Title: Big Data
Project on Motor
Vehicle Collisions
in NYC: Insights
and Reasons

Presenter: Garima Goyal and Sachin Garg

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Introduction

Problem Statement:

- Motor vehicle collisions are a major public safety concern, causing significant injuries, fatalities, and property damage.
- New York City (NYC) experiences a high volume of motor vehicle collisions annually.
- Understanding the factors contributing to motor vehicle collisions in NYC is crucial for developing effective prevention strategies.

Objective:

- Analyze big data on motor vehicle collisions in NYC to gain insights into the underlying causes and patterns.
- Identify key risk factors associated with motor vehicle collisions in NYC.
- Develop recommendations for reducing motor vehicle collisions in NYC.

Data Collection and Preprocessing

Data Sources: Primary data source will be motor vehicle collision records from open data portals like Data.gov.

Data Preprocessing: This is very big dataset contains 2040203(2M) rows/observations and 29 columns/variables.

Data Cleaning: Handling missing values, outliers, and inconsistencies.

Data transformation: Converting multiple irrelevant attributes into meaningful one.

MISSING VALUE COLUMNS

Values	Columns	Values
0	NUMBER OF CYCLIST INJURED	0
0	NUMBER OF CYCLIST KILLED	0
634709	NUMBER OF MOTORIST INJURED	0
634951	NUMBER OF MOTORIST KILLED	0
231352	CONTRIBUTING FACTOR VEHICLE 1	6504
231352	CONTRIBUTING FACTOR VEHICLE 2	312925
	CONTRIBUTING FACTOR VEHICLE 3	1895102
	CONTRIBUTING FACTOR VEHICLE 4	2007586
		2031372
	COLLISION_ID	0
1/01/2/	VEHICLE TYPE CODE 1	13042
18	VEHICLE TYPE CODE 2	384146
31	VEHICLE TYPE CODE 3	1900233
0	VEHICLE TYPE CODE 4	2008690
0	VEHICLE TYPE CODE 5	2031640
	0 0 634709 634951 231352 231352 231352 430849 766605 1701727 18 31 0	0 NUMBER OF CYCLIST INJURED 0 NUMBER OF CYCLIST KILLED 634709 NUMBER OF MOTORIST INJURED NUMBER OF MOTORIST KILLED CONTRIBUTING FACTOR VEHICLE 1 CONTRIBUTING FACTOR VEHICLE 2 CONTRIBUTING FACTOR VEHICLE 3 CONTRIBUTING FACTOR VEHICLE 4 CONTRIBUTING FACTOR VEHICLE 4 CONTRIBUTING FACTOR VEHICLE 5 COLLISION_ID 1701727 VEHICLE TYPE CODE 1 18 VEHICLE TYPE CODE 2 31 VEHICLE TYPE CODE 3 VEHICLE TYPE CODE 4



Factors Contributing to Accidents

Data cleaning (Outliers and Inconsistencies)

We fix the some typos/misspelling ('Illnes', 'Illness'), ('Cell Phone (hand-Held)', 'Cell Phone (hand-held)'), data inconsistency ('Fell Asleep', 'Drowsy', Lost Consciousness') and invalidation ('80', '1') for all the CONTRIBUTING FACTOR VEHICLE involved.



Data cleaning (Outliers and Inconsistencies)



Also, there were multiple attributes for contributing factor vehicle which are similar (in a way) to each other, we specified them in few different category to better understanding of insights.

For example:

Overspeeding

Following Too Closely

Driver Inattention/Distraction

Pavement Slippery or Defective

Fatigued/Drowsy/Sleep/Unconscious

Outside Car Distraction

Drugs or Alcohol Involvement

Driver Inexperience

Obstruction/Debris

Unsafe Speed

Failure to Yield Right-of-Way

Traffic Control Disregarded



2) For the vehicle type code, lot of data inconsistencies, misspelling values and invalid data. So, to encounter that we are performing 'fuzzy-wuzzy' method (a python library, used to compare strings and determine the similarity between them, which can be useful in big data analytics).

Similarly, we worked on vehicle type code which are similar(in a way) to each other, we specified them in few different category to better understanding of insights

- SUV /Sedan cars
- Taxi
- Pick-Up/Tow-Trucks
- Bike/Scooter/2-Wheel Vehicles
- Van
- Bus
- All Other Type Vehicles 30798
- Other Commercial/Utility Vehicles
- Heavy Truck/Trailor
- City/Government Vehicles
- Construction/Dump Vehicles
- Other Mini Vehicles





























Standardizing Formats:

Standardize the format of street names (e.g., convert to uppercase, remove leading/trailing spaces).

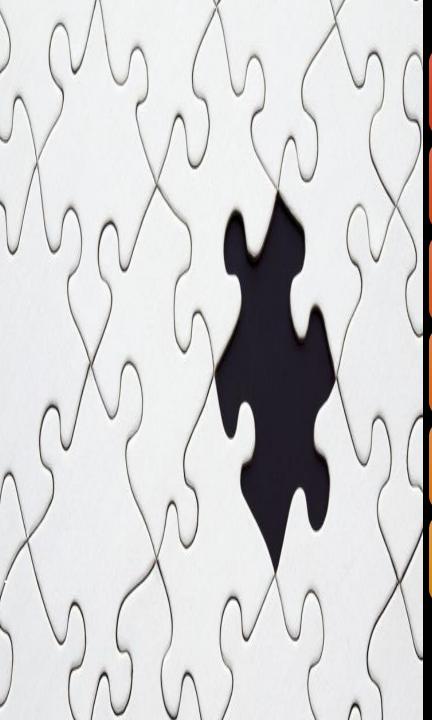
Handling Abbreviations:

Expand abbreviations to make the data more consistent. (e.g., convert St to Street, Ave to Avenue, etc.)

Removing Special Characters:

Remove any special non-alphanumeric values or symbols that might cause issues.





Imputing Missing Data

For the columns 'NUMBER OF PERSONS INJURED' and 'NUMBER OF PERSONS KILLED' contains only 18 and 31 missing values respectively, which are very low values related to the whole dataset. So, we use the simple statistical 'mean' strategy to impute the missing values in those columns.

For the columns 'CONTRIBUTING FACTOR VEHICLE 1' and 'VEHICLE TYPE CODE 1' contains 6452 and 12940 missing values respectively, which are only 0.0031% and 0.0063% of the total values. So, we just use the simple 'mode' strategy to impute missing values.

In the other contributing factor vehicle columns, some of the missing values are not true. For example if vehicle 1 and 2 are involved in an accident, vehicle 3, 4 and 5 are not applicable and similar for all cases. So, to counter those missing values, we assume and label them as 'Not Applicable'. Same we performed with off street, on street and across street.

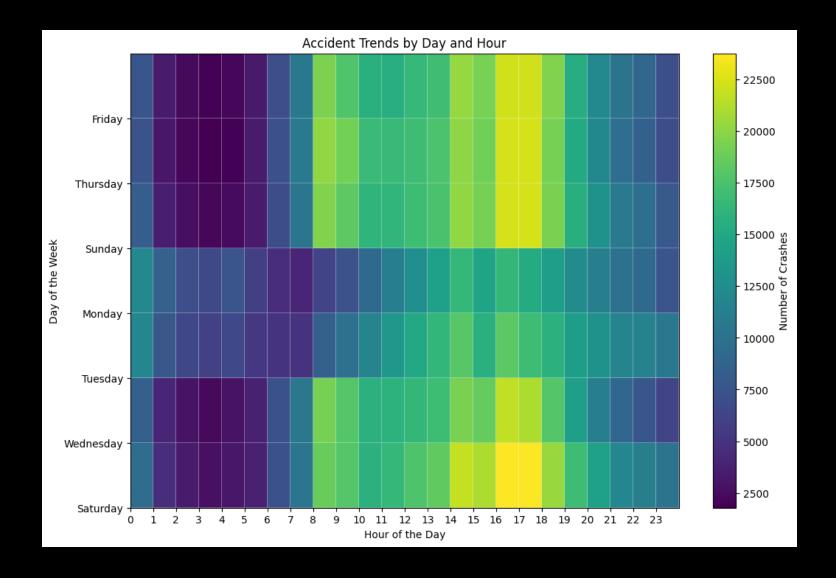
We have imputing the locations using Geo pandas, the approach we have used is the geometry of nearby features to estimate the missing values.

For missing zip-codes, we have used Machine learning algorithms-Random Forest Regressor along with Simple Imputer, One Hot Encoder, Label Encoder, mean absolute error.

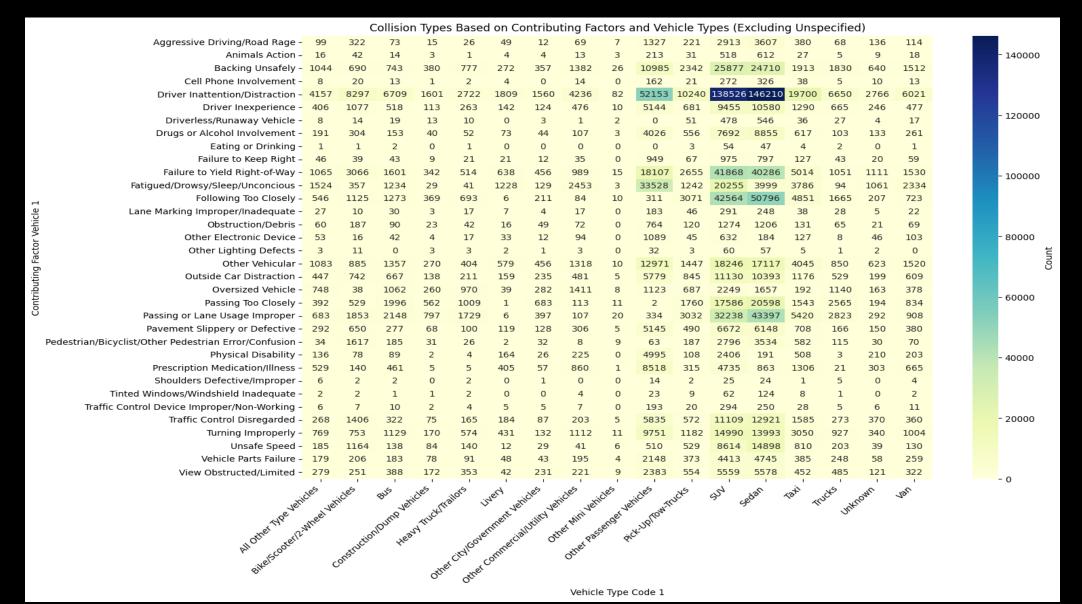
Descriptive Statistics:

- Number of collisions The total number of collisions in the dataset over a certain timeframe (e.g. per year). Gives an overall sense of frequency.
- Collision severity The number or percentage of collisions by severity level (e.g. property damage only, injury, fatality). Shows the harm caused.
- Collision type The number or percentage of collisions by type (e.g. rearend, angle, pedestrian-involved). Describes the common configurations.
- Primary collision factor The main factor that contributed to collisions, like speeding, impairment, distraction. Helps understand causes.
- Temporal statistics Number or share of collisions over timeframes like month, day of week, time of day. Reveals temporal patterns.
- Environmental statistics Number or proportion of collisions related to factors like weather, lighting, road surface condition. Shows environmental influences.
- Vehicle statistics The number/share of different vehicle types involved passenger cars, trucks, motorcycles etc.
- Demographic statistics Age and gender distributions of drivers involved in collisions. Allows demographic analysis.
- Location statistics Collisions summarized by geographic units state, county, city, intersection etc. Pinpoints high frequency areas.

Accident Trends by Day and Hour

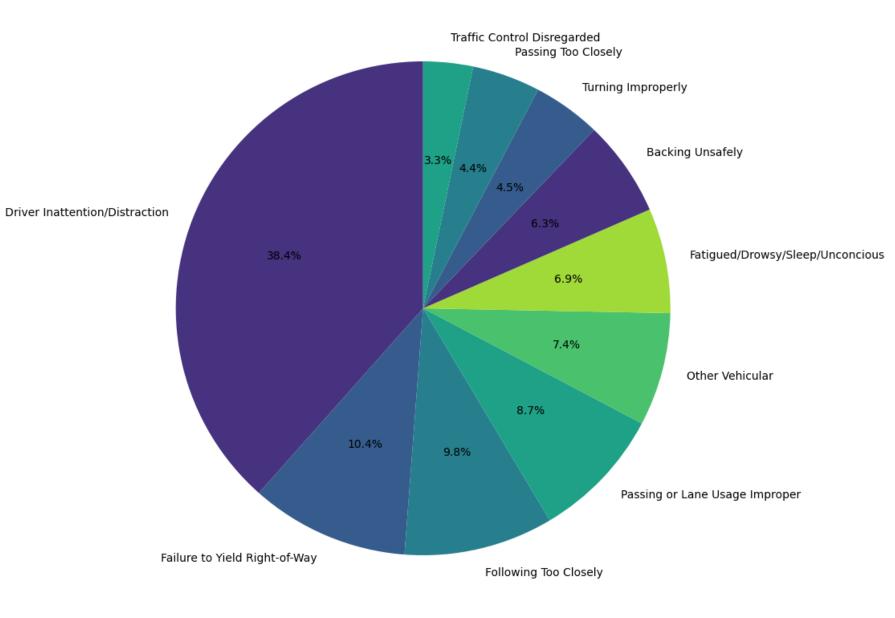


Collision Types Based on Contributing Factors and Vehicle Types

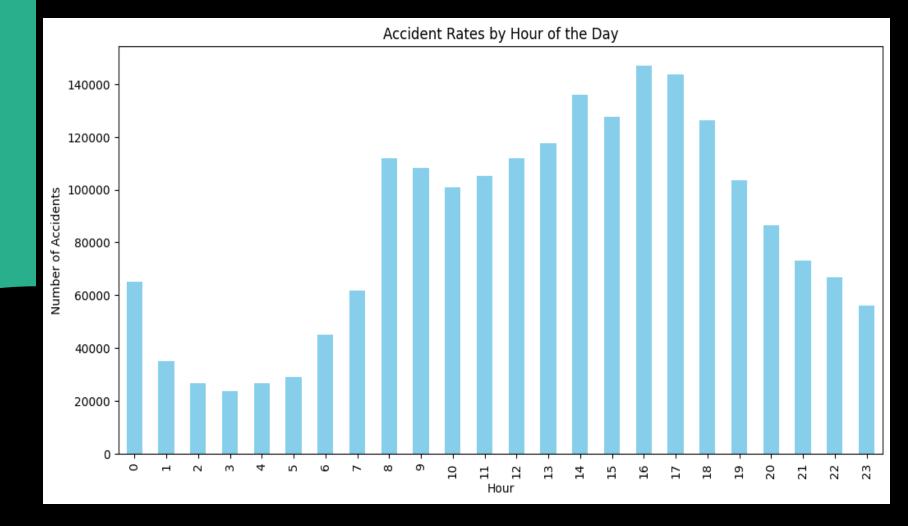


Distribution of Top 10 Contributing Factors for Accidents

10 Most Common Contributing Factors for Accidents

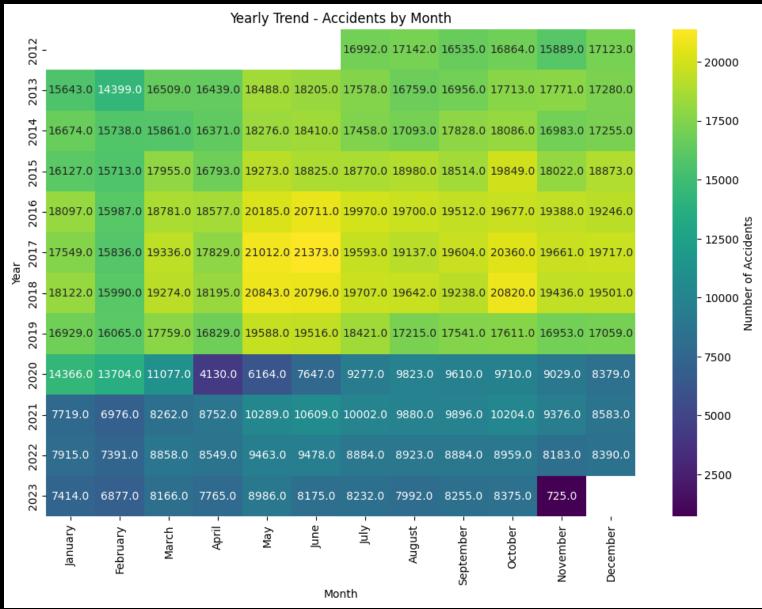


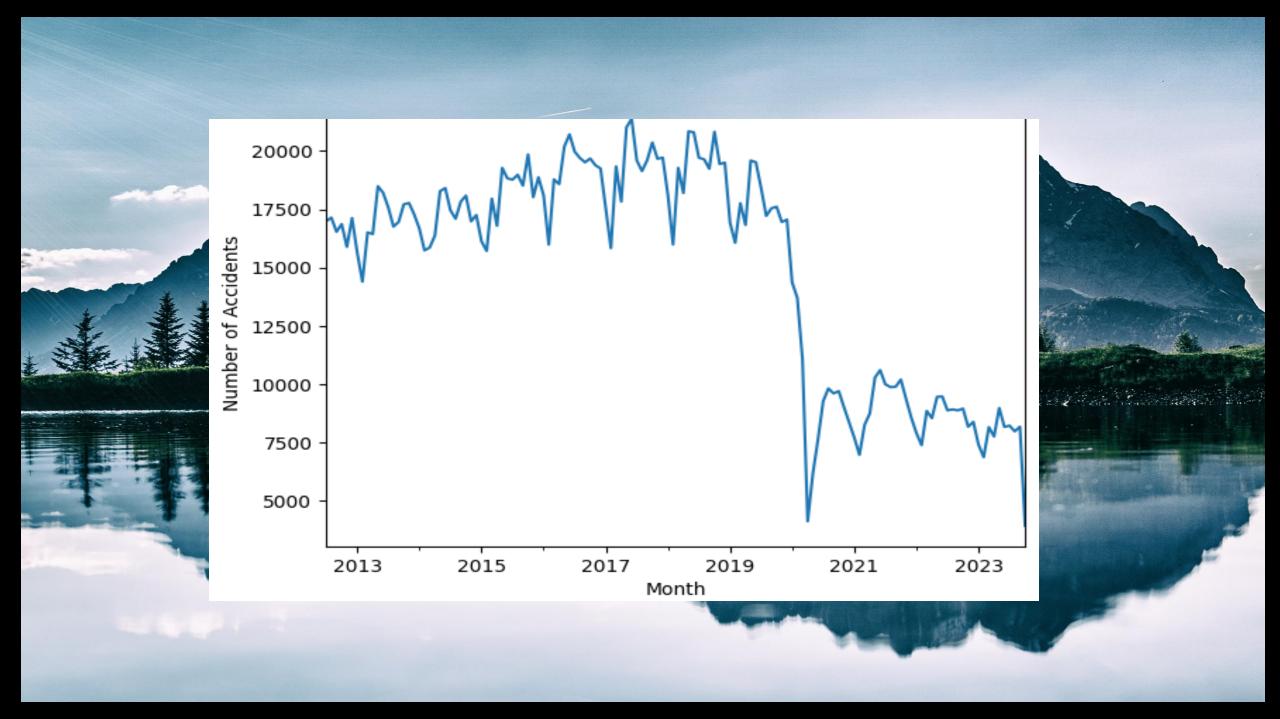
Accident Rates by Hour of the Day



Yearly and Monthly Trend

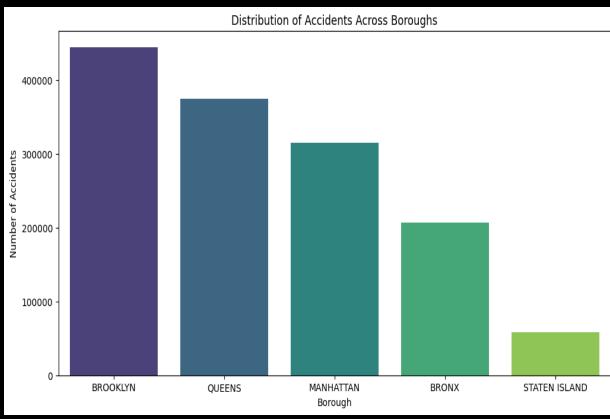






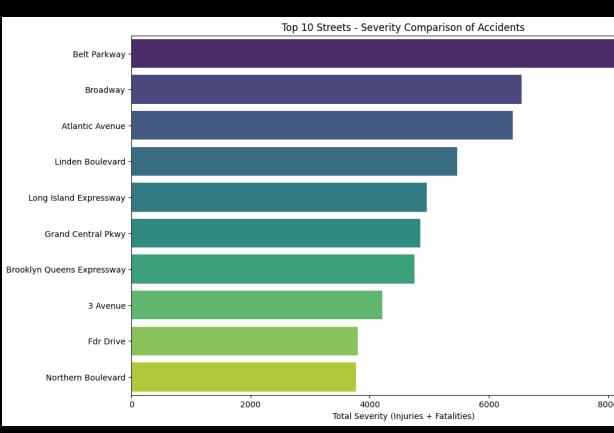
Which Borough has Most Accidents?



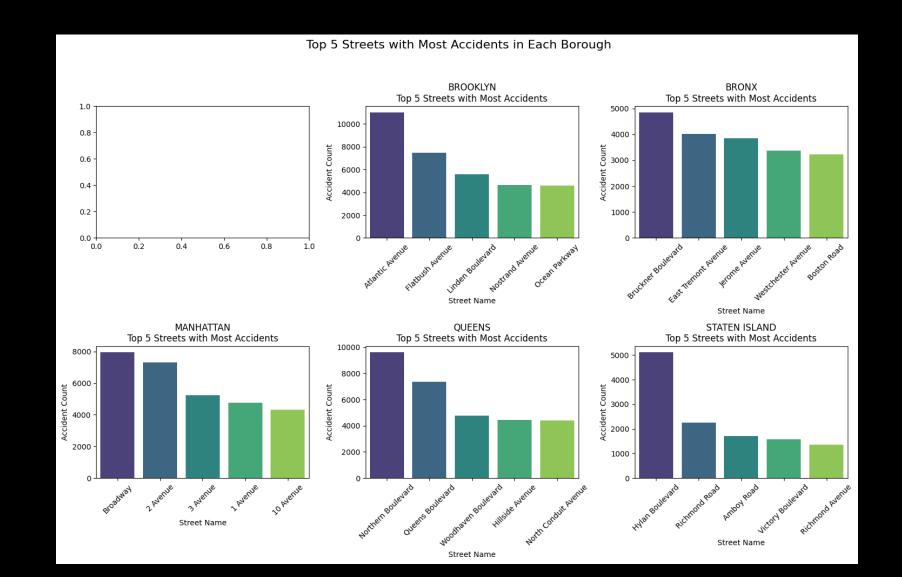


Which Streets have Most Dangerous Accidents Occur?





Top 5 Streetes with Most Accidents in Each Borough



Conclusion

By summarizing the distribution of these key variables, we can gain valuable insights into the overall patterns and trends of motor vehicle collisions. This information can be used to:

- Develop targeted interventions: Focus resources and efforts on areas, times, vehicle types, and contributing factors posing the highest risk.
- Prioritize safety initiatives: Allocate funding and implement programs based on the most prevalent risks and vulnerabilities identified.
- Design effective prevention strategies: Develop campaigns and policies tailored to address specific risk factors and conditions.
- Track progress and evaluate effectiveness: Monitor changes in collision patterns over time to assess the impact of interventions and safety initiatives.



