Crime Time, Together with Weather

[Final Report]

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ABSTRACT

Crime fluctuates throughout the year, it can be difficult to narrow down exactly the reasoning for these changes. For this project we decided to analyze the crime statistics in Denver, Using data acquired from the Denver Police database. They provided us a way to see all sorts of different crimes in the area, and characteristics about them. Using our knowledge of data mining methods, we are able to derive the reasoning for different crime fluctuations. Providing this information requires analysis and correlation of a vast amount of information, in order to parse this information we first had to clean the dataset that we were using. After cleaning this information, using python and excel analysis, we correlated the information to show the relationships and trends. Denver in general has a low level of crime per day, because of this, we were unable to analyze specific crime trends during a single day. What we observed is a general trend for crime over the entire data set, was an increase when the weather gets hotter or it is raining. In both situations there were cutoffs and outliers, but the general trend followed through. The second major segment of our project was the analysis of location in our area in response to crime. Besides fairly obvious information, like shoplifting in shopping malls, there were a few interesting points that were not inside our standard thought convention. This project did show us the standard trending for crimes in response to our environment, and revealed much deeper correlations than we expected.

1. INTRODUCTION

The motivation behind our project is simple: to discover the correlation, if any, between crime, weather, and the time period of the occurrence. We want to take a deeper look at the data for these things in order to understand any patterns that may exist within them. Could a warm, sunny day make it more likely for crime to be committed? Is crime more frequent during the snowy winter months when the days are shorter? Do crimes occur more frequently during specific times of the year, such as holidays? These are all questions we intend to answer using the data we have found.

In addition to answering these, we also want to form analytical theories as well. For instance, if we find a tie between summer and high crime, we would theorize what reasons there might be to commit a crime when weather is typically nicer. Our goal is to uncover the strongest and most pronounced correlation or pattern in our data.

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2. RELATED WORK

Crime is a major aspect of any society. This leads to it being heavily analyzed by cities and law enforcement agencies in order to get the best idea of when and where crime occurs. Most cities have a fairly good understanding of where high crime areas are, which crimes are occurring, and when everything is happening. Like most cities, Denver, has statistical information such as a heat map of crimes and their locations[3]. All this information is then utilized in order to better predict and understand crime.

In terms of weather and its role on crime, many people have heard of some type of environmental condition potentially having some effect on crime. Intuitively, most people might assume less crime would occur when its the middle of winter and freezing outside. An article in the New York Times, which looked at a couple dozen studies regarding conflict and weather, found that there is a correlation between conflict and higher temperatures[1]. Very similar statistics were also found in a study for crime in Chicago from 2001 which graphed temperature data against criminal activity[6]. However, what is particularly interesting about this study is that while things like total crime increase with average temperature (**Figure 1**), when looking at individual crimes, such as prostitution, it's not guaranteed to increase with temperature (**Figure 2**).

It has also been frequently hypothesized that things like the moon cycle could have an effect on crime. While it still is debated on if the Moon actually effects society, there have been studies that have found higher levels of crime occurring on full moons as opposed to other lunar phases[5].

3. DATA SETS

Our analysis will primarily consist of utilizing two data sets. One of which is criminal activity and the other is weather. We intend to focus exclusively on Denver, Col-

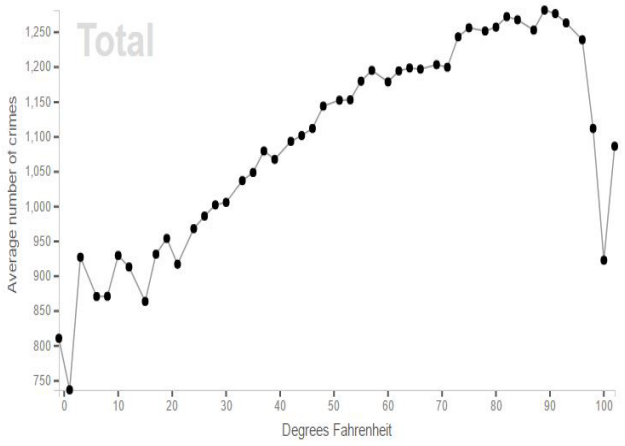

Figure 1: Average number of crimes vs temperature (crime.static-eric.com)[6]

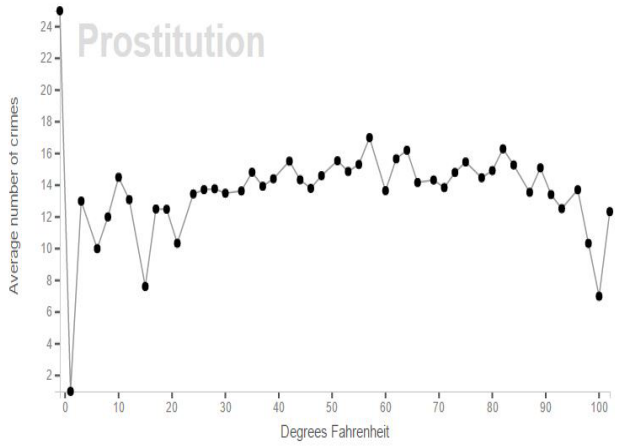

Figure 2: Prostitution crimes vs temperature (crime.static-eric.com)[6]

orado. This ultimately means our data and analysis will only be for the Denver Metro area.

3.1 Crime Data

The crime data comes from a data set[2] of crimes reported in the City and County of Denver. It is provided by the Denver Police Department for public use. To insure its accuracy the data is constantly being updated. This includes additions, deletion, and any possible modifications to entries. Due to legal reasons, the data does not include crimes involving juveniles and does not include location data for sexual assaults.

For the purpose of our analysis we intend to use the data from the start of 2012 to the start of February 2017. Due to the data being dynamic there is a possibility that some of the data we use could change. However, since most of the entries tend to remain unchanged and the data set includes roughly 500,000 incidents, our analysis should remain accurate regarding the potentially changing data.

As seen in **Table 1**, the attributes for the crime data includes the specific type of crime(homicide, trespassing, etc.), dates regarding the incident, as well as general location information.

3.2 Weather Data

The weather/environmental data set[4] comes from National Oceanic and Atmospheric Administration(NOAA). The data was taken from NOAA's "Daily Summaries" data set corresponding to the same time range as the crime data. Each day includes entries from multiple weather stations around the Denver area.

As seen in **Table 2**, the attributes for the weather data includes precipitation/snow and temperature values. The actual data for temperate, precipitation, wind and other weather values are all broken up into separate csv files. Each data entry also includes error flags and other factors for insuring if they are accurate or not.

If the weather data we currently intend on using does not provide us with enough information for analysis we have access to data sets that includes information such hourly weather data and wind speeds.

4. MAIN TECHNIQUES APPLIED

This entire project required us to follow all the aspects of data mining. We began with cleaning and preprocessing the data in order to get the hundreds of thousands of data entries into a more manageable and usable form. We also utilized the idea of a data marts to once again make the data more usable and structure the data in order to tailor it to our specific needs. Once we got much of the tenuous work of organizing the data to how we wanted we began to focus on the analytical side of data mining. We focused on aspects such as clustering, correlations, patterns, and a variety of other techniques.

4.1 Data Cleaning and Preprocessing

The initial crime data was fairly messy and had a lot of missing data and other various issues. There were hundreds of thousands of incidents logged in the crime data set that were not even crimes, in most cases they were traffic accidents because the data includes all incidents reported by the Denver Police Department. Since we are only focusing on crimes, those data points had to be removed.

Table 1: Crime data example entries[2] (Subset of available attributes)

Incident ID	Offense Code	Offense Type	Offense Category	First Occ.	Geo Lon	Geo Lat	Neighborhood ID
20138493	1202	robbery-business	robbery	1/6/13 2:45	-104.9	39.76	northeast-park-hill
2016638673	3512	drug-heroin-possess	drug-alcohol	10/5/16 14:05	-104.98	39.72	speer
2015250914	1102	sex-aslt-rape-pot	sexual-assault	4/25/15 14:30			regis

Table 2: Weather data example entries[4] (Subset of available attributes)

Station Name	Date	Prcp	Snwd	Snow	Tavg	Tmax	Tmin	Tobs
Denver Museum CO US	20170214	0	0	0		48	26	33
Denver Water Department CO US	20170214	0	0	0		48	22	24

In terms of the weather data, it needed a lot of work. As expected, there were many errors and inconsistent data values recorded by the hundreds of Denver based weather stations for things like temperature or precipitation. Most of the data was probably automatically recorded daily by data instruments which obviously will make mistakes occasionally. Some of the errors were easily removed/ignored because the data usually included a separate error flag indicating the station data was bad. However, there were many data entries that appeared normal at a glance but in reality were outliers that could severely alter our analysis. In some instances, the entries had values like -9999 indicating no data instead of using the error flags. In other instances, which were much more difficult to detect, was when a data value for something like the maximum daily temperature equaled something like 150 degrees. Obviously to anyone this is clearly a bad value and should be ignored, but when having to work with all the various data types it became increasingly difficult to have to detect these noisy data values. It was not as simple as checking if the value was null, but instead we had to use reasoning involving our real world understanding of the weather to account for any bad data.

If we had wanted to be as accurate as possible without having to bring in so much of the human element in deciding what values were acceptable when cleaning the data, we could have used an outlier technique. Instead of simply saying 150 degrees is too high, we could instead run an algorithm against all the temperature entries and found that a value like 150 was too high. If we were to implement this in a more professional/real manner and wanted to insure our results were robust, detecting outliers would be a more mathematically sound using some algorithm.

After cleaning up a lot of the weather data the multiple flag values for each entry were completely removed from our data sets as they severed no purpose going forward. They were useful from cleaning the data and insuring it's accuracy; however, there is no need to keep attributes that would not be used for the actual analysis.

Once we completed a lot of the data cleaning we began to integrate the data. For much of the weather data there was multiple station readings for the same day. In most instances, for things like daily max temperature or total precipitation, we decided to average the values for any data on the same day. This obviously solved the issue of data redundancy in terms of having multiple weather values for a single day, but it also gave us a more accurate data set for the weather near Denver by combining all the individual data sources.

4.2 Data Warehouse and Data Marts

After getting much of the data into a more usable form, we loaded the data into a MySQL server. The server acted as our data warehouse where we held all the data to be used for analysis. Obviously, the data would not be changing so insuring the data was not being updated like you would if the data was coming from a transactional database was not a reason for the server, but instead it's intention was to maintain all the different data we worked with in a single spot. This then allowed us to very easily run queries across all the data and not have to worry about separate file or parsing data.

Within the MySQL server we created some data marts that were used for certain individual aspects of our analytical work. For instance, we took all the crime data and did things like grouping by type of crime or day in order to create tables that only held specific data. This allowed us to more easily work with the data because we could focus on a subset of it instead of every entry. When doing anything computationally intensive it also greatly helped us out, by avoiding data that was not relevant. For instance, when we only wanted to focus on one type of crime we simply looked at the couple thousand reports for that crime instead of having to iterate over every single report.

4.3 Clustering

A big area of our analysis included the locations of crimes within the Denver area. Almost every crime included a Longitude and Latitude attribute for it's location of occurrence. This lent its hand to plotting the points on a basic coordinate graph. From there we run a clustering algorithm against the data to create clusters which allowed for us to analyze the locational data of crimes even further.

While there are many clustering algorithms that could have been applied we choose to use the basic k-means clustering algorithm. While another algorithm could have potentially gave us better/more distinct clusters, we choose the one we did because it was simple to implement for our purposes and it created fairly distinct clusters. One of the major downsides to K-means is that it can be very dependent on the initial centroids used which could result in very different clusters. It is also dependent on choosing the number of clusters to create prior to running. So while the algorithm does cluster points by their closest centroid, it can potentially result in clusters that are not always what would consider "good". To solve this we simply ran the clustering algorithm against a data set multiple times with a different number of clusters in order to generate plots/clusters which we felt fit the data the best.

The actual clustering points were plotted onto a graph with a corresponding real world map of that location. The map was acquired from a Google map api. Without the map the actual information presented by the plots would have been pretty much useless. It would be very hard to actually analyze the clusters and see the plotted location data for crimes if you did not know their relevance and position in the real world.

4.4 Correlation

The first correlations we began to see were simply by looking at frequency of crimes depending on certain characteristics. For many of the correlations, we performed group by functions in MySQL and aggregated the total number of crimes occurring at a certain time or day. For some pieces of data, like when working with weather, we had to perform averages for the number of crimes in order to account for the unweighted nature of the weather data. For instance, we couldn't just say this is the number of crimes that occur at 70 degrees compared to 30 degrees because in reality there are more 70 degree days than 30, so this needed to be taken into consideration. On the other hand, when looking at time of day data, we could just show the percentages of crimes occurring throughout the day because there is always 24 hours a day.

When we branched off into trying to find correlations with weather and time, we began looking for correlations in an obvious manner. For example, we first looked at the average number of crimes on rainy days versus the average number of crimes on non-rainy days. This allowed us to compare the two averages together in the hopes of finding a correlation. Once we had done this, we noticed that this data is both mutually exclusive and collectively exhaustive. This allowed us to try and use techniques like, Bayesian classification, and the law of total probability.

While these two techniques normally work well for finding correlations, it wasn't entirely applicable for our project. This is because the probability of a crime occurring is 1. Thus when applying this to Bayes theorem or the law of total probability, we didn't get very useful information.

To compensate for the aforementioned techniques not producing the best results, we narrowed down our data to look for correlations between aggravated assault and rain. Once we narrowed down our data, we looked for correlations using the Lift measure. To begin this process we first created the Lift measurement equation:

$$Lift(R, AA) = \frac{R/AA}{(RColumnSum/Total)(AARowSum/Total)}$$

where R stands for rain and AA stands for aggravated assault. After creating this equation, we constructed a correlation matrix (see below) to plug in the appropriate data. Look at the results section to see the outcome of this correlation.

5. RESULTS

Most of our results show a very basic look at our data and analysis. We looked at and analyzed the data in a variety of manners. Some things turned out to show very clear and concise results while other results were very volatile and showed very little. It would have helped to have more accurate weather data instead of just daily values; however, we were still able to find some insightful results with the data sets we had.

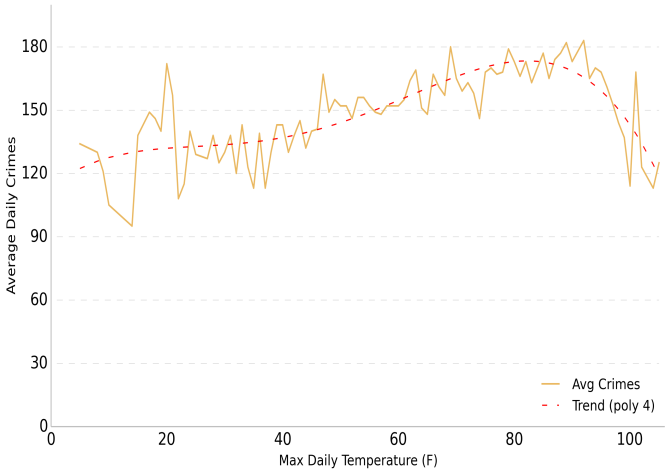

Figure 3: Average number of daily crimes vs the maximum daily temperature

5.1 Temperature

The biggest area we planned to focus on was weather, primarily temperature, and crime occurrence. In **Figure 3** our data shows that there is some positive correlation between the average number of daily crimes and increasing temperature. There is some variance in data points, primarily because some temperatures do not occur all that often(really cold or hot temperatures) causing there to be a fewer number of days to average the crime rate over which ultimately causes some variability. This can be seen in the random spikes in the yellow avg crimes line. However, when the data is fitted with a polynomial regression order 4 line, the dashed red trend line, it is clear there is a correlation between crime and temperature. At around roughly 50 degrees the number of average daily crimes increases up until about 90 degrees where it begins to fall down again. It should be mentioned that the temperatures are the maximum temperature of the day and not the temperature at which a crime occurred. While it is probably safe to assume that most crimes occurred at some temperature within reason to the max temperature, it is possible for instance that a crime occurs at night where the temperature could be significantly lower. When using the minimum daily temperature instead of the max, a very similar graph is generated.

Mainly for visual purposes, **Figure 5** depicts the information of **Figure 3** in a non averaged format. Instead the plot shows the number of crimes that occurred on a day and the respective maximum temperature of that day. It clearly shows the data points tend to raise up as the temperature increases, but at the same time it also shows the variability in the total number of crimes for a particular temperature. What is also interesting about the graph is the lack of days where the number of crimes was around 120.

While the data from a glance does show a positive correlation between temperature and crime rate, it is potentially the case that the number of crimes does not heavily depend on the temperature like someone may infer. Instead the increase could potentially come just from the overall en-

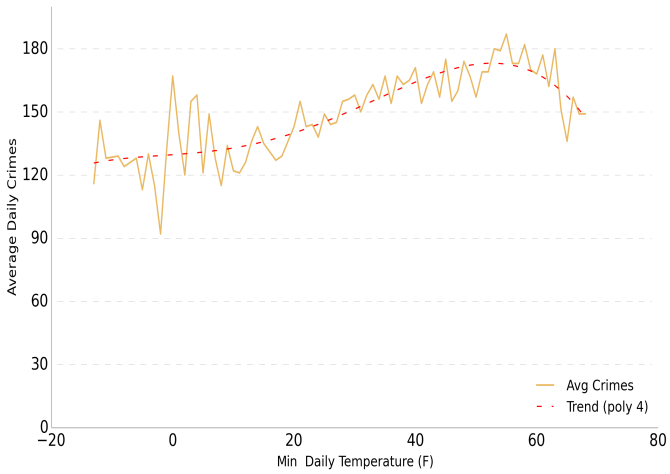

Figure 4: Average number of daily crimes vs the minimum daily temperature

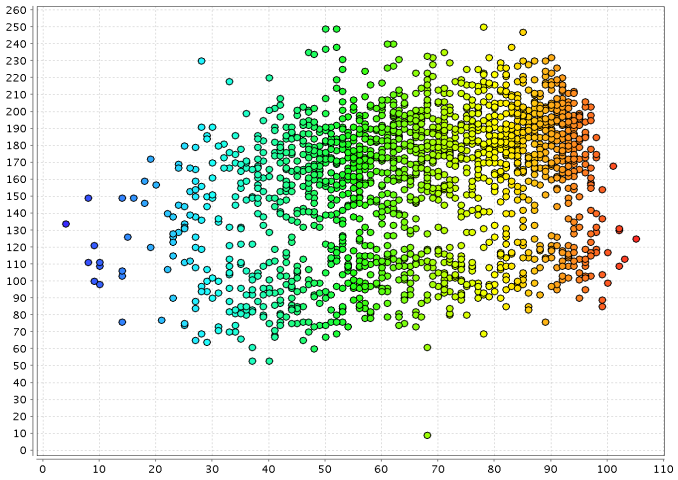

Figure 5: Total number of crimes occurring on a day vs the maximum daily temperature

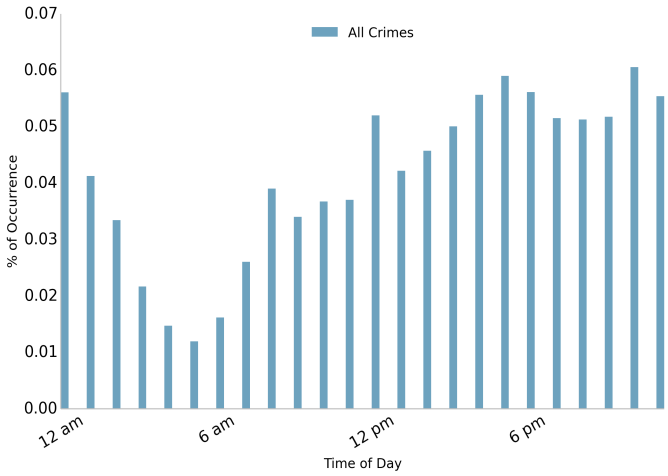

Figure 6: Percentage of all crimes occurring at certain hours of the day

vironment of the season. More accurate temperature data that is tied closer to the actual time of the crime would be needed to get a better understanding.

5.2 Time of Day

Another area we have looked at and generated some results for has been with crime occurrence and the time of day. In **Figure 6** the percentage of crimes occurring at each hour is graphed. It clearly shows a lower percentage of crimes occur at the early morning and slowly increases throughout the day. There is some random spikes at times like 8 am and noon. While correlation does not mean causality, the graph makes basic intuitive sense as we would expect less crimes to occur when most people are asleep. Or likewise, more crimes to occur at a time like noon when more people are going out for lunch. These are obviously only hypothesis to the results and there could be some completely other reason for the data we see.

We also dove into looking at more specific crimes and how they compare against all the crimes that occur. While the average of all crimes causes what is shown in **Figure 6** where there amount of crimes dies down pretty quickly at around midnight, when looking at sexual assault rape crimes in **Figure 7** something completely different is shown. There is a much higher number of sexual assaults occurring at the early mornings especially when compared to all crimes. This is an odd correlation, at least to how we have understood it. One could potentially infer more of these cases later at night, especially with people out of the house. With other crimes such as residential burglary we also saw the same things with different levels when compared to all crimes. **Figure 8** shows burglary crimes occurring more in the early afternoon which could support the idea that more robbers attempt to burglarize a house when they expect someone not to be home.

5.3 Precipitation

Being that the focus of our project was trying to find correlations with weather and crime, we wanted to look at how rain may or may not affect the frequency of crimes. After cleaning and combining data from our crime data set

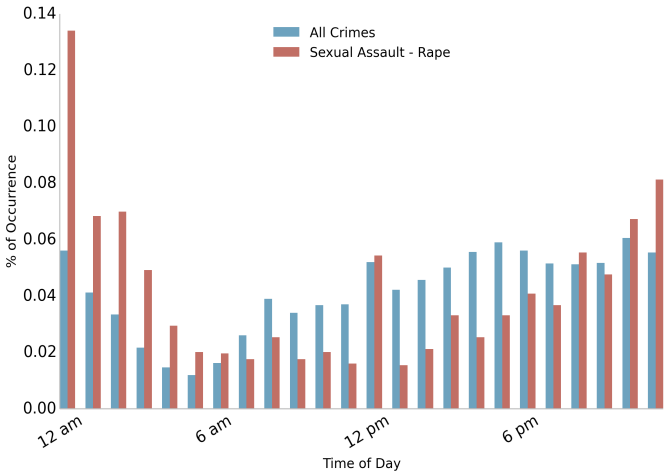

Figure 7: Percentage of sexual assaults(red) and percentage of all crimes(blue) occurring at certain hours of the day

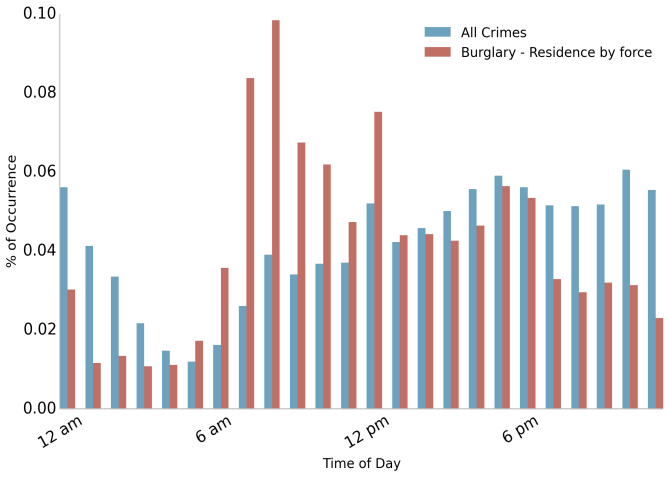

Figure 8: Percentage of residential burglary by force(red) and percentage of all crimes(blue) occurring at certain hours of the day

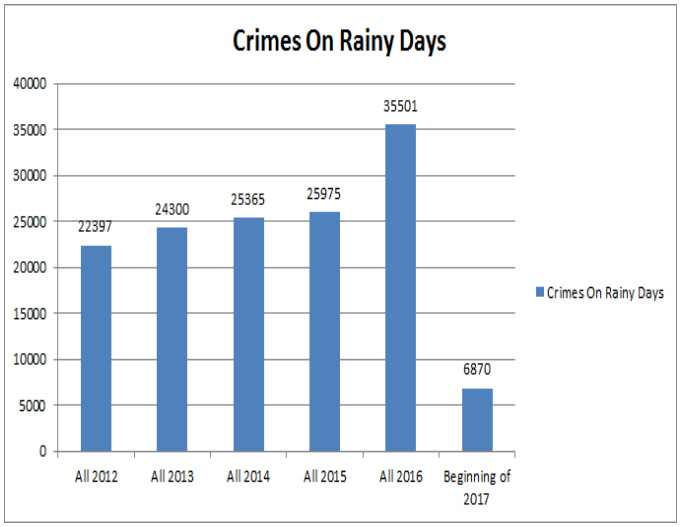

Figure 9: Total number of crimes occurring on a rainy days

and our precipitation data set we found some interesting results. To begin looking for correlations we set our time range to be from 2012 to the beginning of 2017. We found that, on average, there were roughly 139 crimes on days where it had rained and 142 crimes on days where it hadn't rained. However, by looking at the graph of **Figure 9** there were 140,408 total crimes committed on rainy days in our time range.

Comparing this to the graph of **Figure 10** we see that the number of crimes on rainy days is greater than the 123,218 crimes done on days without rain.

While the average number of crimes on rainy days is slightly less than crimes on days without rain, the fact that more crimes on rainy days occurred showed us that rain might be the cause for a slightly higher crime frequency over a long enough time line.

We wanted to see if there were any interesting correlations with rain and crime. However, as we mentioned previously, when we tried to use Bayes theorem or the law of total probability, we didn't get the most useful results. Instead, we decided to focus our efforts to see if there was a correlation with rain and aggravated assault. To do this we created a correlation matrix ADD DESTINATION, and then applied the Lift measure. Setting up the Lift measure equation and solving it gave us this result:

$$Lift(R, AA) = 1.04$$

After calculating this Lift measurement we were able to conclude that rain and aggravated assault are positively correlated. This means that both rain and aggravated assault seem to move in tandem with each other, if more rain occurs the higher frequency of aggravated assault follows.

5.4 Location

Location plays a big role in the amount of crime and types of crime that could occur. Many of these relationships are fairly obvious such as shoplifting occurring primarily in areas of large shopping centers. The general trend for all crime in the Denver area was a trend toward the West side. In neighborhoods such as Cherry Creek, there is lower amounts of

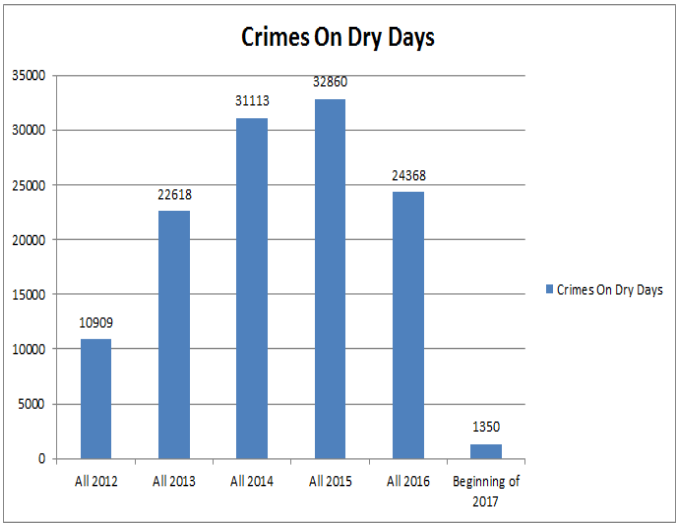

Figure 10: Total number of crimes occurring on non-rainy days

	Rainy Days	Non-Rainy Days	Sum Row
Aggravated Assaults	4801	3828	8629
All Other Crimes	135607	119390	254997
Sum Column	140408	123218	263626

Figure 11: Correlation matrix for rain and aggravated assault

crime. One interesting point that we have found is that much of the area around the Denver Zoo and the Denver Museum of Nature and Science is devoid, or contains a much lower amount of crime. We plotted the information corresponding to individual types of crime on scatter plots overlaying the map of Denver **Figures 12-14**.

Much of the drug and alcohol related incidents occurred in the Downtown Denver area or along main streets. Whereas crimes like motor vehicle theft tend to be consistent across all areas, instead of appearing just in business and high traffic areas they also show up in the more residential areas.

6. APPLICATIONS

We found this project very enlightening after the discoveries we made in our research. Our team was able to find some correlations regarding crime and time of day, crime and weather, crime and temperature, and crime and location. The former three are more interesting results than the latter, and were also easier to work with comparatively. Not only is this information helpful in the general sense of safety, it is also all valuable to know from a common sense point of view if you didn't know already! The applications for each of these groups in daily life is pretty equivalent to common sense, but it is definitely information that can be used to one's advantage.

6.1 Crime and Time of Day

Everyone gets told by their parents not to go out late at night on your own, or to stay away from certain parts of town, but the research we did allows us to validate these ideas with convincing and thorough data. With our research, we discovered a correlation between the hour of the day and the amount of crimes that occurred.

This data was obtained from our 2012-2017 databases, which we cleaned and condensed into graphs (Reference Figures 6 - 8 on crimes by hour). This data shows a strong absence of crimes before, during, and after 5 o'clock in the morning, which gradually rises and spikes around 10 o'clock to midnight.

This information makes complete sense logically, as 5 in the morning is the time when the majority of people are sleeping, or those who work are heading in for their morning jobs and the sun is typically rising soon. On the flip side, the majority of these crimes occurred around midnight because it is the quietest and darkest period of the night when most people are not around to witness the crime.

Having said this, we can apply this information to our daily lives in a couple different way. It is already common knowledge that night hours are more dangerous for people who are walking alone, or for people in locations with higher crime (discussed shortly in subsection 6.4) but this data simply confirms any lingering suspicion as well as reinforces the assumptions. All in all, avoid putting oneself in an unsafe situation by staying in between the peak hours of crime we see from 10 pm to midnight.

6.2 Crime and Weather

The main perspective of our data is the analysis of weather status on average crime. We see a very slight increase in crime when the weather is anything but clear skies and sunshine (rainy, snowy, overcast, fog, etc.). It seems that any weather that adds chaos, or more stress has a clear effect on the personalities of the citizens involved in it (Please reference **Figures 9 and 10**).

Obviously, traffic accidents were also included in our Denver Police Department data set. This would have skewed our crime data on the rainy/inclement weather days because of the worsened road conditions. To abate this, we were careful to remove the traffic data from our final graphing of the data.

As far as applying this information to one's daily life, the most straightforward application is to avoid unsafe scenarios where there is inclement weather present, simply because the chances for crime occurring are higher.

One of the questions we sought to answer in this project was if there is a correlation between rain and crime, specifically in the Denver metropolitan area. After analyzing the data that we found, we discovered that there are slightly more crimes committed when rain occurs. While the difference between the frequency of crimes on rainy days versus non-rainy days isn't too great, combining it with our time data allows us to make further application suggestions. For example, if it's raining and it's night time, you're odds of being the victim of a crime are higher. Thus, if it's raining and it's night time, your best bet is to just stay inside.

6.3 Crime and Temperature

We were able to find a pretty obvious correlation between crime and temperature through the work we did with our data sets from Denver Police Department and NOAA. The most significant and noteworthy information we found is displayed in the crime and temperature graph shown in our

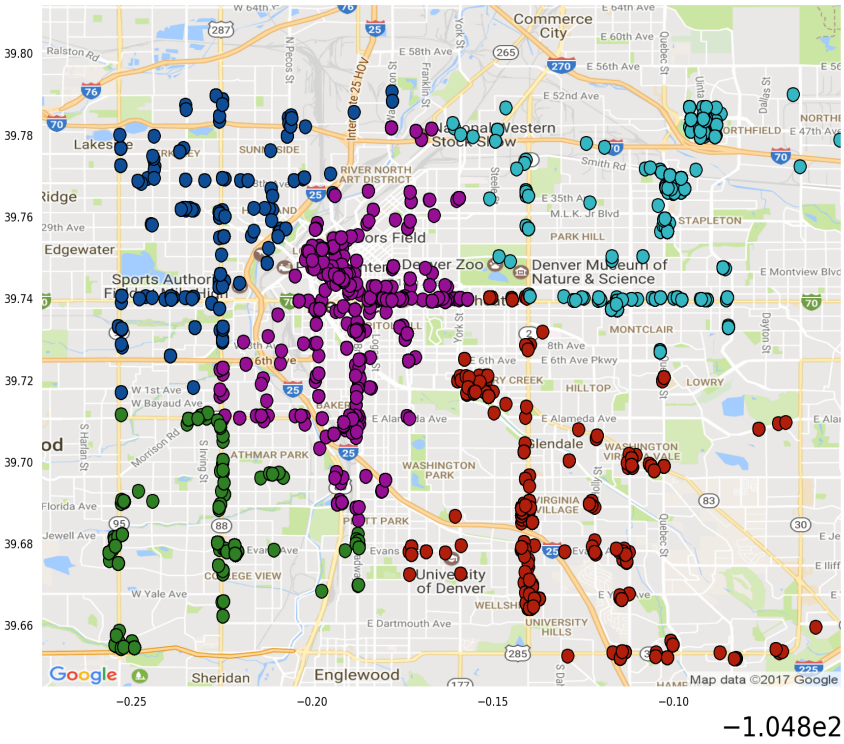

Figure 12: Shoplifting crimes within Denver using k-means(5 centroids) clustering

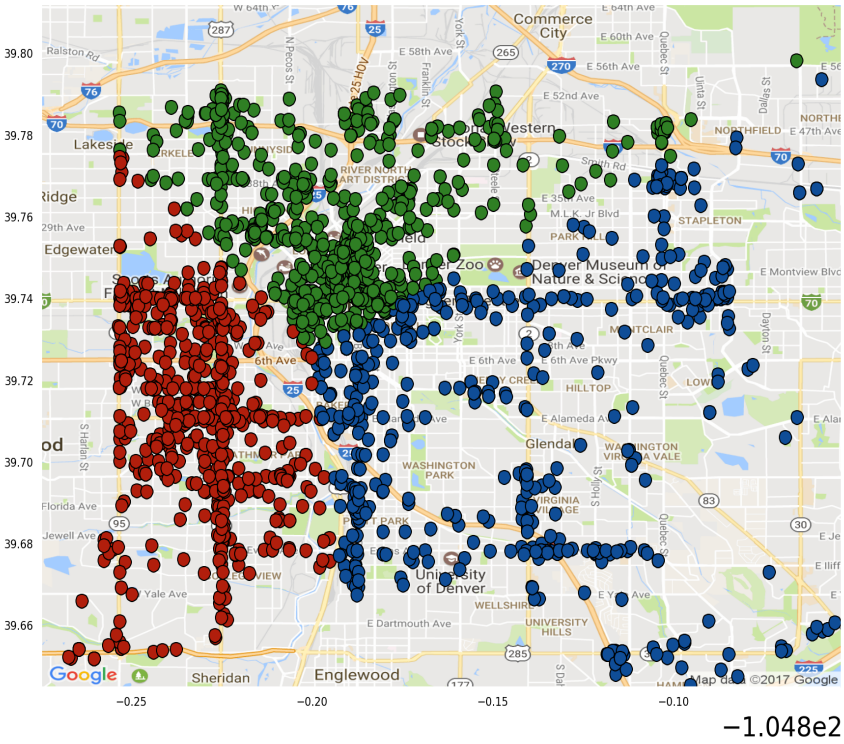

Figure 13: Methamphetamine drug possession within Denver using k-means(3 centroids) clustering

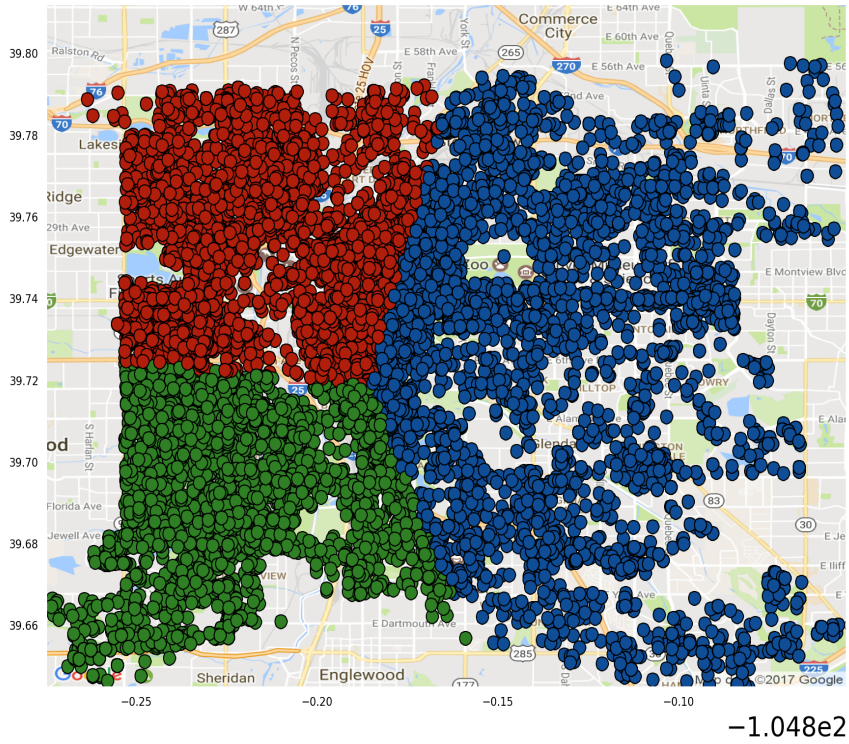

Figure 14: Motor vehicle theft within Denver using k-means(3 centroids) clustering

paper (**Figures 3 - 5**).

After analyzing the data we can see an obvious increase in crime as temperatures rise, peaking at around 80 to 90 degrees Fahrenheit. It was curious to us to consider the data we found for the time of day and crime, in comparison with the data from temperature and crime, simply because the most crimes occurred from 10 - 12 at night.

In terms of applying this information, one is able to think about external factors when interacting with another person. Think about the weather and environment that both of you are involved in, as hot weather or rain (as we have seen) raises tensions with both of you and people around you. It is seemingly impossible to avoid going out during weather that is stress-inducing, but it is something that should be a conscious thought in the back of your mind.

The safest option would be to remain around friends or larger groups of people in public places on the hotter days. This will ensure safety as well as reduce one's risk of being the victim of a crime during their peak.

6.4 Crime and Location

Perhaps the more easily applicable segment of our research is the clustering based off of location versus crime. As seen in the three location cluster graphs (**Figures 12 - 14**) we can understand the most likely places in the Denver Metro area that should be avoided due to an increased average amount of crimes in that area.

Areas in Downtown Denver seem to be specifically more prone to receiving crimes. Places like the Pepsi Center, and Sports Authority field seem to have a very high frequency of crimes in all three of our clustering graphs. This is likely due to the sheer amount of people who are attending events at these places. The more people congregated into one area, the higher likelihood for crimes like motor vehicle theft, shoplifting, pickpocketing, and possession/exchange of drugs.

The other very clear and obvious observation with the location data is the clusters around the shopping areas. It resonates with common sense logic that there would be more shoplifting related crimes in the store and shopping areas where desirable merchandise is located. This contrasts entirely with the motor vehicle theft within Denver, in which case we see widespread crime clustering.

The best way to apply this information in terms of crime and location would be to avoid alleyways and areas with poor visibility (building obstructions, large fences, etc) especially when alone or in small groups. As far as vehicle theft prevention, it would be best to avoid leaving a vehicle unattended for long periods of time in less active areas of the city, and especially overnight. Parking under streetlights or where the vehicle is more visible might help as well. Shoplifting could potentially be avoided in the peak areas by implementing better camera or security systems, perhaps even by hiring security guards to keep an eye on exits and entrances.

The best application here, of course, is simple common sense (which really applies to all areas of avoiding crime).

6.5 Further Research Considered

The project, though over now, did leave us with some unanswered questions that arose during the course of the semester.

Though we did not do any research with regards to possible correlations between crime and astrology, solar flares, moon cycles, or other galactic affairs, we did have some

suggestions to consider these ideas over the course of our research. These topics were definitely peculiar avenues of study in our eyes, and would definitely have made for a fun twist on the project as a whole.

If we had more time, we all thought it would have been interesting to go further with one of these topics to discover if there really are correlations between any of these and crime. It would really be quite shocking to find out if any of the theories surrounding these areas are true. Graphs displaying evidence of a correlation between crime and solar flares would be quite spectacular to procure and witness. Perhaps in the future another group will pursue this fascinating topic.

7. REFERENCES

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