Big Data Investigation: Chicago Crime Dataset with Hadoop MapReduce

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***Abstract*—Visualisation of Big Data is an important part of the big data analytics process, and can often reveal interesting patterns from a dataset. This report examines a Big Dataset, Chicago Crime statistics (2001-present), by using various visualization techniques. The objective is to examine the dataset from a number of visualisation perspectives for the purposes of extracting new potential insights, confirming known facts or just exploring the large dataset in a variety of ways.**

I. Introduction

The Chicago Crime Incidents dataset is a Big Dataset [1]. In order to visualise such a dataset, novel techniques should be employed to deal with the characteristics of big data. Novel big data visualization techniques allow exploration of the dataset in a visual manner, in order to find hidden patterns and to facilitate greater understanding of the dataset.

This report is a follow-up of a previous report, where MapReduce was employed in a variety of ways to process a big dataset. Some of that processed data can now be visualised, and the visualization thereof is part of this report. Some of the visualisations presented here make use of the raw data instead but employ more novel visualisation techniques.

The structure of the report is as follows. Section II will present the visualisations, grouped by the algorithm used to create the data that is being visualised. Additional discussions are presented there as well. Section III will conclude by giving a brief and high-level summary of what has been learned.

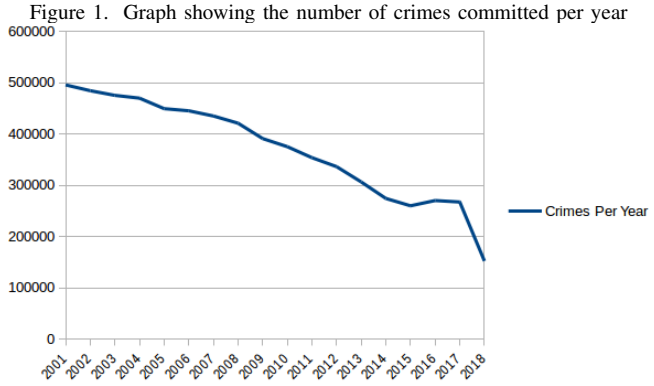
II. Visualisations

The visualisations presented below are grouped into a number of categories based on which algorithm was used to create the data for visualisation, i.e. the results of the previous processing using MapReduce. Analysis of each graph is presented alongside the graph with insights and interpretations provided.

A. MapReduce Aggregations and Summations

Presented in this section are the simpler visualisations of the aggregated dataset that can be produced with MapReduce. These visualisations are important because they can be used to establish a baseline for later visualisations which are designed to extract more complex insights. Additionally, some information from the dataset is difficult to extract with conventional means, in a timeous way due to its size, so MapReduce aids in acquiring these lower level insights faster.

Figure 1. Graph showing the number of crimes committed per year



What can be observed from Figure 1 is that crime is, in fact, decreasing over time. The general trend of the graph indicates that there is a steady downwards trend for crime incidents from the years of 2001–2014. In 2015, there is a slight increase in crime that dips sharply in 2018. Given that 2018 is not fully finished, data from the year is incomplete and this would account for the uncharacteristic decline. However, this information does correlate with the reporting that crime is declining within the city [2].

Figure 2. Graph showing the frequency of domestic crimes per year

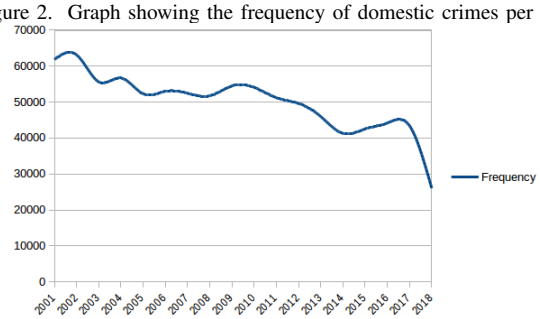


Figure 2 depicts the frequency of crimes of a domestic nature over time. Reports of crimes of this type are never extremely common, as many victims are typically disinclined to report that crimes occurred against them. However, despite this, the graph does show general decline in the rate of crimes of a domestic nature. There are more peaks, periods of increase, than in Figure 1 which suggests that domestic crime is not as steadily decreasing as the rate of overall crime in the city.

Figure 3. Graph showing the arrests made against arrests failed

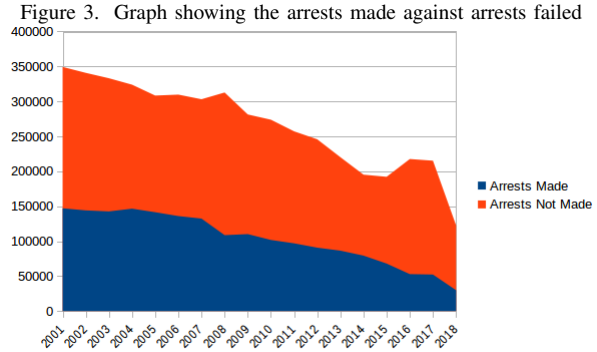


Figure 3 shows the number of crimes that led to an arrest, as well as those that did not. There are many more crimes where arrests were not made than where arrests were made. 2008 and 2016 stand out particularly in this graph as they are peaks for the number of arrests not made. In the case of 2008, the peak in unresolved crimes saw a corresponding dip in arrests made whereas in the case of 2016, the peak did not correspond to a significant trough.

Figure 4. Arrest ratio over the entire period (2001-2018)

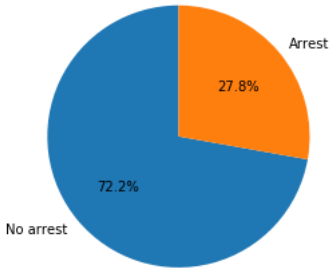


Figure 4 shows the percentage of crimes where arrests were made, over the entire period, and does not take into account any inter-year differences in arrest rate. Slightly more than a quarter of all crimes led to an arrest.

Figure 5. Arrest ratio, per year, over the entire period (2001-2018)

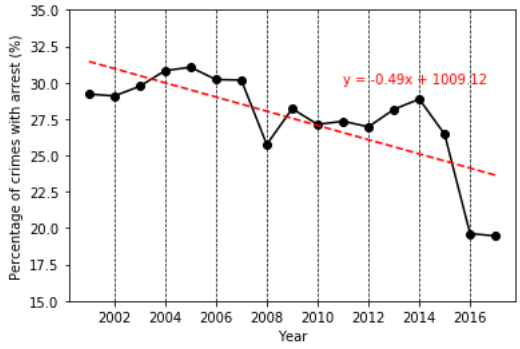
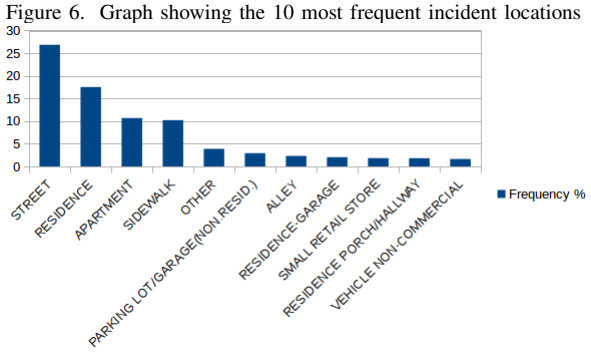


Figure 5 shows that the arrest rate is slightly decreasing over time but in general remains somewhat stable between 25 and 33%. A line is projected onto the graph, with the corresponding equation included. This graph is particularly interesting in quantifying a rate of success over time. It can be seen that the rate of arrests is stable in general. At the same time, the amount of crime (in terms of reported incidents) is also decreasing, as is shown by Figure 1.

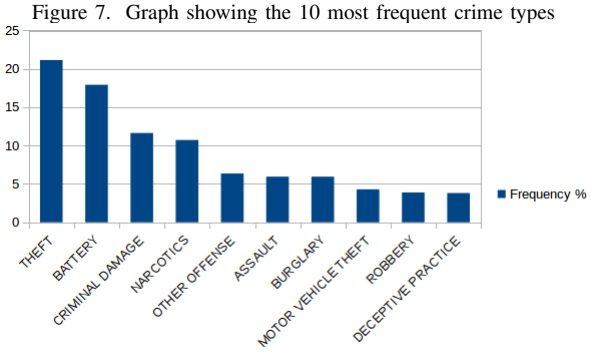
This would imply that overall police effectiveness is reducing crime overall whilst producing fewer arrests over time. One explanation for this is that the police have become better at preventing crime from occurring whilst maintaining their ability to resolve crime. It could also imply that some crime is inherently more difficult to resolve than others and defeats police efforts regardless of the wider criminal situation.

Figure 6. Graph showing the 10 most frequent incident locations



There are over a hundred types of location markers for incidents in the dataset. However, as Figure 6 shows, only a few of the location types account for most of the crime incidents. The top 10 incident location types, by frequency of occurrence in the dataset, account for over 81% of the incidents. In particular, street crime accounts for more than a quarter of all crime in the city and the other types involve similar urban components, like sidewalks and alleys.

Figure 7. Graph showing the 10 most frequent crime types



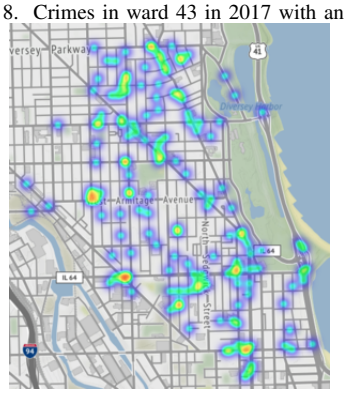
The dataset contains several hundred types of crime incident types. In Figure 7, it can be seen that the top 10, the 10 types with the highest frequency, account for over 91% of the crime in the city over the time period. The most frequent crime, at just over 20% is theft, followed closely by battery., criminal damages and narcotics. Interestingly enough, despite apartments and residential areas being more common as locations of crime, the crime of burglary, is not more common. Also deceptive practice making it onto the list when most of the other crimes involve theft or physical violence is interesting because it shows that there is a criminal element in the city that profits on the gullibility of the citizens if almost 5% of all crime in the city is related to deceptive practice.

B. Geolocation Data

Presented here are visualisations of the geolocation data contained within the dataset. This merits a separate section due to the complexity of including geolocation data with other more conventional

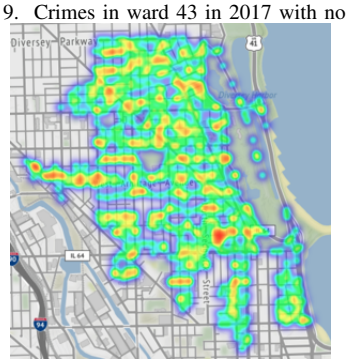
attributes. The visualisations that follow represent various cross-sections of the dataset, across different dimensions, that aim to show how crime is distributed across the city.

Figure 8. Crimes in ward 43 in 2017 with an arrest



Figures 8 and 9 show where arrests were made and not made in ward 43 in 2017. There are several small hotspots where arrests were not made, and this information could be used to increase the arrest rate.

Figure 9. Crimes in ward 43 in 2017 with no arrest



In Figure 8, there are a few spots of dense arrests, mostly located to the lower half of the ward. Conversely, the many spots where arrests are not made in great densities, proliferate away from these areas. With Ward 43 as an example, it is clear that policing efforts have resulted in a sort of equilibrium emerging. The areas which have large rates of arrest, result in other regions where relatively fewer arrests are made. Obviously, this reveals that through either a selective process or some degree of awareness, criminals tend to avoid committing crimes closer to the regions where they are more likely to be caught.

This is a particularly interesting insight as it means the police department can now identify why those regions are more likely to produce arrests and try to replicate the effect on the hotspots where crime is likely to not result in an arrest.

Figure 10. Motor vehicle theft in Chicago at gas stations in 2017

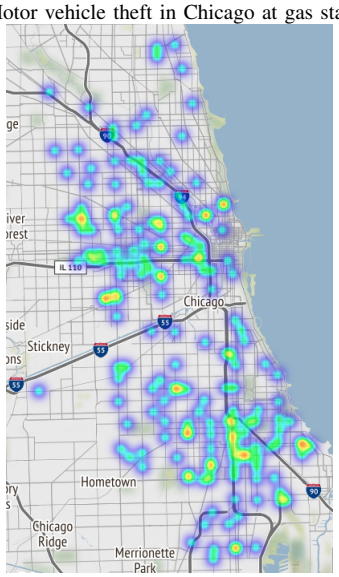


Figure 10 shows the locations and hotspots for motor vehicle theft at gas stations in 2017. Given that Chicago is a city with frequent motor theft, as shown by Figure 7, studying the theft of motor vehicles is an important part of reducing some of the most prevalent crime. So in Figure 10 it can be seen that gas stations, where cars get petrol, are relatively common places for cars to be stolen from. 2017 is the latest complete year of data and so presenting the data from there is valuable to determine recent trends.

Predictably, the largest concentrations of motor theft is located along the main arterial roads of the city. Particularly from the Merrionette Park leading into the city. The incidence of motor theft outside of the main motorways is much lower.

Figure 11. Burglary in Ward 24 in 2002

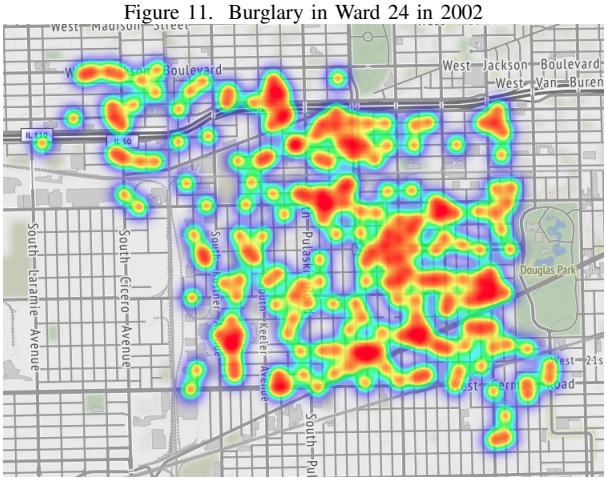


Figure 12. Burglary in Ward 24 in 2010

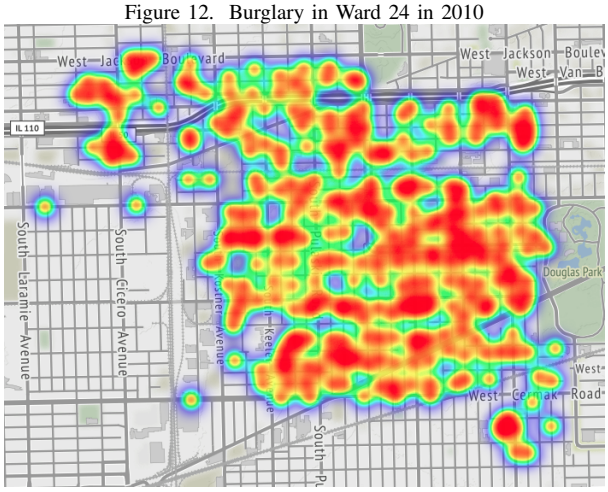
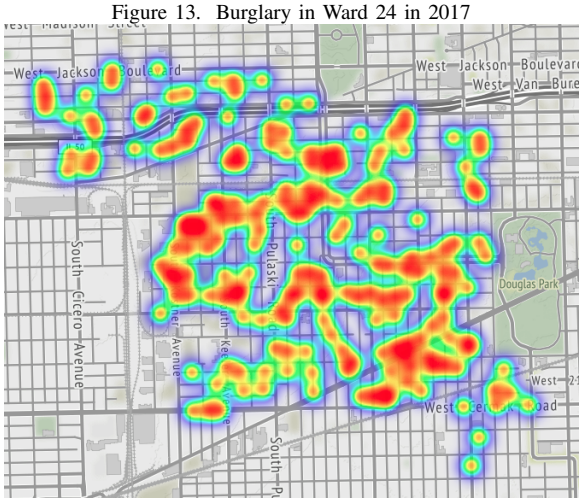


Figure 13. Burglary in Ward 24 in 2017

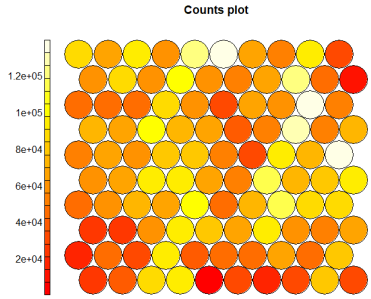


Figures 11, 12, and 13 show burglary events in ward 24 in 2002, 2010, and 2017, respectively. There is a clear difference in where these type of crimes occur in these different years. The heatmap for 2010 shows a drastic increase in the number of burglaries, especially in the eastern regions of ward 24. The heatmap for 2017 shows that burglaries have decreased to 2002-levels, although the spread of burglary has changed when compared to 2002 - burglary is now occurring on the west side, where it was normally prevalent on the east side of ward 24.

C. SOM

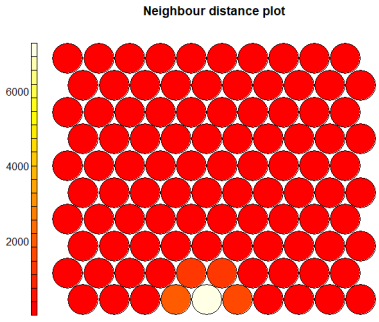
The Self Organising Map (SOM) discussed in an earlier report is useful in terms of being able to provide topological visualisations without strict geographic limitations. So the visualisations presented here provide more general insights that are more condensed, in part because of the compressive capacity of a SOM. In terms of the SOM, two visualisations are presented: a Count matrix and a U-Matrix. The former is useful because it demonstrates how many of the nodes the patterns in the datasets would map to. The latter demonstrates how far each of the nodes are to each other. The usefulness of a counts matrix is to demonstrate clusters in the map as neurons that receive many patterns, will help to define boundaries between the overall topology of the dataset. The U-Matrix also demonstrates the physical distance that separates nodes. Nodes that are close in value, helps to define the way in which the boundaries are formed; that is, whether the nodes are separated by large distances in value, or small. Also note that data has been standardised to ease the training process.

Figure 14. Count Matrix



Graph 14 displays a number of interesting trends. There are 3 massive “hotspots” in terms of 3 nodes that have massive numbers of crimes mapped to them. These hotspots are located around similar regions of high intensity. There are a few lower incident spots, particularly in the left bottom corner which represents a cluster of nodes with very relatively fewer incidents than the surrounding nodes. Broadly speaking, two bands of higher incident density can be seen, more or less partitioning the map along vertical lines of high incidence with less dense incident frequency moving outward from these.

Figure 15. U-Matrix



The U-Matrix in Figure 15 demonstrates a very different situation than what was observed in Figure 14. In particular, the distances between units is generally very low, with one particular exception of a singular node that is extremely different to the other nodes surrounding it. Interestingly enough, the node which is extremely dissimilar to its neighbours, has relatively few incidents mapped to it. This suggests that this node is somehow a geographical outlier in terms of where crimes are committed.

D. Apriori Algorithm

The Apriori algorithm implemented in the prior report produced a number of particular insights in the form of association rules. These rules can represent relatively hard to acquire insights, in part because of the size of the dataset. Visualisation of these rules is relatively difficult to do without disrupting their meaning and so for this section, the most pertinent rules are presented in a tabular format which shows the association rule. The duration specification simply implies that evidence supporting the rule can be found through those years in the

dataset and this adds an additional dimension to the rules as they can be applied to specific time slices.

Table I
ASSOCIATION RULES PRODUCED THROUGH APRIORI MINING OF DATASET

Rule	Duration
theft, motor vehicle, street =>no arrest	2001-2018
narcotics, street =>arrest	2001-2015
criminal damages =>street	2004-2018
Ward 012 =>no arrest	2007-2012
Apartment, burglary =>no arrest	2007-2018
Ward 011, arrests =>narcotics	2015-2018
Sidewalk, battery =>no arrest	2010-2018
Ward 008, Ward 014, Ward 025, street =>no arrest	2010-2018
Ward 018, Ward 019, theft =>no arrest	2010-2012

The rules presented here are mixed bag of insights. Later, more in-depth analysis of them will be presented. The common theme to all of them is of course arrest and types of crime. These rules make some suggestion of what types of crime need to be worked on, as well as suggest problem areas in which policing needs to improve. There are few long running rules, with the exception of the first two which span for 18 and 15 years respectively. A period of 2 to 8 years is what the other rules will typically span and a greater number of them refer to more recent dates. This of course is better as more recent insights are generally more applicable than older insights on data that has been in the more distant past.

E. Textual Wordcloud

Related of course to the mining of textual information conducted above, is a direct visualisation of frequent and important terms. A wordcloud is such a visualisation and displays words relative to their frequency in a given corpus. In our case, the corpus is the dataset of crime incidents.

Figure 16. Wordcloud of the dataset

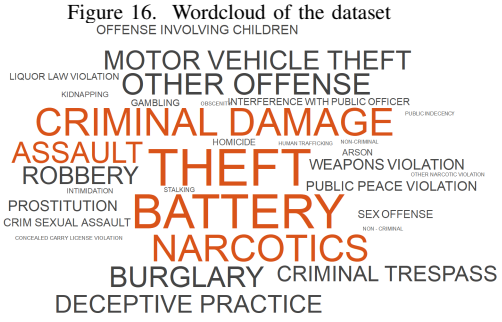


Figure 16 corroborates much of the earlier analysis in terms of important terms. The common types of crimes all appear with the most frequent, theft, taking the center. This visualisation does suggest that most of the crimes are relatively mundane and straightforward in comparison to more serious crimes like kidnapping or human trafficking. A theme of "vice" does permeate through as many of the types listed here include alcohol, drug and sexual offences. All of which seems rather characteristic of a large city like Chicago.

F. Naive Bayes

A Naive Bayes classifier employs probabilities to classify a crime as leading to an arrest, or not. Some of the probabilities for an arrest per feature are displayed and discussed below. The confusion matrix was already presented in a previous paper, and will therefore not be included here.

Figure 17. Arrest ratios for domestic and non-domestic crime types

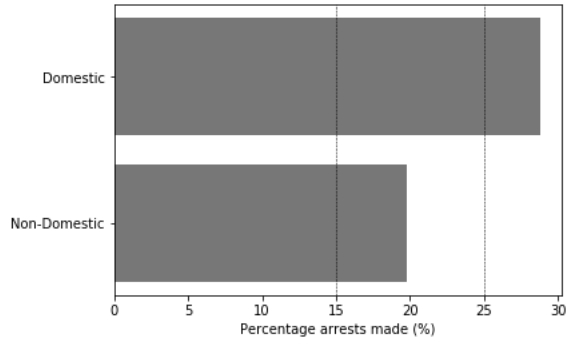


Figure 17 shows that domestic crimes are about 10% more likely to lead to an arrest being made.

Figure 18. Arrest ratios for the top 10 most frequent crime types

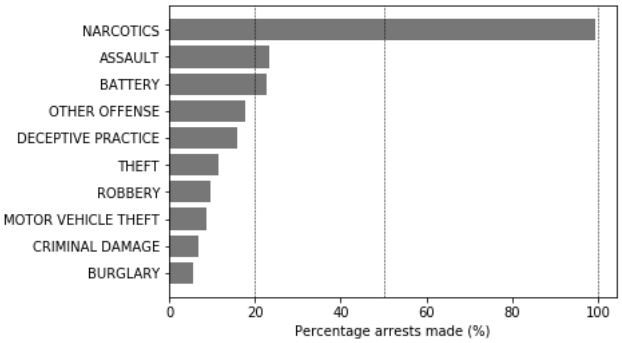


Figure 18 shows the arrest rate of various crime types (the top 10 most occurring types). Narcotics has an arrest rate of almost 100%. This could be explained by the fact that the discovery of narcotics on a person leads to an immediate arrest, unless that person escapes. However, subject matter expertise is required in order to understand this phenomenon better. Assault and battery have an arrest rate of more than 20%, which means that about 1 in 5 crimes of these crime types will lead to an arrest.

Figure 19. Arrest ratios for the 20 most frequent wards (geographic area)

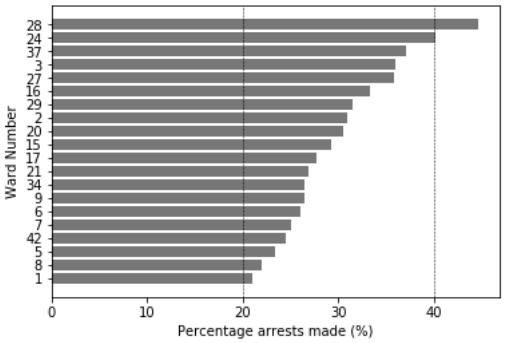


Figure 19 shows the arrest rate of the 20 most active wards. Ward 28 has the highest arrest rate at more than 40%. The lowest arrest rate of the top 20 most active wards is ward number 1, which has an arrest rate of just more than 20%.

Figure 20. Arrest ratios for the 20 most frequent crime locations

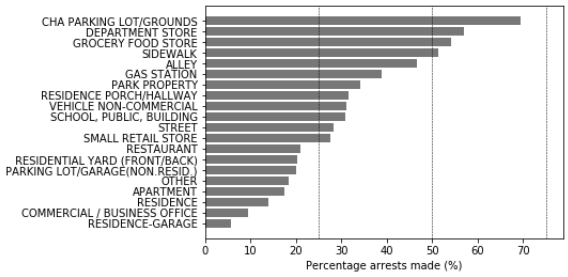
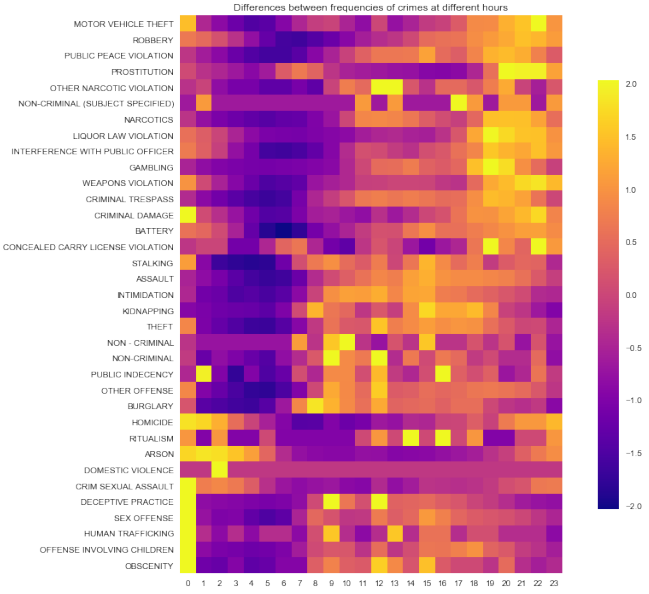


Figure 20 shows the arrest rate of the 20 most frequent crime locations. Parking lots experience an arrest rate of more than 60%, whilst apartments have an arrest rate of less than 20%.

G. Time Based Crime Analysis

Understanding the time component of crime incidents is a vital component of understanding what causes crime. In order to best visualise this, heatmaps are constructed to show the frequency of crimes at a number of hours in the day.

Figure 21. Variations in frequencies of crimes at different hours



From Figure 21, the intensity of the colors vary from blue to yellow (negative values to positive values), representing a lower to higher frequency for the crime to occur at a given time respectively. The right upper part of the heat map shows crimes that experience high peaks at night. Other crimes like public indecency, ritualism, deceptive practice experience high peaks during day time between 9 am and 3 pm. There are low crime peaks in early mornings except for a few cases like arson, homicide and those at the left lower part of the map (midnight cases).

Of course, this does confirm the natural assumption that certain crimes coincide with night time. The overall trend in Figure 21 is that during the early hours of the day, there is a lower tendency for crime, with most of the crime occurring in the daylight or towards the later part of the night.

Figure 22. Crime occurrence in 24Hrs at the top 10 crime locations

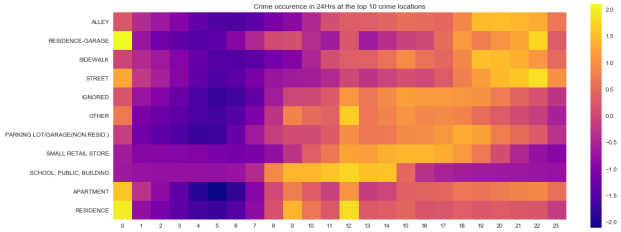


Figure 22 shows that locations such as school, public, building and small retail stores experience high peaks of crimes during day time. Morning hours between 1-7am are safe in these top 10 locations. Streets, alleys, sidewalk, and residence-garage experience higher peaks in evening and night hours. The variable named "IGNORED" is a collection of all locations that are not part of the top 10.

In Figure 22, there are a number of more obvious insights. Such as the occurrence of crime at schools correlated to daylight hours as obviously schools remain closed in other hours. Similarly for most retail stores.

H. Crime and Temperature

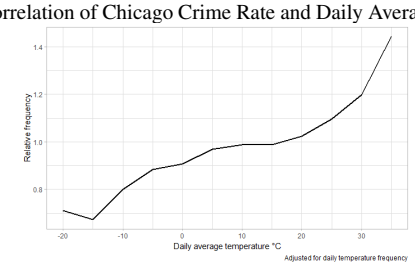
The practice of understanding crime with regards to temperature, and how temperature and climate might affect crime, is a relatively well known one [3]. While hardly conclusive, in most cases, this large dataset does present an opportunity for attempting to examine how the temperature in a city like Chicago might influence the crime it experiences.

For this visualisation, the Chicago Crime data set was combined with the NOAA weather data set's daily temperatures. The temperatures measured by the weather station at the Chicago OHare International Airport, near the centre of Chicago, were used. [4]

The data sets were merged on the dates of the temperature readings and the dates on which crimes occurred. The effect of variations in the daily average temperature was eliminated from the combined data set by dividing the crime frequency by the daily temperature frequency. The results show a strong correlation of temperature and the crime rate. Figure 23 shows the relative frequency of crime as it varies by temperature.

On days with average temperatures between -20 and -15°C, crimes occurred at a relative frequency that was 0.7 times the relative frequency of days with such temperatures. On days with average temperatures between 35 and 35 °C, crimes occurred at a relative frequency that was 1.4 times the relative frequency of days with such temperatures.

Figure 23. Correlation of Chicago Crime Rate and Daily Average Temperature



I. Final Insights and Observations

Crime is of course, a complex socio-economic problem. There are often many factors and many explanations for why crime might occur. This makes analysis of crime difficult in most cases. However, in acquiring a large scale dataset like this one, it is possible to use that massive quantity of data to try and extrapolate more general trends.

The investigation done here has managed to do two things: confirm some known intuitions about the nature of crime in the city of Chicago and reveal some interesting trends about the nature of crime in the city over time. The visualisations have uncovered the most prominent locations for crime, both in a descriptive sense as well as a geographical sense. With this information the police can better target their response efforts to crime as it happens.

The visualisations also were able to capture trends, in particular that crime is on a general downward spiral in terms of incident reports. It also demonstrated that while crime was on a downward spiral in terms of overall incidents, arrests being made were relatively stable. So while crime itself is down, it has not shown a notable increase in the rate of arrest.

This leads of course to the possibility that the police department is having a more pro-active effect on crime than reactive. Rather than being better able to respond to crimes, the department is better at preventing crimes from occurring. Of course, the possibility of a reporting bias in the dataset exists and that many of the crimes that do occur are unreported but that is a different problem to deal with and one beyond the scope of this report.

III. Conclusion

Visualising big datasets requires a different approach to traditional dataset visualisation. For big datasets, the focus is more on data exploration and finding hidden information in the data. The use of heatmaps, geographic maps, and visualisations on processed data delivers insights into the dataset.

By using visualisation techniques on this dataset, various interesting patterns and anomalies were discovered. Simple visualisation of aggregations served as a starting point for analysis, and gave quick feedback about the dataset. Geographic maps with heatmaps overlayed on top showed crime as it relates to location in Chicago, and those visualisations catered for longitudinal analysis over multiple time periods. The visualisation of the SOM and the Apriori table revealed interesting relationships that illuminate the dataset beyond what traditional visualisation could easily achieve. Visualising the probabilities of the Naive Bayes model provided insight into its workings, and shed some light about the difference in arrest rate among wards, for example. Heatmaps allowed visual exploration of the dataset with consideration for the time of day. Lastly, combining the dataset with weather data allowed a simple yet insightful visualisation of a correlation between temperature and crime frequency.

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