

# nypd\_analysis

April 30, 2023

## 0.0.1 Overview

- 1) Introduction
  - Install and load packages
  - Load csv data into R data frame
- 2) EDA
  - Overview of data
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## 1 1 Introduction

This is a comprehensive analysis of the [NYPD Shooting Incident Data \(Historic\) - Catalog](#). This dataset records every shooting incident that occurred in 2006 - 2022. Each record includes information related to the shooting such as suspect and victim demographics, location, and date.

We will study and visualize the data using ggplot2 and tidyverse. Later, we will generate some questions based on our findings about the data. Finally, we will model our processed data and make an analysis about the questions we have formed.

**The purpose of this report is to examine the following questions:** 1) Is the number of shooting incidents going up or down? 2) What is distribution of the Victim's demographic information

### 1.1 1.1 Install and Load Libraries

```
[1]: #install packages
```

```
[2]: #common packages

#data wrangling packages
library(tidyverse)

#data visualization packages
library(forcats)

#utility packages
```

```
library(assert)
```

```
Attaching core tidyverse packages          tidyverse
2.0.0
dplyr      1.1.0      readr      2.1.4
forcats    1.0.0      stringr    1.5.0
ggplot2     3.4.1      tibble     3.2.0
lubridate   1.9.2      tidyr      1.3.0
purrr       1.0.1

Conflicts
tidyverse_conflicts()
dplyr::filter() masks stats::filter()
dplyr::lag()     masks stats::lag()
Use the conflicted package
(<http://conflicted.r-lib.org/>) to force all conflicts to
become errors
```

## 1.2 1.2 Load Data

```
[21]: #check data size, columns and data types
file_path = 'NYPD_Shooting_Incident_Data__Historic_.csv'
original_df = read_csv(file_path)
spec(original_df)
```

```
Rows: 25596 Columns: 19
Column specification
```

```
Delimiter: ","
chr   (10): OCCUR_DATE, BORO, LOCATION_DESC, PERP_AGE_GROUP, PERP_SEX,
PERP_R...
dbl   (7): INCIDENT_KEY, PRECINCT, JURISDICTION_CODE, X_COORD_CD,
Y_COORD_CD...
lgl   (1): STATISTICAL_MURDER_FLAG
time  (1): OCCUR_TIME
```

Use `spec()` to retrieve the full column specification for this data.

Specify the column types or set `show\_col\_types = FALSE` to quiet this message.

```
cols(
  INCIDENT_KEY = col_double(),
  OCCUR_DATE = col_character(),
  OCCUR_TIME = col_time(format = ""),
  BORO = col_character(),
  PRECINCT = col_double(),
  JURISDICTION_CODE = col_double(),
  LOCATION_DESC = col_character(),
```

```

STATISTICAL_MURDER_FLAG = col_logical(),
PERP_AGE_GROUP = col_character(),
PERP_SEX = col_character(),
PERP_RACE = col_character(),
VIC_AGE_GROUP = col_character(),
VIC_SEX = col_character(),
VIC_RACE = col_character(),
X_COORD_CD = col_double(),
Y_COORD_CD = col_double(),
Latitude = col_double(),
Longitude = col_double(),
Lon_Lat = col_character()
)

```

## 2 2 EDA

### 2.1 2.1 Quick Overview of the Entire Data

[22]: `summary(original_df)`

INCIDENT_KEY	OCCUR_DATE	OCCUR_TIME	BORO
Min. : 9953245	Length:25596	Length:25596	Length:25596
1st Qu.: 61593633	Class :character	Class1:hms	Class :character
Median : 86437258	Mode :character	Class2:difftime	Mode :character
Mean :112382648		Mode :numeric	
3rd Qu.:166660833			
Max. :238490103			

PRECINCT	JURISDICTION_CODE	LOCATION_DESC	STATISTICAL_MURDER_FLAG
Min. : 1.00	Min. :0.0000	Length:25596	Mode :logical
1st Qu.: 44.00	1st Qu.:0.0000	Class :character	FALSE:20668
Median : 69.00	Median :0.0000	Mode :character	TRUE :4928
Mean : 65.87	Mean :0.3316		
3rd Qu.: 81.00	3rd Qu.:0.0000		
Max. :123.00	Max. :2.0000		
	NA's :2		

PERP_AGE_GROUP	PERP_SEX	PERP_RACE	VIC_AGE_GROUP
Length:25596	Length:25596	Length:25596	Length:25596
Class :character	Class :character	Class :character	Class :character
Mode :character	Mode :character	Mode :character	Mode :character

VIC_SEX	VIC_RACE	X_COORD_CD	Y_COORD_CD
Length:25596	Length:25596	Min. : 914928	Min. :125757
Class :character	Class :character	1st Qu.:1000011	1st Qu.:182782

Mode :character	Mode :character	Median :1007715	Median :194038
		Mean :1009455	Mean :207894
		3rd Qu.:1016838	3rd Qu.:239429
		Max. :1066815	Max. :271128

Latitude	Longitude	Lon_Lat
Min. :40.51	Min. : -74.25	Length:25596
1st Qu.:40.67	1st Qu.: -73.94	Class :character
Median :40.70	Median : -73.92	Mode :character
Mean :40.74	Mean : -73.91	
3rd Qu.:40.82	3rd Qu.: -73.88	
Max. :40.91	Max. : -73.70	

[23]: `glimpse(original_df)`

```

Rows: 25,596
Columns: 19
$ INCIDENT_KEY      <dbl> 236168668, 231008085,
230717903, 237712309, 22...
$ OCCUR_DATE        <chr> "11/11/2021", "07/16/2021",
"07/11/2021", "12/...
$ OCCUR_TIME        <time> 15:04:00, 22:05:00,
01:09:00, 13:42:00, 20:00...
$ BORO              <chr> "BROOKLYN", "BROOKLYN",
"BROOKLYN", "BROOKLYN"...
$ PRECINCT          <dbl> 79, 72, 79, 81, 113, 113, 42,
52, 34, 75, 32, ...
$ JURISDICTION_CODE <dbl> 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
0, 2, 2, 0, 0, 0...
$ LOCATION_DESC     <chr> NA, NA, NA, NA, NA, NA,
"COMMERCIAL BLDG", NA,...
$ STATISTICAL_MURDER_FLAG <lgl> FALSE, FALSE, FALSE, FALSE,
FALSE, TRUE, TRUE,...
$ PERP_AGE_GROUP    <chr> NA, "45-64", "<18", NA, NA,
NA, NA, NA, NA, "2...
$ PERP_SEX          <chr> NA, "M", "M", NA, NA, NA, NA,
NA, NA, "M", "M"...
$ PERP_RACE         <chr> NA, "ASIAN / PACIFIC
ISLANDER", "BLACK", NA, N...
$ VIC_AGE_GROUP     <chr> "18-24", "25-44", "25-44",
"25-44", "25-44", "...
$ VIC_SEX           <chr> "M", "M", "M", "M", "M", "M",
"M", "M", "M", "...
$ VIC_RACE          <chr> "BLACK", "ASIAN / PACIFIC
ISLANDER", "BLACK", ...
$ X_COORD_CD        <dbl> 996313, 981845, 996546,
1001139, 1050710, 1051...

```

```

$ Y_COORD_CD          <dbl> 187499, 171118, 187436,
192775, 184826, 196646...
$ Latitude            <dbl> 40.68132, 40.63636, 40.68114,
40.69579, 40.673...
$ Longitude           <dbl> -73.95651, -74.00867,
-73.95567, -73.93910, -7...
$ Lon_Lat             <chr> "POINT (-73.95650899099996
40.68131820000008)"...

```

## 2.2 Cleaning and Extracting Data

Before we start exploring our data, we can drop some columns of the data where information overlaps.

We can drop: - *X\_COORD\_CD* & *Y\_COORD\_CD* because *Latitude* & *Longitude* exists - *Latitude* and *Longitude* because *Lon\_Lat* is a column that combines both - *ind* & *INCIDENT\_KEY* - *BORO* because *PRECINCT* contains boro information

```

[25]: df = original_df %>%
      select(-c(X_COORD_CD, Y_COORD_CD, Latitude, Longitude, INCIDENT_KEY,
      OCCUR_TIME, PRECINCT, JURISDICTION_CODE, STATISTICAL_MURDER_FLAG, Lon_Lat))

```

```

[26]: glimpse(df)

```

```

Rows: 25,596
Columns: 9
$ OCCUR_DATE      <chr> "11/11/2021", "07/16/2021",
"07/11/2021", "12/11/2021",...
$ BORO            <chr> "BROOKLYN", "BROOKLYN", "BROOKLYN",
"BROOKLYN", "QUEENS...
$ LOCATION_DESC   <chr> NA, NA, NA, NA, NA, NA, "COMMERCIAL
BLDG", NA, NA, NA, ...
$ PERP_AGE_GROUP  <chr> NA, "45-64", "<18", NA, NA, NA, NA,
NA, NA, "25-44", "2...
$ PERP_SEX        <chr> NA, "M", "M", NA, NA, NA, NA, NA, NA,
"M", "M", NA, "M"...
$ PERP_RACE       <chr> NA, "ASIAN / PACIFIC ISLANDER",
"BLACK", NA, NA, NA, NA...
$ VIC_AGE_GROUP   <chr> "18-24", "25-44", "25-44", "25-44",
"25-44", "25-44", "...
$ VIC_SEX         <chr> "M", "M", "M", "M", "M", "M", "M",
"M", "M", "M", "M", ...
$ VIC_RACE        <chr> "BLACK", "ASIAN / PACIFIC ISLANDER",
"BLACK", "BLACK", ...

```

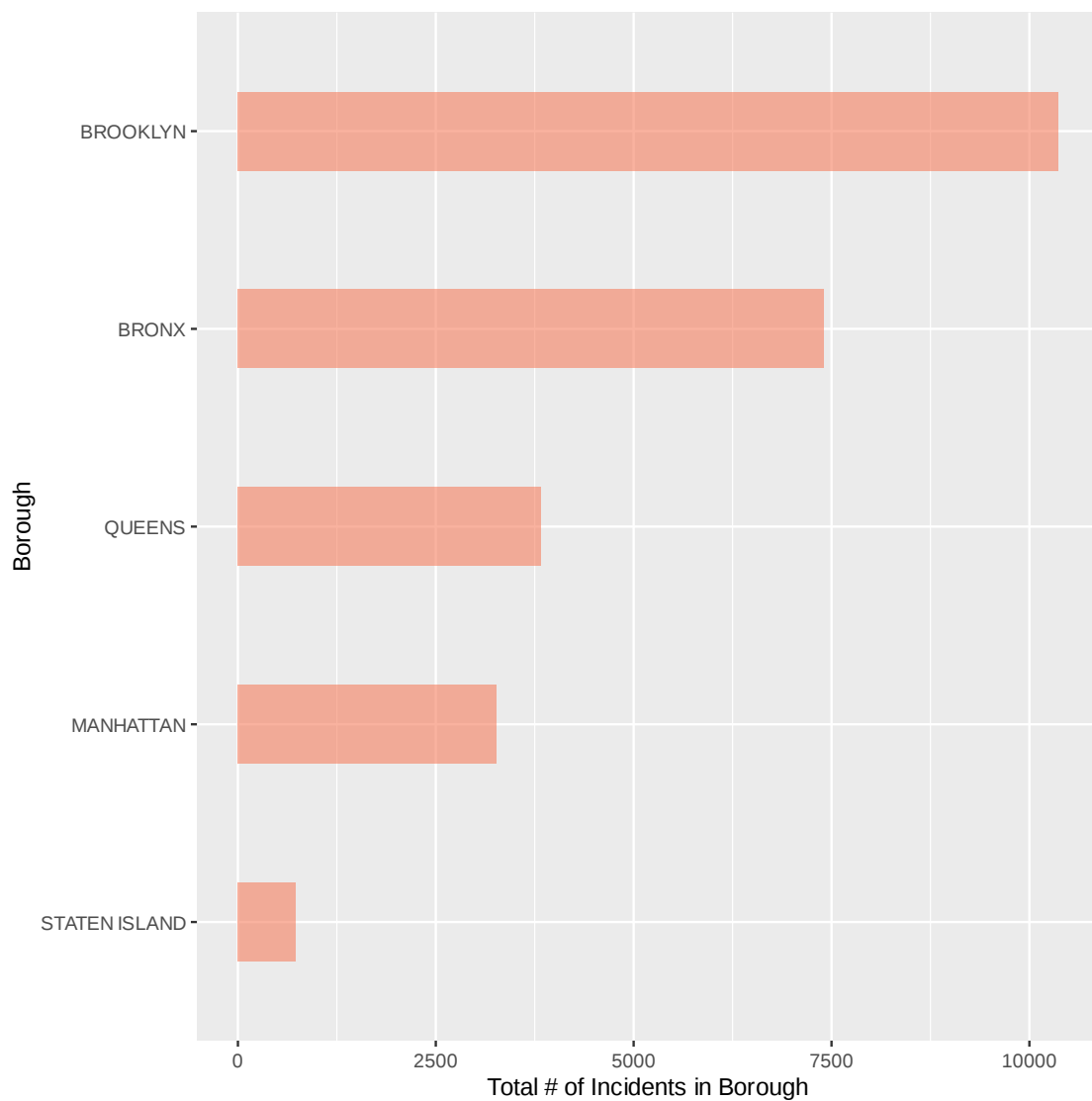
## 2.3 Individual Feature Visualization

### 2.3.1 Distribution of Borough Where Incident Took Place

This is the frequency distribution of where the shooting incident took place:

```
[27]: boro_distribution = df %>%
  group_by(BORO) %>%
  summarise(ct = n())

boro_distribution %>%
  mutate(BORO = fct_reorder(BORO, ct)) %>%
  ggplot( aes(x=BORO, y=ct)) +
  geom_bar(stat="identity", fill="#f68060", alpha=.6, width=.4) +
  coord_flip() +
  xlab("Borough") +
  ylab("Total # of Incidents in Borough")
```



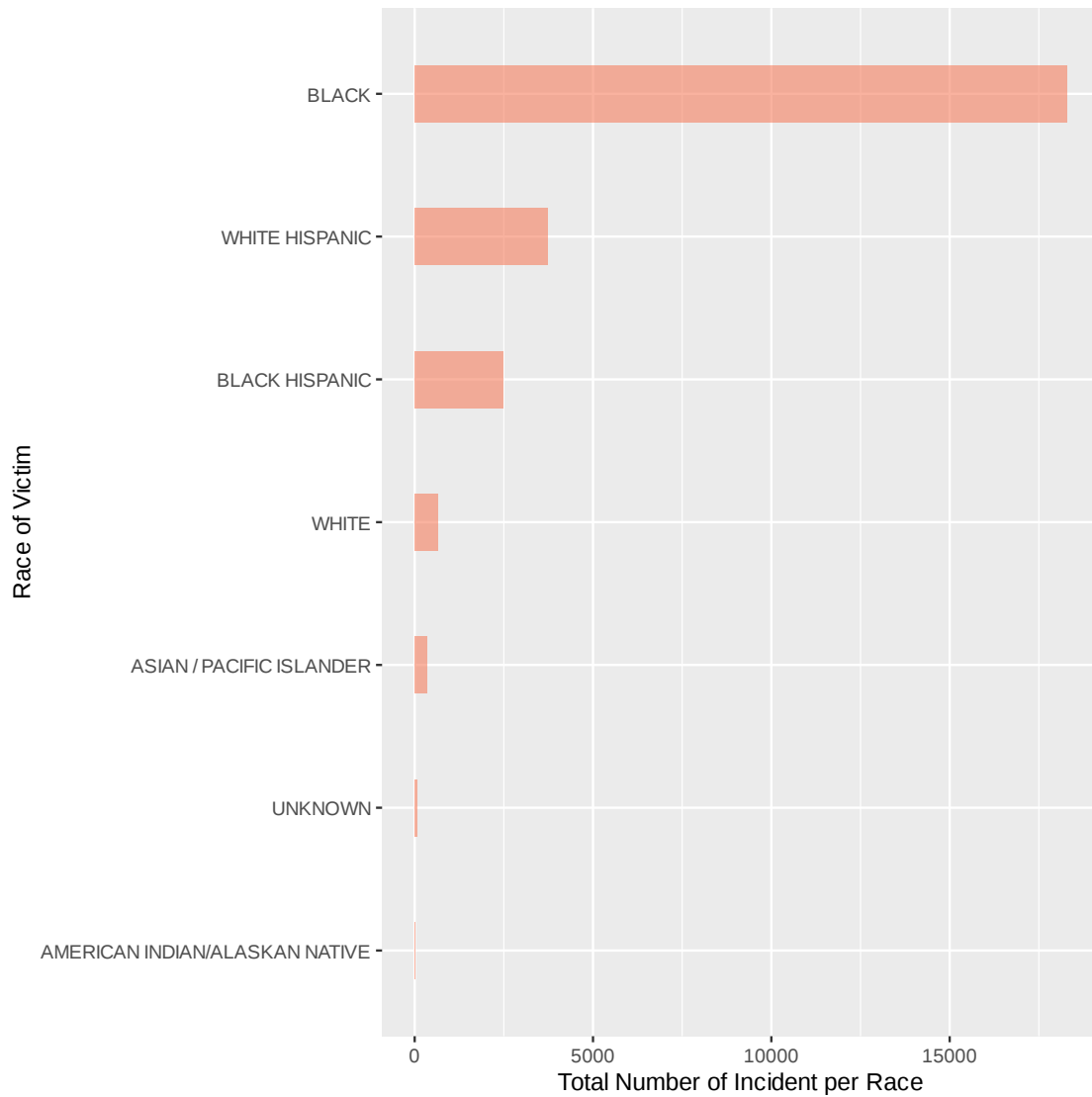
Based on our initial visualization, we can see that Brooklyn has the highest shooting rate with over 10000 cases. Furthermore, if we take a look at the population of each borough, we notice that as the population increases, the number of shooting incidents increases. ### Considering Population in Millions as of April 1st, 2020

- **Brooklyn:** 2.64 million
- **Bronx:** 1.47 million
- **Queens:** 2.41 million
- **Manhattan:** 1.69 million
- **Staten Island:** 0.49 million

However, Queens does not fit the trend. Despite the population similar to Brooklyn, the number of shooting incidents is less than half. Deep dive into Queens demographics may help us uncover methods to decrease shooting rates in other Boroughs.

### 2.3.2 Distribution of Victim Demographics: Race

```
[32]: victim_race_distribution = df %>%  
      group_by(VIC_RACE) %>%  
      summarise(ct = n()) %>%  
      arrange(desc(ct))  
  
victim_race_distribution %>%  
  mutate(VIC_RACE = fct_reorder(VIC_RACE, ct)) %>%  
  ggplot(aes(x=VIC_RACE, y=ct)) +  
    geom_bar(stat="identity", fill="#f68060", alpha=.6, width=.4) +  
    coord_flip() +  
    xlab("Race of Victim") +  
    ylab("Total Number of Incident per Race")
```



Here, we find that a heavy majority of the victim's in the shooting incident were black.

### 2.3.3 Distribution of Perpatrator Demographics: Race

```
[70]: df %>%  
      group_by(PERP_RACE) %>%  
      summarise(ct = n()) %>%  
      arrange(desc(ct))
```



	PERP_RACE	ct
	<chr>	<int>
A tibble: 7 × 2	UNKNOWN	11146
	BLACK	10668
	WHITE HISPANIC	2164
	BLACK HISPANIC	1203
	WHITE	272
	ASIAN / PACIFIC ISLANDER	141
	AMERICAN INDIAN/ALASKAN NATIVE	2

### 2.3.4 Handling Missing Data

There are two ways missing data is handled in the PERP\_RACE col.

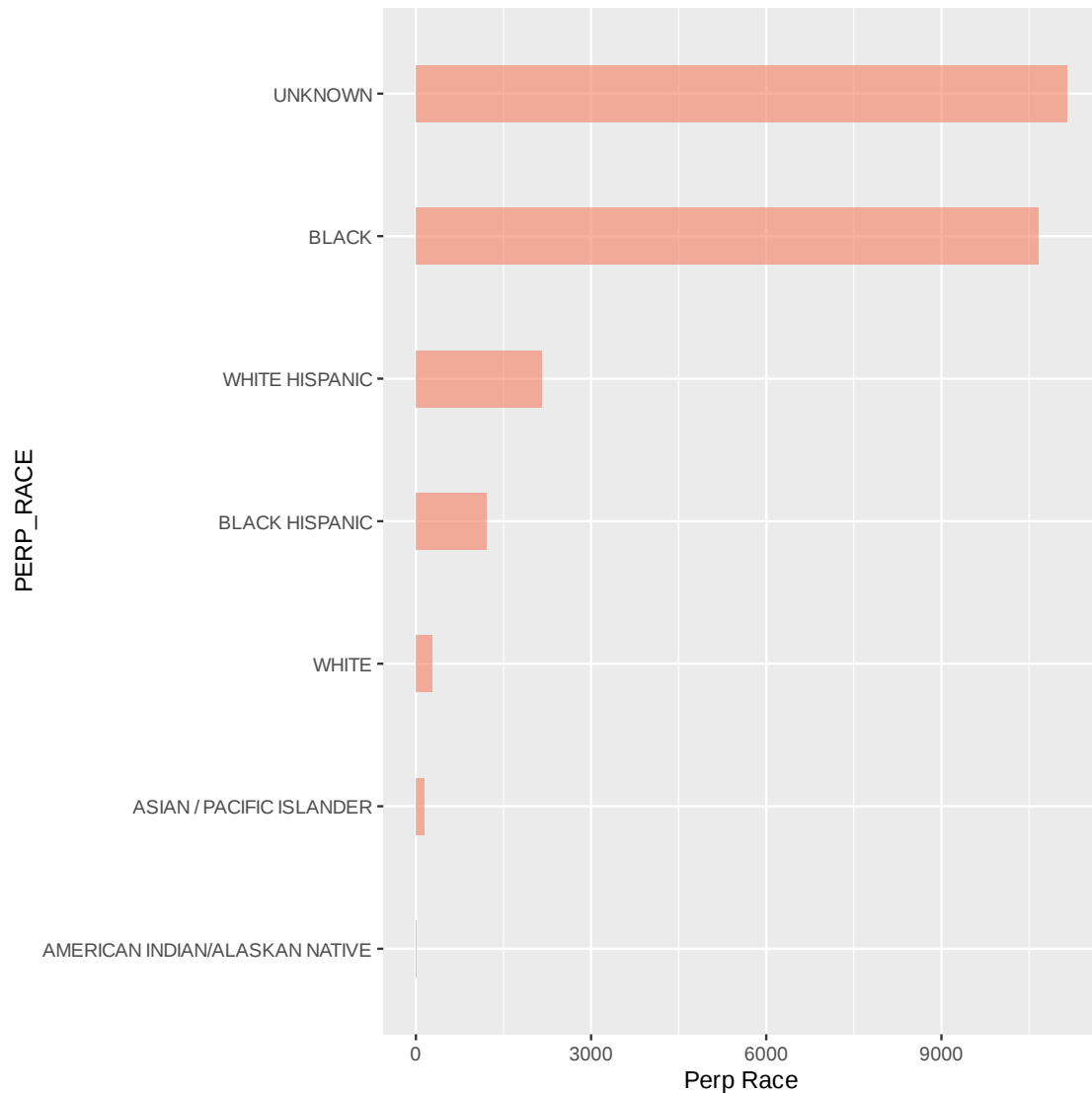
- 1) NA
- 2) UNKNOWN

There were no further information regarding the difference from the source [NYPD Shooting Incident Data \(Historic\) | NYC Open Data](#). Therefore we will make the assumption that NA refers to shooting incidents where the perpetrator has not been found. Unknown refers to cases where they have found the perpetrator but was unable to correctly identify their race. However, for our purposes, we will treat NA as UNKNOWN.

```
[53]: df = df %>% dplyr::mutate(PERP_RACE = replace_na(PERP_RACE, "UNKNOWN"))

perpetrator_race_distribution = df %>%
  group_by(PERP_RACE) %>%
  summarise(ct = n()) %>%
  arrange(desc(ct))
```

```
[54]: perpetrator_race_distribution %>%
  mutate(PERP_RACE = fct_reorder(PERP_RACE, ct)) %>%
  ggplot(aes(x=PERP_RACE, y=ct)) +
    geom_bar(stat="identity", fill="#f68060", alpha=.6, width=.4) +
    coord_flip() +
    xlab("PERP_RACE") +
    ylab("Perp Race")
```



Here, we find that a heavy majority of the Perpatrator's in the shooting incident were black. However, there are many UNKOWN's which may impact the distribution if they are correctly indentified.

### 3 3 Linear Regression Model to Determine Trend in Number of Shooting Incident Per Year

#### 3.1 Feature Engineering

```
[88]: #split the occur_date string into 3 cols:  
      # year, day, and month
```

```

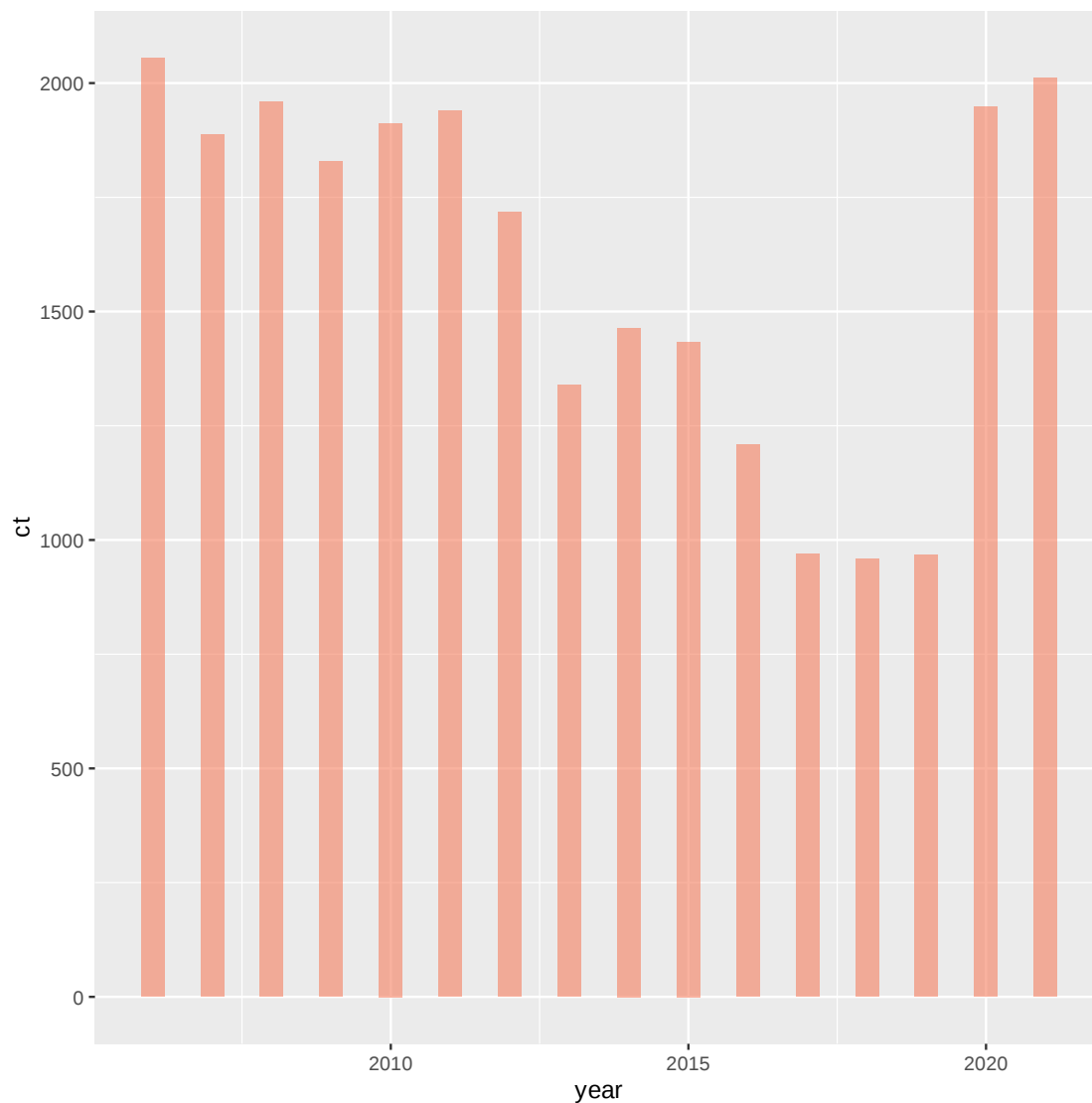
date_df = str_split_fixed(df$OCCUR_DATE, "/", 3)

df$year = as.integer(date_df[,3])
df$day = as.integer(date_df[,2])
df$month = as.integer(date_df[,1])
df$year_month = as.character(df$year + df$month/100)

incident_count_by_year = df %>%
  group_by(year) %>%
  summarise(ct = n()) %>%
  arrange()

incident_count_by_year %>%
  ggplot(aes(x=year, y=ct)) +
  geom_bar(stat="identity", fill="#f68060", alpha=.6, width=.4)

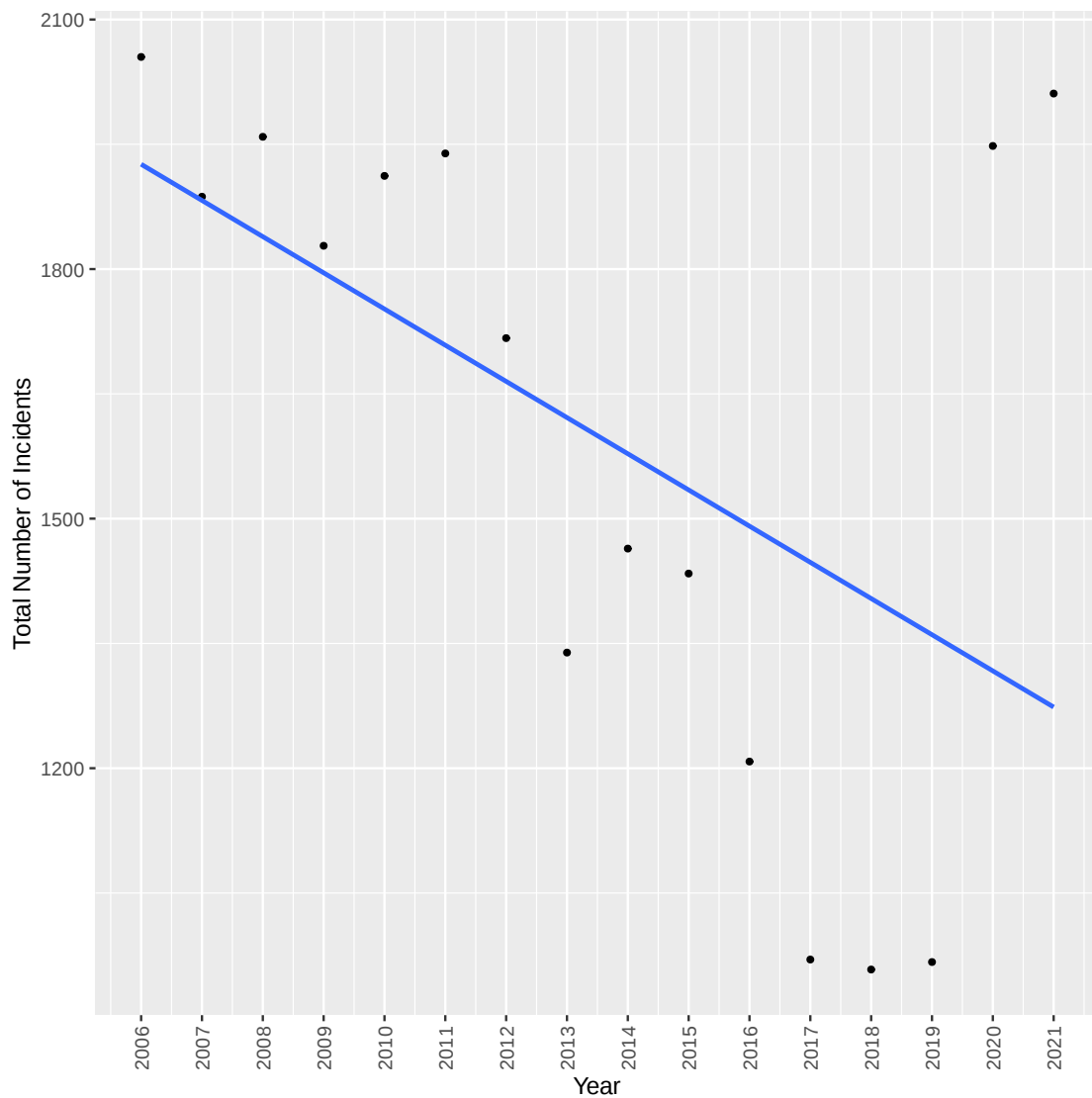
```



Based on the above visualization, from 2006 to 2019, there is a clear down trend. However, there is a big spike up in 2020.

```
[79]: ggplot(incident_count_by_year, aes(x=year, y=ct)) +  
  geom_point(size=1) +  
  geom_smooth(method = "lm", se = FALSE) +  
  scale_x_continuous(breaks = seq(min(df$year), max(df$year), by = 1)) +  
  xlab("Year") +  
  ylab("Total Number of Incidents") +  
  theme(axis.text.x = element_text(angle = 90, vjust = 0.5, hjust=1))
```

`geom\_smooth()` using formula = 'y ~ x'



```
[80]: incidentcountbyyear.lm <- lm(ct ~ year, data = incident_count_by_year)
summary(incidentcountbyyear.lm)
```

Call:

```
lm(formula = ct ~ year, data = incident_count_by_year)
```

Residuals:

Min	1Q	Median	3Q	Max
-477.49	-282.62	18.48	136.73	737.52

Coefficients:

	Estimate	Std. Error	t value	Pr(> t )
(Intercept)	89192.92	39375.83	2.265	0.0399 *
year	-43.50	19.56	-2.225	0.0431 *

---

Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 360.6 on 14 degrees of freedom

Multiple R-squared: 0.2612, Adjusted R-squared: 0.2084

F-statistic: 4.949 on 1 and 14 DF, p-value: 0.04307

### 3.1.1 Predicting Future Shooting Incident Numbers

```
[76]: 89192.92 - (2030*43.50)
```

887.919999999998

## 4 4 Conclusions

In short, we have determined using a linear regression model that there is a down trend in the number of shootings per year in NY. While there is an anomaly in the data, it can be explained with its correlation with the COVID-19 outbreak. By 2030, the number of shooting incidents in NY should approximately be lower than 900.

Because we have a large amount of data, we would like to randomly partition the data into train and validation set. We will perform EDA and modeling on train set. Later, we will use the validation set to test our model.

```
[4]: # set seed
set.seed(42)

#randomly partition original dataset into two: train & validation set
df$ind = seq.int(nrow(df))
```

```

smp_size = floor(0.75 * nrow(df))
train_ind = sample(seq_len(nrow(df)), size=smp_size)
original_train_df = df[train_ind, ]
original_valid_df = df[-train_ind, ]

#make sure train_df row count + valid_df row count equals original cf
nrow(original_train_df) + nrow(original_valid_df) == nrow(df)

valid_df = original_valid_df %>%
  select(-c(X_COORD_CD, Y_COORD_CD, Latitude, Longitude, INCIDENT_KEY, ind,
    →OCCUR_TIME, PRECINCT, JURISDICTION_CODE, STATISTICAL_MURDER_FLAG, Lon_Lat))

```

TRUE