Chicago Crime

An Analysis of Chicago Crime Trends

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PROBLEM STATEMENT

The United States is currently enjoying a period of all time low crime rates, according to the New York University Law School. The number of crimes per 100,000 people in the US's 30 largest cities has dropped from ~9,300 in 1990 to less than 4,000 in 2016, and violent crime has dropped from ~730 to ~386 instances per 100,000.[5] Despite this, Chicago stands out as a city that has experienced a disturbing rise in crime, particularly violent crime, in recent years, with a rate of over 900 violent crimes per 100,000 people. A 2016 article in Time Magazine showed how Chicago responsible for for almost half the increase in the national murder rate in 2016 (13%).

Chicago's spike in crime has received a lot of publicity, and has made the city somewhat of an example city for those interested in talking about or studying crime rates. In January 2017 President Trump tweeted about Chicago crime and suggested that he may "send in the feds" in response to a 24% increase in killings from 2016.

Crime trends in any city can be difficult to interpret, especially in such a large one like Chicago, and it's unclear whether tougher policing would have more positive effects than other potential strategies, like investing in social services such as education, mental health, and drug rehabilitation. An article published by the Atlantic in 2017 discussed how the causes are essentially unknown, despite lots of research.

MOTIVATION

Our goal for this project is to use data mining techniques on a dataset of Chicago crime information in order to uncover novel trends about crime in the city. We hope to realize trends that could potentially help understand the factors causing crime in Chicago, and provide insight leading to possible solutions.

1 Literature Survey

As we began work on this project we explored various articles, notebooks and repositories to understand the existing work that has been conducted on the topic of Chicago Crime using the Chicago Crime Portal data.

The first existing work we evaluated was from the City of Chicago itself and their Crimes - 2001- to Present Dashboard. This dashboard is a comprehensive resource of 13 visualizations covering the entire data set and has an emphasis on the locality of reported crimes, which is a topic we are planning to explore in our research. Their geographical visualizations however tend to implement a regional visualization technique and there is an opportunity to explore other geographic visualization methods, such as a heatmap or point map to better express the volume of crimes and where the literal hotspots are.

In addition to the City of Chicago's visualizations, we explored Kaggle, an online machine learning and data science community, where we found several projects on the use of the Chicago crime dataset that we are utilizing in our analysis. We mainly focused on the work conducted by Djona Fegmen, in his Chicago Crime Data Analysis Jupyter notebook. Fegmen uses Python along with the pandas, seaborn and matplotlib.pyplot libraries to create a number of visualizations on overall counts of primary crime type, arrest volume over time, top 5 crimes and trends over time, and volume and trends in domestic violence arrests.

On Github we found a repository by Tejal Behangle, where she conducted a similar project at the Missouri University of Science and Technology, but her project attempted to predict the location and time of day where crimes and when crimes were likely to be committed. Using both the Chicago crimes dataset and a second dataset of socioeconomic data to explore the impact of socioeconomic factors (such as literacy rate and employment) on the rate of crime occurrence.

Finally, we reviewed an article published on Medium.com by Sadaf Tafazoli. In his article, Tafazoli explains how following preprocessing, he used Spark SQL to explore the data and answer questions. This is an interesting approach and we may consider also utilizing the Spark SQL module, however we'll likely primarily use python for our analysis. This article also sought to answer multiple questions and created visualizations to support their questions, but did not have a cohesive or particularly interesting outcome or story. It was simply a lot of count queries that were later graphed in some manner.

2 Proposed Work

Data collection: Data was collected by the Chicago Police Department and the data set was made available by the city of Chicago

Preprocessing:

- Remove unneeded columns and attributes
- Clean string data (ensure uniformity between descriptions, locations, etc.)
- Bin by location
- Filter by crime type/arrest

Process for derived data: We may be able to derive a boolean "Likely gang related" or "Not" value with the following process: One area of obvious interest for this project is gang-related crime. While our dataset provides minimal information on the gang-affiliation of certain crimes, perhaps it could be inferred from the series in which crimes of a type occur in. For example, if a murder in a neighborhood known for gang activity is closely followed by another murder, it may likely be gang-related. We propose to look for neighborhoods or "beats" with serial episodes of violent crimes, to identify areas with potentially higher violent gang activity. We can contrast this information with supplemental information on the geographical distribution of gangs. Information gained from this work could inform law enforcement of areas that need increased response after an instance of a violent crime.

Design: We also propose to create an arrest prediction model for crimes in Chicago, and infer why certain crimes result in an arrest made, while others do not. We anticipate that several of the attributes in our dataset will correlate with arrest, for instance: crime type, neighborhood,

date, and whether or not a crime was domestic in nature. By using logistic regression we can examine these relationships and extrapolate factors that lead to unsolved crimes.
How it is different from previous work: Our work differs from the previous work surveyed in that we are looking to explore a relationship between violent crime and gang activity. The closest work we surveyed related to this topic was Tajal Behangle's analysis which looked at predicting location and time of crimes being committed and socioeconomic factors.

3 **Data Set**

The data set which we are using for our project comes from https://data.cityofchicago.org/Public-Safety/Crimes-2001-to-present/ijzp-q8t2, which has been made available by the Chicago Police Department. It includes crimes that are reported in Chicago, IL from 2001 to present. There are 7.08 million instances and 22 attributes for the data. Here is a list of all of the attributes:

- ID (Number) - Unique key for tuple
- Case Number (Text) - Unique number for the case
- Date (Floating Timestamp) - Date and time when the crime occured.
- Block (Text) - Partial address of crime location.
- IUCR (Text) - Illinois Uniform Crime Reporting Code which is based on crime type and description.
- Primary Type (Text) - Primary description from IUCR code.
- Description (Text) - Secondary description of the IUCR code.
- Location Description (Text) - Description of the location where the crime occured.
- Arrest (Boolean) - Whether an arrest was made for the crime or not.
- Domestic (Boolean) - Whether the crime was domestic or not.
- Beat (Text) - Beat where crime occured. A beat is the smallest geographic area that police coverage is divided into.
- District (Text) - Police district where crime occured.
- Ward (Number) - Ward where crime occured.
- Community Area (Text) - Community area where the crime occured.
- FBI Code (Text) - FBI's crime classification.
- X coordinate (Number) - X coordinate where crime occured.
- Y coordinate (Number) - Y coordinate where crime occured.
- Year (Number) - Year crime occured.
- Updated On (Floating Timestamp) - Date and time record was updated.
- Latitude (Number) - Latitude where crime occured.
- Longitude (Number) - Longitude where crime occured.
- Location (Location) - Coordinates of where crime occured.

4 **Evaluation Methods**

We will make use of metrics such as accuracy, error rate, and tools like confusion matrices for classification tasks. We also plan to use mean squared error for inference/prediction tasks and the holdout method to train and test sections of data.

5 **Tools**

- Python
- Jupyter Notebook
- Sklearn (KNN)
- Python statsmodels.api (Linear/Logistic Regression)
- Numpy
- Pandas
- Tableau

- Python apyori module to mine for rules

MILESTONES

1 Milestones Completed

- **Data Collection:** The data has been collected and we have copies of the original data set stored on our local machines. As part of our work, we have been exploring different ways to collaborate through the use of various tools, such as Google Collaboratory, Github and Juptyer Notebooks.
- **Data Preprocessing & Cleaning:** Fortunately, the data set is fairly clean to begin with, however we have reviewed the data to remove “N/A” or Null fields and narrow the scope of attributes we will be utilizing in our final project. Some key discussions have occurred (and are ongoing) regarding which geographical attributes will be the most valuable in identifying where crimes are likely to occur. The original data set includes 9 geographical attributes:
    - Block
    - Beat
    - District
    - Ward
    - Community Area
    - X coordinate
    - Y coordinate
    - Latitude
    - Longitude
    - Location

  We narrowed the scope to Block, Beat, and Location, this was partially due to a large volume of Null values in the fields of Ward and Community Area. The Location attribute also contained the Latitudinal and Longitudinal coordinates, enabling us to remove the duplicate fields of X Coordinate, Y Coordinate, Latitude, and Longitude.

  In addition to narrowing down the geographical attributes, we have reviewed the different Crime Codes applied to the data set. Each crime has an IUCR (Illinois Uniform Crime Reporting Code) and an FBI code attribute. In reviewing these attributes, it appeared that the FBI code was at a higher level and lacked the detail that we would like to include in our project, while the IUCR code was more granular and would allow us to see connections between similar crimes that may not be as obvious using the FBI code.

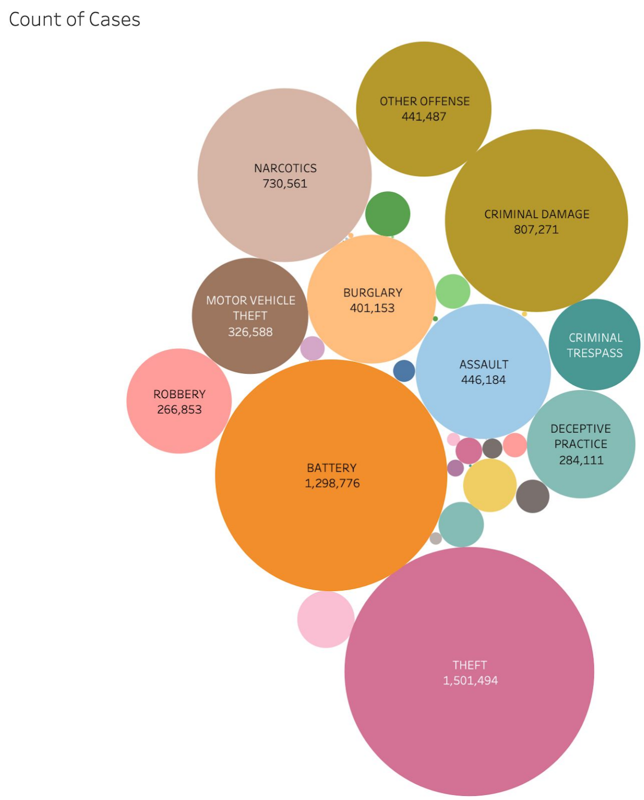
  Finally, the ‘Identity Theft’ Primary Type attribute was dropped due to null values and seemed less relevant to our project, since we are mainly interested in violent crime.

2 Milestones To Complete

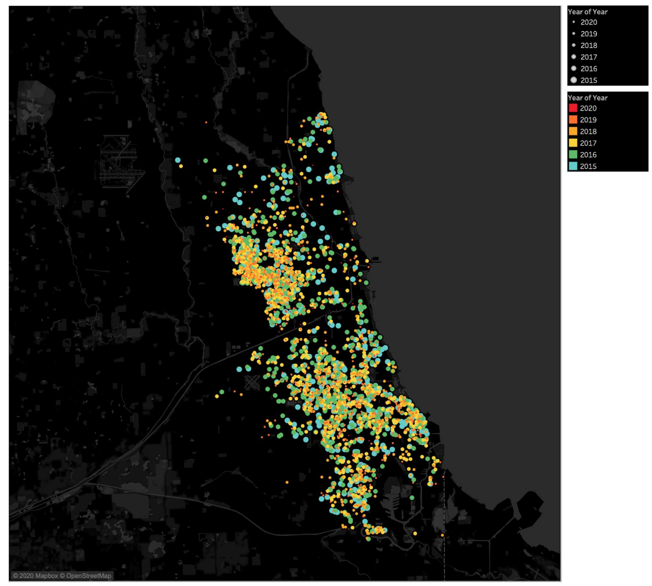
- Analysis of data: April 20
    - Use Forward Feature Selection to Find the Most Important Attributes in Predicting Arrests
    - Create a New Column to Reduce the Number of Categories of Crime
    - Create Model to Predict Arrests
    - Mine the Data for Any Interesting Rules
- Write up Final Report: 1 May

RESULTS TO DATE

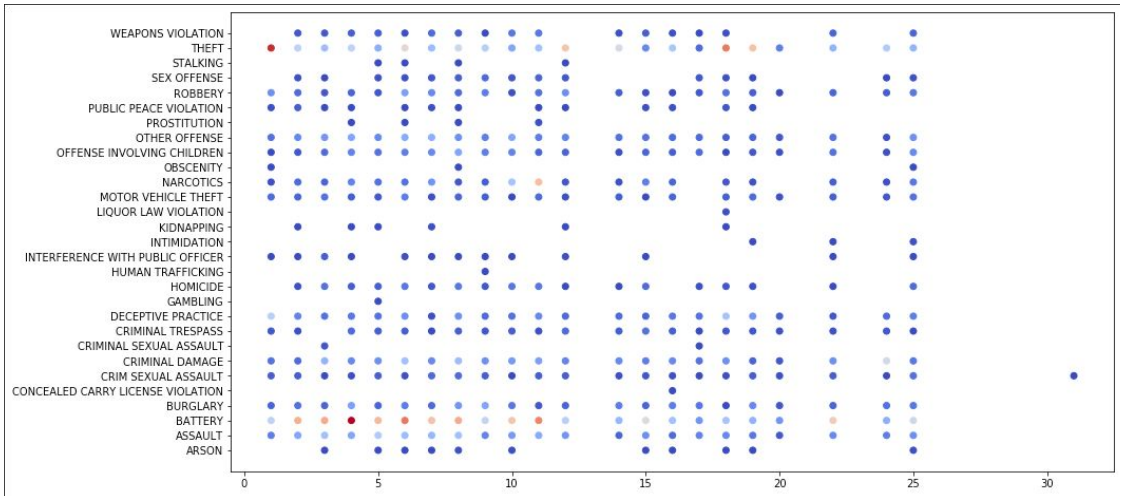
Up until this point we have been focused on the cleaning and preprocessing of data. However, we have begun to manipulate the data. In particular, using data visualization tools to identify any interesting visual patterns to explore furthering in our data analysis. This started with a simple count of distinct cases and their Primary Type of crime. While we were expecting violent crime to have the highest volume, Theft actually was the top offender. As we dig into the data further, it will be interesting to see if there is any relationship between theft and violent crime.



Another interesting outcome of using visualization tools to do some initial data exploration was utilizing the geographical data to see if there were clusters of violent crime, specifically homicide, that were immediately obvious. Looking at the Primary Type - Homicide and the Years 2015-2020 inclusive, and stacking the cases on top of eachother, we can see there are not only geographical clusters where homicides occur, but areas where there are homicides appear year over year. This will be another interesting question to explore as we dig further into the data.



In our exploratory analysis we also noted that the rate of homicide, compared to the rate of other crimes has increased, noticeably over the 20 year period, while the rate of arrest for homicide has gone down significantly.



In our proposal, we discussed looking for ways to identify neighborhoods with gang activity by the pattern of homicides. We figured that if homicides in a certain district tended to "clump" together, that might be a sign of revenge killings. To measure the "clumpiness" of homicides, we borrowed the entropy measure from information theory. As was published in 2013 by a group of researchers from UPenn[7], entropy can be used to measure the expected amount of information in a time series of events. If there was a pattern of revenge killing in certain districts, the entropy metric might allow us to find it. It calculates the sum of the time intervals (between homicides) multiplied by the log of the time intervals. We calculated this statistic for each of the 25 districts in the city, expecting to see higher entropy in e.g. district 11 which is known for gang activity. Unfortunately this approach was ineffective because of the disproportionate amount of homicides in different districts, i.e. district 11 had over 1000 homicides in the 20 year period, compared to 68 in district 20. We thus determined it was not realistic to try to compare patterns of homicide between the districts.

Finally, in the above data visualization the x-axis is District and the y-axis is Primary Type of crime. The color represents the frequency of that type of crime in the corresponding district. A third variable, frequency of the type of crime per district, had to be derived for this result. (The above result represents a subset of the data in order to facilitate efficient discovery. The full dataset will be used for the final results.) One of our original questions was "Is there a correlation between type of crime and location description or district?" The above result in our data mining effort facilitates answering this question.

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