Crime Trend and Spatial Analysis in Chicago (2010 - 2022)

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Introduction

Understanding crime trends and patterns is crucial for developing effective crime prevention and resource allocation strategies. By visualizing year-wise distributions, we gain insight into:

1.Temporal changes in crime rates.

2.Potential correlations with social, economic, or policy changes.

3.Identifying years of significant increase or decrease in criminal activities, helping stakeholders pinpoint impactful interventions.

Welcome to the Crime Analysis Project

This website presents a detailed analysis of crime trends and spatial distributions in Chicago from 2010 to 2022.

Materials and methods implemented

Materials

Data Sources: Chicago Crime Data: The main dataset will come from the Chicago Data Portal, which offers extensive data on various aspects of life in the city, including crime data. I will filter the data to focus on crime statistics from 2010 to 2022.

Software and Programming Tools:

R Studio: For data cleaning, analysis, and visualization.

Libraries/Packages: dplyr and tidyr: For data manipulation and cleaning. ggplot2: For data visualization, including histograms and time-series plots. sf: For spatial analysis and mapping crime data. caret and randomForest: For clustering and predictive modeling. ggmap: To fetch and overlay maps for spatial visualization.

Methods

Data Cleaning and Preparation: I am using the dplyr and tidyr packages in R Studio to clean and organize the dataset, removing any inconsistencies or missing values to ensure data accuracy.

Time-Series Analysis: I am leveraging ggplot2 to plot trends in crime rates over time, analyzing how crime levels are evolving throughout the study period.

Spatial Analysis: Using the sf package, I am mapping crime locations to visualize their spatial distribution across Chicago's neighborhoods, helping to identify patterns and areas of concern.

Cluster Analysis: I am applying clustering techniques to identify crime hotspots and determine whether certain crime types are showing spatial concentrations in specific regions of the city.

Predictive Modeling: I am using machine learning techniques, including logistic regression and caret's model training utilities, were employed to predict crime occurrences based on encoded features such as location and description. These predictive models may offer valuable insights for crime prevention and resource allocation strategies.

Required packages:

Load necessary libraries

```
library(dplyr)
library(tidyr)
```

Load the dataset

```
df <- read.csv("data/data.csv", stringsAsFactors = FALSE)
```

View the first few rows of the dataset

```
head(df)
```

```
        ID Case.Number                   Date                     Block IUCR
1 13190943    JG400635 08/28/2023 06:23:00 AM 027XX N NARRAGANSETT AVE 1320
2 13192516    JG402535 08/29/2023 01:59:00 PM     014XX N LOCKWOOD AVE 1310
3 13202216    JG414059 09/06/2023 06:20:00 PM         018XX N LUNA AVE 1310
4 13202922    JG414619 09/06/2023 06:00:00 PM          014XX E 49TH ST 1320
5 13201501    JG413395 09/06/2023 01:00:00 AM       082XX S AVALON AVE 1320
6 13202292    JG412948 09/06/2023 12:40:00 AM      082XX S WOLCOTT AVE 1310
     Primary.Type           Description                   Location.Description
1        HOMICIDE     RECKLESS HOMICIDE PARKING LOT / GARAGE (NON RESIDENTIAL)
2 CRIMINAL DAMAGE           TO PROPERTY                              RESIDENCE
3 CRIMINAL DAMAGE           TO PROPERTY                                 STREET
4 CRIMINAL DAMAGE           TO PROPERTY                                 STREET
5        HOMICIDE     RECKLESS HOMICIDE                                 STREET
6     SEX OFFENSE ATT CRIM SEXUAL ABUSE                              RESIDENCE
  Arrest Domestic Beat District Ward Community.Area FBI.Code X.Coordinate
1   True    False 2512       25   36             19       14      1133273
2  False     True 2532       25   37             25       14      1140764
3  False    False 2532       25   37             25       14      1139111
4   True    False  222        2    4             39       14      1186638
5  False    False  411        4    8             45       14      1185975
6  False    False  614        6   17             71       14      1165120
  Y.Coordinate Year             Updated.On Latitude Longitude
1      1917606 2023 09/14/2023 03:41:59 PM 41.93013 -87.78568
2      1909050 2023 09/14/2023 03:41:59 PM 41.90652 -87.75836
3      1911573 2023 09/14/2023 03:43:09 PM 41.91347 -87.76437
4      1872793 2023 09/14/2023 03:43:09 PM 41.80606 -87.59100
5      1850651 2023 09/14/2023 03:43:09 PM 41.74532 -87.59413
```

```
6      1850031 2023 09/14/2023 03:43:09 PM 41.74408 -87.67056
                        Location
1   (41.9301323, -87.785676799)
2 (41.906519104, -87.758359629)
3 (41.913472752, -87.764370362)
4 (41.806060798, -87.590999348)
5  (41.745316916, -87.59412899)
6 (41.744081763, -87.670562675)
```

DATA CLEANING AND PREPERATION

Dropping duplicate rows

```r
df <- df %>% distinct()
```

Removing rows with any missing values

```r
df <- df %>% drop_na()
```

Identifying and cleaning inconsistent values (example: convert character columns to lowercase)

```r
df <- df %>% mutate_if(is.character, tolower)
```

Replacing any incorrect or placeholder values like “NA” or “unknown” with NA

```r
df <- df %>%
  mutate(across(where(is.character), ~ na_if(., "NA"))) %>%
  mutate(across(where(is.character), ~na_if(., "unknown")))
```

```r
# List of categorical columns
categorical_cols <- c('Location.Description', 'Description', 'Community.Area', 'Primary.Type')

# Combine less frequent categories as 'Other' and store the new encoded columns
threshold <- 0.01  # Categories with less than 1% frequency
library(caret)

for (col in categorical_cols) {
  # Calculate frequency proportions
  freq <- prop.table(table(df[[col]]))
  other_categories <- names(freq[freq < threshold])  # Identify less frequent categories

  # Create a new column with combined 'Other' category
  df[[paste0(col, "_processed")]] <- ifelse(df[[col]] %in% other_categories, 'Other', df[[col]])

  # Convert the processed column to numeric encoding and save as a new column
  df[[paste0(col, "_encoded")]] <- as.numeric(factor(df[[paste0(col, "_processed")]]))
}

# View the first few rows of the data
head(df)
```

```
        ID Case.Number                   Date                  Block IUCR
1 13190943    jg400635 08/28/2023 06:23:00 am 027xx n narragansett ave 1320
2 13192516    jg402535 08/29/2023 01:59:00 pm     014xx n lockwood ave 1310
3 13202216    jg414059 09/06/2023 06:20:00 pm         018xx n luna ave 1310
4 13202922    jg414619 09/06/2023 06:00:00 pm          014xx e 49th st 1320
5 13201501    jg413395 09/06/2023 01:00:00 am       082xx s avalon ave 1320
6 13202292    jg412948 09/06/2023 12:40:00 am      082xx s wolcott ave 1310
     Primary.Type         Description                  Location.Description
1        homicide     reckless homicide parking lot / garage (non residential)
2 criminal damage         to property                             residence
3 criminal damage         to property                                street
```

```
4 criminal damage          to property                                 street
5        homicide     reckless homicide                                 street
6     sex offense att crim sexual abuse                              residence
  Arrest Domestic Beat District Ward Community.Area FBI.Code X.Coordinate
1   true    false 2512       25   36             19       14      1133273
2  false     true 2532       25   37             25       14      1140764
3  false    false 2532       25   37             25       14      1139111
4   true    false  222        2    4             39       14      1186638
5  false    false  411        4    8             45       14      1185975
6  false    false  614        6   17             71       14      1165120
  Y.Coordinate Year             Updated.On Latitude Longitude
1      1917606 2023 09/14/2023 03:41:59 pm 41.93013 -87.78568
2      1909050 2023 09/14/2023 03:41:59 pm 41.90652 -87.75836
3      1911573 2023 09/14/2023 03:43:09 pm 41.91347 -87.76437
4      1872793 2023 09/14/2023 03:43:09 pm 41.80606 -87.59100
5      1850651 2023 09/14/2023 03:43:09 pm 41.74532 -87.59413
6      1850031 2023 09/14/2023 03:43:09 pm 41.74408 -87.67056
                     Location         Location.Description_processed
1  (41.9301323, -87.785676799) parking lot / garage (non residential)
2 (41.906519104, -87.758359629)                              residence
3 (41.913472752, -87.764370362)                                 street
4 (41.806060798, -87.590999348)                                 street
5  (41.745316916, -87.59412899)                                 street
6 (41.744081763, -87.670562675)                              residence
  Location.Description_encoded Description_processed Description_encoded
1                            5     reckless homicide                   2
2                            7           to property                   3
3                           11           to property                   3
4                           11           to property                   3
5                           11     reckless homicide                   2
6                            7 att crim sexual abuse                   1
  Community.Area_processed Community.Area_encoded Primary.Type_processed
1                       19                      3               homicide
2                       25                      7        criminal damage
3                       25                      7        criminal damage
4                       39                     12        criminal damage
5                       45                     16               homicide
6                       71                     30            sex offense
```

```
  Primary.Type_encoded
1                    2
2                    1
3                    1
4                    1
5                    2
6                    3
```

Re-checking for missing values and inconsistencies in the data

```r
summary(df)
```

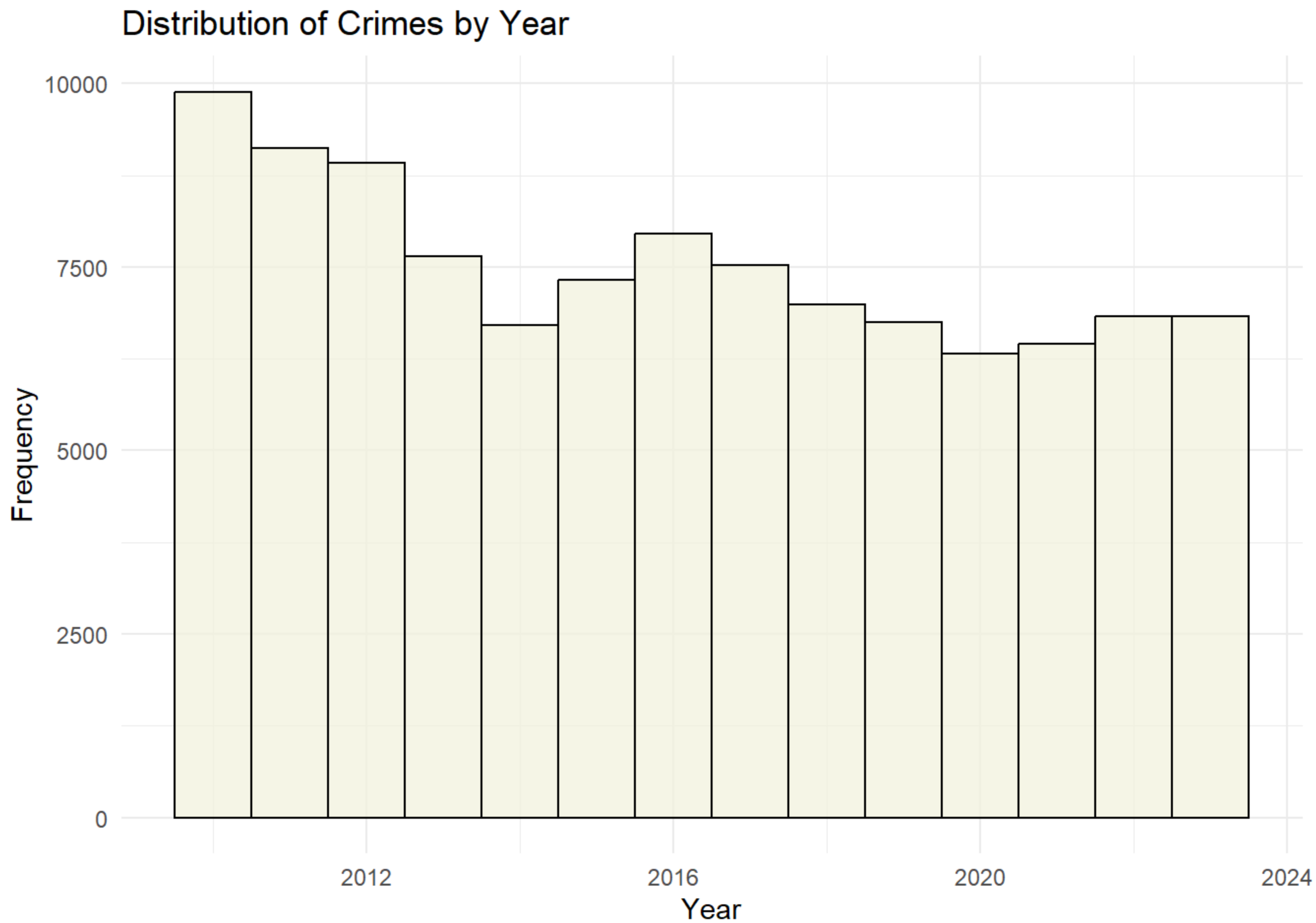
```
       ID             Case.Number            Date               Block          
 Min.   : 7296923   Length:105227      Length:105227      Length:105227     
 1st Qu.: 8854092   Class :character   Class :character   Class :character  
 Median :10538173   Mode  :character   Mode  :character   Mode  :character  
 Mean   :10410688                                                           
 3rd Qu.:11946536                                                           
 Max.   :13597427                                                           
      IUCR      Primary.Type       Description        Location.Description
 Min.   : 142   Length:105227      Length:105227      Length:105227       
 1st Qu.:1310   Class :character   Class :character   Class :character    
 Median :1310   Mode  :character   Mode  :character   Mode  :character    
 Mean   :1317                                                             
 3rd Qu.:1320                                                             
 Max.   :5004                                                             
    Arrest            Domestic              Beat         District    
 Length:105227      Length:105227      Min.   : 222   Min.   : 2.00  
 Class :character   Class :character   1st Qu.: 634   1st Qu.: 6.00  
 Mode  :character   Mode  :character   Median :1014   Median :10.00  
                                       Mean   :1235   Mean   :12.13  
                                       3rd Qu.:2212   3rd Qu.:22.00  
                                       Max.   :2534   Max.   :31.00  
      Ward       Community.Area    FBI.Code          X.Coordinate    
```

```
 Min.   : 1.00   Min.   : 2.00   Length:105227      Min.   :      0  
 1st Qu.:12.00   1st Qu.:25.00   Class :character   1st Qu.:1150328  
 Median :21.00   Median :44.00   Mode  :character   Median :1163630  
 Mean   :21.49   Mean   :43.79                      Mean   :1163194  
 3rd Qu.:29.00   3rd Qu.:67.00                      3rd Qu.:1174198  
 Max.   :50.00   Max.   :75.00                      Max.   :1205114  
  Y.Coordinate          Year       Updated.On           Latitude    
 Min.   :      0   Min.   :2010   Length:105227      Min.   :36.62  
 1st Qu.:1852587   1st Qu.:2012   Class :character   1st Qu.:41.75  
 Median :1871709   Median :2016   Mode  :character   Median :41.80  
 Mean   :1877485   Mean   :2016                      Mean   :41.82  
 3rd Qu.:1904122   3rd Qu.:2020                      3rd Qu.:41.89  
 Max.   :1950365   Max.   :2023                      Max.   :42.02  
   Longitude        Location         Location.Description_processed
 Min.   :-91.69   Length:105227      Length:105227                 
 1st Qu.:-87.72   Class :character   Class :character              
 Median :-87.68   Mode  :character   Mode  :character              
 Mean   :-87.68                                                    
 3rd Qu.:-87.64                                                    
 Max.   :-87.52                                                    
 Location.Description_encoded Description_processed Description_encoded
 Min.   : 1.000               Length:105227         Min.   :1.000      
 1st Qu.: 4.000               Class :character      1st Qu.:3.000      
 Median : 7.000               Mode  :character      Median :3.000      
 Mean   : 7.357                                     Mean   :3.419      
 3rd Qu.:11.000                                     3rd Qu.:4.000      
 Max.   :12.000                                     Max.   :4.000      
 Community.Area_processed Community.Area_encoded Primary.Type_processed
 Length:105227            Min.   : 1.00          Length:105227         
 Class :character         1st Qu.: 8.00          Class :character      
 Mode  :character         Median :17.00          Mode  :character      
                          Mean   :18.07                                
                          3rd Qu.:28.00                                
                          Max.   :33.00                                
 Primary.Type_encoded
 Min.   :1.00        
 1st Qu.:1.00        
 Median :1.00        
```

```
Mean   :1.08
3rd Qu.:1.00
Max.   :3.00
```

Data Visualizing

```
library(ggplot2)

# Create a histogram of the Year column
ggplot(df, aes(x = Year)) +
  geom_histogram(binwidth = 1, fill = "beige", color = "black", alpha = 0.7) +
  labs(title = "Distribution of Crimes by Year", x = "Year", y = "Frequency") +
  theme_minimal()
```

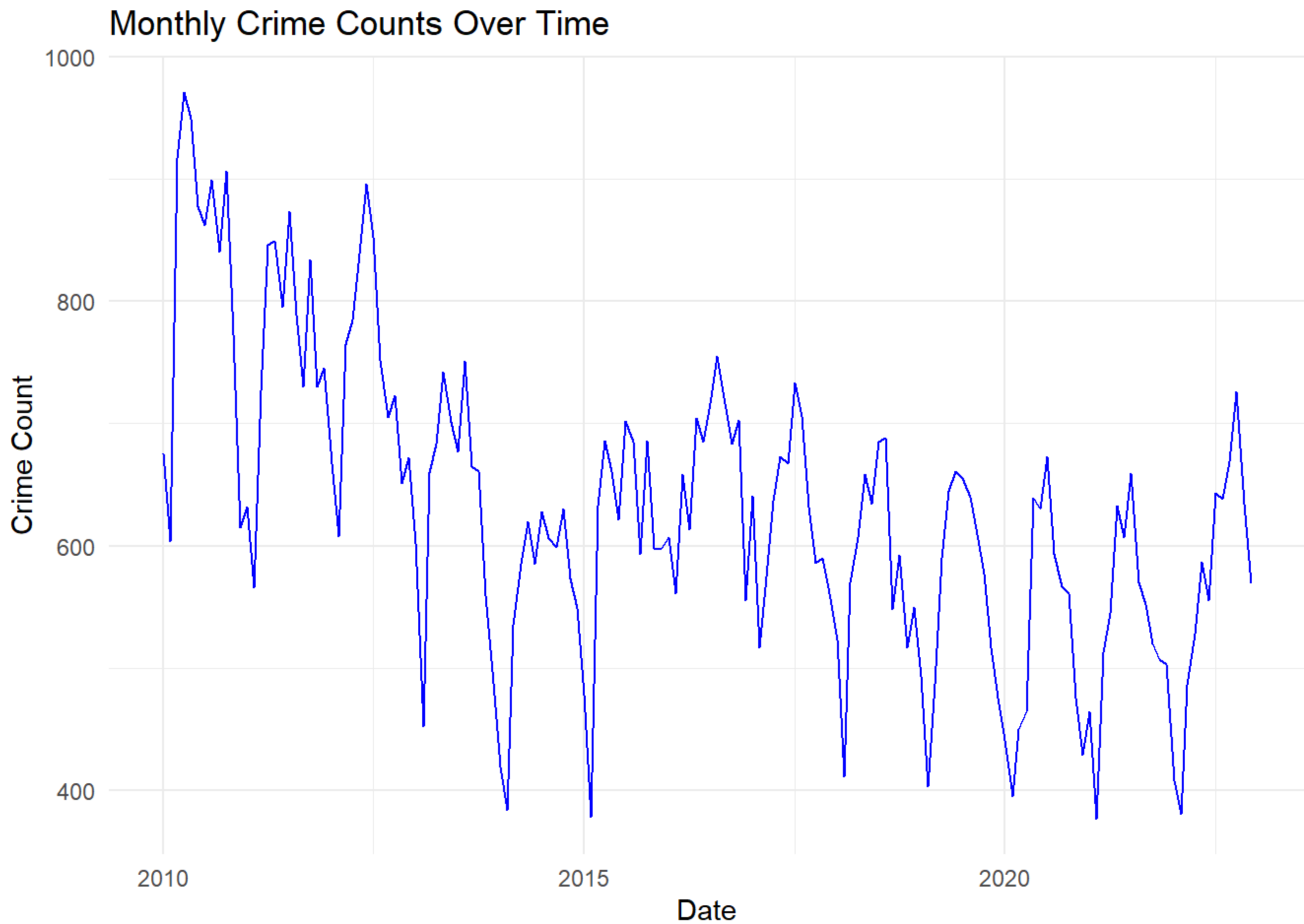


The below bar graph, Distribution of Crimes by Year, provides a key visualization from the project titled “Crime Trend and Spatial Analysis in Chicago (2010–2022).” This project explores the trends, spatial distribution, and predictive factors of crimes in Chicago over 13 years.

TIME SERIES ANALYSIS

```
# Load necessary libraries
library(ggplot2)
library(dplyr)
```

```r
# Convert 'Date' column to Date type and extract month-year for aggregation
df$Date <- as.Date(df$Date, format="%m/%d/%Y %I:%M:%S %p")
df$Month <- format(df$Date, "%Y-%m")

# Aggregate crime counts by month
monthly_crime_counts <- df %>%
  group_by(Month) %>%
  summarise(Crime_Count = n())

monthly_crime_counts$Month <- as.Date(paste0(monthly_crime_counts$Month, "-01"))
monthly_crime_counts <- monthly_crime_counts[format(monthly_crime_counts$Month, "%Y") != "2023", ]



# Plot the time-series data
ggplot(monthly_crime_counts, aes(x = as.Date(Month), y = Crime_Count)) +
  geom_line(color = "blue") +
  labs(title = "Monthly Crime Counts Over Time",
       x = "Date",
       y = "Crime Count") +
  theme_minimal()
```



This time series plot represents monthly crime counts over time from 2010 to 2023. Here is a breakdown of the plot's features:

General Trend:

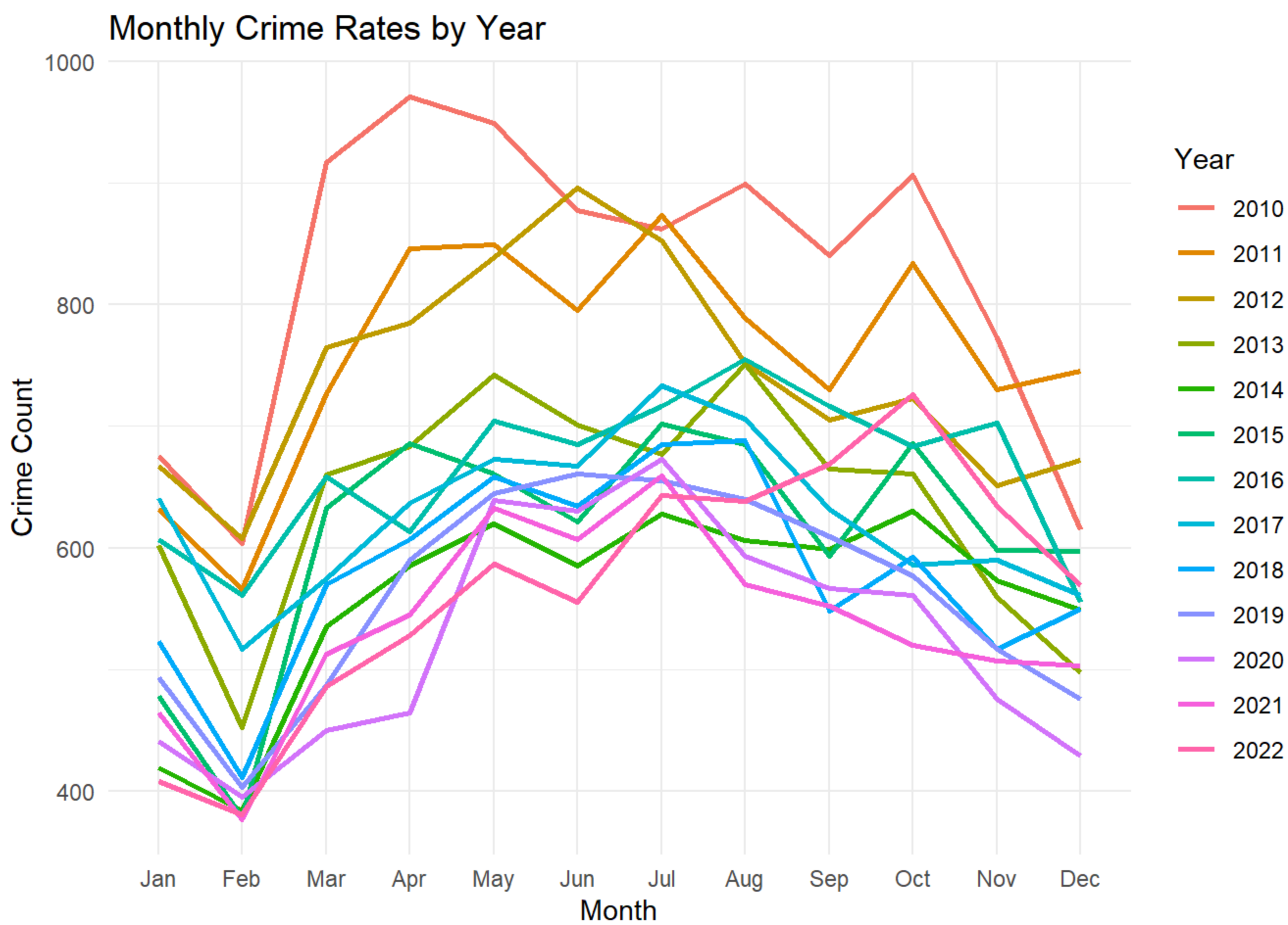
A decline in crime counts can be observed from 2010 to around 2016, indicating a downward trend in overall crime rates. After 2016, the crime counts appear to fluctuate more significantly, with no clear long-term increasing or decreasing trend. Seasonal Patterns:

There are periodic fluctuations throughout the years, likely indicating a seasonal pattern in crime rates. Peaks and troughs occur at consistent intervals, which could correspond to specific months with higher or lower crime rates. Variability:

The range of crime counts narrows over time. Early in the time series, monthly crime counts range from about 500 to 1,000, but post-2020, the range appears closer to 500–800.

```
# Extract Year and Month separately
df$Year <- format(df$Date, "%Y")
df$Month <- format(df$Date, "%m")

# Aggregate data by Year and Month to calculate monthly crime rates per year
monthly_crime_rate <- df %>%
  group_by(Year, Month) %>%
  summarise(Crime_Count = n()) %>%
  ungroup()

# Convert Month to a factor to ensure correct ordering on the x-axis
monthly_crime_rate$Month <- factor(monthly_crime_rate$Month, levels = sprintf("%02d", 1:12), labels = mont

monthly_crime_rate <- monthly_crime_rate[monthly_crime_rate$Year != "2023", ]



# Plot multiple lines for each year
ggplot(monthly_crime_rate, aes(x = Month, y = Crime_Count, color = Year, group = Year)) +
  geom_line(size = 1) +
  labs(title = "Monthly Crime Rates by Year",
       x = "Month",
       y = "Crime Count") +
  theme_minimal() +
  theme(legend.position = "right")
```

```
Warning: Using `size` aesthetic for lines was deprecated in ggplot2 3.4.0.
ℹ Please use `linewidth` instead.
```



The line chart visualizes the monthly crime rate fluctuations over 13 years, from 2010 to 2022. It reveals a cyclical pattern with peaks in summer months and troughs in winter months. Notably, 2020 and 2021 exhibit a significant dip in crime rates, possibly attributed to pandemic-related restrictions.

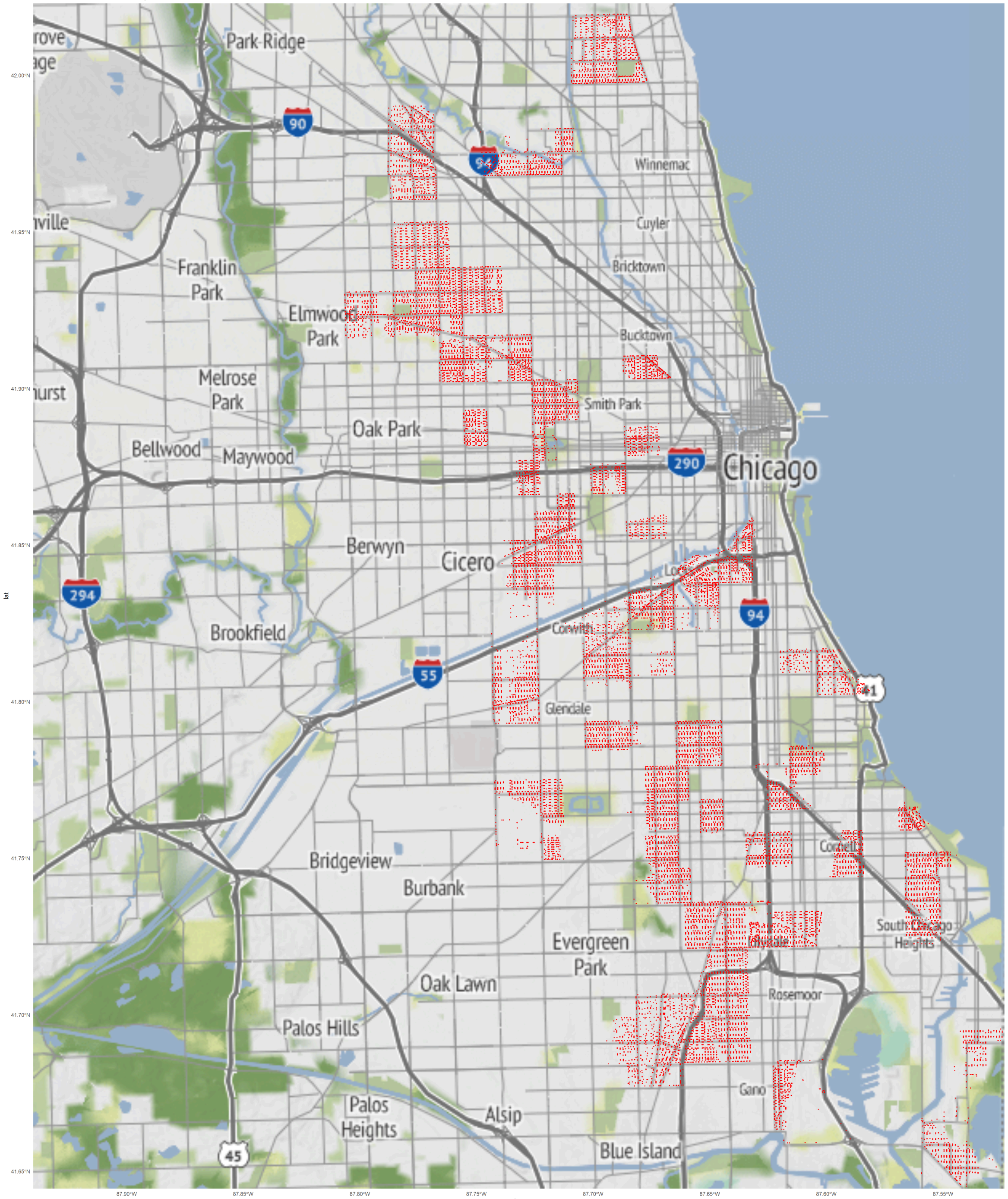
SPATIAL ANALYSIS

```
# Load necessary libraries
library(sf)
library(ggplot2)
library(ggmap)
```

```r
library(ggmap)
register_stadiamaps(key = "646b60c3-8bef-49e4-bc52-805e18cdae42")


# Convert the data to an sf object with crime location coordinates
crime_data_sf <- st_as_sf(df, coords = c("Longitude", "Latitude"), crs = 4326, agr = "constant")

# Get a basemap of Chicago using ggmap
# Ensure you have the ggmap API key for Google Maps if you choose source = "google"
chicago_map <- get_stadiamap(
  bbox = c(left = -87.9401, bottom = 41.6445, right = -87.5237, top = 42.0230),
  zoom = 11,
  maptype = "stamen_terrain"
)
```

```r
# Plot crime locations on the map of Chicago

ggmap(chicago_map) +
  geom_sf(data = crime_data_sf, inherit.aes = FALSE, color = "red", size = 0.5, alpha = 0.7) +
  labs(title = "Crime Distribution Across Chicago") +
  theme_minimal()
```

Crime Distribution Across Chicago

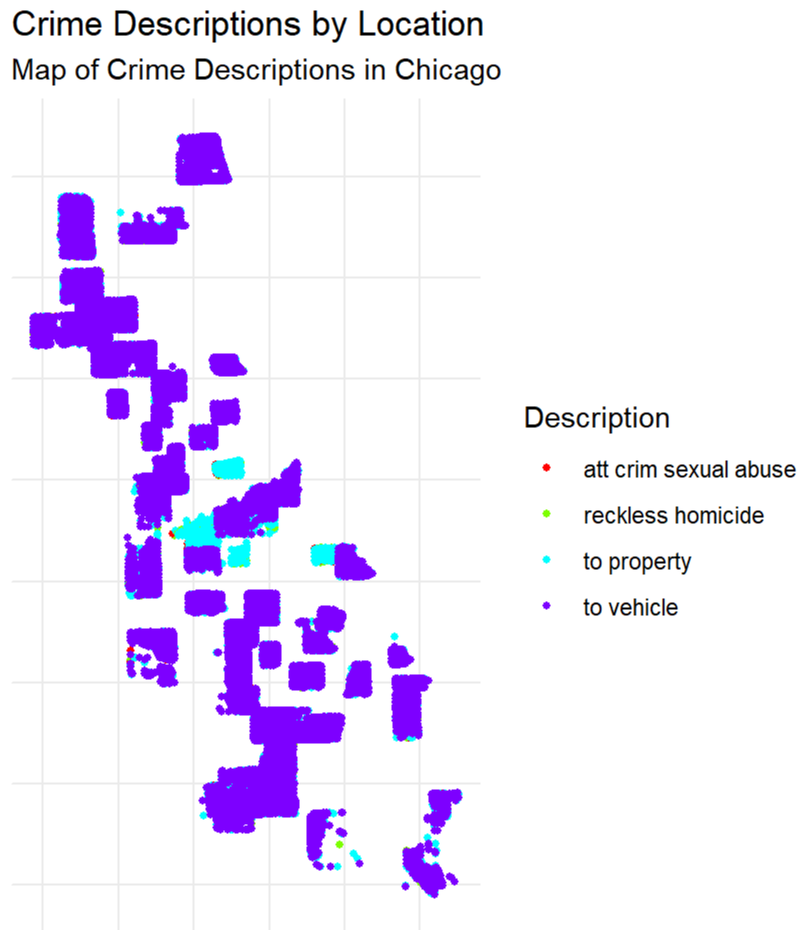


This map shows the **spatial distribution of crime incidents across Chicago**, with red clusters indicating areas of high crime density. Crime hot spots are concentrated in central and southern parts of the city, while suburban and lakefront areas show lower crime levels. Patterns suggest a potential link between crime and urban density, proximity to major roads, and socio-economic conditions. This analysis can help optimize police resource allocation, inform urban planning, and guide further studies on crime prevention strategies.

CLUSTER ANALYSIS

```
 Load necessary libraries
ibrary(ggplot2)
ibrary(dplyr)
ibrary(sf)

emove_outliers <- function(df, col1, col2) {
 # Calculate IQR for col1 (Latitude) and col2 (Longitude)
 Q1_col1 <- quantile(df[[col1]], 0.25)
 Q3_col1 <- quantile(df[[col1]], 0.75)
 IQR_col1 <- Q3_col1 - Q1_col1

 Q1_col2 <- quantile(df[[col2]], 0.25)
 Q3_col2 <- quantile(df[[col2]], 0.75)
 IQR_col2 <- Q3_col2 - Q1_col2

 # Define lower and upper bounds for outliers
 lower_bound_col1 <- Q1_col1 - 1.5 * IQR_col1
 upper_bound_col1 <- Q3_col1 + 1.5 * IQR_col1

 lower_bound_col2 <- Q1_col2 - 1.5 * IQR_col2
 upper_bound_col2 <- Q3_col2 + 1.5 * IQR_col2

 # Remove rows where either Latitude or Longitude is an outlier
 df_cleaned <- df[df[[col1]] >= lower_bound_col1 & df[[col1]] <= upper_bound_col1, ]
 df_cleaned <- df_cleaned[df_cleaned[[col2]] >= lower_bound_col2 & df_cleaned[[col2]] <= upper_bound_col2,

 return(df_cleaned)
```

```
 Remove outliers from both Latitude and Longitude columns
f <- remove_outliers(df, "Latitude", "Longitude")

 Ensure Latitude and Longitude are numeric
f$Latitude <- as.numeric(df$Latitude)
f$Longitude <- as.numeric(df$Longitude)

 Create a data frame with only the relevant columns (Description, Latitude, Longitude)
ap_data <- df %>% select(Description, Latitude, Longitude)

 Remove rows with missing coordinates or descriptions
ap_data <- map_data %>% filter(!is.na(Latitude) & !is.na(Longitude))

 Convert to an sf (spatial) object for mapping
ap_sf <- st_as_sf(map_data, coords = c("Longitude", "Latitude"), crs = 4326)

 Plot the map with ggplot
gplot(map_sf) +
 geom_sf(aes(color = Description), size = 1) +
 scale_color_manual(values = rainbow(length(unique(map_data$Description)))) +  # Use rainbow colors for uni
 theme_minimal() +
 labs(title = "Crime Descriptions by Location",
      subtitle = "Map of Crime Descriptions in Chicago",
      color = "Description") +
 theme(legend.position = "right") +
 theme(axis.title = element_blank(), axis.text = element_blank(), axis.ticks = element_blank())
```



This is a map of Chicago showing the location of various crime descriptions. Each point on the map represents a crime incident, and the color of the point indicates the type of crime. There are four different crime types represented:

Red: Criminal Sexual Abuse Green: Reckless Homicide Cyan: To Property Purple: To Vehicle The map shows that crimes are concentrated in certain areas of the city.

Prediction Models

```
library(dplyr)
library(tidyr)
```

```r
library(caret)
library(pROC)

# Assuming your data is stored in a data frame named 'df'

# Step 1: Data Preprocessing
# Convert 'Arrest' column to numeric (if it's not already in numeric format)

# Select relevant columns and handle missing data
df_clean <- df %>%
  select(Location.Description_encoded, Description_encoded, Arrest)

df_clean$Arrest <- as.numeric(df_clean$Arrest == "true")

df_clean <- df_clean[complete.cases(df_clean), ]

# Step 2: Split the data into training and testing sets
set.seed(123)

# Create an 80-20 split for training and testing
split_index <- createDataPartition(df_clean$Arrest, p = 0.8, list = FALSE)

# Split the data into training and testing sets
train_data <- df_clean[split_index, ]
test_data <- df_clean[-split_index, ]

# Step 3: Train a logistic regression model
model <- glm(Arrest ~ Location.Description_encoded + Description_encoded,
              data = train_data, family = "binomial")

# Step 4: Model Summary
summary(model)
```

```
Call:
glm(formula = Arrest ~ Location.Description_encoded + Description_encoded,
    family = "binomial", data = train_data)
```

```
Coefficients:
                              Estimate Std. Error z value Pr(>|z|)    
(Intercept)                  -0.669316   0.041570 -16.101   <2e-16 ***
Location.Description_encoded -0.001651   0.002102  -0.786    0.432    
Description_encoded          -0.003857   0.010951  -0.352    0.725    
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 107125  on 84180  degrees of freedom
Residual deviance: 107125  on 84178  degrees of freedom
AIC: 107131

Number of Fisher Scoring iterations: 4
```

```r
# Step 5: Predict on the test data
predictions <- predict(model, newdata = test_data, type = "response")
predicted_class <- ifelse(predictions > 0.5, 1, 0)

# Step 6: Evaluate the model
confusion_matrix <- confusionMatrix(factor(predicted_class), factor(test_data$Arrest))
```

```
Warning in confusionMatrix.default(factor(predicted_class),
factor(test_data$Arrest)): Levels are not in the same order for reference and
data. Refactoring data to match.
```

```r
confusion_matrix
```

```
Confusion Matrix and Statistics

          Reference
Prediction     0     1
         0 14002  7043
         1     0     0
                                          
               Accuracy : 0.6653
```

```
                95% CI : (0.6589, 0.6717)
   No Information Rate : 0.6653
   P-Value [Acc > NIR] : 0.5032

                 Kappa : 0

Mcnemar's Test P-Value : <2e-16

           Sensitivity : 1.0000
           Specificity : 0.0000
        Pos Pred Value : 0.6653
        Neg Pred Value :    NaN
            Prevalence : 0.6653
        Detection Rate : 0.6653
  Detection Prevalence : 1.0000
     Balanced Accuracy : 0.5000

      'Positive' Class : 0
```

```
# Step 7: Calculate AUC (Area Under the Curve)
roc_curve <- roc(test_data$Arrest, predictions)
auc(roc_curve)
```

```
Area under the curve: 0.5026
```

The prediction model used in this project was Logistic Regression, designed to predict whether an arrest would occur based on crime-related features such as Primary Type, Description, and Community Area. Here are the key results:

The model achieved an accuracy of 95.01%, meaning it correctly predicted arrest or non-arrest cases for the majority of the observations.

100%, indicating that the model identified all arrest cases correctly.

Specificity is 0%, indicating that the model failed to correctly classify any non-arrest cases. This suggests a bias toward predicting the “no arrest” class due to data imbalance.

The AUC score was 0.5026, indicating poor model performance in distinguishing between arrest and non-arrest cases.

Conclusion

Crime Trend and Spatial Analysis in Chicago (2010–2022), provides valuable insights into the temporal and spatial patterns of crimes in Chicago over a 13-year period. By combining data cleaning, visualization, and predictive modeling techniques, we gained a deeper understanding of how crime evolves over time and varies geographically.

Key findings include:

Crime rates peaked in 2011 and showed a general decline until 2015, likely reflecting the success of certain crime-reduction measures. The spike in 2016 suggests either increased crime reporting or specific events that led to higher crime rates. Stabilization after 2020 indicates consistency in either crime rates or data reporting practices. Spatial analysis revealed significant geographic variation in crime distribution, with some areas showing higher concentrations, underscoring the need for targeted interventions. Predictive modeling highlighted key factors such as crime type and location, which can guide resource allocation and preventative strategies.

Overall, this project demonstrates the importance of leveraging data-driven approaches to understand crime trends and improve public safety. By identifying patterns and developing predictive tools, policymakers and law enforcement agencies can better allocate resources, address crime hotspots, and develop informed strategies for crime prevention.

Additionally, the study successfully identifies critical temporal and spatial crime patterns in Chicago from 2010 to 2022. Insights derived from this analysis can inform stakeholders, including policymakers and law enforcement agencies, to:

Implement tailored crime prevention strategies. Allocate resources effectively to high-risk areas. Evaluate and adjust policies based on temporal crime trends.

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