

Week 3 Assingment - NYPD Shooting Incident Data

```
library(tidyverse)
```

Importing tidyverse and lubridate libraries.

```
## -- Attaching packages ----- tidyverse 1.3.1 --

## v ggplot2 3.3.5      v purrr  0.3.4
## v tibble  3.1.6      v dplyr  1.0.7
## v tidyr   1.1.4      v stringr 1.4.0
## v readr   2.1.1      v forcats 0.5.1

## -- Conflicts ----- tidyverse_conflicts() --
## x dplyr::filter() masks stats::filter()
## x dplyr::lag()    masks stats::lag()
```

```
library(lubridate)
```

```
##
## Attaching package: 'lubridate'

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

Step 1: Importing Data

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

Importing csv file from data.cityofnewyork.us

	INCIDENT_KEY	OCCUR_DATE	OCCUR_TIME	BORO	PRECINCT	JURISDICTION_CODE
## 1	24050482	08/27/2006	05:35:00	BRONX	52	0
## 2	77673979	03/11/2011	12:03:00	QUEENS	106	0
## 3	203350417	10/06/2019	01:09:00	BROOKLYN	77	0
## 4	80584527	09/04/2011	03:35:00	BRONX	40	0
## 5	90843766	05/27/2013	21:16:00	QUEENS	100	0

```
## 6      92393427 09/01/2013    04:17:00 BROOKLYN      67      0
##  LOCATION_DESC STATISTICAL_MURDER_FLAG PERP_AGE_GROUP PERP_SEX PERP_RACE
## 1
## 2
## 3
## 4
## 5
## 6
##  VIC_AGE_GROUP VIC_SEX      VIC_RACE X_COORD_CD Y_COORD_CD Latitude Longitude
## 1      25-44      F BLACK HISPANIC   1017542   255918.9 40.86906 -73.87963
## 2      65+      M  WHITE   1027543   186095.0 40.67737 -73.84392
## 3      18-24     F   BLACK   995325   185155.0 40.67489 -73.96008
## 4       <18     M   BLACK  1007453   233952.0 40.80880 -73.91618
## 5      18-24     M   BLACK  1041267   157133.5 40.59780 -73.79469
## 6       <18     M   BLACK  1001694   170112.9 40.63359 -73.93715
##                               Lon_Lat
## 1 POINT (-73.87963173099996 40.86905819000003)
## 2 POINT (-73.84392019199998 40.677366895000034)
## 3 POINT (-73.96007501899999 40.674885741000026)
## 4 POINT (-73.91618413199996 40.808797805000004)
## 5 POINT (-73.79468553799995 40.597796249000055)
## 6 POINT (-73.93715330699996 40.633588181000005)
```

Step 2: Tidy and Transform Data

```
df_new <- df %>% select(OCCUR_DATE, OCCUR_TIME, BORO, STATISTICAL_MURDER_FLAG, PERP_AGE_GROUP, PERP_SEX)
head(df_new)
```

Since I don't think a lot of the columns are relevant, I will only choose "OCCUR_DATE", "OCCUR_TIME", "BORO", "STATISTICAL_MURDER_FLAG", "PERP_AGE_GROUP", "PERP_SEX", "PERP_RACE", "VIC_AGE_GROUP", "VIC_SEX", and "VIC_RACE".

```
##  OCCUR_DATE OCCUR_TIME      BORO STATISTICAL_MURDER_FLAG PERP_AGE_GROUP
## 1 08/27/2006 05:35:00    BRONX
## 2 03/11/2011 12:03:00   QUEENS
## 3 10/06/2019 01:09:00 BROOKLYN
## 4 09/04/2011 03:35:00    BRONX
## 5 05/27/2013 21:16:00   QUEENS
## 6 09/01/2013 04:17:00 BROOKLYN
##  PERP_SEX PERP_RACE VIC_AGE_GROUP VIC_SEX      VIC_RACE
## 1
## 2
## 3
## 4
## 5
## 6
```

There are numbers of missing perpetrator information in this dataset, maybe due to the fact that the perpetrator was never caught, or it's under active investigation, so I will change the

blank spaces to unknown to match rest of the dataset. I will also update time and dates to a more readable format for easy analysis.

```
df_new[df_new == ''] <- NA
df_new <- replace_na(df_new, list(PERP_AGE_GROUP = "UNKNOWN", PERP_SEX = "U", PERP_RACE = "UNKNOWN"))
df_new$OCCUR_DATE<-mdy(df_new$OCCUR_DATE)
df_new$OCCUR_DATE<-wday(df_new$OCCUR_DATE, label=TRUE, abbr=FALSE)
df_new$OCCUR_TIME<-hour(hms(df_new$OCCUR_TIME))
df_new[df_new == 1020] <- "UNKNOWN"
df_new[df_new == 224] <- "UNKNOWN"
df_new[df_new == 940] <- "UNKNOWN"
df_new[df_new == "true"] <- "1"
df_new[df_new == "false"] <- "0"
head(df_new)
```

While doing analysis of this dataset, I found that there are strange numbers in the PERP_AGE column, so I will also replace these numbers with “UNKNOWN”. I will also change true and false to 1 and 0 respectively to make it easier for modeling.

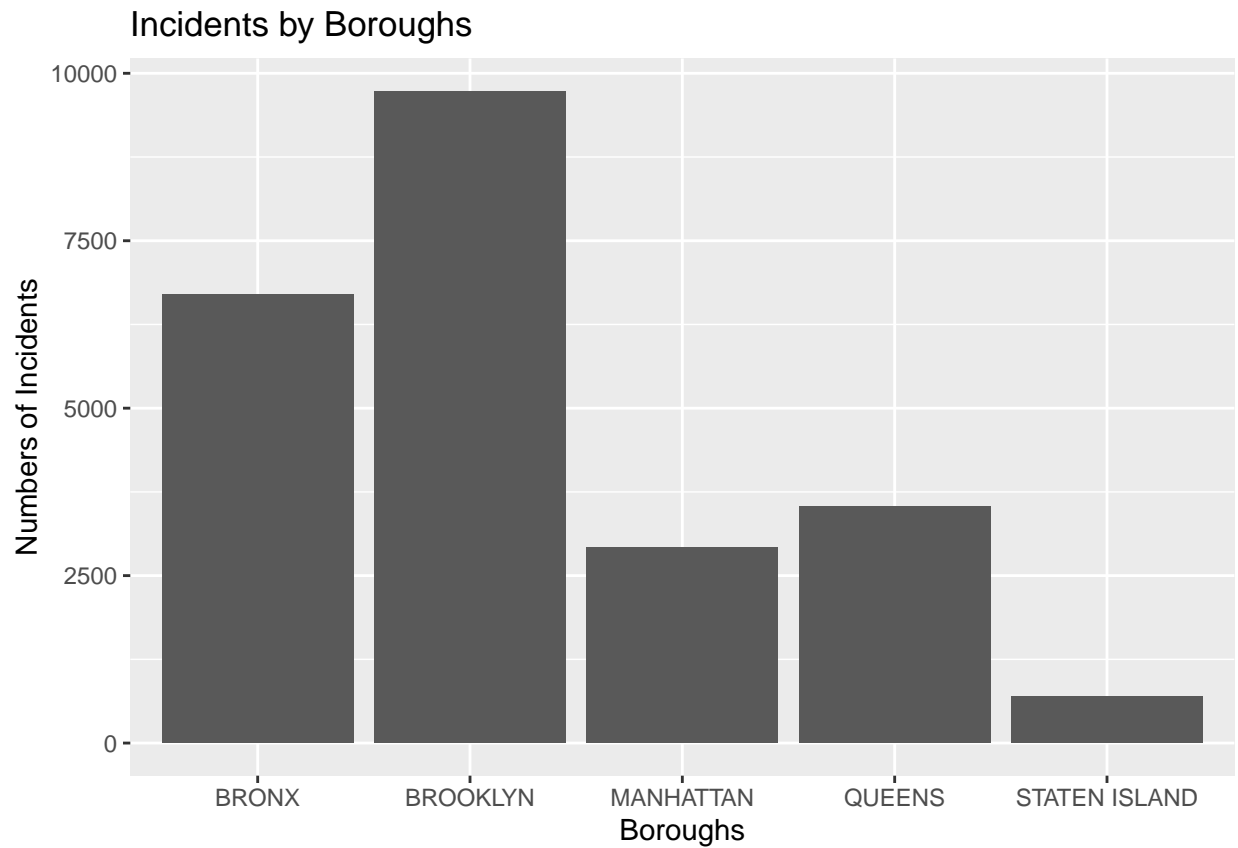
##	OCCUR_DATE	OCCUR_TIME	BORO	STATISTICAL_MURDER_FLAG	PERP_AGE_GROUP
## 1	Sunday	5	BRONX	1	UNKNOWN
## 2	Friday	12	QUEENS	0	UNKNOWN
## 3	Sunday	1	BROOKLYN	0	UNKNOWN
## 4	Sunday	3	BRONX	0	UNKNOWN
## 5	Monday	21	QUEENS	0	UNKNOWN
## 6	Sunday	4	BROOKLYN	0	UNKNOWN

##	PERP_SEX	PERP_RACE	VIC_AGE_GROUP	VIC_SEX	VIC_RACE
## 1	U	UNKNOWN	25-44	F	BLACK HISPANIC
## 2	U	UNKNOWN	65+	M	WHITE
## 3	U	UNKNOWN	18-24	F	BLACK
## 4	U	UNKNOWN	<18	M	BLACK
## 5	U	UNKNOWN	18-24	M	BLACK
## 6	U	UNKNOWN	<18	M	BLACK

Step 3: Visulizing Data

We will now plot the amount of shootings by all the boroughs of NYC.

```
ggplot(df_new, aes(BORO))+geom_bar()+labs(title="Incidents by Boroughs", x="Boroughs",y="Numbers of Incidents")
```



```
table(df_new$BORO)
```

```
##
##      BRONX      BROOKLYN      MANHATTAN      QUEENS      STATEN ISLAND
##      6701      9734      2922      3532      696
```

For this dataset, let's find out the following:

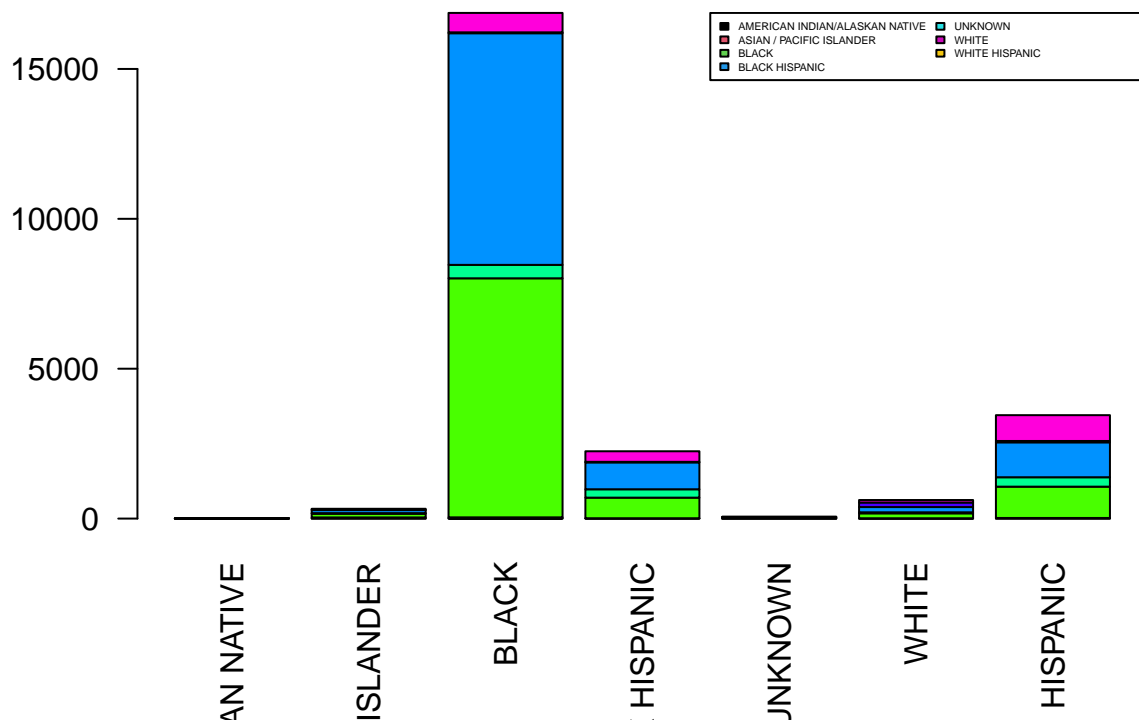
1. Which Borough have the highest shootings?
1. What race is more likely to be shooter and which race is more likely to be victim?
2. What age group is more likely to be part of these shootings?
3. Which sex is more likely to be part of these shootings?

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

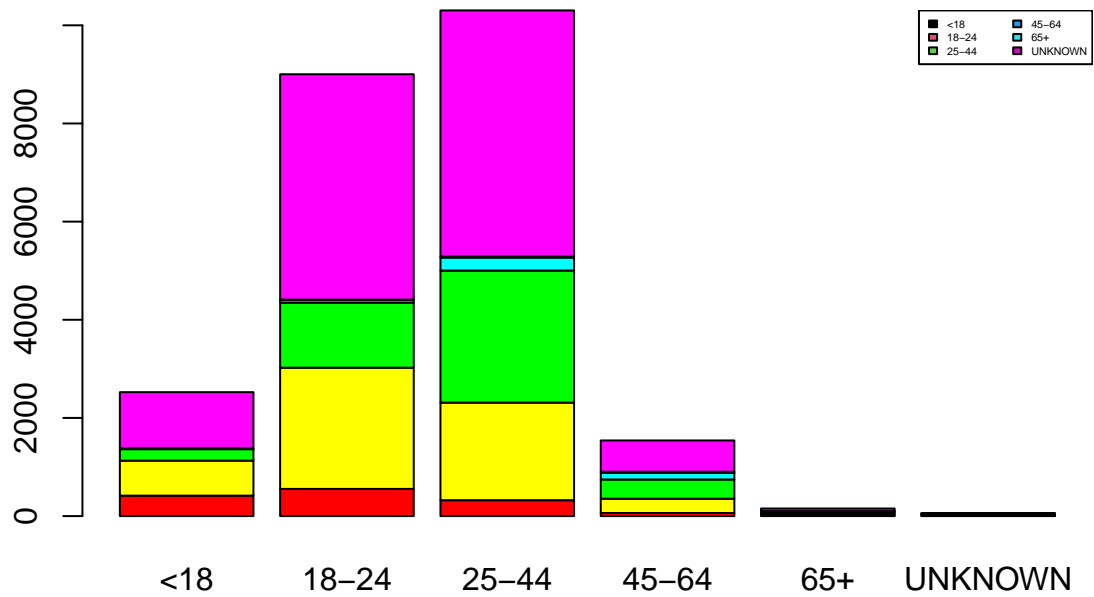
We can see that Brooklyn has the most amount of shooting incidents followed by Bronx. Based on this graph, let's find out how many of these shootings are results in murder.

```
##
##           0      1
##  BRONX      5454 1247
##  BROOKLYN   7836 1898
##  MANHATTAN  2407  515
##  QUEENS     2835  697
##  STATEN ISLAND 553  143
```

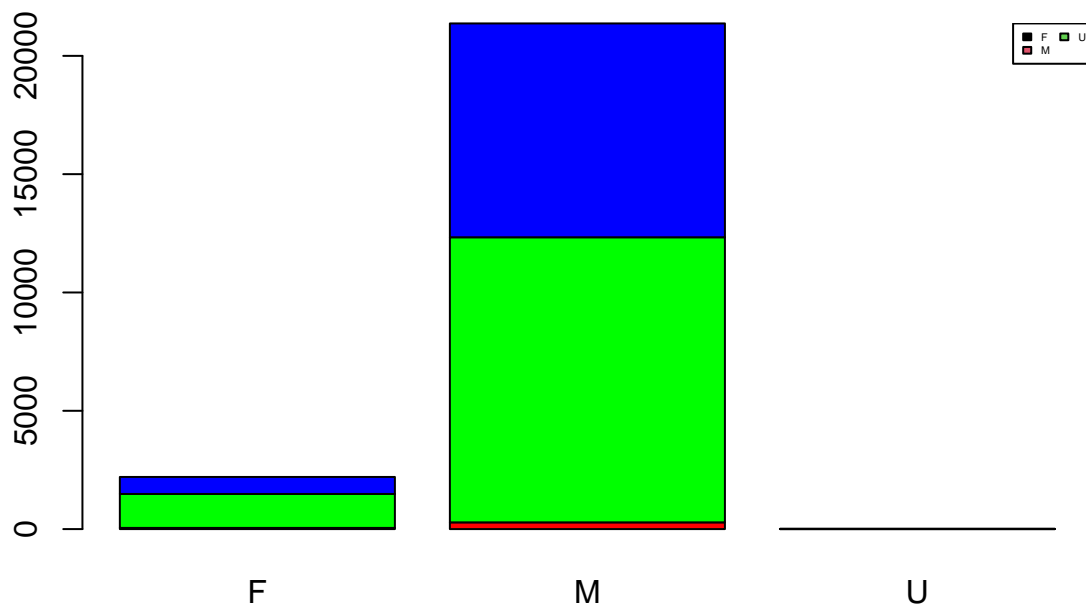
```
r=table(df_new$PERP_RACE, df_new$VIC_RACE)
barplot(as.matrix(r), col = rainbow(7), las=2)
legend("topright", legend = rownames(r), fill = 1:7, ncol = 2, cex = 0.35)
```



```
a=table(df_new$PERP_AGE_GROUP, df_new$VIC_AGE_GROUP)
barplot(as.matrix(a), col = rainbow(6))
legend("topright", legend = rownames(a), fill = 1:6, ncol = 2, cex = 0.35)
```



```
s=table(df_new$PERP_SEX, df_new$VIC_SEX)
barplot(as.matrix(s), col = rainbow(3))
legend("topright", legend = rownames(s), fill = 1:3, ncol = 2, cex = 0.35)
```



We can see from the graphs that black men tend to be perpetrators and black/black hispanic men tend to be victims.

Step 4: Modeling Data

```
df_new$STATISTICAL_MURDER_FLAG<-as.numeric(df_new$STATISTICAL_MURDER_FLAG)
mod <- glm(STATISTICAL_MURDER_FLAG~OCCUR_DATE+PERP_AGE_GROUP+PERP_SEX+PERP_RACE, data=df_new, family="b
summary(mod)
```

We will now build a model using logistic regression to predict if the incident will result in murder.

```
##
## Call:
## glm(formula = STATISTICAL_MURDER_FLAG ~ OCCUR_DATE + PERP_AGE_GROUP +
##     PERP_SEX + PERP_RACE, family = "binomial", data = df_new)
##
## Deviance Residuals:
##      Min       1Q   Median       3Q      Max
## -1.8992  -0.6757  -0.6149  -0.2176   2.9081
##
```

```
## Coefficients:
##               Estimate Std. Error z value Pr(>|z|)
## (Intercept)    -10.832962   84.415755  -0.128 0.897889
## OCCUR_DATE.L    -0.055538    0.041519  -1.338 0.181003
## OCCUR_DATE.Q    -0.099699    0.043684  -2.282 0.022472 *
## OCCUR_DATE.C    -0.048915    0.044911  -1.089 0.276090
## OCCUR_DATE^4    -0.039325    0.045668  -0.861 0.389172
## OCCUR_DATE^5    -0.005101    0.048043  -0.106 0.915448
## OCCUR_DATE^6    -0.040959    0.049663  -0.825 0.409520
## PERP_AGE_GROUP18-24  0.162911    0.078116   2.086 0.037023 *
## PERP_AGE_GROUP25-44  0.503244    0.077999   6.452 1.10e-10 ***
## PERP_AGE_GROUP45-64  0.827764    0.119213   6.944 3.82e-12 ***
## PERP_AGE_GROUP65+    1.034956    0.290415   3.564 0.000366 ***
## PERP_AGE_GROUPUNKNOWN -2.223419    0.172367 -12.899 < 2e-16 ***
## PERP_SEXM        -0.150656    0.129302  -1.165 0.243959
## PERP_SEXU        2.480248    0.271977   9.119 < 2e-16 ***
## PERP_RACEASIAN / PACIFIC ISLANDER 9.944287   84.415952   0.118 0.906225
## PERP_RACEBLACK     9.443813   84.415716   0.112 0.910924
## PERP_RACEBLACK HISPANIC 9.303813   84.415749   0.110 0.912240
## PERP_RACEUNKNOWN    8.977274   84.415968   0.106 0.915308
## PERP_RACEWHITE     10.119528   84.415815   0.120 0.904580
## PERP_RACEWHITE HISPANIC 9.589109   84.415728   0.114 0.909560
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##    Null deviance: 22990  on 23584  degrees of freedom
## Residual deviance: 22127  on 23565  degrees of freedom
## AIC: 22167
##
## Number of Fisher Scoring iterations: 9
```

#Biases and Pitfalls

Biases and pitfalls would be assuming a certain borough would have more crime than others, or certain race/age group would commit more crimes than other race/age groups. Such as one would assume Brox will have more crimes and shootings due to media exposure, but Brooklyn actually has more shootings.

So maybe have an open mind and neutral mindset before starting any analysis.