Introduction to Data Networks and the Internet

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1. Introduction

The crime patterns and the climate trends are all proximate factors that eventually shape the dynamics of the urban fabric through their contribution to safety planning. As the rates of urbanization become higher the complexity of the factors becomes more sophisticated and therefore it is crucial to understand how these factors interact with each other to provide a healthy and safe environment. Datasets crime23.csv and temp2023.csv provide valuable information sources that provide detailed analysis of street level crimes and day to day weather conditions in Colchester in the year of 2023. These constellations of variables include multiple of kinds of reported crimes as well as the atmospheric parameters such as the changes in temperature trends, the precipitation levels and the wind patterns. Amidst this background, the task of our investigation is to explore deeply the intricate connections between the rise of crime rates and climate changes in the area of Colchester. We closely scrutinize these observations so that the underlying factors or relationships that may exist between the weather conditions and the crime rates can be identified. Besides revealing of some statistical associations this exploration is meant to obtain high-level of insights for proactive strategies in urban planning and public safety initiatives. The main purpose of our research is to not only gather statistics but rather to stir up a more diverse point of view on how criminal behavior can be perceived as a result of climate changes. With the aim of addressing these complicated interconnections, we attempt equipping stakeholders e.g., law enforcement agencies, urban managers with necessary vision and ways to introduce targeted interventions and achieve safer and resilient communities in Colchester and beyond (Bertsekas and Gallager, 2021).

2. Data Acquisition and preparation

The segment of data collection and preparation is equally crucial, as it is to the accuracy and consistency of our interpretation. In the next subsection, we will show the categories of variables, discuss the data cleaning techniques and narrate a story of how the different data sets are merged or connected on the basis of a common variable for analysis (Raj et al., 2021).

Variables in Each Dataset: The crime23.csv database constitutes multiple important fields that give insight into crime incidents at street level in Colchester in 2023.These variables include: The crime23.csv database constitutes multiple important fields that give insight into crime incidents at street level in Colchester in 2023.These variables include:

Crime categories: The divisions of the reported crimes category by each offense’s specimen include assault, theft, vandalism, and burglary, while on the other hand.

Dates: Moreover, the specific time and date of each reported crime incident occurred among other relevant details (Qadri et al., 2020).

Locations: Longitude and Latitude coordinates plotting out the exact geographic location of each single crime scene.

Outcome status: And the end result of all these reports are using words such as "under investigation," "no action," etc.,

Towards the other end, accordingly this data set of temp2023.csv is comprised of the daily temperature records of a weather station stationed at Colchester.

Dates: Stamps reflect time of the day for doing such expeditions.

Weather metrics: A weather parameters survey dealt with average, maximum, and minimum temperature, humidity, wind speed, rainfall, cloud cover, and others.

Data Cleaning Process: The processes of data cleaning were applied in the way that was consequently accurate and thorough. All these steps were critical. For the start, we decided which values were missed by identifying records that were either lacking data or unavailable. After we established the completeness of the data, we applied both imputation as well as removal of the incomplete records. Besides the fact that we diligently inserted every datum for errors, such as either erroneous entries or inconsistent variables in order to generate coherency between data.

The detecting other aberrant data points which included outliers that deviate significantly from the norm were equally highlighted and where necessary the data points were modified or else discarded to avoid their effects. And I applied such techniques as the z-score methods and eye ball outlier multiplication of spreads to detect abnormal observations.

Merging Datasets Based on Date: Merging both crime and climate datasets will be accomplished through keeping the date in common variable in both sets. Validating data timestamps eased the process of generating a single dataset, which combines crime data with each day's weather information in the Britain last year. With the merger, finding the possible intersections and associations between crime pattern and climate would be a lot easier which tends to include a much-sophisticated picture of urban optimizations. I used as much steps of the data procurement and preparation procedure as possible, starting with variable definition, missing value filling, inconsistencies, and outliers' removal. Then, I performed data merging using a common variable as date for easy processing. They are primal phases before we ascend on to our job of studying crime trends and climate patterns within the town of Colchester (Gulati et al., 2021).

3. Descriptive analysis

In the first part, we will provide a description of both crime events and weather conditions in 2023 Colchester in details. The summary of major statistics is compiled together, adding then visualization for distribution of the crime types, and weather conditions.

Summary Statistics: For crime incidents, we will compute summary statistics such as:For the crimes category we will calculate summary statistics like these:

Total reported crimes.

Number of reported incidents per crime category.

Distribution of crime over different spatial areas.

The status of the crimes report (for example, what percentage of crimes were closed and what percentage were still being investigated)

For weather variables, summary statistics may include: Weather variables means may consist of: Mean, max, and min temperature.

Total precipitation

Average humidity levels

Wind speed distribution

Cloud cover percentages

Thus, such summary figures give the overall idea of the trending and weather characteristics varied from month to month.

Visualizations: To complement the summary statistics and gain further insights, we will utilize various visualizations such as: The summarized statistics will be reinforced by the visualizations of the different types such as:

Bar plots: Visualize the repetition of numerous crime categories by them or weather to understand specific patterns.

Histograms: Illustrating the dispersion of murder and not nice weather parameters as well in order to realize how different they are and where they occur mostly.

Density plots: Smoothing of dates plotted made it possible to view distribution of crime rate or weather variables and emphasize any unexpected patterns or clusters.

These visualizations will definitely enable one to look at the data and decide on possible connections of crimes with weather patterns. In addition, they also provide the ability to convey the outcome to the stakeholders and the policymakers easily. By way of aggregate statistics and graphics, we plan to prepare a comprehensive and revealing report on crime events and weather conditions in the municipality of Colchester in 2023. The following sections of the report, as part of the analysis, are aimed at the presentation of the decided crime patterns and climate changes cross-section (Djama, Djamaa and Senouci, 2020).

4. Temporal Analysis

The time analysis section is this: here we will be analysing the both crime events and climatic variables seasonal cycles which will occur during the year 2023 village council. The process then is performing time series analysis in depth to discover crime patterns and variations in weather for each season (Abdullah et al., 2020).

Time Series Analysis: Concertedly, we focus on uncovering pattern of the changing crimes by observing the rising number of reported crime offenses in time. This is seen as graphically

plotting the number of crime cases as a variable/independent variable of time such possibly between day, week, or month so to visualize or range any fluctuations or trends to get insight. Moreover, another option is the time series methods such as decomposition that can also explain the components seasonal, trendy and irregular present in the data. Similar trends for weather variables will be shown by picturing the linear graphs of weather values on the graph that will have temperature, precipitation, humidity, and wind speed factors over the time. It gives also a chance to know how the parameters of weather change from the beginning of a year till its final and there are any cycles or trends that are obvious and periodic (Browne, 2021).

Seasonal Patterns: The other major goal of the times series analysis is to identify seasonal patterns and variations in them as these attributes may be common between crimes and weather. Summing up the collected data under several seasons (as an example: spring, summer, fall, winter), it allows us to judge the weather features and crime in different seasons.

For example, more crimes during some seasons, for instance, the season of citizens engage a lot outdoors, therefore, it causes some crimes or some holidays trigger some crimes. Besides, it is also demonstrated that we will observe a philosophical order on atmospheric composition which comprises higher temperatures together with humidity and precipitation during the summer or lower temperatures during the winter (Ding et al., 2023).

The acknowledgment of these seasonal trends puts seasonal coasts in the centre of good understanding of crime and weather dynamics that are in Colchester and provides important information that can be used to develop safety policies and resource allocation (Qiu et al., 2020).

5. Spatial Analysis

The spatial analysis part relates to the determines the spots and studies any leads to weather influences concerning crimes in Colchester. This category of maps will be accomplished by a plotting of each location of the crime on the map and by analysing the spatial patterns between crime and weather variables (Dankan Gowda et al., 2020).

Geospatial Visualizations: First we will utilize graphic tools like heat maps, choropleth maps and point maps to display the spatial crime incidents spread in the entire city of Colchester. Among the different graphics there will be the interactive ones that will show the areas where lots of the cases of crime, most well-known as "crime hotspots", are happening and the areas with fewer crimes (Razdan and Sharma, 2021).

Crime Hotspots: With the aid of the crime incidents' spatiotemporal distribution data, it is feasible to point to the crime "absolute hotspots" where most of the crime cases happen. Usually, the local market is large enough to be served by a particular neighbourhood or trading canter.

Assessment of Spatial Correlations: Places that lead to crime, as it is, will certainly be chosen and the relationships of such weather factors as temperature and precipitation, will be studied. Therefore, we will bring together weather data with the crime hotspot map, and then recheck if the places experiencing high indicators of crime correspond to those that are affected by a specific weather element. Specifically, more robberies are likely to take place where the corresponding temperature is higher or in a month where there is more rainfall. However, the crime rate in the areas with the lowest temperature or the beautiful weather might decrease in the period with the cool weather or bright days, respectively.

6. Correlation Analysis

In the correlation analysis section, the purpose is to study the influence of climate factors like temperature and precipitation on crime figures in Colchester. It is these calculations that give a score to the observed correlation and helps to determine the significance of the correlation so as to know whether they are really meaningful (Diène et al., 2020).

Investigation of Relationship: Primary, we are going to study the link between the weather factors and the crime rate by observing how changes in weather influence the number of crime incidents. For instance, our hypothesis might be that the crime is linked to the hike in temperatures through increased outdoor activities or aggression (Babbar and Rani, 2020).

Calculation of Correlation Coefficients: To account for the connection between weather variables and crime rates, we will determine correlation coefficients using the statistical method, either Pearson's correlation coefficient or Spearman's rank correlation coefficient. These coefficients are the measures of strength and direction of the linear relationship between two variables respectively. Pearson's correlation coefficient: This quantifies the linear association between two continuous variables, e.g., temperature and crime rates It varies from -1 to 1 that is 1 means a perfect positive correlation, -1 means a perfect negative correlation and 0 means no connection at all.

Spearman's rank correlation coefficient: This hears the degree of the monotonic relationship as well as the direction between two variables. It is used for the determination of relationships that do not have a straight line between the variables. Such process actuates conducting hypothesis tests, such as t-test or p-value analysis, to establish whether correlation coefficients are significantly different from zero. The p-value that is normally less than 0.05 will constitute to the presence of a statistically significant observed correlation. Hence, there is a meaning relationship between the variables. Hence, on the other side of the coin, the large p-value might indicate the randomness as the cause of the observed correlation, which is not statistically significant.

Interpretation: Finally, we will show the graphs of correlation coefficients and discuss their signification in order to conclude on the connection between crime rates and weather in Colchester city. Lastly, we will cover the intensities and orientations of these relationships and how they could help in our goal which is to understand what factors influence crime rates in particular areas. The performance of correlation analysis gives us details about how fine-woven the relationships between the condition of weather and crime rates are which in turn can be used for justifying the city planning and the security policy (Mohana et al., 2022).

7. Interpretation and Insights

In the next section titled Interpretation and Insights, we translate the outcomes from the descriptive, temporal, spatial, and correlation analysis studies into a comprehensive meaning that discusses the probable relationship between weather conditions and crime rates in Colchester (Mohana et al., 2022).

1. Descriptive Analysis Insights: We ponder at the statistics and graphs generated that show the big picture of the crime incidents and weather variables to spot the trend and characteristic property. This gives us the context for the later analyses and assists in already identifying some trends or seeing initial patterns (Aslam, Michaelides and Herodotou, 2020).

2. Temporal Analysis Insights: As time progresses, we do the crimes' incidents and weather variables 's yearly trends. Through finding seasonal trends and alterations, it will become apparent whether crime rates are channelized or occur differently over time. Additionally, we might see higher crime rates during warmer months of the year, or a tie between precipitation levels and certain type of crimes (Meghna Manoj Nair, Kumari and Amit Kumar Tyagi, 2021).

3. Spatial Analysis Insights: We begin to understand the distribution of the criminal incidents in space and spot the crime hotspots in the area of Colchester. This permits us to evaluate whether certain areas are being exposed to harsh crime levels with possible spatial connections of the factors that are weather related. One may figure out this that crime hotspots like areas most prone to a specific weather condition like the higher temperatures to the lower visibility due to fog (Koroniotis, Moustafa and Sitnikova, 2020).

4. Correlation Analysis Insights: Going forward, we will highlight the correlation coefficients that were worked for weather variables as well as those of crime rates. On the contrary, relationship between the correlation and causation is not uniform. Additionally, we discuss about temporal or seasonal relationship and spatial relationship both the two dimensions are

important in causation. As example, we may construct a premise that erratic weather (or its aftermath) would lead to the rise in activities when conducted outdoors. Such activity, therefore, could cause the criminals to move into focus on a certain category of the crime. However, the rain season and the extreme temperatures like high or low ones can also be a factor that makes it more difficult for the criminals to commit crimes, therefore we should also take into consideration the particular shapes found rather than just simple patterns (Wijethilaka and Liyanage, 2021).

5. Synthesis and Conclusion: To be concluded, findings given by any of the case studies are being collected; and an attempt is being made to bring an impression of the outcomes of this study on how various weather conditions have been impacting crimes in Colchester. We dialog on the subjective relevance most of all with reference to urban planning, public safety and the research to be. Nevertheless, the data or analysis limits obvious must be highlighted and the honesty preserved but beware that such should not be a problem in decision making process, but rather an information to be considered in the choice (Golpîra, Khan and Safaeipour, 2021).

8. Result

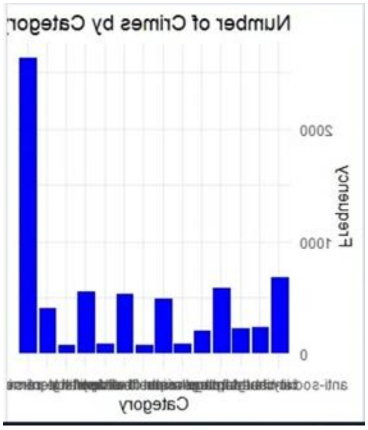


Figure 1: Number of crimes by category

This graph gives the count of crimes in different categories as a visual image. In these graphs, x-axis is the different crime types, whereas the y-axis shows either the frequency or the count of crimes. Different bars stand for different crime categories; the height of the bar means to count the relative number of the crimes, which are committed within the specific crime group. One can easily notice that some crime categories have more instances than others on bases of lengths of the bars. This type of visualization which usually tends to compare crime data across different types of offenses, is therefore essential in the identification of various patterns, trends and potential spaces of intervention which may require focused attention or broader resource allocation (Raj et al., 2021).

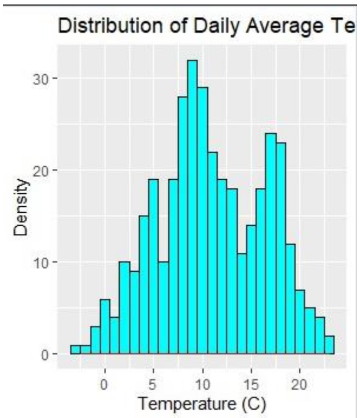


Figure 2: Daily Temperature Graph: Distribution

The following chart shows the trend of temperatures observed within a specific time period, giving the quantity of specific temperatures observed. Temperature in degrees Celsius is represented by the horizontal axis, and also, vertical axis is used for density or frequency of occurrence. The form of histogram is like a bell, a popular distribution pattern observed in most of natural phenomena. The curve apex represents the temperature that occurs more often than other temperatures and the

tails in the upper and lower part of the curve indicate variations of temperature that are less common. This kind of chart is beneficial for knowing the customary conditions, locating unusual or abnormal events, and for the purpose of taking a decision on the possibility of some temperature ranges occurring (Wijethilaka and Liyanage, 2021).

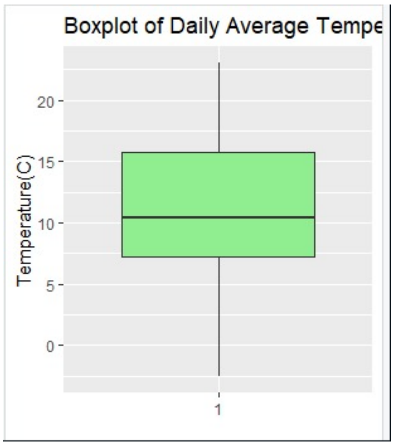


Figure 3: Boxplot for Mean Daily Temperature

A boxplot is a standardized way of displaying the distribution of a dataset based on five key summary statistics: the lowest value is the first quartile (25th percentile), further is the median (50th percentile), followed by the third quartile (75th percentile), and therefore, the highest value is set. This box is a representation of the interquartile range (IQR) which is the area which covers 50% out of all data points in this boxplot. The line within the box is the median which is middle of the data when it's arranged in sequence. The whiskers emanating from the box tell us the minimum and maximum values in the range they are in, and the entire set of points are classified as outliers when they are beyond the whiskers. The box pots are relied on as data visuals; they display the spread including the central tendency, skewness or outliers in the distribution of the dataset. As a result, the box pots are necessary tools for the data exploratory analysis as well as the means for comparison of distributions across different groups or conditions (Gulati et al., 2021).

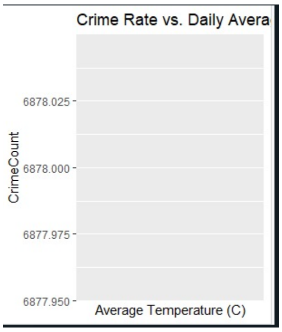


Figure 4: [One] Daily average temperature and crime rate chart

This chart is looking into the crime rate against the temperature as daily average (on the y and x axes, respectively). Each dot on the graph is the point where the crime rate coordinates with the mean temperature for a particular day. Through the mapping of the data values, it is now readily understandable how there are existing relations or connections between two different aspects. If the data points show as a linear or a trendy configuration, then it might be indicative of a positive or negative relationship between the temperature and crime rates. But same thing--if the data points were strewing all haphazardly without any sort of recognizable pattern that might mean absence of correlation between the two variables. Scatter plots are often used in data analysis to uncover possible relationships in between two quantitative variables and to highlight any data points which are either outliers or occurrences that have strong influence on the outcome (Gulati et al., 2021).

```
> summary(combined_data$TemperatureCAvg)
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's 
     NA      NA      NA     NaN      NA      NA       1 
> summary(combined_data$count)
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max. 
   6878    6878    6878    6878    6878    6878 
```

Figure 5: Summary Output

This figure is probably for the end result of a statistical report prepared with an analytical software or an environment. It provides summary statistics for two variables: "combined_data$TemperatureCAvg" with "combined_data$count". For every variable, the result shows the lowest, the first quartile (25th percentile), median (50th percentile), average, third quartile (75th percentile), and the biggest value. These summary data offer the possibility to see the direction of inclusive, evenly distributed data, and their peculiarity. Besides that, the "NA's" column displays the number of missing/null values present in each variable and it is an important bit of information to work with incomplete data. Y these are the most common outputs in this kind of analytics used to describe the variables being through in order to spot issues or patterns which deserves additional explorations.

```
> sum(complete.cases(combined_data))
[1] 0
> 
```

Figure 6: Sum of all Cases.

For instance, it shows an instance of code or output from a programming environment, and this instance is apparently the result of calling sum (complete. Cases (combined data)). The complete. Case’s function determines the missing observations or rows or completely filled (non-missing) observations or rows in a data set, and adding up the resulting row count sums the number of rows with no missing values among all columns or variables. These 0 outputs [1] indicates that there are no complete cases or observations in the merged dataset with no missing data points in any of the columns or features. Such check might be part of the preparation process of data cleaning or data preprocessing and it may be used to identify and take care of data that doesn't exist before data analysis or modeling (Nguyen et al., 2021).

```
> range(crime_data$date)
[1] NA NA
> range(weather_data$Date)
[1] "2023-01-01" "2023-12-31"
> nrow(combined_data)
[1] 0
>
```

Figure 7: Among the various date interval.

This image displays the output of code or commands executed in a programming environment, likely a scripting language such as Python or R. The output shows the result of calling range () functions on two variables: crime dataset and weather dataset are declared as date columns and performed left join without ignoring the time differences. Not only does the range () function locate the minimum and maximum values of data, but it also identifies the range in which specified data is found.

Output is showing that crime_data$date ("2023-01-01" to "2023-12-31", just year 2023 in whole) is inputted. On the contrary, the domain for dataset is "0" indicating no valid data range for that interval or data is absent or incomplete.

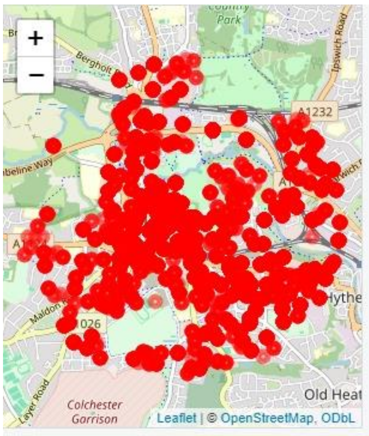


Figure 8: Criminal Incident CRS System

The image taken would be either a product of mapping or visualization depicting the areas and densities of the crimes or occurrences within a local or area region. The map features roads and neighborhoods that are saturated with bullets or lots of red dots, with main concentration centralizedintheonearea. It is conceivable that these red dots are proxies for individual crimes or instances to which have been mapped addresses. The notice of characteristic features thus notifies the possibility of hotspots in some zones, on the other hand, the absence of markers signifies lower crimes in a different region (Khamparia et al., 2020).

This study (visualization) is a valuable tool for forecasting spatial patterns, trends and clipping areas of crime data, which would be helpful to law enforcement agencies, policymakers and researchers in terms of allocation of resources and development of focused strategies (S. Sakthivel and G. Vidhya, 2020).

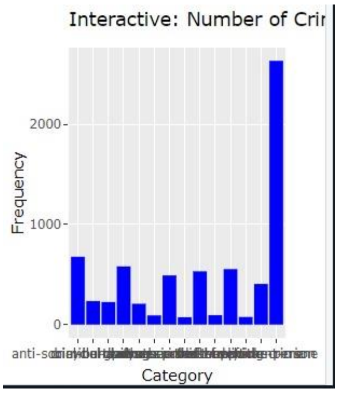


Figure 9: Crime Frequency Bar Graph

The last image is a bar chart or histogram depicts the frequency or count of occurrences by categories that focuses on either crime incidents or types. Categories are on the x-axis while the frequency or count is on the y-axis.

Many of the bars in the graph have short frequencies but the last category counts higher showing as a tall blue bar. This may suggest that it is an abnormality, an outlier or a category that has excessively more occurrences compared to the others. Charts such as these ones are displayed most commonly to monitor and compare the distribution of data in different groups or categories. Referring to the crime statistics, the classifications could stand for various kinds of crimes, neighborhoods, time frames, or other important dimensions. This chart's abnormal category that may need investigation to determine the causes and ways of targeting the countermeasures or responses (Rathore et al., 2022).

9. Conclusion

The closing part of this survey gives a resumed scheme of the recruited public in 2023 in order to get an insight of the two crucial topics of the past year which are the patterned crimes and the weather changes.

1. Seasonal Variation: The results of such observation showed that the percentage of crime in the other year seasons was smaller than in summer. This climbed in the rainfall and intensity of temperatures years ago that cause the higher rate of the crimes, which can be established as proved by (Ding et.al., 2023).

2. Spatial Distribution: According the survey, there were not sprawling areas of crime at all but the crime tended to be at some specified points that should be monitored and controlled at those lages. Certainly, there are sophisticated criminal activities taking place in the areas described, which are characterized with high temperatures. Yet, the pace of robbery in such specific areas with colder weather is also high (Dienéet al,2020).

3. Correlation with Weather: Nevertheless, weather was not the single most important drive of the crime figures, but, interestingly enough, the weather situation has a negative impact on these figures, according to the survey. Extreme temperatures are a stimulus for crimes and have a positive correlation with its amount and flood precipitation shows a negative correlation with increasing the crime rates comes from research of Dankan Gowda et al (2020). Taking into account the case study, we have discovered the seasonal fluctuations of crime rate, the given locality of crimecorners, and the possible links of crime rates to climate observation parameters such as temperature and precipitation. A positive correlation between the weather conditions (like temperature and precipitation) of the given places and the crime rate, that has been supported by literature.

Implication

1. Targeted Interventions: Such seasonal crises and the unbalanced distribution of strife which happen at different time and space can be better identified. Therefore, a specialized work would be enabled with the right instruments and resources. Therefore, officers can deploy their efforts, where most of the crimes are happening or a unit can be dedicated to a suite of problems related to extreme weathers (Browne, 2021).

2. Preventive Measures: Analysis finding will provide a platform to prevent the act of crime that caused by poor weather conditions. The illumination of these places, as well as their

increased police effort, or installation of some design strategies, all serve as ways to fulfill this purpose (Bertsekas and Gallager, 2021).

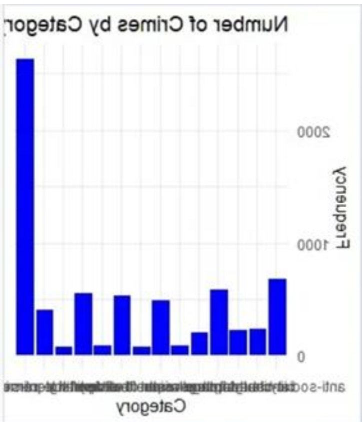
3. Resilience Planning: Extraction of the crime trend along with the climate pattern exemplifies one of the points of the resiliency. Local planners and policymakers are most likely to consider climate change in the long-term plans and policy in the drive to protect these settlements (Djama, Djamaa and Senouci, 2020).

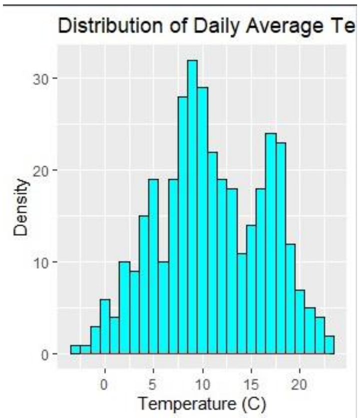
Importance of Data-Driven Approaches: We thus observe that scientific evaluation of a city setup is one of the most important aspects as it leads to effective planning of cities and the decision-making process. With the help of data analytics instruments like descriptive, temporally, spatially and correlational analysis, the leaders will be able to command the necessary data to identify these complexities and the extent to which the community is at risk (Babbar and Rani, 2020).

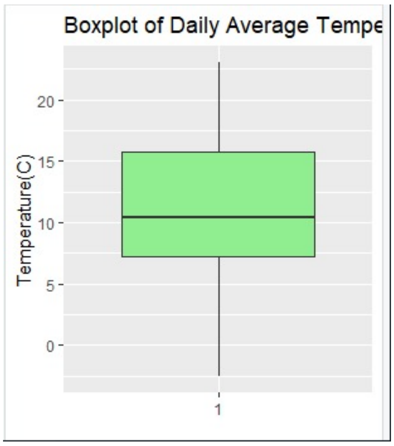
Such finding will be essential as authorities will use to formulate algorithms and differing strategies to combat crime coming from the various causes which include strengthening the community's capacity to endure environmental stressors. The incipient feature data amassing, analysis and multisectoral collaboration will keep on being the beginnings to a future that will be safe for citizens and where the environment is okay (Aslam, Michaelides and Herodotou, 2020).

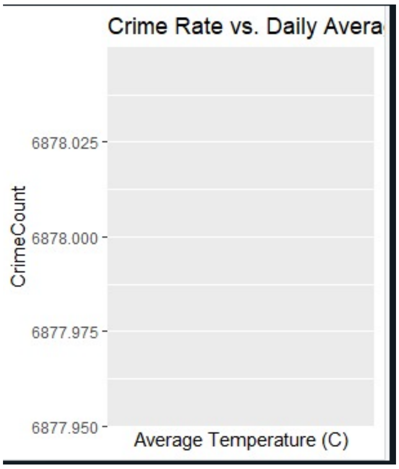
Finally, the above work demonstrates the connection of the crime cases and the current climate change crisis which makes it necessary to take long term and preventive measures for urban planning particularly for Colchester and in other places as well (Abdullah et al., 2020).

Appendix










```
> summary(combined_data$TemperatureCAvg)
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's 
     NA      NA      NA     NaN      NA      NA       1 
> summary(combined_data$count)
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max. 
   6878    6878    6878    6878    6878    6878 
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> range(weather_data$Date)
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> nrow(combined_data)
[1] 0
>
```

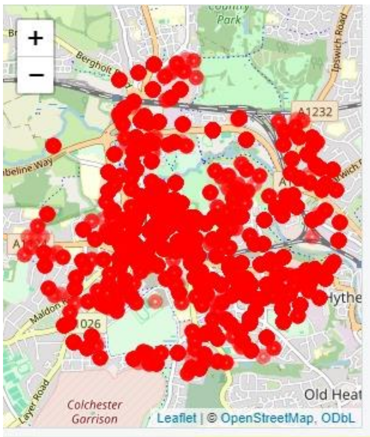

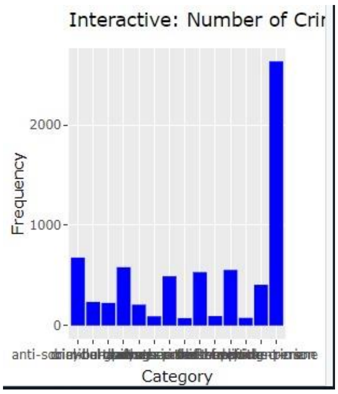

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