

Temporal Crime Trends at the Johns Hopkins East Baltimore Campus

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Introduction

Baltimore City consistently ranks as one of the most dangerous cities in America [1, 2, 3]. 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 [4, 5].

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 [6]. The Hopkins Security crime log can be used to determine whether certain types of crime occur more frequently at certain 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 [7]. For example, increased security personnel can be strategically deployed 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. As seen in the Hopkins Corporate Security crime reports, crime at Hopkins remains a major issue and data-driven preventive strategies are needed to improve campus safety [4, 5].

Currently, the crime analysis and graphs available through Hopkins Corporate Security provide limited utility in informing safety precaution recommendations and crime prevention measures. For instance, on the Campus Crime Statistics page of the Johns Hopkins Medicine Security website, the “View the crime statistics graphs” link only provides calendar year crime comparisons in the form of two bar graphs [8]. Nevertheless, the data collected through Hopkins Corporate Security represents a rich source of crime data that can help improve our understanding of crime at Hopkins and inform practices that can potentially make the campus safer.

Rather than simply summarizing crime trends by total crime counts per year, this project explores more granular approaches to analyzing and visualizing temporal crime trends, specifically to determine the effect of times of day, days of the week, and month on crime. Furthermore, daily crime patterns are visualized with calendar heatmap plots,

which allows for the visualization of the daily total crime counts through a gradient of colors. These methods applied to the Hopkins Corporate Security crime data have the potential to improve our comprehension of the patterns that currently may lay hidden within the crime logs.

Overall, the goal of the project is to answer the following question: are there temporal patterns in the crimes that occur at the Hopkins East Baltimore Medical Campus? To answer this question, this project provides the analysis of the temporal trends in the Hopkins East Baltimore Medical Campus crime data for 2015, 2016, and 2017 from Hopkins Corporate Security to address the current gaps in our understanding of crime patterns at the Hopkins East Baltimore Medical Campus.

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 [9]. Afterwards, the spreadsheets were saved in CSV formats and loaded into R[10] for further analysis. The data were cleaned and a total of five rows were removed from the analysis. Three of the rows had all crime information missing, suggesting that these were just blank entries that could be ignored. Two of the rows only had information about crime type, but all other information was missing. Since the crime types were labeled as “21” and “18” and there was no other information available, these two rows were also ignored. After the removal of these five rows, there were a total of 917 entries in the crime dataset. The crime report entries included data from January 1, 2015 to September 11, 2017.

The fields in the crime log included the crime type (e.g. assault, theft, vandalism) and the date and time of the crime occurrence (e.g. 1/1/15 7:50 AM). For this analysis, the date and time information were further processed and variables were added for time of day, day of the week, and month. Times were classified into “Night” (“00:00” - “6:00”), “Morning” (“6:01” - “12:00”), “Afternoon” (“12:01” - “18:00”), and “Evening” (“18:01” - “23:59”) (see the “format” code chunk section titled `Format data` in the `final_code.rmd` file for details on data processing) [11].

To visualize the crime trends, total crime count was plotted by month, day of week, hour, and time of day. To visualize daily crime counts across all three years, a calendar heatmap was used. In the calendar heatmap, each square represents a different day and the color of the square corresponds to the crime count for that particular day. This calendar heatmap visualization of the crime count allows for a global visualization of three years of data on one plot (see the “heatmap” code chunk section titled `Calendar heatmap` in the `final_code.rmd` file for further details) [12, 13].

For quantitative analysis and statistical testing, the Tukey test was used to calculate effect sizes, 95% confidence intervals, and p-values adjusted for multiple comparisons. The Tukey tests were performed to determine the effect of time of day on the total number of crime during that time, and to determine the effect of the day of the week on the total number of crime on that day (See the “Tukey” code chunk section titled `Statistical testing` in the `final_code.rmd` file for further details) [14, 15].

Results

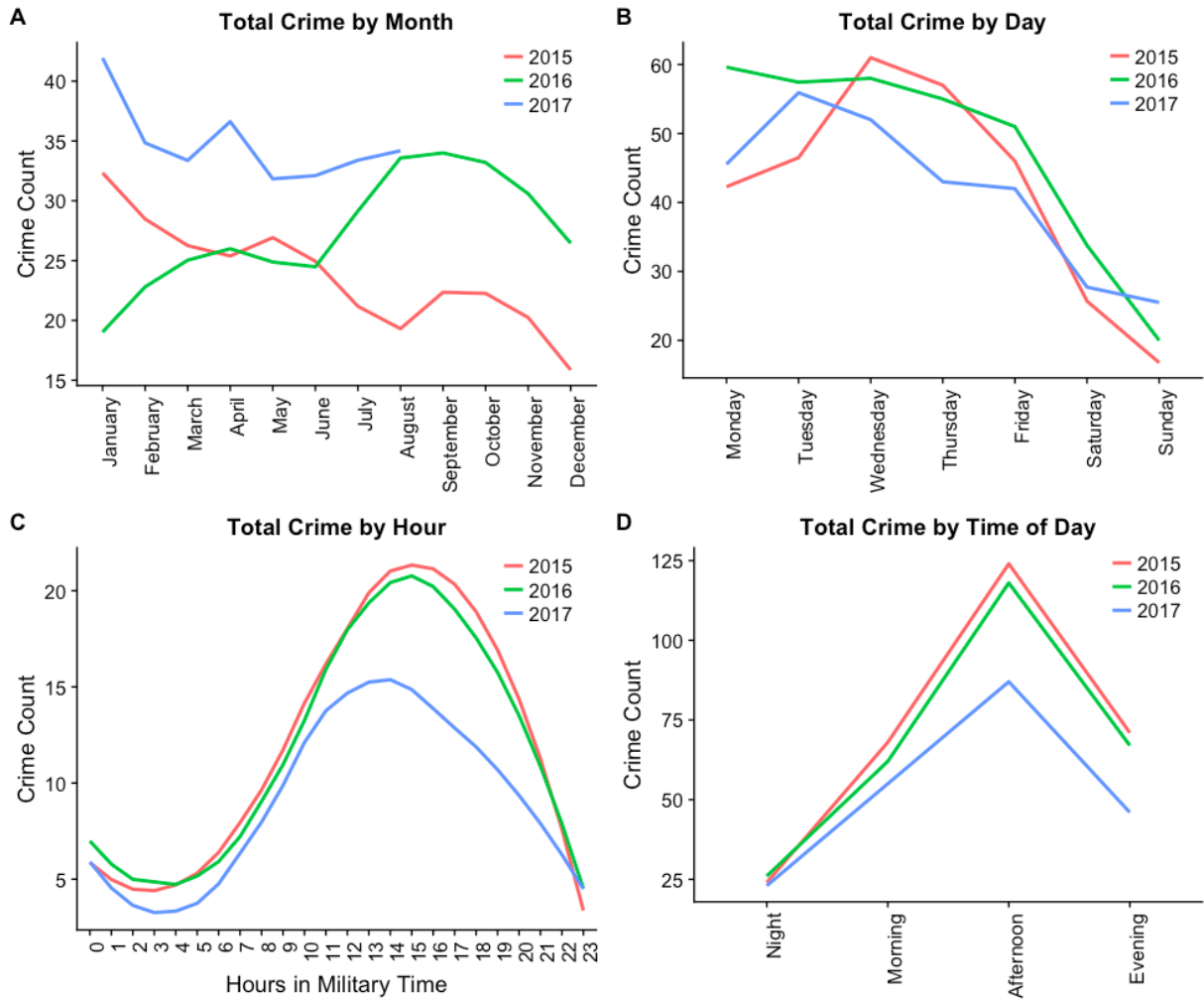


Figure 1: Temporal Crime Trends: A) total crime by month for 2015, 2016, and 2017 (note: 2017 plot is truncated in August because August is the last complete month of 2017 crime data available at the time of this analysis, B) total crime by day of the week, C) total crime by hour of the day (denoted in military time), D) total crime by time of the day (“Night” (“00:00” - “6:00”), “Morning” (“6:01” - “12:00”), “Afternoon” (“12:01” - “18:00”), and “Evening” (“18:01” - “23:59”))

Over the course of time from 2015 to 2017, the number of crime categories for the crime types changed from 13 in 2015 (Supplemental Table 1) to 22 in 2016 (Supplemental Table 2) to 29 in 2017 (Supplemental Table 3). Across all three years, assault and theft were the most common crime types (Supplemental Tables 1-3). Because of the changing categories of crime types over time, the project focuses on analyzing aggregated crime rather than incidents of crime separately by type. In total, there were 287 crime incidents in 2015, 331 crime incidents in 2016, and 289 crime incidents in 2017 (at the time of data collection, the crime log only includes records until September 11, 2017).

Visualizing the total crime by month across the three years reveals differing trends (Figure 1A). In 2015, there is a decreasing crime trend, with the highest crime count in January and lowest crime count in December. In 2016, there is a general increase in crime

count from January to September and then a decrease from September to December. For 2017, since the data are only available for records until mid-September, the crime counts are only plotted for January to August. The visualization in Figure 1A reveals that the crime counts in 2017 are greater than those in 2015 and 2016 for all months from January to August.

When analyzing trends by the day of the week, there is a general decreasing trend in the crime count, with the lowest crime on the weekend days, across all three years (Figure 1B).

When analyzing trends by hour of the day, the crime count is lower in the early hours of the day (around 1 to 6 AM) and is higher in the afternoon, reaching the peak in the late afternoon (Figure 1C).

When analyzing trends by time of day (categorized as Night, Morning, Afternoon, and Evening), it can be seen that the crime count peaks in the afternoon time (Figure 1D).

With the calendar heatmap, patterns in the crime occurrences from 2015 to 2017 can qualitatively be seen through the visualization of the color gradient, with darker red indicating a greater number of crime incidents (Figure 2). Visually, it can be seen that the darker squares generally occur on weekdays. Further analysis with the Tukey test indicate significant differences between Saturday vs. Monday, Sunday vs. Monday, Saturday vs. Tuesday, Sunday vs. Tuesday, Saturday vs. Wednesday, Sunday vs. Wednesday, Saturday vs. Thursday, Sunday vs. Thursday, Saturday vs. Friday, and Sunday vs. Friday (Supplemental Figure 1 and Supplemental Table 4). Significance testing for the differences in crime occurrences by time of day (Morning, Afternoon, Evening, Night) indicate significant differences in all the pairwise comparisons with the exception of evening vs. morning (Supplemental Figure 2 and Supplemental Table 5).

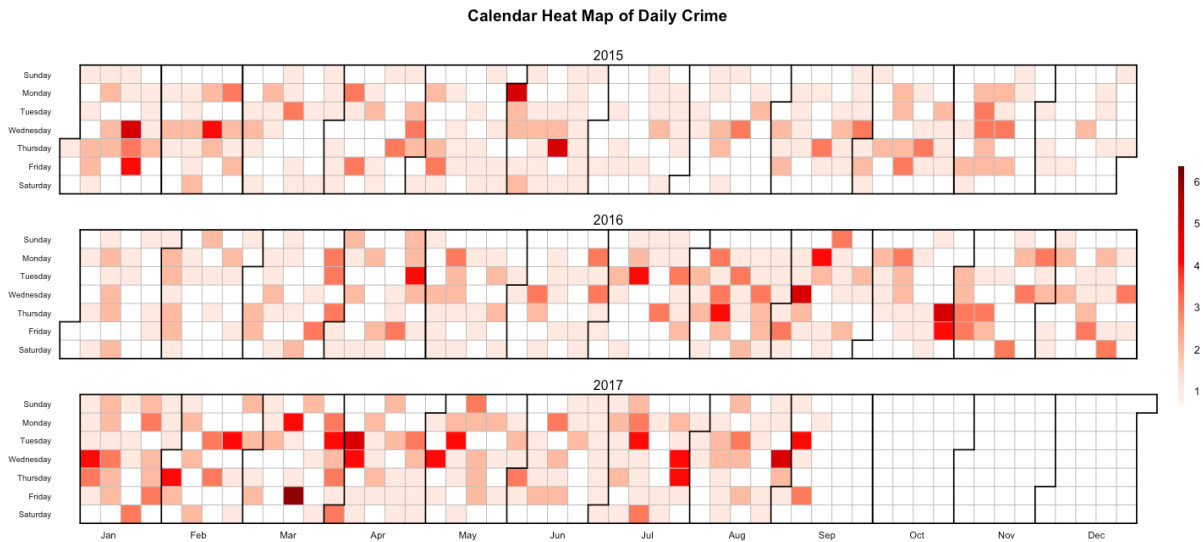


Figure 2: 2015-2017 Crime Calendar Heatmap: each square represents a different day and the color of the square corresponds to the crime count for that particular day (white cells indicate zero crimes; the lightest red indicates 1 crime; the darkest red indicates 6 crimes)

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 can help the Johns Hopkins East Baltimore Campus move towards strategies for lower crime rates, there are a number of limitations to this project. Hopkins Security was only able to share the crime logs for 2015, 2016, and 2017. Additionally, the 2017 data was not for the complete year since the data were obtain in September. The availability of a larger number of total records could allow for further analysis of crime patterns. Furthermore, the occurrences of crime would be more informative if the number of people on campus on each day is taken into account. For example, there may be less total crime on the weekend days because there are less people on campus. In contrast, total crime may be highest in the afternoon because there are more people on campus at this time.

Overall, there is increasing crime over the years from 2015 to 2017. Further investigation is necessary to determine whether there is an increase in crime because there are more crime incidents or because more people have been reporting crime to corporate security. Regardless of the explanation for why crime has been on the rise, there remains a great need to further our understanding of the crime patterns at the Hopkins East Baltimore Campus and implement data-driven measures for crime prevention. This project demonstrates that there are temporal trends in the crime patterns and further research into these patterns as well as other patterns that may be present, such as the location of the crime, can help inform practices that will increase campus safety. Ultimately, crime remains a challenging issue for the Hopkins East Baltimore Campus and this project provides novel analyses that can help inform further research and policies to improve the safety at Johns Hopkins.

References

- [1] Kelsey Warner. *D.C., Baltimore City among the most dangerous places in U.S.*, 2017. URL <https://wtop.com/local/2016/02/d-c-baltimore-city-among-most-dangerous-places-in-u-s/>.
- [2] Forbes. *The 10 Most Dangerous U.S. Cities*, 2017. URL <https://www.forbes.com/pictures/mlj45jggj/7-baltimore/#d3e9c2c54875>.
- [3] CBS. *Baltimore Ranks On New List Of 'Worst American Cities To Live In'*, 2017. URL <http://baltimore.cbslocal.com/2017/06/16/baltimore-ranks-on-new-list-of-worst-american-cities-to-live-in/>.
- [4] Hopkins Medicine. *Johns Hopkins Medicine: Campus Security*, 2017. URL http://www.hopkinsmedicine.org/security_parking_transportation/security/.

- [5] Johns Hopkins University. *Annual Security and Fire Safety Report*, 2016. URL http://security.jhu.edu/_template-assets/documents/annual_report.pdf.
- [6] Kun Dong, Yunbai Cao, Beatrice Siercke, Matthew Wilber, and Scott G McCalla. Advising caution in studying seasonal oscillations in crime rates. *PLoS one*, 12(9): e0185432, 2017.
- [7] Martin A Andresen and Nicolas Malleson. Crime seasonality and its variations across space. *Applied Geography*, 43:25–35, 2013.
- [8] Hopkins Corporate Security. *Calendar Year Crime Comparison (1993 - 2016)*, 2017. URL http://www.hopkinsmedicine.org/security_parking_transportation/_downloads/2016graph.pdf.
- [9] *PDFTables*, 2017. URL <https://pdftables.com/>.
- [10] R Core Team. *R: A Language and Environment for Statistical Computing*. R Foundation for Statistical Computing, Vienna, Austria, 2016. URL <https://www.R-project.org/>.
- [11] Stack Overflow. *Converting T time column to specific strings*, 2017. URL <https://stackoverflow.com/questions/21848211/converting-r-time-column-to-specific-strings>.
- [12] Hadley Wickham. *ggplot2: Elegant Graphics for Data Analysis*. Springer-Verlag New York, 2009. ISBN 978-0-387-98140-6. URL <http://ggplot2.org>.
- [13] RDocumentation. *calendarHeat function*, 2017. URL <https://www.rdocumentation.org/packages/iClick/versions/1.2/topics/calendarHeat>.
- [14] RDocumentation. *TukeyHSD function*, 2017. URL <https://www.rdocumentation.org/packages/stats/versions/3.4.1/topics/TukeyHSD>.
- [15] The R Graph Gallery. *Tukey test*, 2017. URL <http://www.r-graph-gallery.com/84-tukey-test/>.