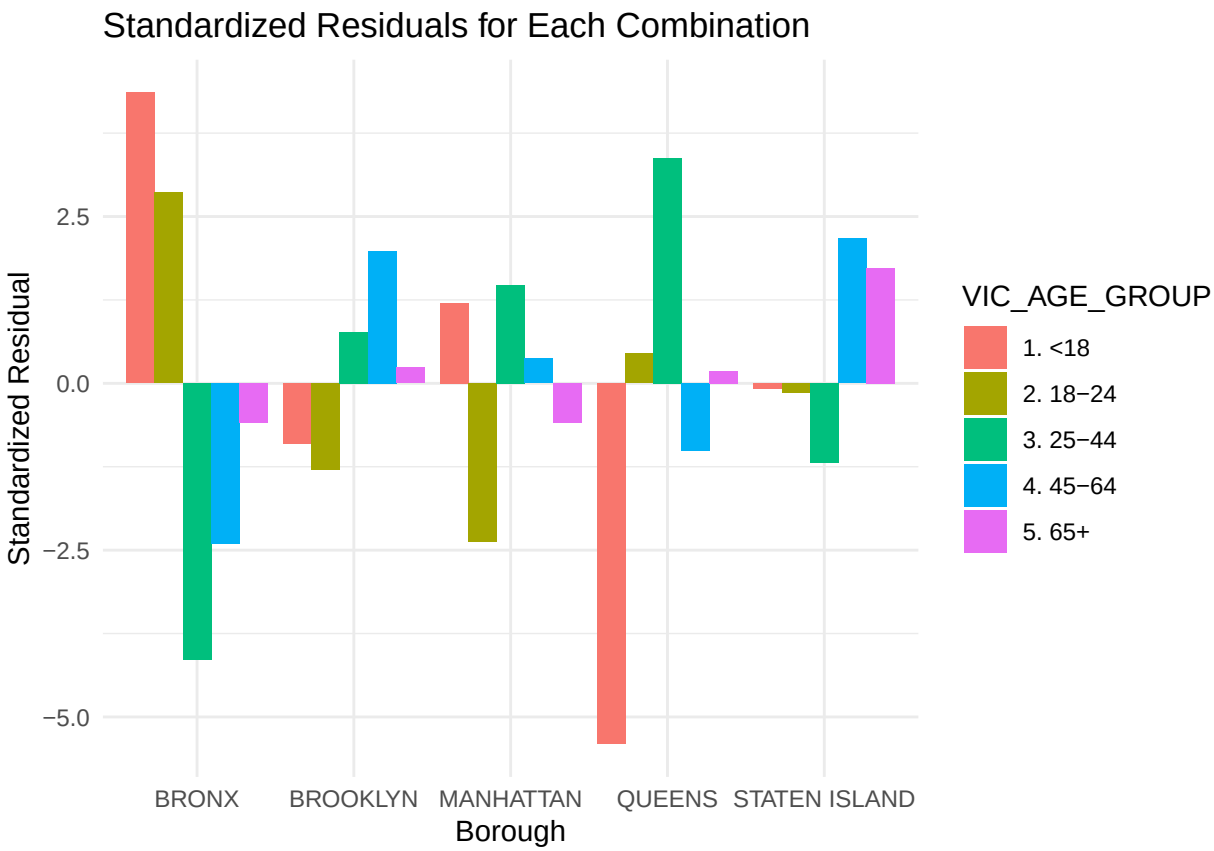
```
##
##                      1. <18    2. 18-24    3. 25-44    4. 45-64      5. 65+
##   BRONX          4.36130889  2.86213394 -4.13942715 -2.40353196 -0.59231168
##   BROOKLYN      -0.89951021 -1.29627712  0.76776056  1.97877949  0.23748047
##   MANHATTAN      1.20426435 -2.37637111  1.47577128  0.37034345 -0.59398710
##   QUEENS        -5.41034172  0.44874221  3.37296493 -1.01837163  0.18385613
##   STATEN ISLAND -0.08853754 -0.13959704 -1.19211805  2.16826016  1.72832299
```

Step 18 Lets graph the standard residual. But first we need to turn it into a data frame, and change the column names

```r
std_res_df <- as.data.frame(chi_squared_test$stdres) %>%
  rename(Borough = Var1,
         VIC_AGE_GROUP = Var2)
```

Step 19 Now we can graph it. We can no clearly see '<18' year-olds in the Queens are less likely to be victims, while in the Bronx, anyone less than 24 is more likely.

```r
ggplot(std_res_df, aes(x = Borough, y = Freq, fill = VIC_AGE_GROUP)) +
  geom_bar(stat = "identity", position = "dodge") +
  labs(title = "Standardized Residuals for Each Combination",
       y = "Standardized Residual")  +
  theme_minimal()
```



Final thoughts - bias reduction Recognizing the influence of personal perspectives is crucial in analyzing the NYPD Shooting Incident data. The choice to explore this dataset is not devoid of potential biases, as personal experiences and predispositions can shape the framing of questions and interpretation of results. Additionally, the selection of specific variables for scrutiny may inadvertently reflect certain viewpoints. To counteract these biases, a conscious effort will be made to approach the analysis with an open mind, considering alternative perspectives and remaining vigilant about the potential impact of preconceived notions on the interpretation of the data. The aim is to conduct a nuanced and fair analysis, acknowledging and mitigating biases to ensure the reliability and objectivity of the findings.