

NYPD_Shooting_Basic_Exploration

```
library(ggplot2)
library(dplyr)
library(shiny)
library(zoo)
library(chron)
```

Cursory visual and summary examination:

```
df = read.csv("https://data.cityofnewyork.us/api/views/833y-fsy8/rows.csv?accessType=DOWNLOAD")
head(df, 1)
```

```
## INCIDENT_KEY OCCUR_DATE OCCUR_TIME BORO LOC_OF_OCCUR_DESC PRECINCT
## 1 228798151 05/27/2021 21:30:00 QUEENS 105
## JURISDICTION_CODE LOC_CLASSFCTN_DESC LOCATION_DESC STATISTICAL_MURDER_FLAG
## 1 0 false
## PERP_AGE_GROUP PERP_SEX PERP_RACE VIC_AGE_GROUP VIC_SEX VIC_RACE X_COORD_CD
## 1 18-24 M BLACK 1058925
## Y_COORD_CD Latitude Longitude Lon_Lat
## 1 180924 40.66296 -73.73084 POINT (-73.73083868899994 40.662964620000025)
```

```
str(df)
```

```
## 'data.frame': 27312 obs. of 21 variables:
## $ INCIDENT_KEY : int 228798151 137471050 147998800 146837977 58921844 219559682 85295722
## $ OCCUR_DATE : chr "05/27/2021" "06/27/2014" "11/21/2015" "10/09/2015" ...
## $ OCCUR_TIME : chr "21:30:00" "17:40:00" "03:56:00" "18:30:00" ...
## $ BORO : chr "QUEENS" "BRONX" "QUEENS" "BRONX" ...
## $ LOC_OF_OCCUR_DESC : chr "" "" "" "" ...
## $ PRECINCT : int 105 40 108 44 47 81 114 81 105 101 ...
## $ JURISDICTION_CODE : int 0 0 0 0 0 0 0 0 0 0 ...
## $ LOC_CLASSFCTN_DESC : chr "" "" "" "" ...
## $ LOCATION_DESC : chr "" "" "" "" ...
## $ STATISTICAL_MURDER_FLAG: chr "false" "false" "true" "false" ...
## $ PERP_AGE_GROUP : chr "" "" "" "" ...
## $ PERP_SEX : chr "" "" "" "" ...
## $ PERP_RACE : chr "" "" "" "" ...
## $ VIC_AGE_GROUP : chr "18-24" "18-24" "25-44" "<18" ...
## $ VIC_SEX : chr "M" "M" "M" "M" ...
## $ VIC_RACE : chr "BLACK" "BLACK" "WHITE" "WHITE HISPANIC" ...
## $ X_COORD_CD : num 1058925 1005028 1007668 1006537 1024922 ...
## $ Y_COORD_CD : num 180924 234516 209837 244511 262189 ...
## $ Latitude : num 40.7 40.8 40.7 40.8 40.9 ...
## $ Longitude : num -73.7 -73.9 -73.9 -73.9 -73.9 ...
## $ Lon_Lat : chr "POINT (-73.73083868899994 40.662964620000025)" "POINT (-73.9249423"
```

```
summary(df)
```

```
## INCIDENT_KEY OCCUR_DATE OCCUR_TIME BORO
```

```

## Min.      : 9953245      Length:27312      Length:27312      Length:27312
## 1st Qu.: 63860880      Class :character  Class :character  Class :character
## Median : 90372218      Mode  :character  Mode  :character  Mode  :character
## Mean      :120860536
## 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      Length:27312      Length:27312
## Class :character  Class :character  Class :character
## Mode  :character  Mode  :character  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.:1000028      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

```

Single variable examination

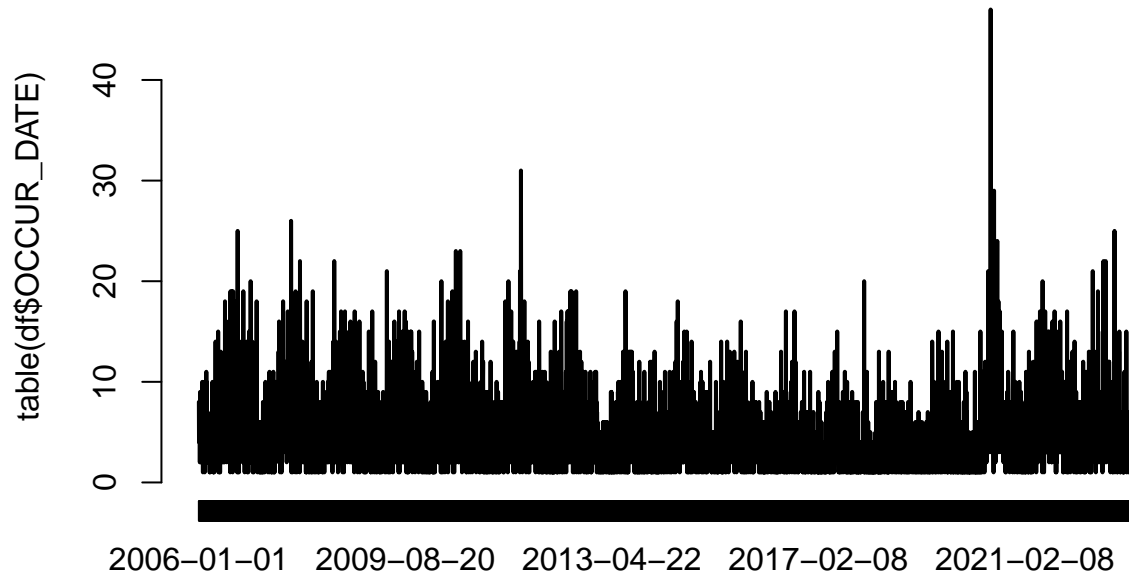
Date

```

#parse OCCUR_DATE to date format
df$OCCUR_DATE = as.Date(df$OCCUR_DATE, format = "%m/%d/%Y")

```

```
plot(table(df$OCCUR_DATE), type = 'l')
```



#this chart is messy but we can see a few things:

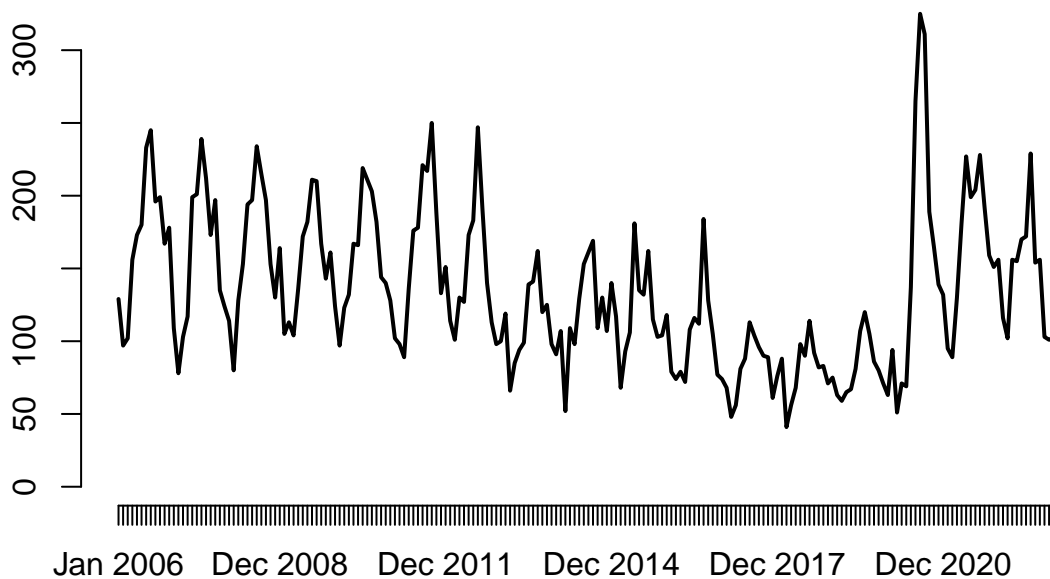
#-seasonal peaks and lulls in shootings - presumably lower in the winter and higher in the summer

#-an overall drop in shooting incidents from the beginning of the data in 2006 until 2020

#-a large spike around the period of unrest following the killing of George Floyd with overall levels s

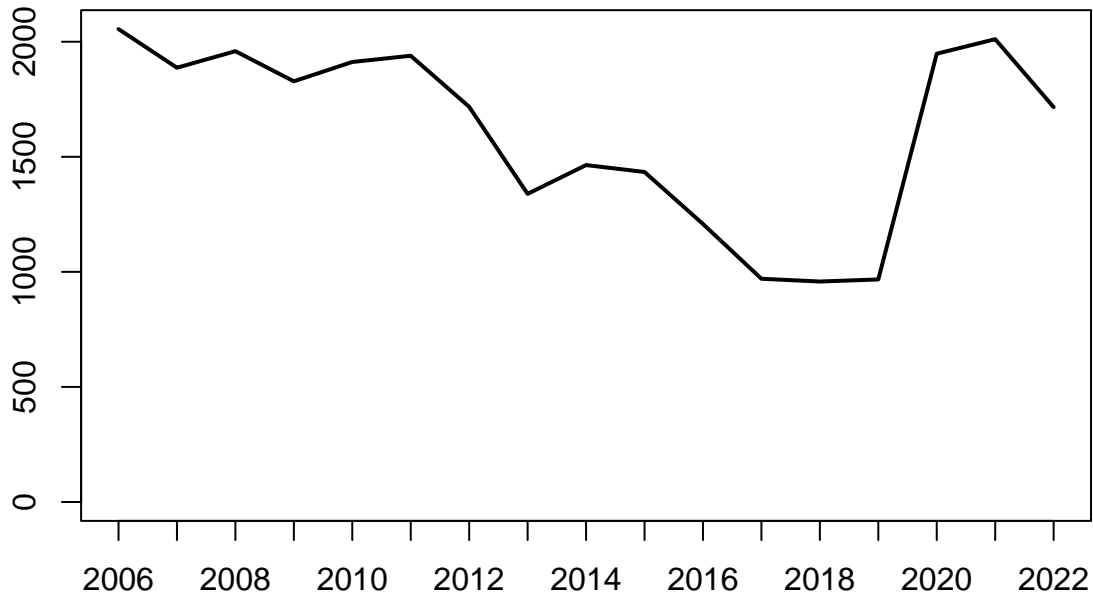
#let's bin the dates into individual months to produce a clearer chart

```
df$Month = df$OCCUR_DATE %>% as.yearmon()
df$Month %>% table() %>% plot(type = 'l')
```



#this monthly plot is better, but it would be nice to plot each year separately and have the x-axis be
#as well as to simply aggregate by year

```
df$Year = df$OCCUR_DATE %>% format("%Y")
df$Year %>% table() %>% plot(type = "l")
```



with this yearly plot we can see a sizeable reduction in shootings - almost 50% over about 10 years, # that has persisted until the end of the dataset in 2022

```
df$Year = df$OCCUR_DATE %>% format("%Y") %>% as.integer()
df$Month = df$OCCUR_DATE %>% format("%m") %>% as.integer()
yearmon_df = df %>% group_by(Year, Month) %>% summarise(Count = n()) %>% as.data.frame()
```

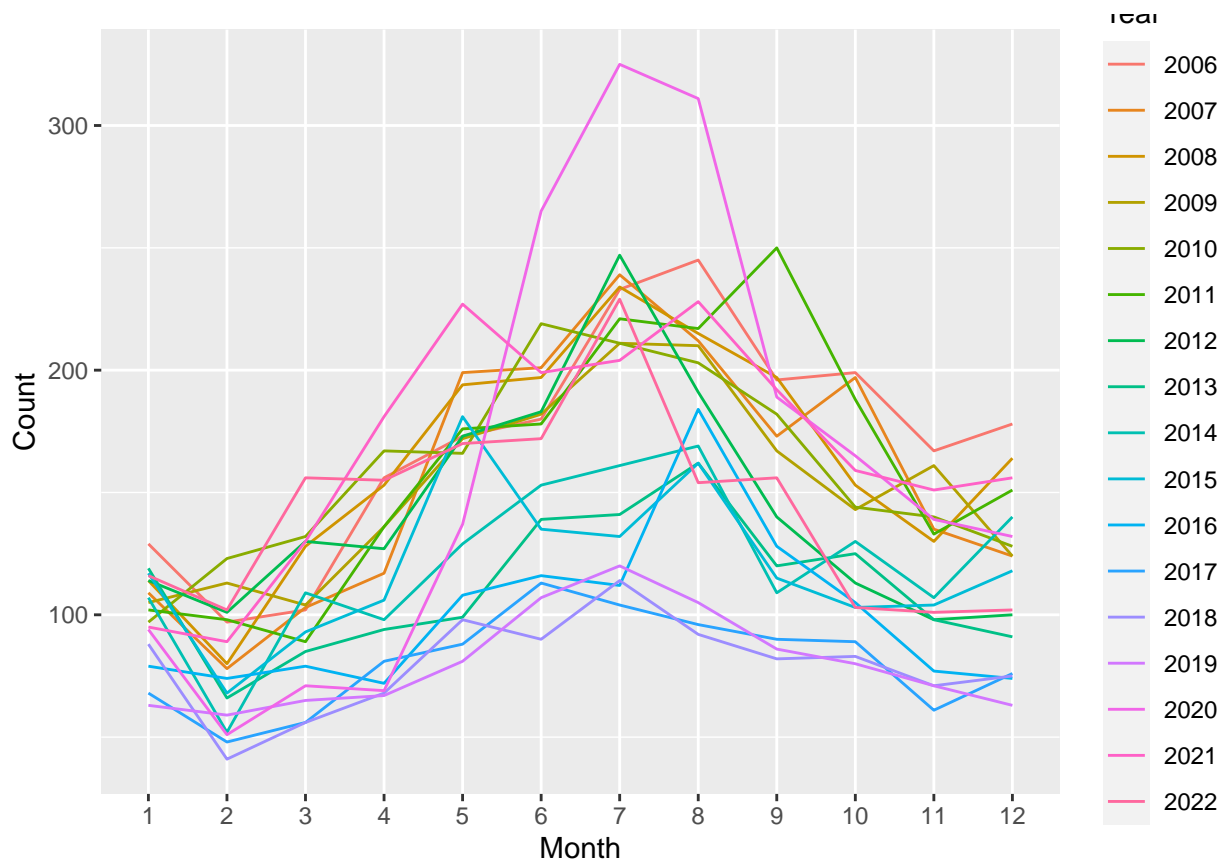
`summarise()` has grouped output by 'Year'. You can override using the
`.groups` argument.

```
yearmon_df$Year = yearmon_df$Year %>% as.factor()
yearmon_df$Month = yearmon_df$Month %>% as.factor()
```

```
yearmon_df %>% head(3)
```

```
##   Year Month Count
## 1 2006     1   129
## 2 2006     2    97
## 3 2006     3   102
```

```
ggplot(yearmon_df, aes(x = Month, y = Count, group = Year, col = Year)) + geom_line()
```



*#here we can confirm that shootings tend to peak in the summer.
#we can also see the surge in shootings in the summer of 2020 after the killing of George Floyd*

Time

```
df$OCCUR_TIME %>% unique() %>% head(20)
```

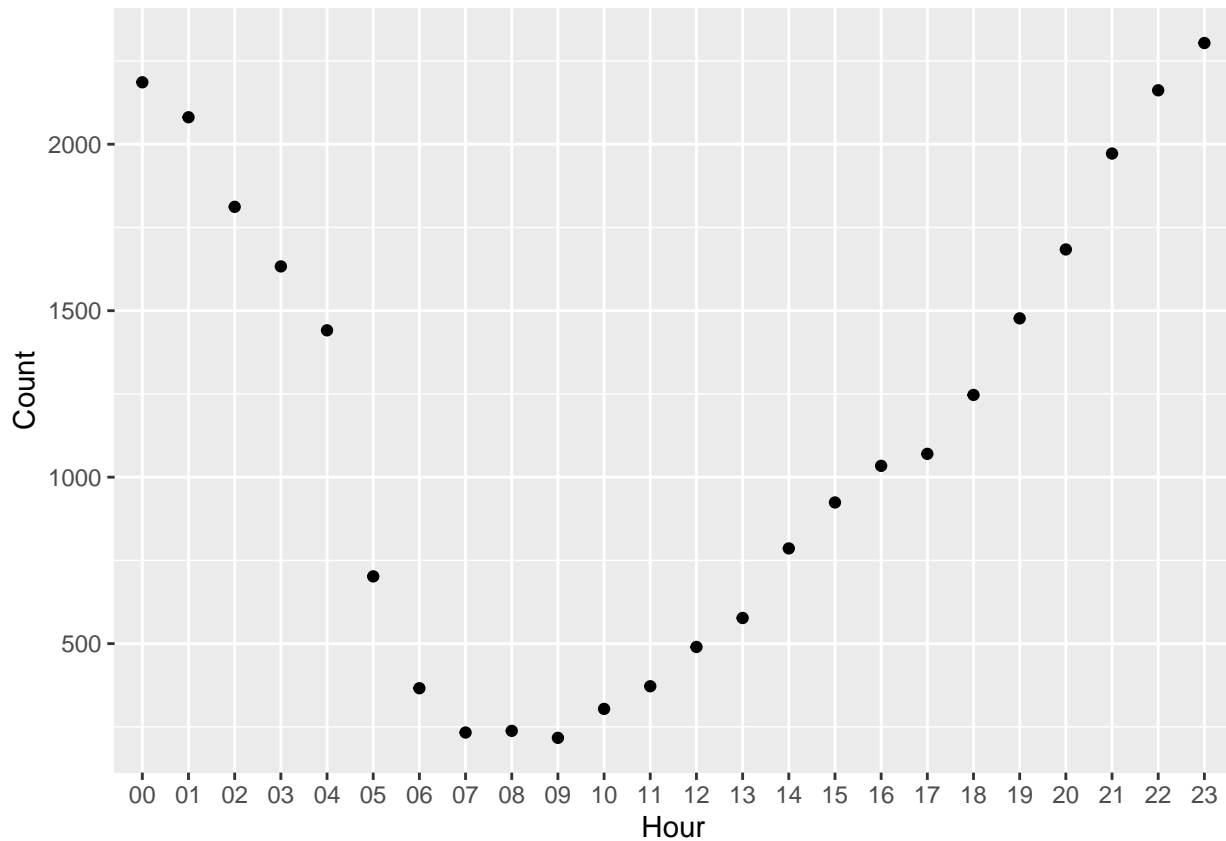
```
## [1] "21:30:00" "17:40:00" "03:56:00" "18:30:00" "22:58:00" "21:36:00"
## [7] "22:47:00" "19:41:00" "05:45:00" "01:10:00" "03:21:00" "01:27:00"
## [13] "20:17:00" "21:58:00" "20:13:00" "02:22:00" "21:07:00" "02:44:00"
## [19] "21:17:00" "23:16:00"
```

```
df$OCCUR_TIME %>% table() %>% sort(decreasing = TRUE) %>% head(20)
```

```
## .
## 23:30:00 00:30:00 01:30:00 02:00:00 21:00:00 22:30:00 01:00:00 04:00:00
##      179      156      153      148      145      140      133      130
## 23:00:00 21:30:00 22:00:00 02:30:00 00:50:00 03:30:00 01:15:00 03:00:00
##      130      125      121      108      105      104      103      100
## 04:30:00 00:15:00 20:00:00 23:50:00
##       99       98       97       96
```

*#unfortunately while there are time bins included down to the minute, many have been apparently categor
we will group into uniform bins in order to get a decent visualization of the time distribution*

```
df$Hour = df$OCCUR_TIME %>% substr(0,2)
hour_df = df$Hour %>% table() %>% as.data.frame() %>% setNames(c("Hour", "Count"))
ggplot(hour_df, aes(x = Hour, y = Count)) + geom_point()
```



are lowest in the morning and then rise throughout the day, peaking late at night

Borough

```
table(df$BORO)
```

```
##
##      BRONX      BROOKLYN      MANHATTAN      QUEENS STATEN ISLAND
##      7937      10933      3572      4094      776
```

straightforward categories with complete data

“LOC_OF_OCCUR_DESC”

```
table(df$LOC_OF_OCCUR_DESC)
```

```
##
##      INSIDE OUTSIDE
##  25596      242      1474
```

not particularly helpful with the vast majority of values missing

Precinct

```
table(df$PRECINCT)
```

```
##
##      1      5      6      7      9     10     13     14     17     18     19     20     22     23     24     25
```

```
## 25 58 28 109 109 73 60 56 10 34 20 40 1 487 105 461
## 26 28 30 32 33 34 40 41 42 43 44 45 46 47 48 49
## 149 343 229 634 225 316 908 494 850 758 1020 182 895 953 787 353
## 50 52 60 61 62 63 66 67 68 69 70 71 72 73 75 76
## 154 583 372 153 70 282 46 1216 32 466 459 579 109 1452 1557 167
## 77 78 79 81 83 84 88 90 94 100 101 102 103 104 105 106
## 795 62 1012 799 500 124 280 315 86 170 489 210 593 102 479 224
## 107 108 109 110 111 112 113 114 115 120 121 122 123
## 101 67 115 160 11 23 802 369 179 572 112 61 31
```

#clearly there is large variance in shooting incidents between different precincts. Some have none while others obviously need to be mapped to be meaningful

```
df$PRECINCT %>% table() %>% sum()
```

```
## [1] 27312
```

#confirming that all incidents are placed in a precinct - no missing values

Jurisdiction Code

```
table(df$JURISDICTION_CODE)
```

```
##
## 0 1 2
## 22809 74 4427
```

#according to NYC's data website, 0=Patrol, 1=Transit, 2=Housing

“LOC_CLASSFCTN_DESC”

```
table(df$LOC_CLASSFCTN_DESC)
```

```
##
## COMMERCIAL DWELLING HOUSING OTHER PARKING LOT
## 25596 100 127 280 31 7
## PLAYGROUND STREET TRANSIT VEHICLE
## 30 1103 15 23
```

#vast majority have missing value

“LOCATION_DESC”

```
table(df$LOCATION_DESC)
```

```
##
## (null) ATM
## 14977 977 1
## BANK BAR/NIGHT CLUB BEAUTY/NAIL SALON
## 3 628 112
## CANDY STORE CHAIN STORE CHECK CASH
## 7 5 1
## CLOTHING BOUTIQUE COMMERCIAL BLDG DEPT STORE
## 14 292 9
## DOCTOR/DENTIST DRUG STORE DRY CLEANER/LAUNDRY
## 1 14 31
```

```
##          FACTORY/WAREHOUSE          FAST FOOD          GAS STATION
##              8              104              71
##          GROCERY/BODEGA      GYM/FITNESS FACILITY      HOSPITAL
##              694              3              65
##          HOTEL/MOTEL          JEWELRY STORE          LIQUOR STORE
##              35              12              41
##          LOAN COMPANY      MULTI DWELL - APT BUILD      MULTI DWELL - PUBLIC HOUS
##              1              2835              4832
##              NONE          PHOTO/COPY STORE          PVT HOUSE
##              175              1              951
##          RESTAURANT/DINER          SCHOOL          SHOE STORE
##              204              1              10
##          SMALL MERCHANT      SOCIAL CLUB/POLICY LOCATI      STORAGE FACILITY
##              37              72              1
##          STORE UNCLASSIFIED      SUPERMARKET          TELECOMM. STORE
##              36              21              11
##          VARIETY STORE          VIDEO STORE
##              11              8
```

#interesting categories here but more than half still have missing value

STATISTICAL_MURDER_FLAG

```
table(df$STATISTICAL_MURDER_FLAG)
```

```
##
## false true
## 22046 5266
```

from NYC's data website: "Shooting resulted in the victim's death which would be counted as a murder"

Shooter Age/Sex/Race

```
table(df$PERP_AGE_GROUP)
```

```
##
##          (null)      <18      1020      18-24      224      25-44      45-64      65+      940
##      9344      640      1591      1      6222      1      5687      617      60      1
## UNKNOWN
##      3148
```

```
table(df$PERP_SEX)
```

```
##
##          (null)      F      M      U
##      9310      640      424      15439      1499
```

```
table(df$PERP_RACE)
```

```
##
##
##          (null)
##          9310      640
## AMERICAN INDIAN/ALASKAN NATIVE      ASIAN / PACIFIC ISLANDER
##          2      154
##          BLACK      BLACK HISPANIC
##          11432      1314
```



```
##                UNKNOWN                WHITE
##                1836                283
##                WHITE HISPANIC
##                2341
```

*#naturally there is a substantial proportion of missing values. Presumably police can't necessarily even
#typical profile of categorized shooter is young, male, black/hispanic
#based on number of null/missing values it looks like a perp description (i.e. these columns in a single row)*

Victim Age/Sex/Race

```
table(df$VIC_AGE_GROUP)
```

```
##
##    <18    1022   18-24   25-44   45-64    65+ UNKNOWN
##    2839      1  10086  12281   1863    181      61
```

```
table(df$VIC_SEX)
```

```
##
##      F      M      U
##  2615  24686    11
```

```
table(df$VIC_RACE)
```

```
##
## AMERICAN INDIAN/ALASKAN NATIVE      ASIAN / PACIFIC ISLANDER
##                                10                                404
##                                BLACK      BLACK HISPANIC
##                                19439                                2646
##                                UNKNOWN      WHITE
##                                66                                698
##                                WHITE HISPANIC
##                                4049
```

*#naturally victims have many fewer missing values (they got shot, much easier to find)
#profile again is young, male, black/hispanic*

Geolocation Data - [needs to be visualized with geographical package]

Modeling fatality proportion vs precinct number of shootings

```
#create a dataframe with each precinct's shooting count, fatality count, and proportion of shootings that are fatal
df$Fatal = df$STATISTICAL_MURDER_FLAG %>% recode('true' = 1, 'false' = 0)
fatality_prop_df = df %>% group_by(PRECINCT) %>% summarise(Count = n(), Fatalities = sum(Fatal), Fatal_prop = sum(Fatal)/Count)
fatality_prop_df %>% head(5)
```

A typical question that arises from examining crime data is whether police/emergency resources are being fairly distributed throughout a jurisdiction. While we don't have any sort of deployment or response time data here for NYPD we can check to see if there is any relationship between the number of shootings in a precinct and the proportion that are fatal as a sort of proxy for the speed/efficacy of emergency response in general.

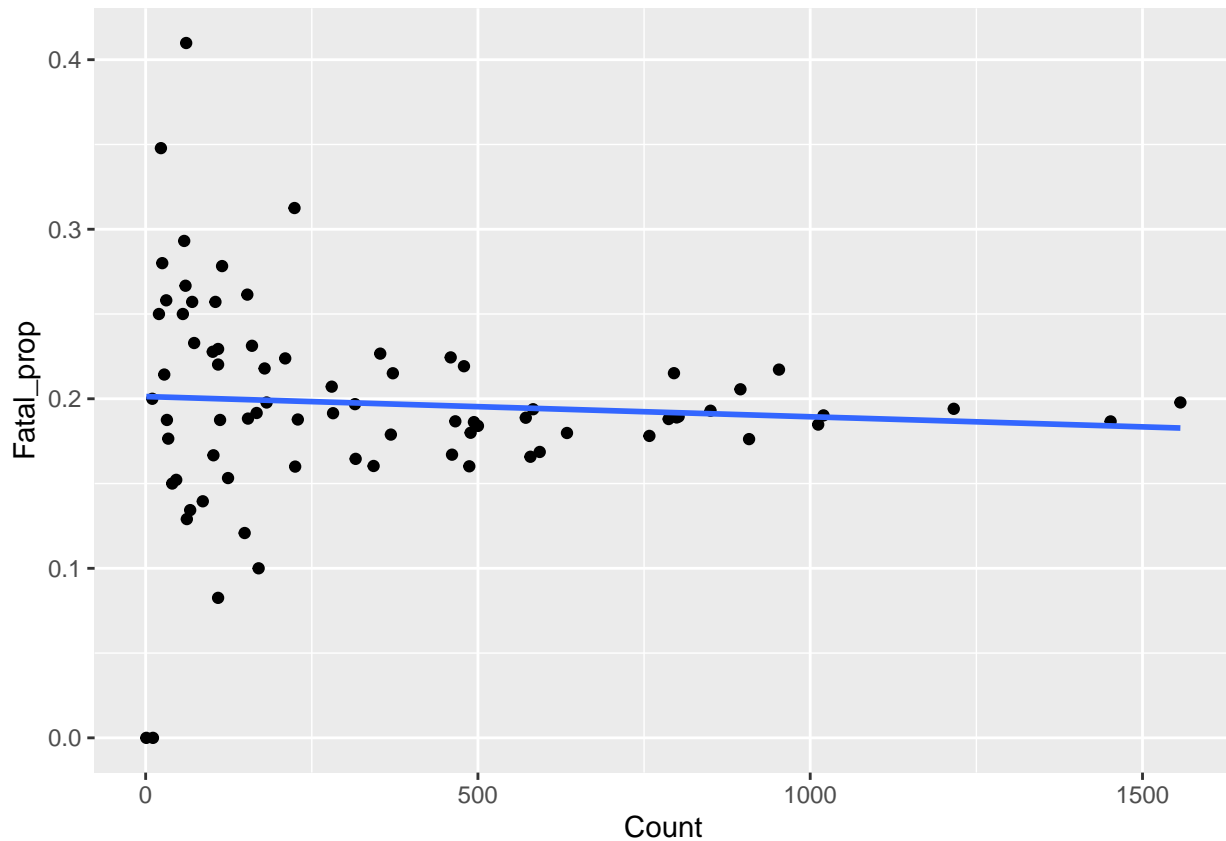
```
## # A tibble: 5 x 4
##   PRECINCT Count Fatalities Fatal_prop
##   <int> <int>      <dbl>      <dbl>
## 1      1    25          7      0.28
```

```
## 2      5      58      17      0.293
## 3      6      28       6      0.214
## 4      7     109       9      0.0826
## 5      9     109      25      0.229
```

*#Calculate linear model with x=number of shootings in a precinct and y=proportion of shootings that are
 #As we can see from the model and the graph below there is essentially no correlation,
 #so there is no suggestion *in this data* that more dangerous precincts are experiencing a generally wo
 #emergency response.*

```
model = lm(formula = Fatal_prop ~ Count, data = fatality_prop_df, )
summary(model)
```

```
##
## Call:
## lm(formula = Fatal_prop ~ Count, data = fatality_prop_df)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -0.201298 -0.024434 -0.002226  0.027257  0.209253
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)  2.013e-01  9.720e-03  20.711  <2e-16 ***
## Count       -1.192e-05  1.932e-05  -0.617    0.539
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.06047 on 75 degrees of freedom
## Multiple R-squared:  0.005046, Adjusted R-squared:  -0.00822
## F-statistic: 0.3804 on 1 and 75 DF, p-value: 0.5393
ggplot(fatality_prop_df, aes(x = Count, y = Fatal_prop)) + geom_point() + geom_smooth(method = 'lm', se
## `geom_smooth()` using formula = 'y ~ x'
```



Data Bias and Quality Discussion

- It is not clear whether this data includes instances where people literally were hit with a bullet or if there are also incidents where a victim was just shot at; either way there are presumably more 'shots fired' incidents not included in this data set which have different feature distributions from this dataset
- A lot of the location description columns are missing so many values that they are not particularly useful
- Perpetrator description columns may be subject to direct bias as they may be garnered from witness statements which can be faulty
- Victim description columns should be better since it is easier to actually locate and confirm a shooting victim