

NYPD SHOOTING INCIDENT REPORT

The purpose of this project is to find out an analysis of the probability of death based on the perpetrator's demographics, the location, and the time of the shooting in New York city.

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#### Introduction

Since at least the 1800s, crime statistics have been kept track of in New York City. Since the post-World War II era, they have increased.

The NYPD keeps statistics that are utilized as a management tool to cut crime, enhance practices and training, and increase openness with the general public and governmental oversight bodies.

As the crack epidemic grew, crime rates peaked in the late 1980s and early 1990s. After that, they steadily decreased into the 2000s.

When the agency implemented CompStat in 1994, crime successfully decreased to historic lows not seen since the 1950s thanks to management, statistics, and accountability.

On the citywide, borough, and precinct levels, the department publishes current crime-related statistics in the seven primary crime categories, as well as historical crime data.

The New York City Police Department (NYPD) made a significant effort to lower crime throughout the 1990s by implementing CompStat, broken windows policing, and other tactics. Following, there was a decline in crime that has been variously attributed to the end of the crack epidemic, the rise in incarceration rates across the country, gentrification, an ageing population, and a decrease in lead poisoning in youngsters.

## **Dataset Understanding**

This dataset contains a list of every shooting incident that occurred in NYC going back to 2006 through the end of 2021.

This is a breakdown of every shooting incident that occurred in NYC going back to 2006 through the end of 2021. 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 the time of occurrence. In addition, information related to suspect and victim demographics is also included.

The purpose of this exploratory data analysis is to explore the nature of the threat and uncover hidden insights for the detection of potential threat locations, demographics & ethnicity of the victim & the perpetrator, and estimation of the number of casualties.

# **Attributes types and descriptions**

Table 1: Attributes Description

Row	Attribute	Туре	Description
1	INCIDENT_K EY	Ordinal	Randomly generated persistent ID for each arrest
2	OCCUR_DA TE	String	Exact date of the shooting incident (mm/dd/yyyy)
3	OCCUR_TIM E	String	Exact time of the shooting incident (hh:mm:ss)
4	BORO	nominal	Borough where the shooting incident occurred
5	PRECINCT	numeric	Precinct where the shooting incident occurred
6	JURISDICTI ON_CODE	nominal	Jurisdiction where the shooting incident occurred.  Jurisdiction codes  (0: Patrol, 1: Transit, 2: Housing)
7	LOCATION_ DESC	Nominal	Location of the shooting incident
8	STATISTICA L_MURDER_ FLAG	Boolean	Shooting resulted in the victim's death which would be counted as a murder  (False: Survived, True: Death)
9	PERP_AGE_ GROUP	Nominal	Perpetrator's age within a category (<18, 18-24, 25-44, 45-65, 65+)
10	PERP_SEX	Nominal	Perpetrator's sex description (M: Male, F: Female)
11	PERP_RACE	nominal	Perpetrator's race description
12	VIC_AGE_G ROUP	nominal	Victim's age within a category

			(<18, 18-24, 25-44, 45-65, 65+)	
13	VIC_SEX	nominal	Victim's sex description (M: Male, F: Female)	
14	VIC_RACE	nominal	ninal Victim's race description	
15	X_COORD_C D	string	Midblock X-coordinate for New York State Plane Coordinate System	
16	Y_COORD_C D	string	Midblock Y-coordinate for New York State Plane Coordinate System	
17	Latitude	string	Latitude coordinate for Global Coordinate System	
18	Longitude	string	Longitude coordinate for Global Coordinate System	
19	Lon_Lat	point	Longitude and Latitude Coordinates for mapping	

# **Data Preparation**

First of all, we looked for duplicate data which there weren't any duplicates in our dataset.

Then, we checked the dataset and found some cells had no value and their number was high and also we could not remove them, we filled the cells with mode() replacement for each attribute.

Based on our goal, we found that the following attributes are not useful and have no effect on our prediction:

- INCIDENT\_KEY
- PRECINCT
- JURISDICTION\_CODE
- X\_COORD\_CD
- Y\_COORD\_CD
- Latitude
- Longitude

Lon\_Lat

So we removed these columns.

In the following, we categorized PERP\_AGE\_GROUP and VIC\_AGE\_GROUP to the following age groups:

- ➤ Child for age <18
- ➤ Adult for 18-24 and 25-44
- **Senior for 45-64 and 65+**

Also we created Time\_Category for OCCUR\_TIME to the following time groups:

- > Day for times between 6 am to 6 pm
- ➤ Night for time between 6 pm to 6 am

In addition, we split OCCUR\_DATE into 3 columns which are month, day and year and then removed the day and categorized the months (Month\_Category) into 3 groups:

- ➤ Cold Weather for November, December, January, February and March
- ➤ Nice Weather for April, may, June and October
- ➤ Hot Weather for July, August and September

Finally, changed the values in the STATISTICAL\_MURDER\_FLAG as the following:

- > False to 0 which means survived
- True for 1 which means death

At the end, we saved the dataset as a CSV file named NYPD\_ Shooting\_ Incident\_ Data\_\_\_ Historic\_Processed.

Here is a screenshot of several first rows with their titles:

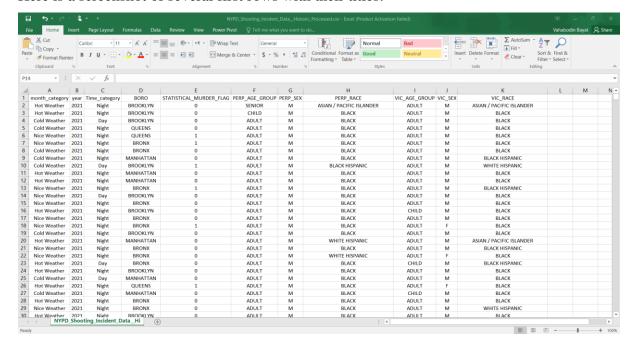


Figure 1: Dataset

In the next step we loaded the file (NYPD\_Shooting\_Incident\_Data\_\_Historic\_Processed.csv) in Weka for checking each attribute type and we found two attributes such as Year and STATISTICAL\_MURDER\_FLAG have to convert from Numeric to Nominal then we applied filter from the process tab>filters>unsupervised>attribute selected NumericToNominal to convert them and save it by name NYPD\_Shooting\_Incident\_Data\_\_Historic\_Converted.arff. Here is a screenshot of distribution of the STATISTICAL\_MURDER\_FLAG attribute as our class:

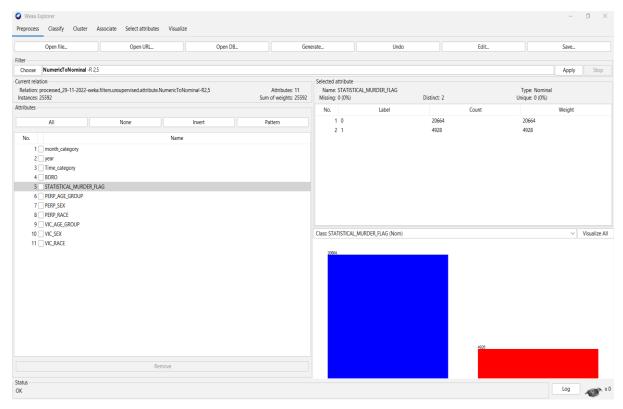


Figure 2: distribution of the class attribute

### **Attribute values**

Table 1: Value of Month\_Category attribute

RowLabelCount1Hot Weather84272Cold Weather102803Nice Weather6885

Table 2: Value of Year attribute

Row	Label	Count
1	2006	2055
2	2007	1887
3	2008	1959
4	2009	1828
5	2010	1911
6	2011	1939
7	2012	1717
8	2013	1338
9	2014	1464
10	2015	1433
11	2016	1208
12	2017	970
13	2018	958
14	2019	967
15	2020	1948
16	2021	2010

Table 3: Value of Time\_Category attribute

Table 4: Value of Boro attribute

Row	Label	Count
1	Night	19491
2	Day	6101

Row	Label	Count
1	BROOKLYN	10363
2	QUEENS	3828
3	BRONX	7400
4	MANHATTAN	3265
5	STATEN ISLAND	736

Table 5: Value of STATISTICAL\_MURDER\_FLAG attribute

Table 6: Value of PERP\_AGE\_GROUP attribute

Row	Label	Count
1	0 (Survived)	20664
2	1 (Death)	4928

Row	Label	Count
1	SENIOR	592
2	CHILD	1463
3	ADULT	23537

Table 7: Value of PERP\_SEX attribute

Table 8: Value of PERP\_RACE attribute

Row	Label	Count
1	M	25221
2	F	371

Row	Label	Count
1	ASIAN / PACIFIC ISLANDER	141
2	BLACK	21812
3	BLACK HISPANIC	1203
4	WHITE HISPANIC	2162
5	WHITE	272
6	AMERICAN INDIAN/ALASKAN NATIVE	2

Table 9: Value of VIC\_AGE\_GROUP attribute

Table 10: Value of VIC\_SEX attribute

Row	Label	Count
1	ADULT	21046
2	CHILD	2681
3	SENIOR	1865

Row	Label	Count
1	M	23189
2	F	2403

Table 11: Value of VIC\_RACE attribute

Row	Label	Count	
1	ASIAN / PACIFIC ISLANDER	354	
2	BLACK	18344	
3	BLACK HISPANIC	2485	
4	WHITE HISPANIC	3740	
5	WHITE	660	
6	AMERICAN INDIAN / ALASKAN NATIVE	9	

# **Modeling & Evaluation**

#### **kNN** Clustering Method

We ran our dataset in Weka with lazy.IBK classifier to take results from kNN with 10-fold cross-validation and a percentage split of 70%.

Our next step is to modify the k in the Nearest-Neighbors algorithm to check which condition is the best for our data and its class.

Performing of kNN clustering with 10-fold cross validation:

Table 12: kNN clustering with 10-fold cross validation, Seed 1

 K
 Percentage of correctly classified instances

 3
 79.57 %

 5
 80.18 %

 7
 80.42 %

 9
 80.56 %

Table 13: kNN clustering with 10-fold cross validation, Seed 2

K	Percentage of correctly classified instances
3	79.58 %
5	80.19 %
7	80.48 %
9	80.56 %

#### Performing of kNN classification percentage split of 70%:

Table 14: kNN clustering percentage split of 70%, Seed 1

T-	1-1- 45	1.0101	-1		124	- £ 700/	C 1 2
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K	Percentage of correctly classified instances
3	79.51 %
5	80.33 %
7	80.48 %
9	80.60 %

K	Percentage of correctly classified instances
3	79.77 %
5	80.20 %
7	80.47 %
9	80.47 %

As we can see in table 12 to 15 in 4 tables, the best conditions will occur when k is 9 for both 10-fold cross validation and percentage split of 70%.

#### **Decision Tree Method**

In this method, we used j48 model with minimum number object 15 and True for unpruned option for decision tree, the results of which are set according to the following attributes selected such as Time\_category, BORO, STATISTICAL\_MURDER\_FLAG, PERP\_AGE\_GROUP, VIC\_AGE\_GROUP, VIC\_RACE.

```
=== Confusion Matrix ===

a b <-- classified as

20615 49 | a = 0

4890 38 | b = 1
```

Figure 3: confusion matrix with 10- fold cross validation

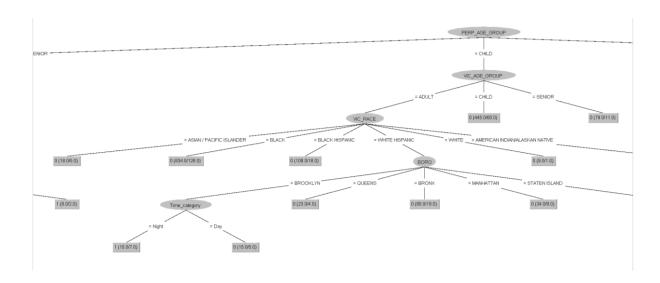


Figure 4: Visualize decision tree

From the obtained tree (DecisionTree.model) that we show a part of that which is a subset of the child group we can predict which people in which age group and under what conditions survived.

If the person who was shot was white Hispanic and in adult group, and the shooting happened in Brooklyn, if it happened during the day, it is likely that the person survived, but if it happened at night, they would not have survived.

#### **Random Forest Method**

In order to measure accuracy, we used RandomForest with a split of 70.0% between the train and the test for our class attribute, as well as a maximum depth of 5 (RandomForest-S.M.F.model), and found that the accuracy of about 72.2% can be obtained if STATISTICAL\_MURDER\_FLAG is considered as the class. The output is as follows:

```
=== Detailed Accuracy By Class ===
                TP Rate FP Rate Precision Recall
                                                    F-Measure
                                                              MCC
                                                                       ROC Area
                                                                                PRC Area
                                                                                         Class
                        0.993 0.808
                                           0.993
                                                    0.891
                0.993
                                                              0.002
                                                                       0.538
                                                                                0.824
                                                                                          0
                0.007
                        0.007
                                 0.200
                                           0.007
                                                    0.014
                                                              0.002
                                                                       0.538
                                                                                 0.218
                                                                                          1
Weighted Avg.
                                                  0.722
                0.803
                        0.803
                                 0.691
                                           0.803
                                                              0.002
                                                                       0.538
                                                                                 0.708
=== Confusion Matrix ===
            <-- classified as
       44 |
6156
               a = 0
1467
       11 |
               b = 1
```

Figure 5: Random Forest Method for STATISTICAL MURDER FLAG as the class

In the following, to further examine the data, we plotted different graphs based on different criteria whith python (plot.ipynb), the most important of which are shown:

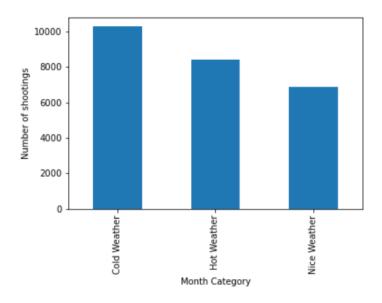


Figure 6: Number of shootings per month

From the graph above, we can see that shooting has increased in the year's cold months.

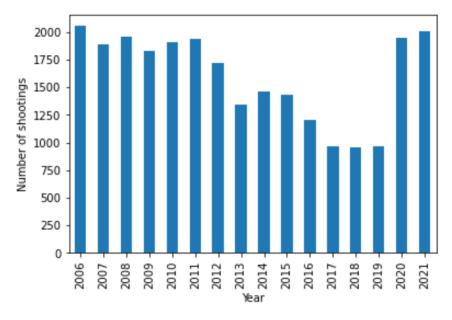


Figure 7: Number of shootings per year

Graph shows us 2006 had the most shooting incident and 2018 had the least.

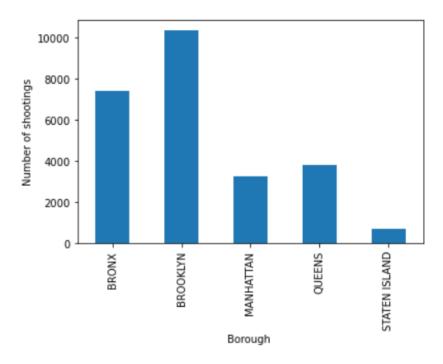


Figure 8: Number of shootings per borough

Brooklyn had the most with 10363 and Staten Island had the least with 736.

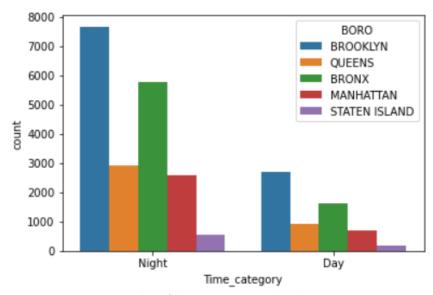


Figure 9: Number of shootings per borough and time category

There were 7667 shootings in Brooklyn at night and 176 in Staten Island during the day.

Also we did an analysis of the most shooting incident perpetrators age category by borough.

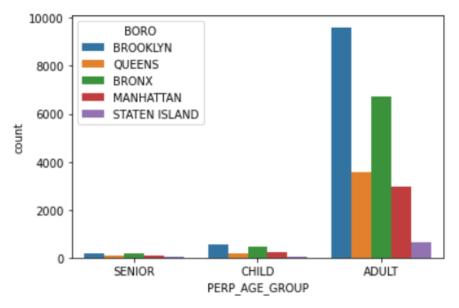


Figure 10: Number of shooting per borough and perpetrator age category

The results show us that the highest number of shootings by adults was in Brooklyn with 9,608 shootings and the lowest number of shootings by seniors was in STATEN ISLAND with 31 shootings.

In order to investigate more deeply, we increased the number of factors and obtained the following graph based on the borough, the perpetrator age category, victims age category, and also the shooting time.

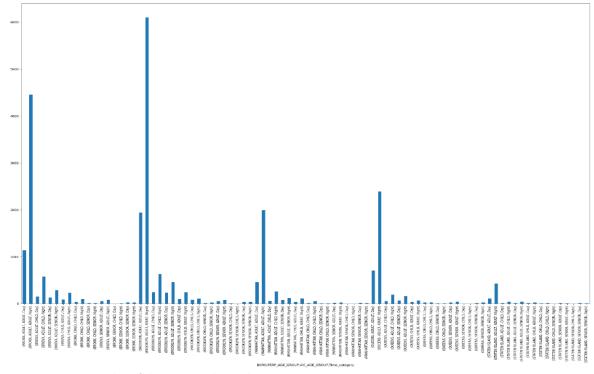


Figure 11: Number of shootings per borough, perpetrator age group, victims age group and time category

Brooklyn had the most shooting at night for Adult perpetrator and Adult Victim with 6096.

#### **Discussion of Results**

As per our analysis in 2006 we had the most shooting incident and 2018 we had the least shooting incident.

The probability of shooting at night is higher, and if the shooting happened in the borough of Brooklyn and both the shooter and the victim were adult black man, it led to the death of the victim.

In total 20665 victim survived, while 4928 victim passed away.

#### **Conclusion**

We discovered through exploratory data analysis that the majority of gunshot occurrences occur at night and in cold weather. Men make up the majority of both perpetrators and victims. The plots claim that Brooklyn is generally the most hazardous part of New York City.

Random forest performs the best among all algorithms in terms of predictive models. It may be deduced that ensemble algorithms outperform single algorithms on our dataset as the random forest model is an ensemble learning technique that combines a number of decision tree models to create a stronger learner.