# Traffic Collisions Hotspots in New York City

Awais Malik, Bartosz J. Bonczak and Radu Stancut

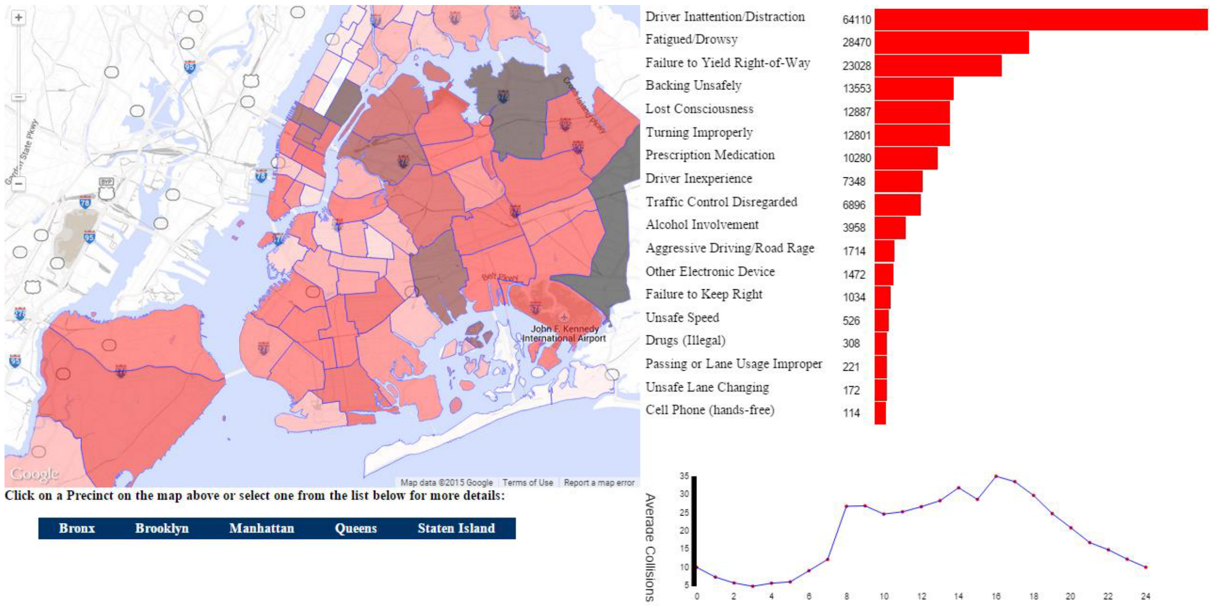


Fig. 1. Screenshot of online visualization tool for identifying traffic collisions hotspots in New York City.

**Abstract**—This project aimed at providing the NYPD with enhanced cognition of traffic collision patterns in New York City by identifying collision hotspots and correlating them with specific enforcement-related causes. Our visualization shows the collision hotspots for each Police Precinct, and identifies the main factors that contributed to these accidents. We also provide collision trends by hour of day for each Precinct. An Overview for the entire City of New York is also presented. Our research shows that the most common causes of accidents are not the usual suspects (such as DUI, alcohol involvement and cell phone use), but rather Driver Inattention, Fatigue/Drowsiness and other improper driving manoeuvres.

**Index Terms**—Information visualization, traffic accidents, collision hotspots, accident causes, collision patterns.

## 1 Introduction

Last year, 268 fatal traffic crashes occurred in New York City.[5] In order to achieve 'Vision Zero' (the ideal scenario where NO fatal traffic accidents take place), the New York City Police Department (NYPD) will need to better understand city traffic patterns in order to prioritize allocation of resources to any collision 'hotspots.' The objective of this project is to provide the NYPD with the desired enhanced cognition of traffic collision patterns in the city by identifying these hotspots and correlating them with specific enforcement-related causes (such as DUIs and cell phone use).

Injuries and deaths related to motor vehicle accidents take a heavy toll on communities worldwide. According to the World Health Organization, 3,400 people die each day due to traffic collisions around the world.[4] The United States has experienced an annual death toll of 30,000 to 40,000 people over the past decade, with another two and a half million injured.[6] Additionally, road traffic injuries are a leading cause of deaths around the world for children and young adults.[14]


- *Awais Malik is a PhD Candidate in Civil & Urban Engineering at NYU. E-mail: am5801@nyu.edu.*
- *Bartosz J. Bonczak is a Masters Candidate in Urban Informatics at NYU. E-mail: bjb417@nyu.edu.*
- *Radu Stancut is a Masters Candidate in Urban Informatics at NYU. E-mail: E-mail: rs1933@nyu.edu.*


The crisis surrounding car accident deaths and injuries is a serious public health issue, one that all countries/cities must contend with (in fact, the name "Vision Zero" comes from a Swedish initiative started in the 1990s to deal with these issues). We view this project as a practical step towards better understanding the nature of NYC collisions by aiming to create an interactive visual platform that is meant to extract meaning and information not inherently accessible in its current state. We hope our visualization tool will allow the NYPD to aggregate and visualize the available data in a way that will be easier to understand and explore than before.

## 2 Related Work

The majority of identified papers using visualizations in their collision research leveraged figures, graphs, and maps for the sake of supporting, informing, and explaining their work and findings. The major focus was rarely to develop an information visualization tool, though there were exceptions.[20] More often the spatial and visual elements were used to motivate and review statistical findings and models.[9]

Before running down the different visualization uses below, a quick rundown of common approaches to mapping collisions and roadway safety included 1) a map identifying the area of study, 2) collision incidents plotted, 3) tables listing accidents broken out by features (speed, date, route, etc.), and 4) statistical formulas/models used. Beyond the aforementioned, below are a few common uses of visualizations.

### 2.1 Physical Form: Intersection or Motorway Focus

In a few instances the focus of study was drilled down to the street level and dealt with the geometry of the roads in question.[19] Examples of this included diagram/figures portraying common road types (four-approach intersection) and a subsequent collision matrix with arrows meant to portray direction/movement of cars and point of accidents.[20] This approach was interesting but too granular for our purposes, though there is a thematic overlap with collision points containing accident features (date, road condition) and chart summaries for intersections (location v. condition). The granular exploration of intersection collisions might be relevant for future study on identified New York City hot spots.

### 2.2 3D Rendering

Related to the focus on physical form was the use of three-dimensional (3D) tools. In one instance LiDAR images were overlaid on shape files to create a more robust representation of the physical environment, with photos for drivers' passing sight used to supplement 3D rendering.[11] Again, an approach not immediately applicable to our project purposes. Loosely connected to this section was the placement of bars showcasing accidents and risks on a map projection to 3D. This was an idiom that was more visually appealing than informative. The map/chart proved difficult to read; a choropleth would have sufficed.

### 2.3 Collision Spatial Area & Density (Hot Spots)

There were different levels of sophistication in charting collisions on maps, from simple accident density[18], to seasonal hot spots based on monsoons[15], to taking roadway congestion[19] or population density[12] into consideration, to finally intricate statistical means and models of grouping accidents[10]; this latter example has to do with algorithm creation, beyond the scope of the project, but helps to motivate ideas about how hot spots are to be grouped generally.

### 2.4 Choropleth Mapping

Examples of choropleth, which we intend to use to some extent, highlighted accident fatalities and accident fatalities per capita[7], maps identifying sections of traffic casualties side-by-side with average traffic speeds[16], and accident specific choropleths of pedestrian and bicycle crashes[17].

### 2.5 Supportive Graphs & Plots

This section contains examples and concepts most applicable to our work. Visualizations include stacked bar charts of monthly accidents over 10 years, accidents as bar plot by day of week, and a pie chart for collisions over hourly range of day[10]; currently we plan on combining day of week and hour of day into what we believe will be a more helpful vis tool, described in sketch section below.

Many of the remaining examples are variations of the same theme: line graph of average hourly traffic volume by time of day, weekdays and weekend superposed[19]; side-by-side bar chart of road deaths per 100,000 population/10,000 vehicles in 2010 for various countries[9]; crash risks by day of week, time of day, and road type/day of week[13]; and line graphs of hourly and monthly incidents, as well as a spider web chart plotting accidents by day of week, which was more visually appealing than readable for comparison.

### 2.6 Prediction/Modeling

From the granular aspect of investigating specific road sections we come to the global scope of predicting motor vehicle collisions. These projects used visualizations to highlight their models'/algorithms' findings and projections. Either a map was shaded to reflect model predictions against actual accidents[12] or stretches of roads were color-coded based on danger exposure[9]. Though not tasked with providing a predictive element in our project, the concept of highlighting specific stretches of road or city cross sections as specifically dangerous is immediately applicable.

### 2.7 Growth Ring Maps

An interesting method for displaying precinct collisions, in both time and space, might be implemented from the work by researchers looking at mice activity with respect to censors[8]. These rings, the visual representations, are centered on the sensors (possible metaphor for collision intersections), colored by location (metaphor: collision cause), and have a size proportional to the visits (metaphor: number of collisions). One of the main focuses of the visual representation dealt with non-overlapping censors; this is expected to be modified in some respect (i.e., display only one cause at a time or tolerate some level of overlapping) in our work as collisions routinely have more than one cause.

## 3 Data Analysis & Abstraction

The main dataset used for this project is NYPD Motor Vehicle Collisions available on the NYC Open Data platform[3] and can be downloaded directly from the NYC Open Data website in either CSV or JSON, among other formats. The dataset comes from processed TrafficStat reports made by NYPD and was used inter alia as a basis for developing the Vision Zero View web application. It represents each collision reported to NYPD from 7/1/2012 onward. The dataset is updated daily with an one or two day delay, making it a dynamic dataset with more than 543,000 observations, as of 9th of March 2015. The data type is a flat table consisting of 29 attributes describing each collision, which can be grouped into 6 categories, such as temporal and geographical reference, victims, contributing factors, vehicles involved and finally collision unique identification number.

For the purpose of this project, the dataset is treated as a static table limited to collisions from 07/01/2012 to 02/28/2015. The size of the generated CSV (comma-separated value) file is approximately 100 MB. The dimensions of the filtered table is 541,764 rows by 29 columns. Because the project is focused mostly on presenting spatial distribution of collisions, location information is crucial. Therefore, it was decided to keep only the collision entries that provided geographical latitude and longitude values. There are 455,575 such items which accounted for 84% of the total reported collisions over the selected time period.

The main geographical unit of analysis is the NYC Police Precinct. The official precincts shape file (.shp) was obtained from BYTES of the BIG APPLE database.[1] In order to more easily work with this spatial data in D3 it was necessary to convert it into GeoJSON file. Conversion was achieved by using the 'ogr2ogr' utility, which is part of the Geospatial Data Abstraction Library (GDAL)[2] package. The transformation created a 4 MB JSON file that maps the borders of all 77 precincts of New York City. In order to provide user geographical reference with greater level of detail up to street level with additional infrastructure features we used openly available Google Map as a basemap. It helps to precisely identify particular collision locations.

Beyond the initial data cleaning process, the data set required additional steps in order to make it useful for the purpose of creating visualization. First, each collision had to be attributed to the precinct it occurred in; this was done by mapping both collisions and police precincts and then using spatial join tool available in ESRI ArcMap software. This step resulted with an additional attribute for each collision called "Precinct."

Though location is the primary encoding channel for collision hotspots, our goal was to provide more complex analysis by incorporating additional information, such as contributing factors and temporal characteristics. In order to provide temporal information, the next step was to extract date and time for each collision. It was achieved using Python's Pandas package. Attributes 'DATE' and 'TIME' were converted from plain text into 'datetime' objects what allowed to easily create new attributes for each item called 'year,' 'month,' 'day,' 'weekday' and 'hour.'

Because information about both contributing factors and types of vehicle involved in an accident was mapped to each collision row, it was necessary to perform additional data manipulation. For analytical purposes these attributes were deconstructed into new columns for each category and calculated based on description for each vehicle involved in an accident. This operation created 46 new attributes for each contributing factor and 17 for each vehicle type. Additional column for number of vehicles involved in accident was added as well. This way prepared database was exported into the CSV file of approximately 160 MB.

For the purpose of main choropleth presenting overall number of collisions per precinct encoded by color saturation, the raw data set required substantial aggregation. It was achieved using Pandas package and Python scripts. All accidents were grouped by precinct and aggregated by given attribute. This resulted in total number of collisions within each precinct and also divided by year, month, day of the week, hour of the day. Total number of collisions and their annual breakdown was used for the general view map. Hourly breakdown was used for 24 hour line-plot. Occurrences of different contributing factors and types of vehicles were summed up and average number of vehicles involved in collision was calculated. These variables were used for bar plot of most common factors. In order to achieve easy visual comparison and distinction between different precincts, the absolute values were normalized and mapped to values in range between 0 and 1. This action allowed easier color saturation assignment in d3 as well. This way prepared data was stored in Python dictionary format and later added to properties of each police precinct in previously created JSON file mentioned before.

The main functionality of the visualization is on the individual precinct level, where users can see where the actual incident hotspots occurs. In order to do it, previously prepared database was again aggregated by precinct number. We took advantage of the fact that collisions were approximated to the nearest intersection, making it possible to group them using the latitude and longitude information provided. Contributing factors were summed up and time characteristics were counted as well. Similarly to data for overview map, also here the ratio from 0 to 1 was calculated, where 0 stands for the smallest and 1 for the maximum value in particular precinct. It will allow easier point size assignment for given aggregated collision location. Prepared this way a dictionary for every individual precinct was exported into separate JSON files using Pandas' built-in function. As a result we obtained 77 distinct JSON files (named 'p'+precinct number). This way, d3 script would only require a small part of the data for detailed view.

Final attributes used for both choropleth and detailed location by precinct are described in Table 1. In addition to specified attributes, as a result of data transformation process, we were able to extract much more information ready to use for future development of the project.

## 4 Task Analysis & Questions

The client for our visualization project is the New York Police Department (NYPD) represented by Alexander E. Chohlas-Wood. He was interested in an interactive visualization tool that would identify collision hotspots and relate these hotspots to different enforcement-related causes. We chose New York City Police Precincts as our geographic unit of analysis, which in practice is the base operational spatial level of the NYPD. We wanted our visualization to identify collision hotspots within each precinct and the main contributing factors. Below is a list of the main task questions we hoped to answer with the support of our visualization.

### 4.1 Where are the collision hotspots within a given police precinct?

An NYPD officer would likely be interested in locating the most dangerous areas within the precinct of interest based on traffic collisions.

### 4.2 Which factors contribute the most to collisions within a precinct of interest?

Being able to identify precinct specific collision causes and later comparing them across the city may yield insights about location specific characteristics; this coupled with further analysis using supplemental data sets can help inform tailored approaches to reducing collisions.

### 4.3 What are the temporal patterns of collision occurrences within the precinct and how do they differ from city-wide patterns?

An NYPD officer can identify the most dangerous times within the precinct of interest based on traffic collisions.

### 4.4 Are there areas of the city seeing unusual collision hotspots?

Precinct-to-precinct analysis can help identify potential outliers that need specific care.

### 4.5 Are there precincts where collisions correspond to increases in enforcement-related causes (such as cell phone use, illegal drug use, or alcohol involvement)?

This information is presented to the user and can be used to identify precincts with specific driver behavior or crime related causes and help NYPD to prioritize its resources to address these challenges.

### 4.6 Which enforcement-related causes should the NYPD pay particular attention toward?

City-wide, which of the enforcement-related causes should be particularly taken into consideration while developing new strategy against traffic collisions in NYC.

## 5 Visualization & Interaction Design

The collision visualization tool has four main sections: 1) an interactive map of New York City divided into precincts; 2) a list of collision causes with a corresponding number count and bar chart; 3) a second list of precincts grouped under boroughs; and 4) a 24 hour line plot. When the tool is first launched, all sections default to the city as a whole, from the zoomed out map view on the left, to the number of causes on the right, and the 24 hour plot in the lower right corner. At this level you are presented with a global view of collisions, as well as a peak into precinct-specific numbers when hovering the mouse over different sections or simply taking the choropleth color gradation into consideration (darker colored precincts signify higher numbers of collisions).

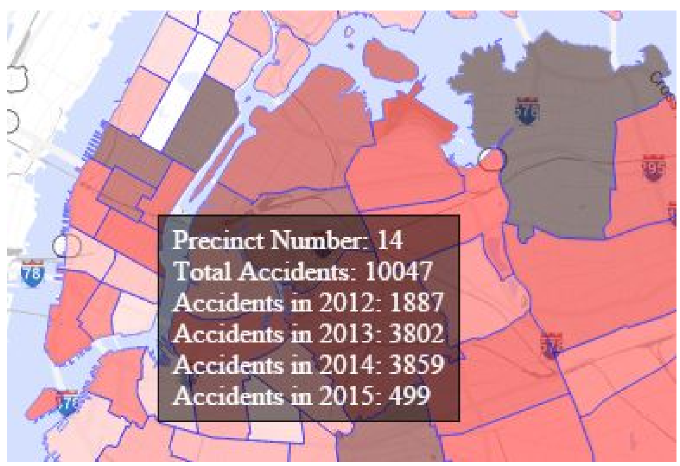


Fig. 2. Hover and Choropleth.

Drilling down to specific precincts can be done in one of two ways, by either clicking on a precinct on the map or expanding the borough lists, to make a precinct selection. The two methods have the same functionality but are provided to grant a user greater flexibility in making a precinct choice. Upon making a selection three transformations occur: 1) the map zooms into the precinct revealing collisions by location 2) the cause of collision bar chart updates to reflect precinct specific numbers 3) the 24 hour plot updates to reflect average collisions by hour of day for the precinct.

Table 1. Attributes Used for Collision Hotspots Visualization.

| Name | Type | Range/Size | Description |
|---|---|---|---|
| PRECINCT | categorical | 77 | Precinct ID |
| YEAR | sequential | 2012 – 2015 | Year in which collision happened |
| HOUR | sequential | 00 - 24 | Hour in which collision happened |
| LATITUDE | diverging | 40.4989488 - 40.9128276 | Geographical latitude of collision |
| LONGITUDE | diverging | -74.2545316 - -73.7005968 | Geographical longitude of collision |
| LOCATION | diverging | Within the range specified in latitude and longitude | Pair of numbers describing geographical location approximated to the nearest intersection |
| CONTRIBUTING FACTORS | categorical | 47 | Factor most contributing to collision for each vehicle involved |
| RATIO | quantitative | 0 – 1 | Ratio calculated for each aggregated value on both city and precinct level |

With respect to these interactive changes, the user now has a better idea of WHERE collisions are occurring, WHAT the contributing factors are, and WHEN collisions are most likely to happen. Specifically, the location and size of dots on the map indicate hotspots; the bar chart provides numbers and representative bars to describe the causes by proportion; and the peaks and valleys over 24 hours show collision activity for a typical day.


Fig. 3. Precinct Zoom In and Hotspots.

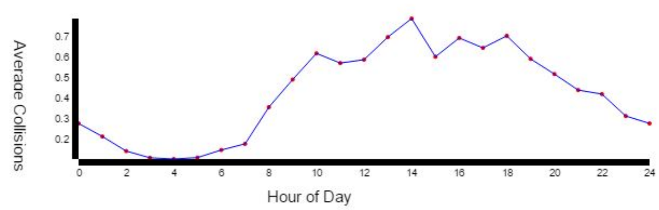


Fig. 4. Updated 24-hour Line Plot (Precinct 14, Manhattan).

The manner in which information is transmitted by the tool may also be described by the visual channels leveraged. Below is a description of these visual channels, followed by a table summarizing these descriptions. The map uses spatial region in two ways: for precinct location when zoomed out and location of collisions when zoomed into a precinct with the use of dots. Color saturation on the city level map defines occurrences of collisions and allows for a quick comparative view across precincts. At the individual precinct level the area of the dots marking collision locations indicates the number of occurrences.

The collision causes bar plot uses position on a common scale to help present the proportional collision factors. The precincts under the borough headings leverages the simplicity of lists and labels. Finally,

Table 2. List of Visualization Tool Features and Channels.

| Features | Visual Channels |
|---|---|
| Map (zoom out; NYC level) | Spatial Region (precinct location) |
| Color Saturation (collision counts) | Map (zoom in; precinct level) |
| Spatial Region (collision location) | Area (collision counts) |
| Collision Causes | Position on Common Scale |
| List of Precincts | Labels/List |
| 24 Hour Plot | Position on Common Scale. Tilt/Angle (change in collision occurrence). |

the 24 hour plot uses position on a common scale, in this case the 24 hours in a day, as well as tilt/angle to provide insight into hours of day when we see a marked change in collisions; the same information could have been presented as vertical bars but the connecting line from hour to hour helps convey more effectively sharp changes.

## 6 Findings & Insights

### 6.1 Finding 1: "Unspecified"

The first finding came from working with the data and is not included in the visualization. The number one cause sited, across the city and in each precinct, was "Unspecified." The number was so large that it dwarfed the other causes and made the bar chart effectively meaningless as a visual tool; the other causes ended up having similar looking bars, even when numbers varied greatly among them. This is an important finding because it could suggest the data collection itself may need looking into. Better data leads to better analysis in the sense of providing greater confidence in the findings.

### 6.2 Finding 2: Top Specified Causes

The top collisions related causes, across the city and the vast majority of the precincts, were not what the group expected and came as a surprise (which is appropriate for non-domain experts). Instead of finding drugs, alcohol, and cell phone usage to lead the pack, the type of factors that routinely receive the most attention, the main causes turned out to be more mundane: Driver Inattention, Fatigue, and Failure to Yield Right-of-Way.

This is an important finding because in order to effectively combat a problem you first need to know what you are up against. Having a count and clear presentation of what the main contributing factors of collisions are helps inform the actions to be taken, from enforcement to public education.

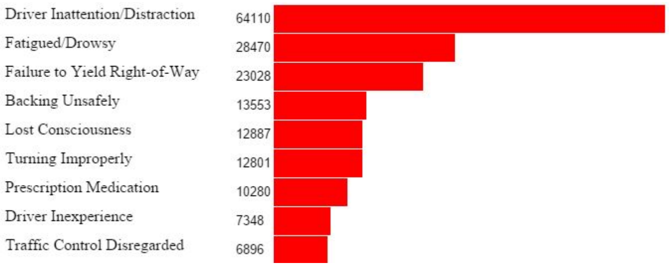


Fig. 5. Top Collision Causes in NYC.

### 6.3 Finding 3: Rush Hour is a Dangerous Time

Across the city, and the vast majority of the precincts, the most dangerous time to drive, as a factor of collisions, is during and in between morning and evening rush hour. This is the kind of finding that makes intuitive sense once you think about it. The more cars are on the road the greater the frequency of collisions.

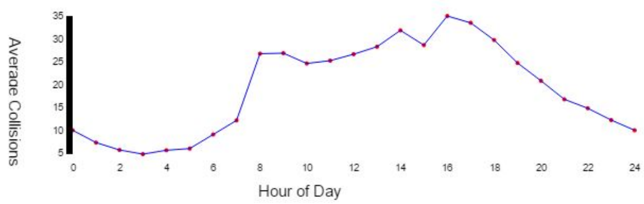


Fig. 6. NYC Collisions Over 24 Hours (average).

This is an important finding to better understand when resources are needed and the specific types of challenges that time of day poses.

### 6.4 Not all Precincts are Created Equal

While our tool is primarily meant to identify the collision profile of specific precincts it is none the less fascinating to do comparative browsing and find out ways in which precincts differ. Some examples are:

- Different peak hours and drop offs in collision activity; suggesting different driving activity and possible approaches to curbing accidents. Also, notice the "Average Collisions" axis and how the numbers change, another precinct specific activity identifier.

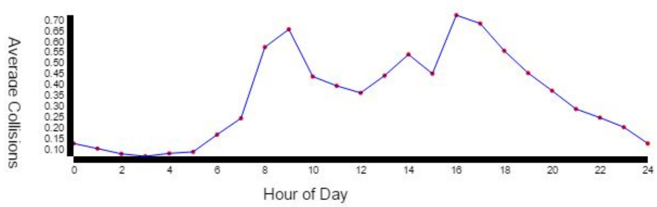


Fig. 7. Precinct 107.

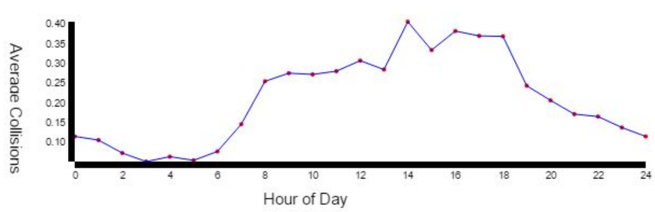


Fig. 8. Precinct 79.

- Different distribution of top causes, raising questions about the driver and precinct profiles that contribute to these outcomes. Looking into these factors may help suggest approaches to dealing with collisions in a particular precinct.

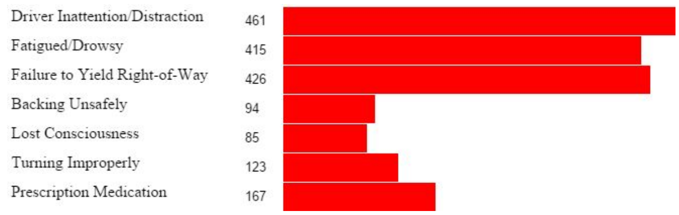


Fig. 9. Precinct 63.

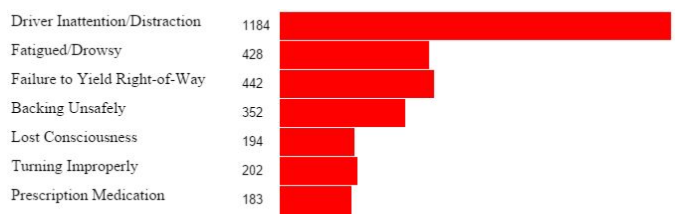


Fig. 10. Precinct 72.

- Collision clusters: where precincts "tell" you where to concentrate attention.

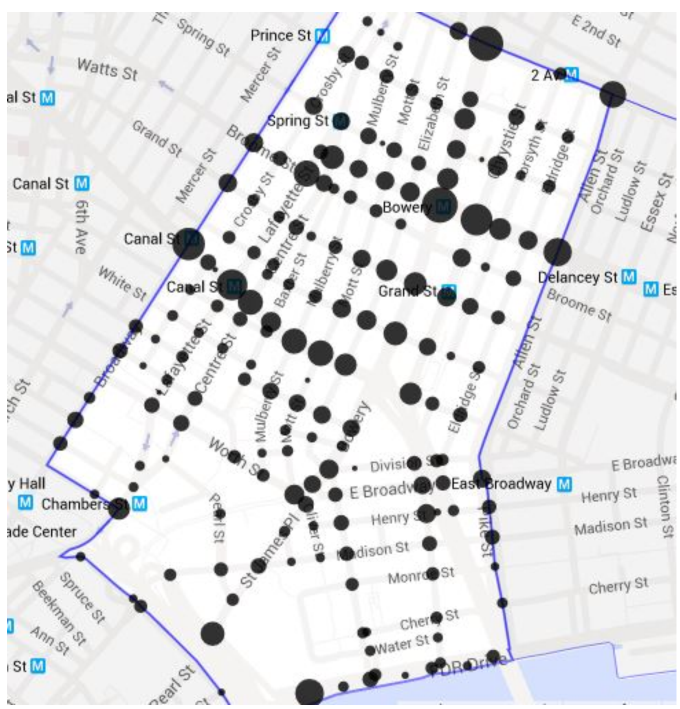


Fig. 11. Precinct 5.


Fig. 12. Precinct 63.

The way in which precincts experience collisions is of primary importance to our work. Identifying both similarities and differences in this experience can be crucial in seeing what works and does not work, as well as copying effective techniques from one precinct to another.

## 7 Limitations & Future Work

The two main limitations faced by our group were time and technical proficiency. The group had sufficient ideas as to the tool's intended features and functionality, but the most challenging aspect of the project proved to be implementation. However, we believe we have delivered a strong starting point from which future work can progress. The following are a few suggestions for future work:

- Temporal Collision Granularity:

  We have extracted collision data by year, month, weekday/weekend etc.

- Spatial Collision Granularity:

  Show dot maps by collision causes.

- Increased Functionality/Brushing and Linking:

  Clicking on a cause in the bar chart would update 1) the dot map to show only said collisions and 2) the 24 hour plot (and any other temporal plots) to show when said collision types occurred.

  Incorporate the ability to filter collisions on year, month, day of week, and user desired time frame on 24 hour chart.

## 8 Conclusions & Lessons Learned

While it is naturally important to vet our understanding of the problem before coding aimlessly, our group may have been able to solve some of our technical issues had we begun the prototyping process earlier. This would have provided the opportunity to turn our attention to any one of multiple areas that could have further improved our solutions, such as performance optimization, enhanced feature options, increased interactivity, and aesthetic modifications. Nevertheless, we believe we have established a solid platform for understanding traffic collision patterns in New York City, and our work can be improved to gain further spatial and temporal insights.

## Acknowledgments

The authors wish to thank Professor Enrico Bertini, Jay Coven, Josua Krause, Cristian Felix and Alexander E. Chohlas-Wood.

## References

[1] Bytes of the big apple. available at: http://www.nyc.gov/html/dcp/html/bytes/applbyte.shtml., 2015.

[2] Gdal - geospatial data abstraction library., 2015.

[3] Nypd motor vehicle collisions. nyc open data. available at: https://data.cityofnewyork.us/public-safety/nypd-motor-vehicle-collisions/h9gi-nx95., 2015.

[4] World health organization. violence and injury prevention. road traffic injuries., 2015.

[5] K. Aaron, J. Ye, L. Ma, J. Keefe, N. Veltman, and K. Stark. Mean streets. available at http://project.wnyc.org/traffic-deaths/., 2014.

[6] N. H. T. S. Administration et al. 2012 motor vehicle crashes: Overview. *US Department of Transportation. Report No. DOT HS-811-856. Available at: http://www-nrd.nhtsa.dot.gov/Pubs/811856.pdf.*, 2013.

[7] J. Aguero-Valverde and P. P. Jovanis. Spatial analysis of fatal and injury crashes in pennsylvania. *Accident Analysis & Prevention*, 38(3):618–625, 2006.

[8] P. Bak, F. Mansmann, H. Janetzko, and D. A. Keim. Spatiotemporal analysis of sensor logs using growth ring maps. *Visualization and Computer Graphics, IEEE Transactions on*, 15(6):913–920, 2009.

[9] M. Driss, K. Benabdeli, T. Saint-Gerand, and M. Hamadouche. Traffic safety prediction model for identifying spatial degrees of exposure to the risk of road accidents based on fuzzy logic approach. *Geocarto International*, (ahead-of-print):1–15, 2014.

[10] S. Erdogan, I. Yilmaz, T. Baybura, and M. Gullu. Geographical information systems aided traffic accident analysis system case study: city of afyonkarahisar. *Accident Analysis & Prevention*, 40(1):174–181, 2008.

[11] A. J. Khattak and H. Shamayleh. Highway safety assessment through geographic information system-based data visualization. *Journal of computing in civil engineering*, 19(4):407–411, 2005.

[12] N. Levine, K. E. Kim, and L. H. Nitz. Spatial analysis of honolulu motor vehicle crashes: I. spatial patterns. *Accident Analysis & Prevention*, 27(5):663–674, 1995.

[13] L. Li, L. Zhu, and D. Z. Sui. A gis-based bayesian approach for analyzing spatial–temporal patterns of intra-city motor vehicle crashes. *Journal of Transport Geography*, 15(4):274–285, 2007.

[14] M. Peden et al. World report on road traffic injury prevention, 2004.

[15] V. Prasannakumar, H. Vijith, R. Charutha, and N. Geetha. Spatio-temporal clustering of road accidents: Gis based analysis and assessment. *Procedia-Social and Behavioral Sciences*, 21:317–325, 2011.

[16] M. A. Quddus. Modelling area-wide count outcomes with spatial correlation and heterogeneity: an analysis of london crash data. *Accident Analysis & Prevention*, 40(4):1486–1497, 2008.

[17] C. Siddiqui, M. Abdel-Aty, and K. Choi. Macroscopic spatial analysis of pedestrian and bicycle crashes. *Accident Analysis & Prevention*, 45:382–391, 2012.

[18] A. Soltani and S. Askari. Analysis of intra-urban traffic accidents using spatiotemporal visualization techniques. *Transport and telecommunication journal*, 15(3):227–232, 2014.

[19] C. Wang, M. A. Quddus, and S. G. Ison. Impact of traffic congestion on road accidents: a spatial analysis of the m25 motorway in england. *Accident Analysis & Prevention*, 41(4):798–808, 2009.

[20] P. Yi, Y. Xiao, A. Ciccolini, G. Frommer, and D. Zhang. Rule-based model for traffic accident visualization and analysis. *Journal of computing in civil engineering*, 15(2):129–136, 2001.

## Links

### Github Repository

https://github.com/NYU-CS6313-Projects/Traffic-Collisions-Hotspots

### Online Interactive Visualization

http://rawgit.com/NYU-CS6313-Projects/Traffic-Collisions-Hotspots/master/code/hotspot.html

### Video Tutorial

http://screencast.com/t/3Rgw9GtCEw