

# DRAFT: Johns Hopkins East Baltimore Campus: Crime Analysis and Visualization

Shannon Wongvibulsin

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## 1 Introduction

Baltimore City consistently ranks as one of the most dangerous cities in America (Forbes, 2017). As a result, discussion about safety concerns at Johns Hopkins is common. To promote a safe and secure environment, the Hopkins Corporate Security provides the University and Hospital communities proactive security and law enforcement practices. Corporate Security maintains a record of the campus crime and provides annual crime statistics (Hopkins Medicine, 2017).

The Hopkins Corporate Security Crime Log represents a rich source of crime data that can be analyzed for crime patterns. For instance, a recent article in PLOS|ONE reported that most crimes exhibit seasonal oscillations (Dong, PLOS|ONE, 2017). The Hopkins Security crime log can be used to determine whether certain types of crime occur more frequently at certain locations, times of day, days of the week, or times of the year at the Hopkins East Baltimore Medical Campus. Furthermore, understanding these patterns can help with crime projections to increase campus safety through crime prevention activities (Andresen, Applied Geography, 2013). For example, increased security personnel can be strategically positioned based upon crime patterns. Additionally, although Corporate Security notifies Hopkins of reported crimes that present a “serious or continuing threat” through “Security Alert” emails, detailed analysis of crime patterns can allow Corporate Security to inform the community about general crime “forecasts” as well as general safety precaution recommendations. To present this analysis in a useful and interactive format, this project involves not only the analysis of the Hopkins crime data but also the development of a Shiny App for interactive analysis and visualization.

Overall, the goal of the project is to answer the following question: are there patterns in the crimes that occur at the Hopkins East Baltimore Medical Campus? To answer this question, this project provides the analysis of the Hopkins East Baltimore Medical Campus crime data and the development of an application for interactive analysis and visualization.

## 2 Methods

The 2015, 2016, and 2017 Hopkins Crime Logs were obtained from the Johns Hopkins University Clery Compliance Administrator. The data logs were provided in tables in the PDF format. The tables were converted into the Excel spreadsheet using PDFTables

(<https://pdftables.com/>). Afterwards, the spreadsheets were saved in CSV formats and loaded into R for further analysis. The data were cleaned and rows with missing data for the crime type were removed from the analysis.

Interactive histograms are plotted using R to visually compare the frequency of different types of crimes using the ggplot2 and plotly libraries. The data will be analyzed by month, season, day of week, and time of day to determine if there are temporal variations in crime patterns. For the analysis with time of day, the lubridate library is used. Times are classified into "Night" ("00:00" - "6:00"), "Morning" ("6:01" - "12:00"), "Afternoon" ("12:01" - "18:00"), and "Evening" ("18:01" - "23:59"). For the analysis with seasons, the seasons are defined as follows: Spring (March, April, May), Summer (June, July, August), Autumn (September, October, November), Winter (December, January, February).

For interactive analysis and visualization, a Johns Hopkins East Baltimore Crime Shiny Application is built using R. The gmap library is used for plotting the crime maps. The building locations are geocoded using the geocode function and the building addresses. Building addresses were determined from the Johns Hopkins website. After geocoding the locations, each crime location was labeled with a corresponding longitude and latitude.

Prior to analysis of crime patterns, crime locations are grouped by buildings and general areas. For instance, rather than considering "Bloomberg Childrens Center 10th floor" and "Bloomberg Childrens Center 9th floor" as two different locations, all floors in the Bloomberg Childrens Center are considered as the same location. Additionally, crime patterns are analyzed after categorizing crime locations as "inside" or "outside" crimes ("inside" meaning that the crime occurred inside a building). Crimes are labeled as "outside" if the word "block" is in the location name. For example, "1500 block Orleans St" is categorized as an "outside" crime location and "933 N. Wolfe Street" is categorized as an "inside" crime location.

For statistical analysis, Tukey multiple pairwise-comparisons and pairwise t-tests are performed. The Tukey multiple pairwise-comparisons tests are performed with the TukeyHSD() R function (Turkey Honest Significant Differences). The pairwise t-tests are performed using the pairwise.t.test() R function. The significance level is set at  $p < 0.05$ . The tables of the results for these tests are generated using the xtable function from the xtable library.

This report focuses on the analysis and visualization of the 2015 crime data. Interactive visualizations and analysis of the 2015, 2016, and 2017 crime data are supported by the Shiny Application.

### 3 Results

The crime analysis of the 2015 Johns Hopkins East Baltimore Campus crime indicate that crime is most concentrated at the main hospital (with 105 incidents), as indicated in Figure 1.

When analyzing the crime occurrences by time of day, there is a peak in the crime incidents in the afternoon. Additionally, it is apparent that theft and assault are the two most common crime types, as shown in Figure 2. When focusing on theft, the largest category of crimes, the Tukey test performed on occurrences of theft by time of day across

2015, 2016, and 2017 indicate that there is a significant difference between the occurrences of theft between afternoon and night ( $p \text{ adj} = 0.0198961$ ) and evening and afternoon ( $p \text{ adj} = 0.0468943$ ), Table 1. The pairwise t-test also indicate a significant difference between thefts in the afternoon and night ( $p\text{-value} = 0.029$ ), but the comparison between thefts in the afternoon and evening ( $p\text{-value} = 0.059$ ) did not reach statistical significance, Table 2.

In general, no visual pattern of crime frequency can be seen by the day of week or season (Figure 3 and Figure 4). For theft, the incidents are lowest during the weekends and in the spring.

By month (Figure 4), January has the highest crime incidents for assault and theft.

## 4 Discussion and Conclusion

This project provides the foundation for the establishing preventive strategies for reducing crime at the Johns Hopkins East Baltimore Campus. The results of this analysis demonstrate that strategies need to be developed targeted specifically at assault and theft as the main priorities to reduce the occurrences of the most common types of crime on this campus. Crime safety information to Hopkins students, faculty, and staff focusing on assault and theft prevention as well as alerting security guards to heighten their surveillance in the afternoon on weekdays for these types of crimes can be initial starting points for crime reduction.

Although this analysis and the Shiny application can help the Johns Hopkins East Baltimore Campus move towards strategies for lower crime rates, there are a number of limitations to this project. The crime logs were provided by Hopkins Security. However, the data they were able to share were only for 2015, 2016, and 2017 (Figure 6). Additionally, the 2017 data was not for the complete year since the data were obtain in September. Furthermore, the occurrences of crime would be more informative if the number of people on campus on each day or at each location were taken into account. For example, there may be less thefts on the weekend days because there are less people on campus. In contrast, there may be more crimes reported at the main hospital because that is the most concentrated area of the Johns Hopkins East Baltimore Campus.

Static tables and figures are provided in this report. For interactive analysis and visualization, the Shiny app can be accessed at the following page:

NOTE: Shiny app under development; link will be placed here in the final report.

## 5 References

To be formatted

<http://wtop.com/local/2016/02/d-c-baltimore-city-among-most-dangerous-places-in-u-s/>  
<https://www.forbes.com/pictures/mlj45jggj/7-baltimore/#68a81b8b5487>  
<http://baltimore.cbslocal.com/2017/06/16/baltimore-ranks-on-new-list-of-worst-america>  
[http://www.hopkinsmedicine.org/security\\_parking\\_transportation/security/](http://www.hopkinsmedicine.org/security_parking_transportation/security/)  
[http://security.jhu.edu/\\_template-assets/documents/annual\\_report.pdf](http://security.jhu.edu/_template-assets/documents/annual_report.pdf)



Figure 1: Crime Locations and Number of Incidents in 2015

	diff	lwr	upr	p adj
Morning-Night	30.67	-5.49	66.82	0.10
Afternoon-Night	43.67	7.51	79.82	0.02
Evening-Night	7.00	-29.15	43.15	0.92
Afternoon-Morning	13.00	-23.15	49.15	0.67
Evening-Morning	-23.67	-59.82	12.49	0.23
Evening-Afternoon	-36.67	-72.82	-0.51	0.05

Table 1: Time of Day Crime Comparisons for Theft with TukeyHSD: diff (difference between means of the two groups), lwr, upr (lower and upper end points of 95% confidence interval), p adj (p-value after adjustment for multiple comparisons)

	Night	Morning	Afternoon
Morning	0.11		
Afternoon	0.03	0.57	
Evening	0.57	0.21	0.06

Table 2: Time of Day Crime Comparisons for Theft with Pairwise t-test

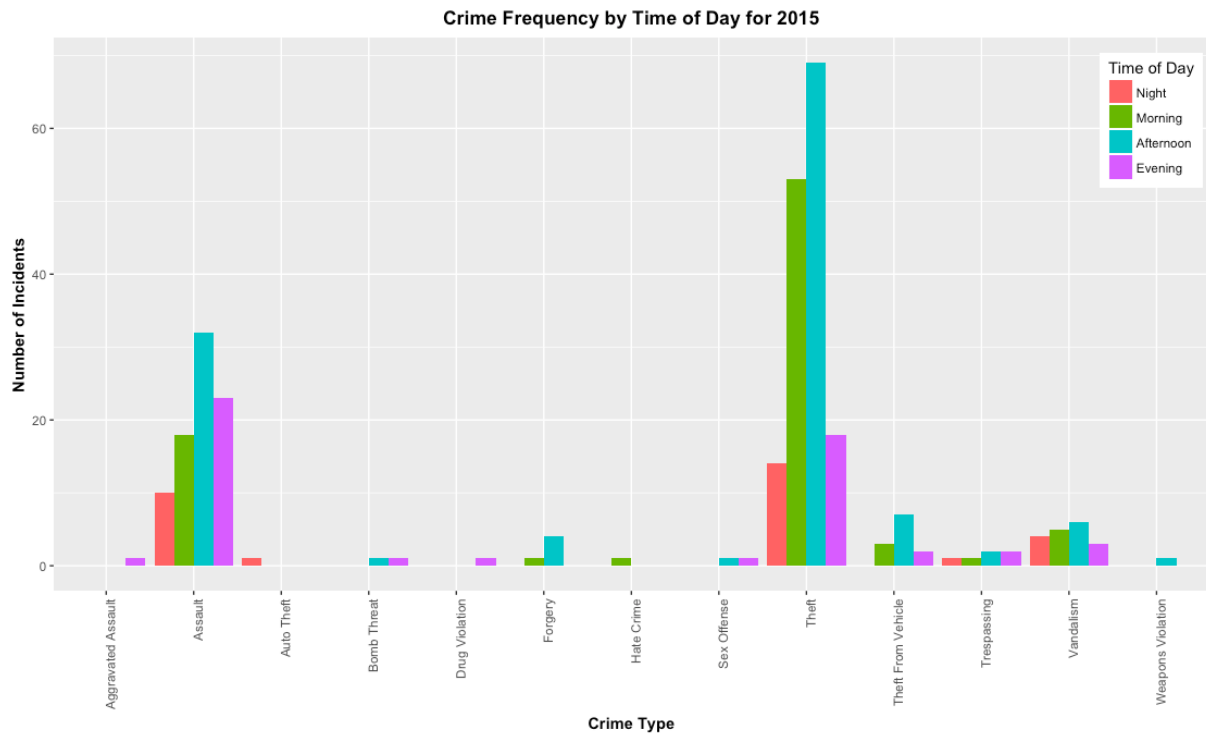


Figure 2: 2015 Crime Frequency by Time of Day

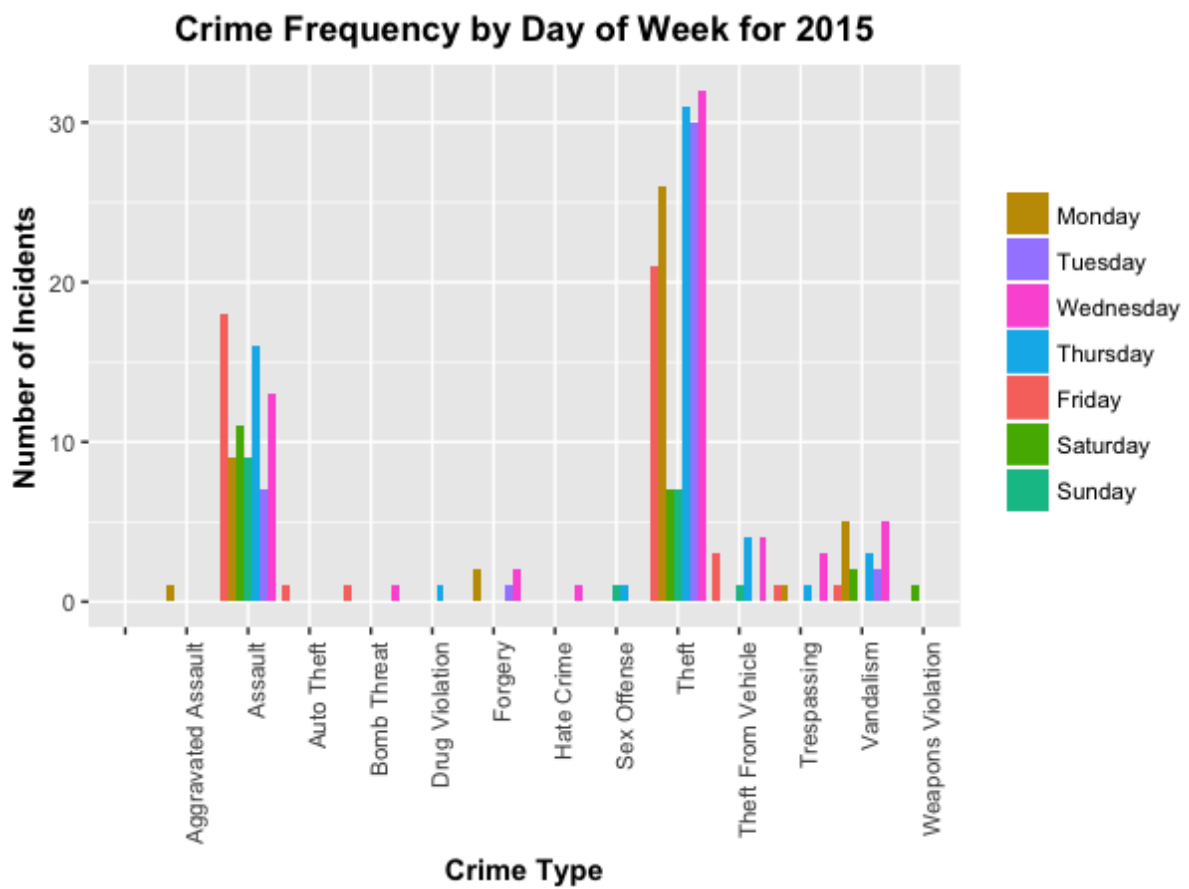


Figure 3: 2015 Crime Frequency by Day of Week

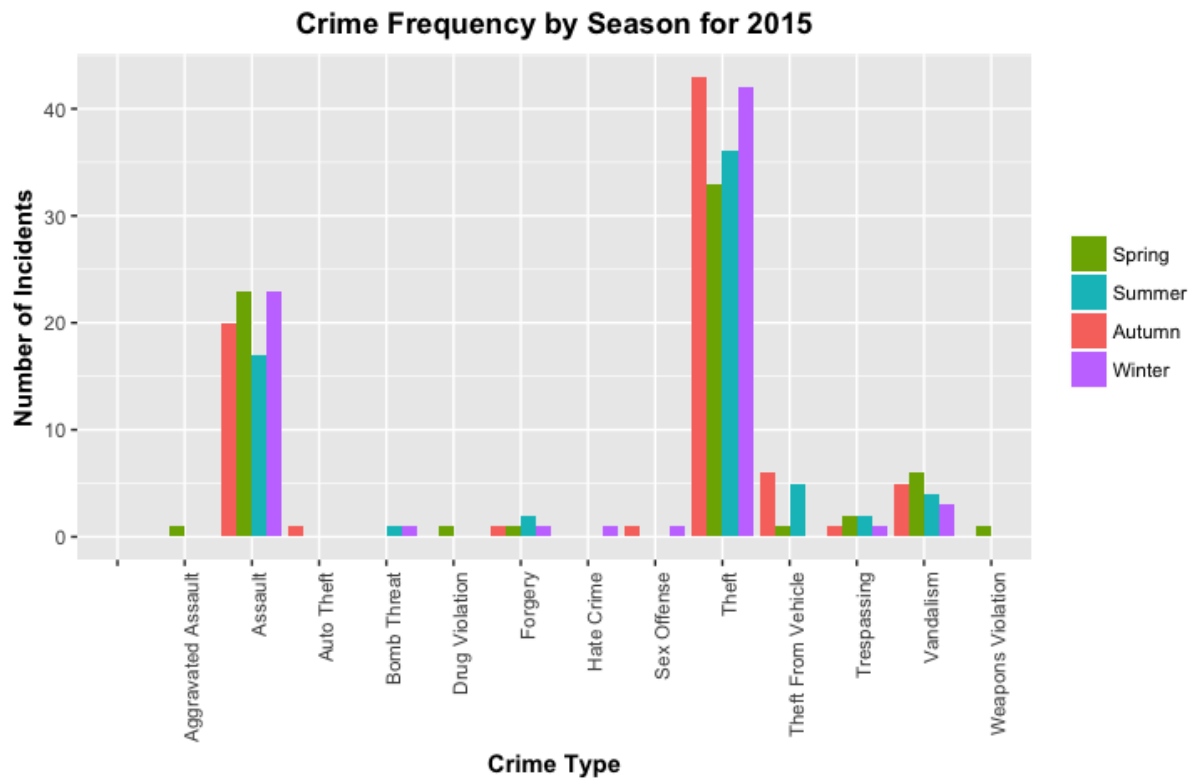


Figure 4: 2015 Crime Frequency by Season

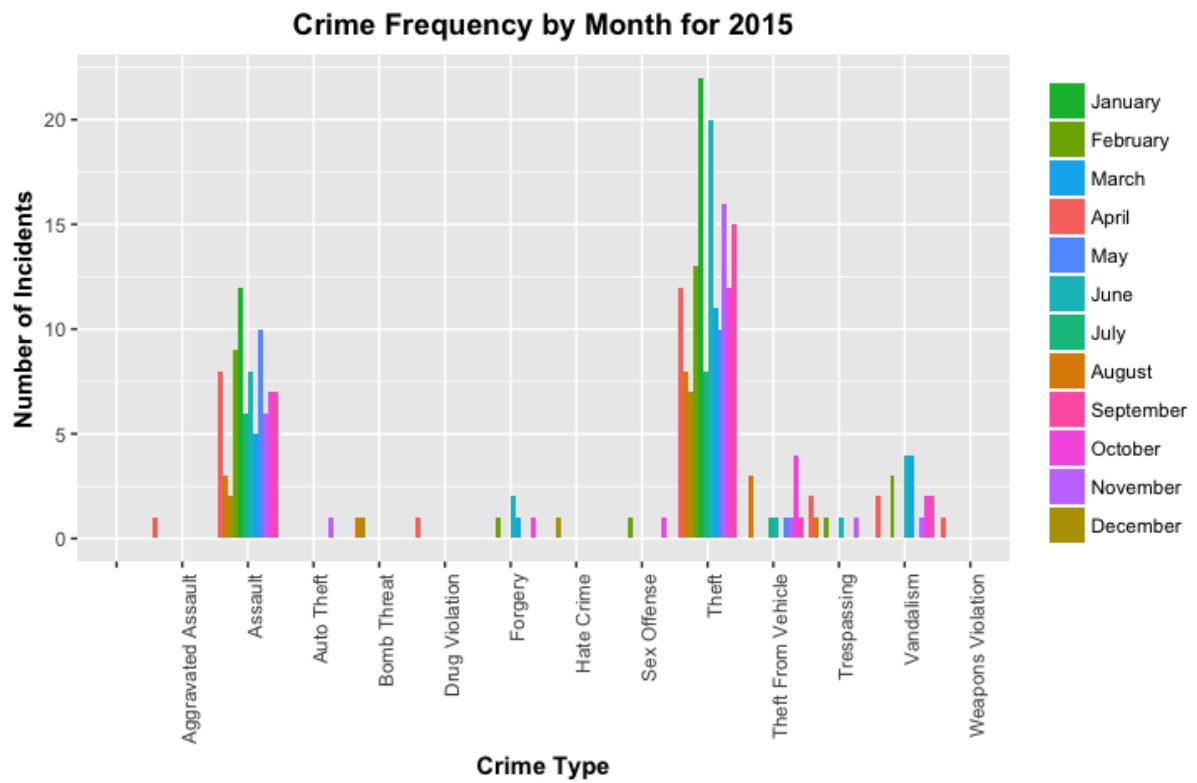


Figure 5: 2015 Crime Frequency by Month

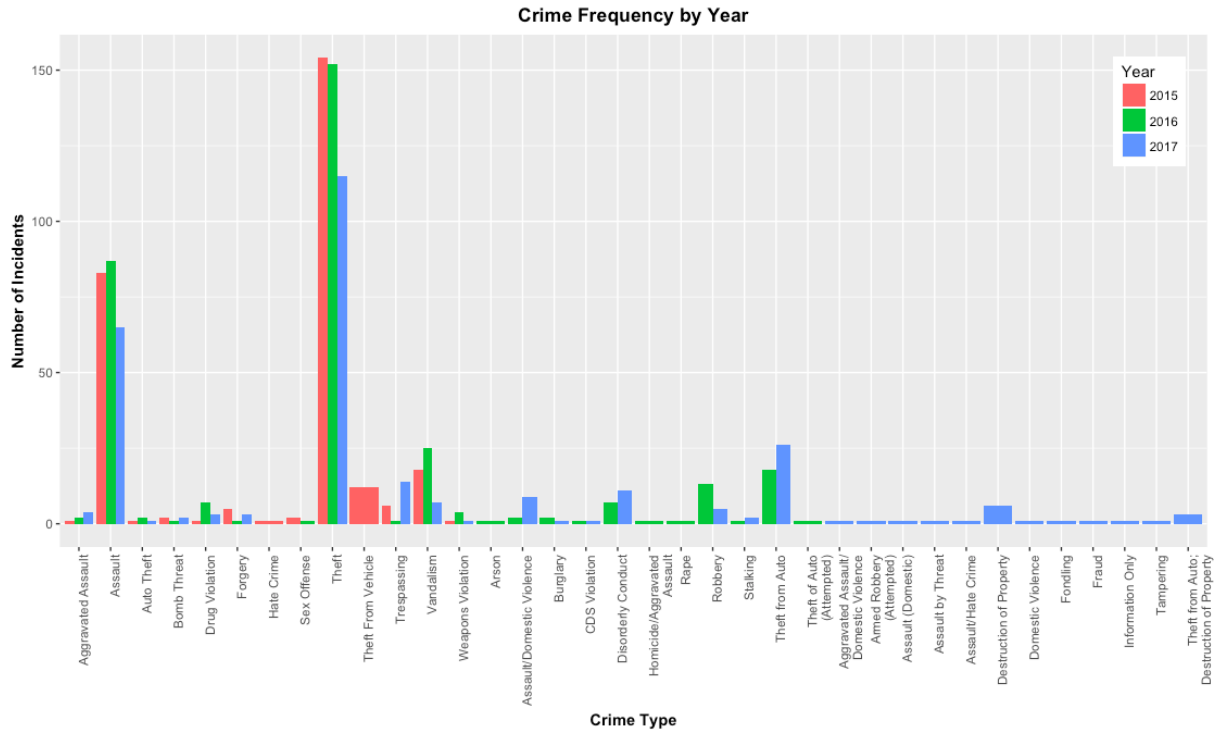


Figure 6: Hopkins East Baltimore Campus Crime Types and Frequency by Year

## 6 Supplemental Materials

	Frequency
Aggravated Assault	1
Assault	83
Auto Theft	1
Bomb Threat	2
Drug Violation	1
Forgery	5
Hate Crime	1
Sex Offense	2
Theft	154
Theft From Vehicle	12
Trespassing	6
Vandalism	18
Weapons Violation	1

Table 1: 2015 Crime Types and Frequencies

	Frequency
Aggravated Assault	2
Arson	1
Assault	87
Assault/Domestic Violence	2
Auto Theft	2
Bomb Threat	1
Burglary	2
CDS Violation	1
Disorderly Conduct	7
Drug Violation	7
Forgery	1
Homicide/Aggravated Assault	1
Rape	1
Robbery	13
Sex Offense	1
Stalking	1
Theft	152
Theft from Auto	18
Theft of Auto (Attempted)	1
Trespassing	1
Vandalism	25
Weapons Violation	4

Table 2: 2016 Crime Types and Frequencies



	Frequency
Aggravated Assault	4
Aggravated Assault/ Domestic Violence	1
Armed Robbery (Attempted)	1
Assault	65
Assault (Domestic)	1
Assault by Threat	1
Assault/Domestic Violence	9
Assault/Hate Crime	1
Auto Theft	1
Bomb Threat	2
Burglary	1
CDS Violation	1
Destruction of Property	6
Disorderly Conduct	11
Domestic Violence	1
Drug Violation	3
Fondling	1
Forgery	3
Fraud	1
Information Only	1
Robbery	5
Stalking	2
Tampering	1
Theft	115
Theft from Auto	26
Theft from Auto; Destruction of Property	3
Trespassing	14
Vandalism	7
Weapons Violation	1

Table 3: 2017 Crime Types and Frequencies