Mini Final Report

Sam Lee, Jeffry Troll

Introduction

Violent crime in Chicago remains a persistent challenge. The Chicago Police Department (CPD), particularly concerned about the situation in District 11, has partnered with Data Insight & Strategy Consultants (DISC) to explore innovative approaches. This project delves beyond traditional methods, incorporating human behavior, weather patterns, and even the lunar cycle, to analyze crime data and uncover potential predictors.

Our goal is to determine if and how these factors influence violent crime rates in Chicago. This knowledge will empower the CPD to proactively implement crime prevention strategies, such as public outreach and community events, during particularly vulnerable periods. By shedding light on the potential relationships between these factors and crime, we aim to make Chicago a safer place for all.

We start by analyzing the the number violent crimes that occur within District 11 over the past decade. We use the City of Chicago's definition (https://www.chicago.gov/city/en/sites/vrd/home/violence-victimization.html) to define violent crimes. To elicit the effect that weather has on crimes, we also divide out the crime by hour. We use historical weather data imported by a weather API to map hourly weather data to the hour the crime happened.

To analyze the predictive performance of these covariates, we employ several models. For more interpretation on the coefficients, we first train a generalized linear model adjusted with time-series components. For more predictive power, we employ more flexible models, including random forests, KNN, and clusters analysis.

We will first introduce the data used for this analysis, followed by some EDA we used to explore the data, the models we estimated, the results of our analysis, and then conclude.

Data Acquisition and Preprocessing

Primary Data Sources:

To conduct a comprehensive analysis of violent crime in Chicago's District 11, DISC acquired data from the following reputable sources:

- Chicago Crime Data: Detailed records of crimes reported in District 11 since 2001 were obtained from the official City of Chicago Data Portal https://data.cityofchicago.org/Public-Safety/Crimes-2001-to-Present/ijzp-q8t2. We opted for this source to ensure data accuracy and consistency with official crime reporting procedures. Additionally, a valuable Kaggle resource https://www.kaggle.com/datasets/chicago/chicago-crime provided insights into the data structure and potential applications.
- Weather Data: Daily weather data for Chicago from 2010 to 2024, encompassing temperature, precipitation, wind speed, and other relevant meteorological variables, was originally retrieved from Visual Crossing (https://www.visualcrossing.com/). However, we asserted that to model the demand for violent crime more granually, as crimes were recorded by the hour; as such, we imported weather data from an historical weather API, https://open-meteo.com/.

Secondary Data Sources:

- Holiday Data: This data was obtained via ChatGPT for initial exploration, followed by cross-referencing with reliable online resources like national holiday calendars and local Chicago event listings.
- Full Moon Data: Dates of full moons since 2005 were sourced from Full Moon Info https://www.fullmoonology.com/full-moon-calendar-2015/, a website recognized for its comprehensive moon phase calendar. This data serves as a starting point for exploring potential lunar influences on crime rates.

Data Harmonization and Feature Engineering:

To ensure a consistent temporal scope across all data sets, a decision was made to utilize data from 2010 to 2024. While this approach sacrifices some crime data from the early 2000s, it allows for a more robust and comparable analysis with the available weather and holiday information.

Furthermore, monthly unemployment data for Chicago from 2010 to 2024 was incorporated as a socioeconomic indicator through using data from the Bureau of Labor Statistics.

Here's how we wrangled all the data files in R:

```r
tryCatch({
  maps.api.key = read_file("Sam/maps_api.txt")
})

crimes <- read_csv("Sam/Data/Crimes.csv")
crimes$DateTime <- mdy_hms(crimes$Date)
crimes$Date <- as.Date(crimes$DateTime)
crimes$hour <- hour(crimes$DateTime)

moons <- read_csv("Sam/Data/full_moon.csv") %>%
```

```r
  mutate(Date = dmy(FullMoonDates))

holidays <- read_csv("Sam/Data/holidays.csv") %>%
  mutate(Date = ymd(Date))

#Weather Data from API
weather.data <- fromJSON("Sam/Data/weather.json")["hourly"] %>%
  as.data.frame()
weather.data$hourly.time = weather.data$hourly.time %>%
  str_replace("T", " ")
weather.data$hourly.time = ymd_hm(weather.data$hourly.time)
weather.data <- weather.data %>%
  mutate(
    Date = as.Date(hourly.time),
    hour = hour(hourly.time) %>%
      as.numeric()
  )
weather.covariates <- colnames(weather.data)[2:(ncol(weather.data)-2)]

cutoff.date = max(
  c(min(crimes$Date), min(holidays$Date), min(weather.data$Date))
)
upper.cutoff = min(
  c(max(crimes$Date), max(holidays$Date), max(weather.data$Date))
)

crimes <- weather.data %>% left_join(crimes) %>%
  mutate(
    DateTime = hourly.time,
    Year = year(DateTime)
  )

week.days <- c("Mon", "Tues", "Wed", "Thurs", "Fri", "Sat", "Sun")

crimes.cleaned <- crimes %>%
  left_join(holidays) %>%
  left_join(moons) %>%
  mutate(
    Holiday = ifelse(is.na(Holiday), "", Holiday),
    DayofWeek = week.days[wday(Date, week_start=1)],
    FullMoon = ifelse(is.na(FullMoonDates),0,1)
  ) %>% filter(
    Date >= cutoff.date & Date <= upper.cutoff
  )
```

```
factors = c("DateTime", "Date", "Primary Type", "Location Description",
            "Arrest", "Domestic", "Community Area", "Year", "Latitude",
            "Longitude", "FullMoon", "DayofWeek", "Holiday", "hour",
            weather.covariates)

crimes.cleaned <- crimes.cleaned[,factors]

#In the FBI's Uniform Crime Reporting (UCR) Program, violent crime is composed
#of four offenses: murder and nonnegligent manslaughter, forcible rape,
#robbery, and aggravated assault.

#https://www.chicago.gov/city/en/sites/vrd/home/violence-victimization.html
allcrimes = crimes.cleaned$`Primary Type` %>%
  unique() %>%
  sort()
violence.key <- c(0,1,1,1,0,1,0,1,0,0,0,1,1,0,1,1,0,0,0,0,
                  0,0,0,0,0,0,0,0,0,0,1,0,0,0,0)
mapping <- setNames(seq_along(unique(allcrimes)), unique(allcrimes))
crimes.cleaned$Violent <- violence.key[
  unname(mapping[crimes.cleaned$`Primary Type`])
]

crimes.cleaned <- crimes.cleaned %>%
  mutate(
    #These are the hours where there weren't any violent crimes
    Violent = ifelse(is.na(Violent), 0, Violent)
  )

crimes.cleaned <- crimes.cleaned %>% group_by(Violent, Date, hour) %>%
  mutate(
    NumViolentCrimes = Violent*n()
  ) %>% ungroup()

#Merge in unemployment data from BLS
unem <- read_csv("Sam/Data/chicago-unemployment.csv") %>%
  dplyr::select(Year, Label, Value) %>%
  mutate(
    Date = ym(Label),
    Month = month.name[month(Date)]
  ) %>% dplyr::select(-Label) %>% setNames(c(
    "Year", "Unemployment", "Date", "Month"
  )) %>% arrange(Date)
```

```
crimes.cleaned$Month <- month.name[month(crimes.cleaned$Date)]

#Add in monthly unemployment
crimes.cleaned <- crimes.cleaned %>%
  left_join(
    unem %>% dplyr::select(-Date), by=join_by(Year, Month)
  )
```

Note that we define `NumViolentCrimes` as the number of violent crimes that happen within a given hour. This is one of our response variables.

EDA

Summary Statistics

Table 1: Summary Statistics of Location Variables

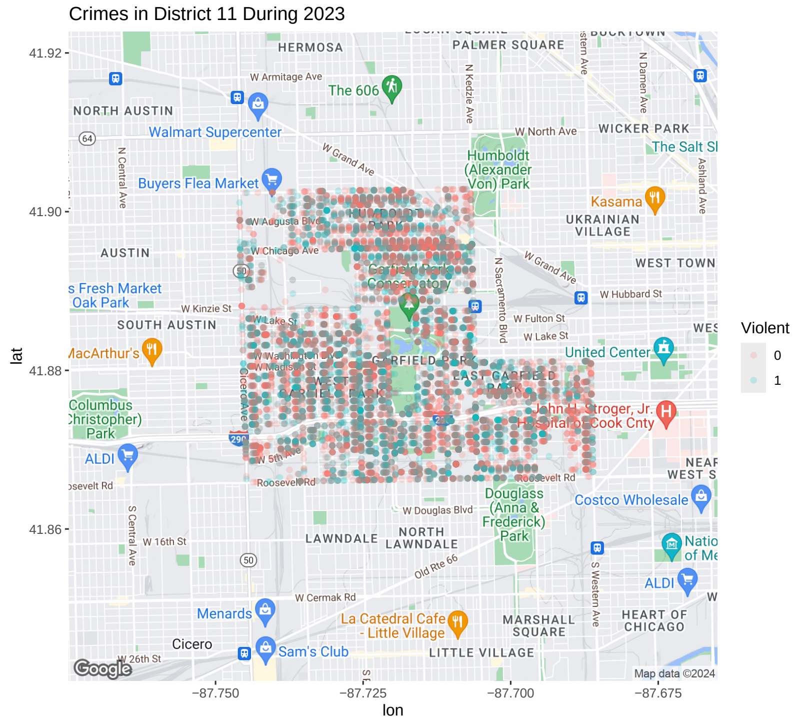
	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.	NA's
Community Area	23.0	23.0	26.0	25.7	27.0	76.0	23768
Latitude	36.6	41.9	41.9	41.9	41.9	41.9	27740
Longitude	-91.7	-87.7	-87.7	-87.7	-87.7	-87.7	27740

Table 2: Summary Statistics of Numerical Variables

	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
Temperature	-33.2	2.4	12.0	11.30000	20.8	37.10
Humidity	11.0	59.0	71.0	70.40000	83.0	100.00
Apparent Temperature	-39.3	-2.3	8.9	9.01000	21.0	43.60
Rain	0.0	0.0	0.0	0.10600	0.0	47.70
Snowfall	0.0	0.0	0.0	0.00708	0.0	2.73
Snow Depth	0.0	0.0	0.0	0.01800	0.0	0.46
Cloud Cover	0.0	8.0	36.0	46.20000	89.0	100.00
Wind Speed	0.0	9.4	13.8	14.80000	19.2	54.50
Wind Gusts	1.8	19.4	27.7	29.00000	36.7	97.90
Is Day Time	0.0	0.0	1.0	0.57600	1.0	1.00
Shortwave Radiation	0.0	0.0	49.0	201.00000	361.0	1015.00
Direct Radiation	0.0	0.0	3.3	129.80000	200.2	910.70
Is Violent Crime	0.0	0.0	0.0	0.31900	1.0	1.00
Hourly Violent Crimes	0.0	0.0	0.0	0.59800	1.0	9.00
Unemployment	3.7	4.9	6.1	6.80000	8.7	16.80

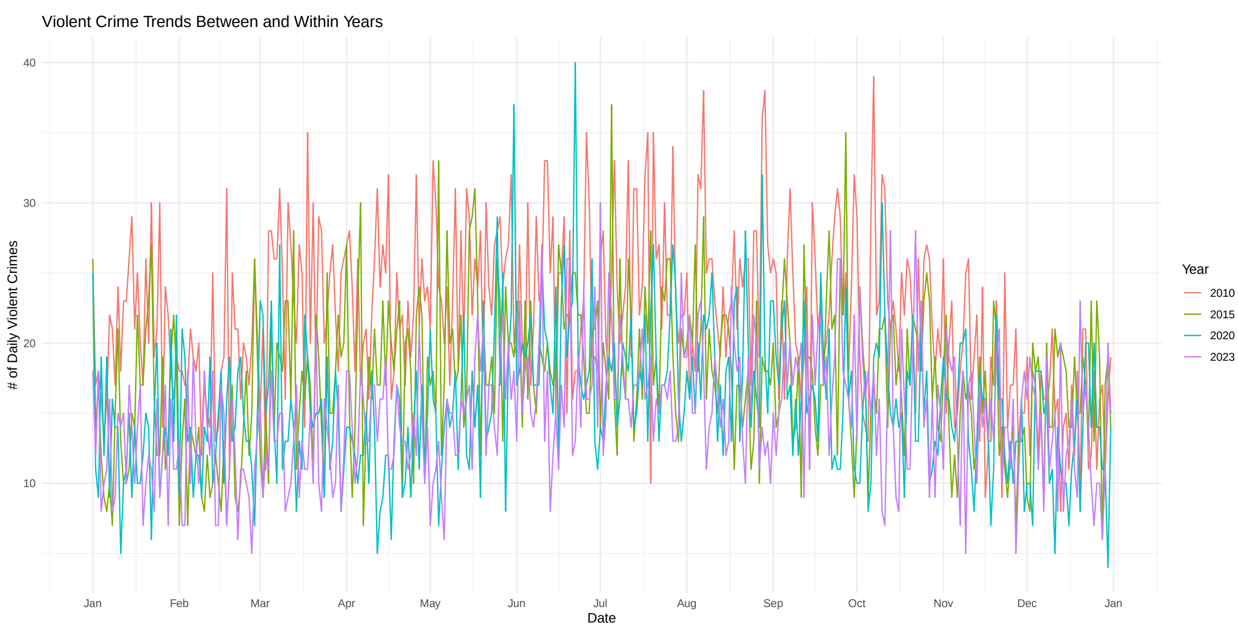
Note that summary statistics come from hourly records of crimes. The NA values on the location summary statistics are the hours where no crimes were observed.

Is there any spatial correlation between where crimes are occurring?



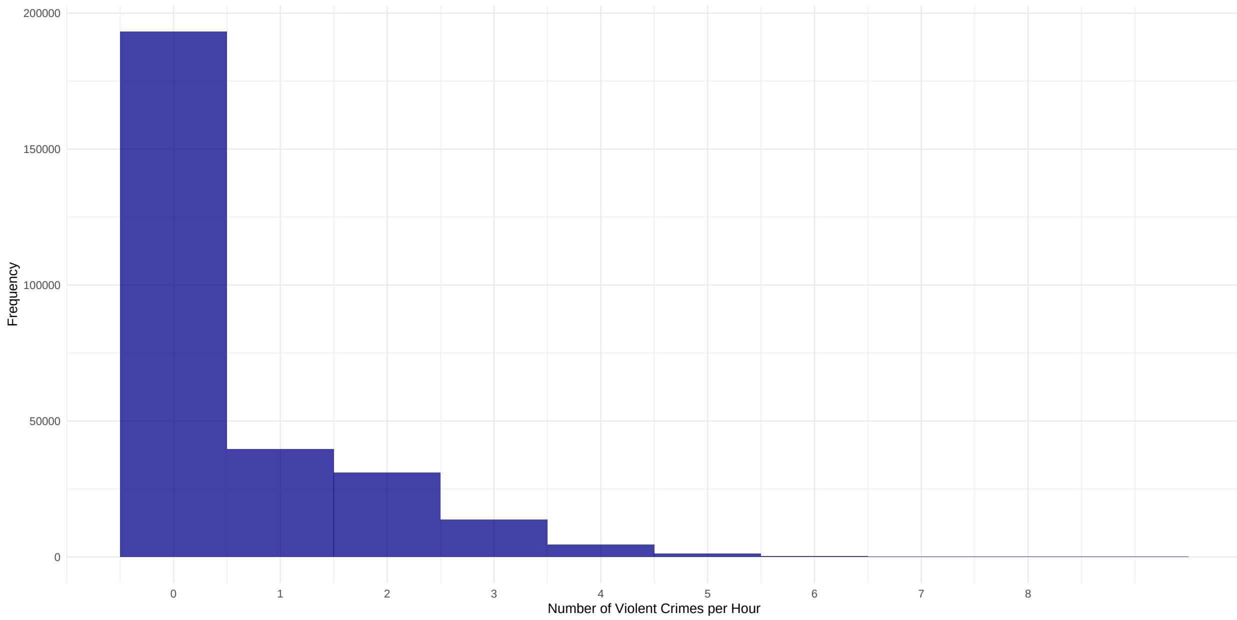
Based on the map above, since District 11 is such a small area, and since we don't have other data on the where crime is occurring in other districts, from this preliminary visual assessment, it doesn't look like there are any strong hotspots for violent crime throughout the year.

How do the number of violent crimes generally fluctuate throughout the year?



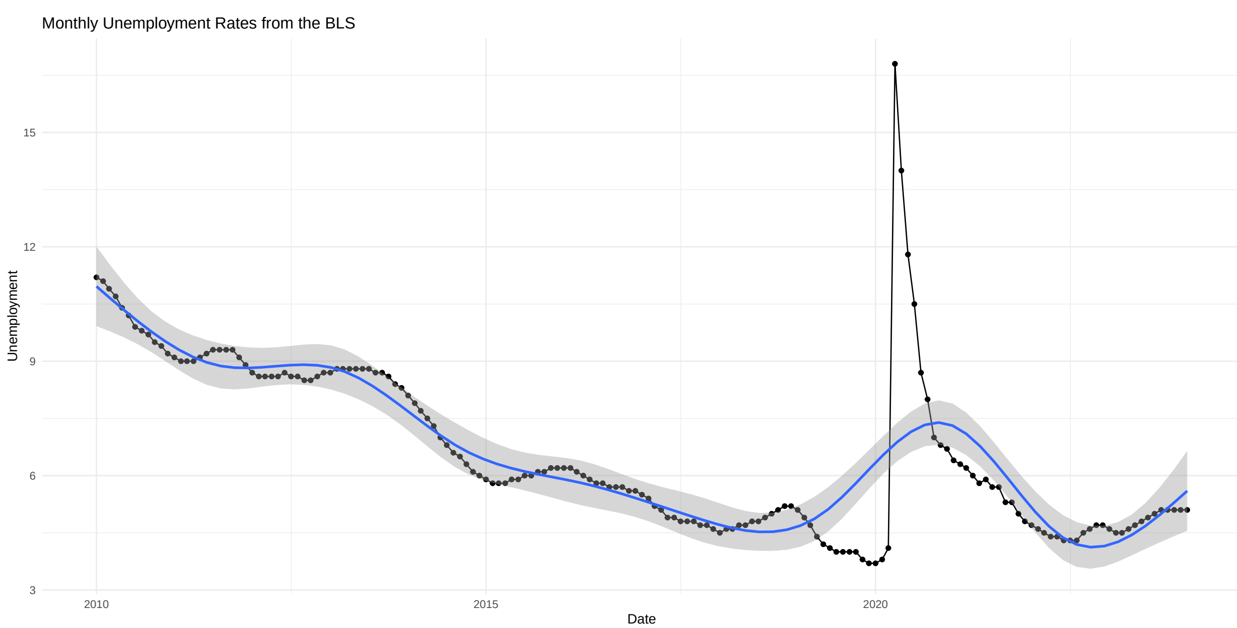
While it’s hard to read in between the lines (literally), this graph shows that crime generally peaks during the summer months, while at the same time, crime has generally been decreasing over the pass decade.

What does the distribution of hourly violent crimes look like?



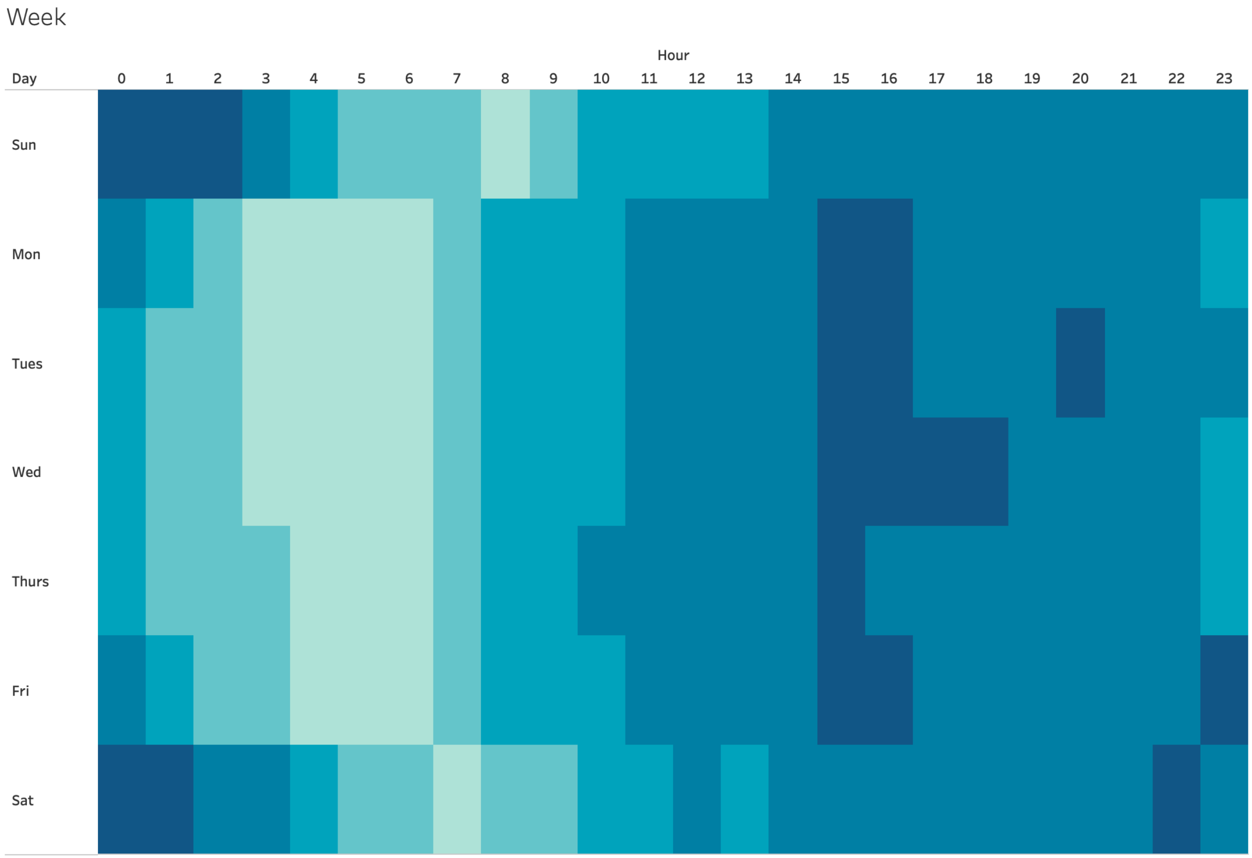
This appears that the distribution of the hourly violent crimes is Poisson-distributed. Specifically, since there’s a (greater than expected) concentration of counts at 0, we first thought about modeling hourly violent number of crimes via a zero-inflated Poisson model (ZIP).

How does unemployment fluctuate throughout the observed decade in Chicago?



Unemployment seems to generally decrease throughout the decade (accounting for the seasonal fluctuations). There is a large spike around the COVID months. This could account for the spike we see in crime in the summer months in 2020. We include unemployment as a factor in our models.

How does the number of violent crime fluctuate throughout the hour of day and day of the week?



It appears that the early hours of the morning are only prone to more violent crime during the weekend, while violent crimes typically occur in the afternoon on weekdays. We want to account for this in our models.

Data Analysis, Model Building, and Interpretation

Generalized Linear Models

We first attempted to understand how the different coefficients were affecting our response variable, the number of violent crimes per hour. We employed several generalized linear models:

1) Poisson Regression
2) Negative Binomial Regression
3) Lasso Regression

4) Zero-Inflated Poisson Regression

The main autoregressive linear model proceeds as follows:

For a given hour (h), day (d), month (m), and year (y), we model the number of number of hourly violent crimes (Y_{hdmy}) as follows:

$$(1a) \quad Y_{hdmy} = \beta_0 + \beta_1 \text{FullMoon}_{dmy} + \beta_2 \text{Unemployment}_{my} + X'_{hdmy}\gamma + \text{Weather}'_{hdmy}\Omega$$

$$+ \sum_{i=1}^{23} \eta_i \mathbb{1}(\text{Hour}_h = i) + \sum_{i=Mon}^{Sat} \delta_i \mathbb{1}(\text{Day}_d = i) + \sum_{i=Jan}^{Nov} \mu_i \mathbb{1}(\text{Month}_m = i)$$

$$+ \sum_{i=1}^{23} \sum_{j=Mon}^{Sat} \xi_{6(i-1)+j} \mathbb{1}(\text{Hour}_h = i)\mathbb{1}(\text{Day}_d = j) + \sum_{i=1}^{24} \psi_i Y_{(h-i)dmy} + \epsilon_{hdmy}$$

$$(1b) \quad \mathbb{E}[\epsilon_{hdmy} | \mathbb{X}_{hdmy}] = 0 \quad \forall h, d, m, y$$

Where $\mathbb{X}_{hdmy}$ is the complete covariate matrix (including fixed effects and autoregressive lags). The X matrix includes covariates such as holidays and other miscellaneous interactions that vary from model to model.

However, to get better predictive power, as discussed previously, we decided to model the functional of Y_{hdmy} more appropriately through a countwise regression. We found that a Zero-Inflated Poisson (ZIP) regression ultimately performed the best out of the four genderalized linear models we performed above. Hence, we generalized (1) to model both the mean ($\mathbb{E}[Y_{hdmy}|\mathbb{X}_{hdmy}]$) of the hourly number of violent crimes and the probability that no violent crimes would be committed during that specific hour (this is structurally equivalent to a ZIP regression model).

Hence, we generalized (1) into the following ZIP regression model:

$$(2a) \quad Y_{hdmy} \sim ZIP(\lambda_{hdmy}, \pi)$$

$$(2b) \quad \lambda_{hdmy} = exp\{\beta_0 + \beta_1 \text{FullMoon}_{dmy} + \beta_2 \text{Unemployment}_{my} + X'_{hdmy}\gamma + \text{Weather}'_{hdmy}\Omega$$

$$+ \sum_{i=1}^{23} \eta_i \mathbb{1}(\text{Hour}_h = i) + \sum_{i=Mon}^{Sat} \delta_i \mathbb{1}(\text{Day}_d = i) + \sum_{i=Jan}^{Nov} \mu_i \mathbb{1}(\text{Month}_m = i)$$

$$+ \sum_{i=1}^{23} \sum_{j=Mon}^{Sat} \xi_{6(i-1)+j} \mathbb{1}(\text{Hour}_h = i)\mathbb{1}(\text{Day}_d = j) + \sum_{i=1}^{24} \psi_i Y_{(h-i)dmy}\}$$

Where π is the probability that 0 crimes occur during a given hour.

Additionally, we used a penalized lasso poisson regression regression to determine which covariates to include in Weather_{hdmy} and X_{hdmy}.

Lasso Poisson Regression Models[1]:

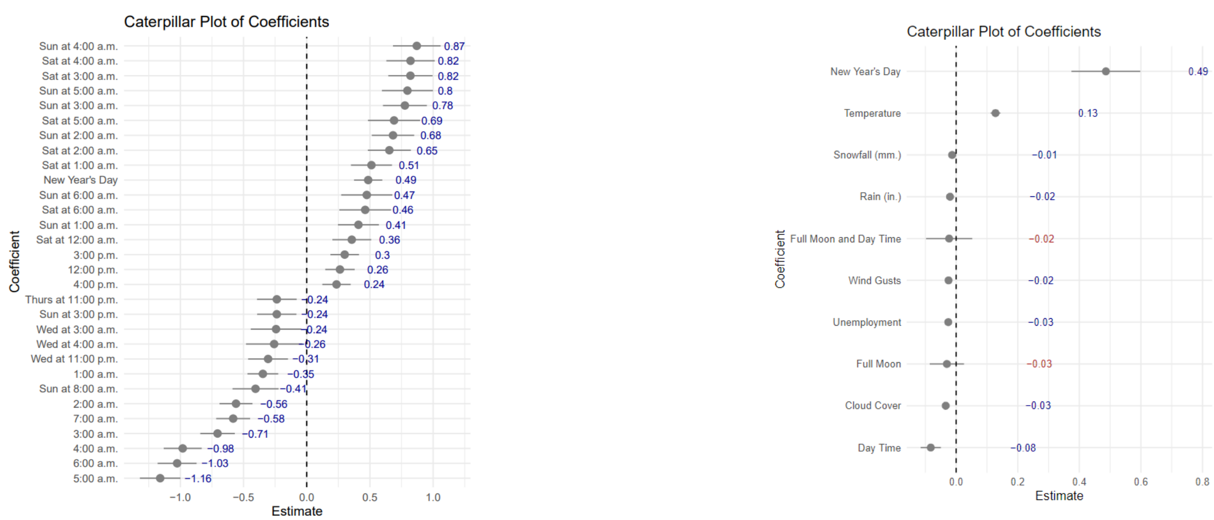
$$(3) \quad \underset{b_0, b}{argmin} \sum_{t=1}^{n} \left(y_{tdmy} - exp\{b_0 + \text{Weather}'_{tdmy} b\}\right)^2 + \alpha([1, ..., 1]'|b|)$$

$$(4) \quad \underset{b_0, b}{argmin} \sum_{t=1}^{n} \left(y_{tdmy} - exp\{b_0 + X'_{tdmy} b\}\right)^2 + \lambda([1, ..., 1]'|b|)$$

Using K-fold CV ($k = 10$), we used $\alpha = 0.0003305944$, and $\lambda = 0.0009574824$. With these hyper parameters, we used the lasso model to find the most important factors to yield a more parsimonious model. Based on the results of the lasso models, we ended omitting `Apparent Temperature`, `Wind Speed`, and `Direct Solar Radiation` out of the weather covariates. In the X covariate matrix, we also omitted the `Columbus Day` dummy variable (we have included indicators for every federal holiday).

Having these variables excluded from model (2), we estimated the parameters using maximum likelihood estimation (MLE).

The ZIP model achieved an in-sample MSE of `0.7667242`, and remarkably, an out of sample MSE of `0.7597959`[2]. Here are the summary plots of the estimated coefficients[3]:



(a) Coefficients with Largest Magnitudes

(b) Coefficients Omitting Time Fixed Effects

Figure 1: Estimated Parameter Coefficients of ZIP Model

As foretold by our EDA, temperature is strongly correlated with the positive propensity to commit violent crimes in Chicago. Interestingly, the most significant (non-fixed effect) is `New Year's Day`. This is the holiday where the most violent crimes are committed. Interestingly enough, the

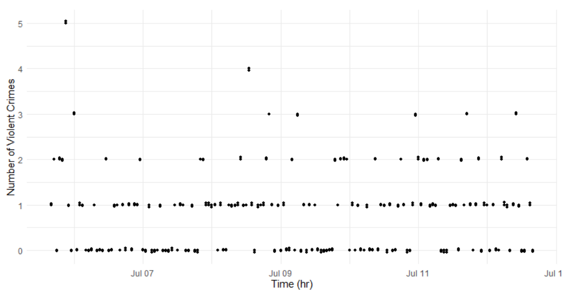
[1] Perhaps a bit of notational inconsistency here, but t represents an individual observation in the data set here, which is equivalently a single observed hour (h) in a given day.

[2] This was based on a random test sample of 20% of the original data. Note: Only in-sample and out-of-sample MSE validation was performed. These are the MSE statistics from that test.

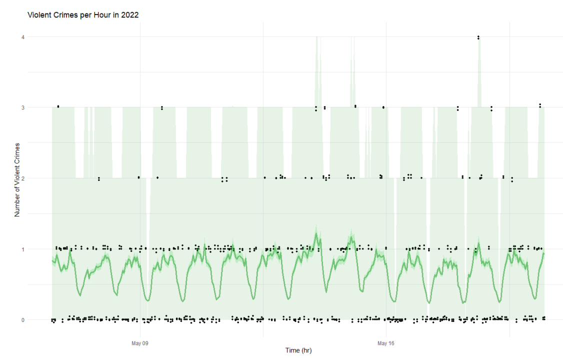
[3] The numerical coefficients were all standardized for relative interpretability.

estimated coefficient for unemployment is significantly negative, implying that when the unemployment rate in Chicago is low, the number of violent crimes decrease in District 11[4].

While visually showing how well the model predicts on all hours may be hard to show in a single plot, we selected a random sample (two weeks) to overlay both the predicted mean of violent crimes and a bootstrap predicted sample of the actual number of violent crimes (shaded in green) to simulate a 95% confidence interval.



(a) The hourly distribution of violent crimes is (zero-inflated) Poisson-distributed



(b) Random sample overlaid with predicted mean and predicted bootstrapped 95% confidence interval

Figure 2: Visual predictive performance of ZIP model

This model explains the effects of the factors included in the model quite well, although the prediction is quite noisy. To achieve better prediction of violent crimes, we explore more flexible machine learning models.

Predictive Models

We experimented with a variety of machine learning models to identify the best approach for predicting violent crime counts. These models included:

- Random Forest Regression: This ensemble method builds multiple decision trees and aggregates their predictions for improved accuracy.
- Decision Tree Regression: This model splits the data based on features to create a tree-like structure for prediction.
- Gradient Boosting Regression: This technique iteratively builds decision trees, focusing on improving predictions for previously poorly classified examples.
- K-Nearest Neighbors (KNN) Regression: This method predicts values by averaging the values of the k nearest neighbors in the training data.

[4]There may be several explanations as to why this is. (1) The economic literature actually supports this. Although property crimes typically increase when unemployment increase, only weak effects have been linked to unemployment and violent crimes. (2) This coefficient doesn't take into account how violent crime changes in the nearby district. The assumption we are making here is that the unemployment rate in District 11 is proportional to the unemployment rate in Chicago.

For this stage of the predictive modeling process, based on the feedback from the case study competition judges, we decided to aggregate the response variable by day. Hence, the evaluation metrics in the prediction models and the generalized linear models are not comparable.

Predictive Performance of Each Model

KNN

```
knn_reg = KNeighborsRegressor(n_neighbors=20)
knn_reg.fit(X_train_scaled, y_train)
```

- Mean Absolute Error: 3.495668789808917
- Mean Squared Error: 18.586433121019112
- Root Mean Squared Error: 4.311198571281438
- R-squared: 0.018065556289428297

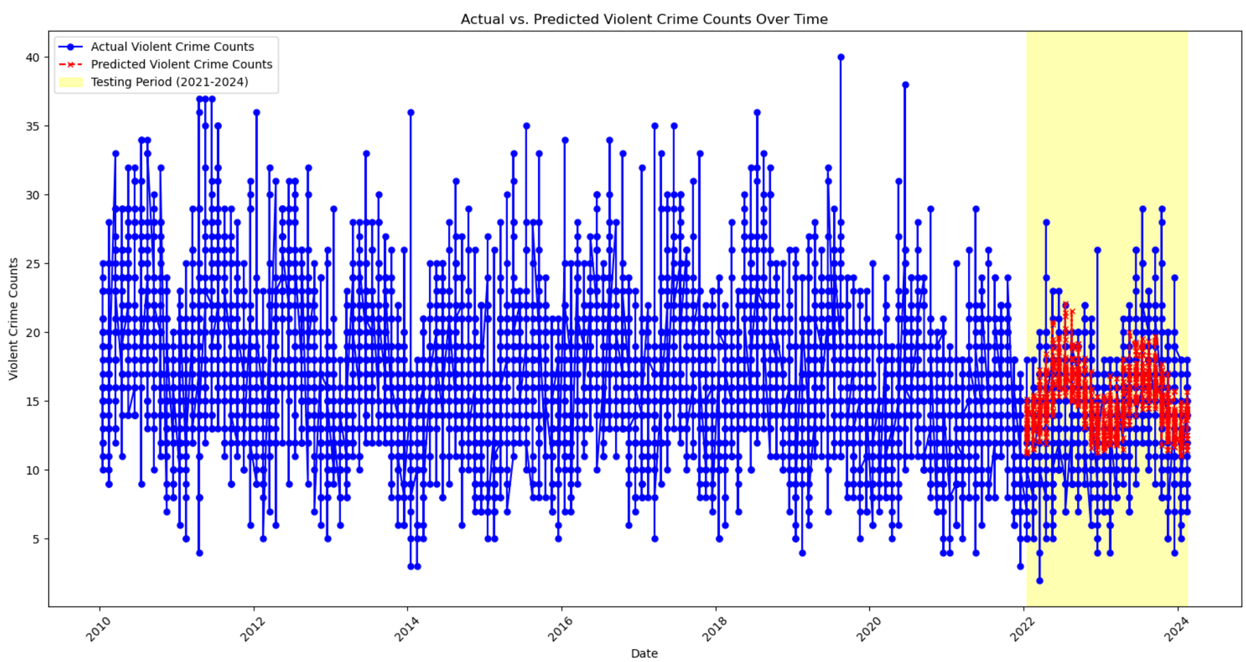


Figure 3: Image Description

Random Forest

- Mean Absolute Error: 3.254050955414013
- Mean Squared Error: 16.357082547770705
- Root Mean Squared Error: 4.044389020330599
- R-squared: 0.1358437281809961

Gradient boosting

- Mean Absolute Error: 3.2315556864642456

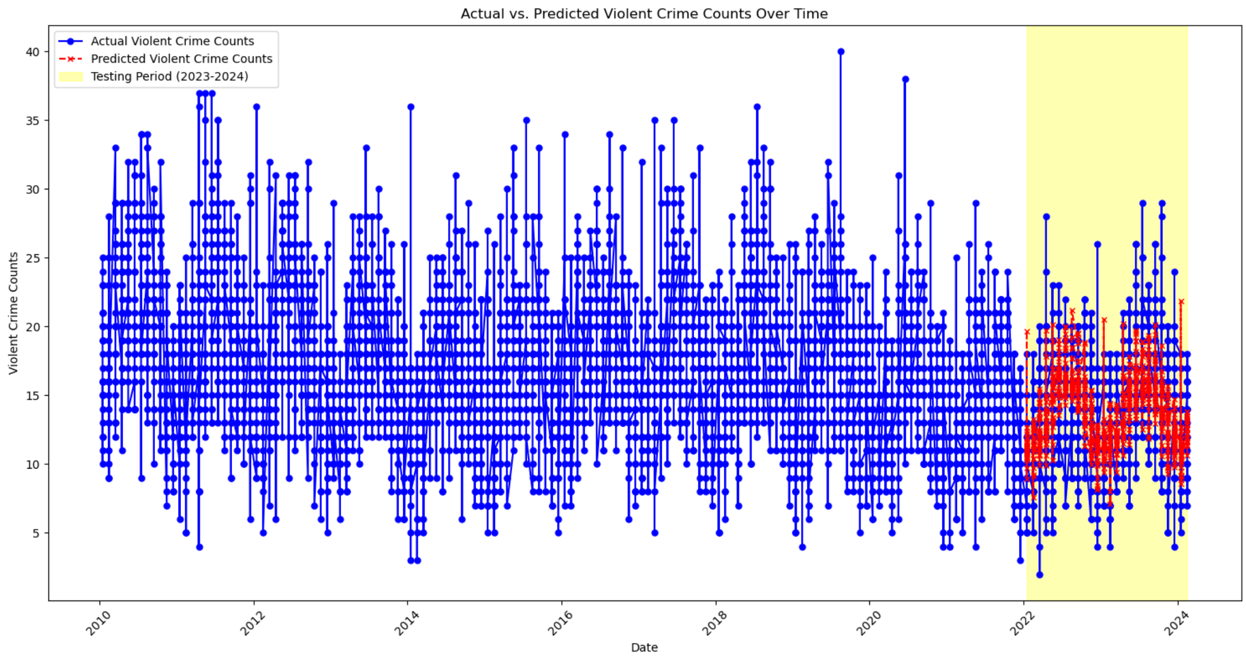


Figure 4: Image Description

- Mean Squared Error: 16.022146503614472
- Root Mean Squared Error: 4.002767355669634
- R-squared: 0.15353863693813885

Significant and Innovative Feature Engineering

Since we noticed that that time was an important factor, To capture seasonality more effectively for machine learning models, we introduced cyclical features for month and day

```
data['Month_Sin'] = np.sin(2 * np.pi * data['Month']/12)
data['Month_Cos'] = np.cos(2 * np.pi * data['Month']/12)
data['Day_Sin'] = np.sin(2 * np.pi * data['Day']/data['Date'].dt.days_in_month)
data['Day_Cos'] = np.cos(2 * np.pi * data['Day']/data['Date'].dt.days_in_month)
```

This feature engineering captures temporal patterns in a way that is more suitable for machine learning models, such as for random forest models. By encoding months and days as cyclical features, the model can understand their cyclic nature and learn patterns effectively, such as monthly or daily seasonality.

Variable Importance Using SHAP

As we mentioned, we used decision trees to understand the factors that impact the frequency of violent crime.

```
rf_model = RandomForestRegressor(n_estimators=20, random_state=42)

# Fit the model
rf_model.fit(X, y)

# Get feature importances
feature_importances = rf_model.feature_importances_

# Map feature names to their respective importances
feature_importance_map = dict(zip(X.columns, feature_importances))

# Sort the features by importance
sorted_features = sorted(feature_importance_map.items(), key=lambda x: x[1],
  reverse=True)

# Extract top 25 features
top_features = sorted_features[:25]
```

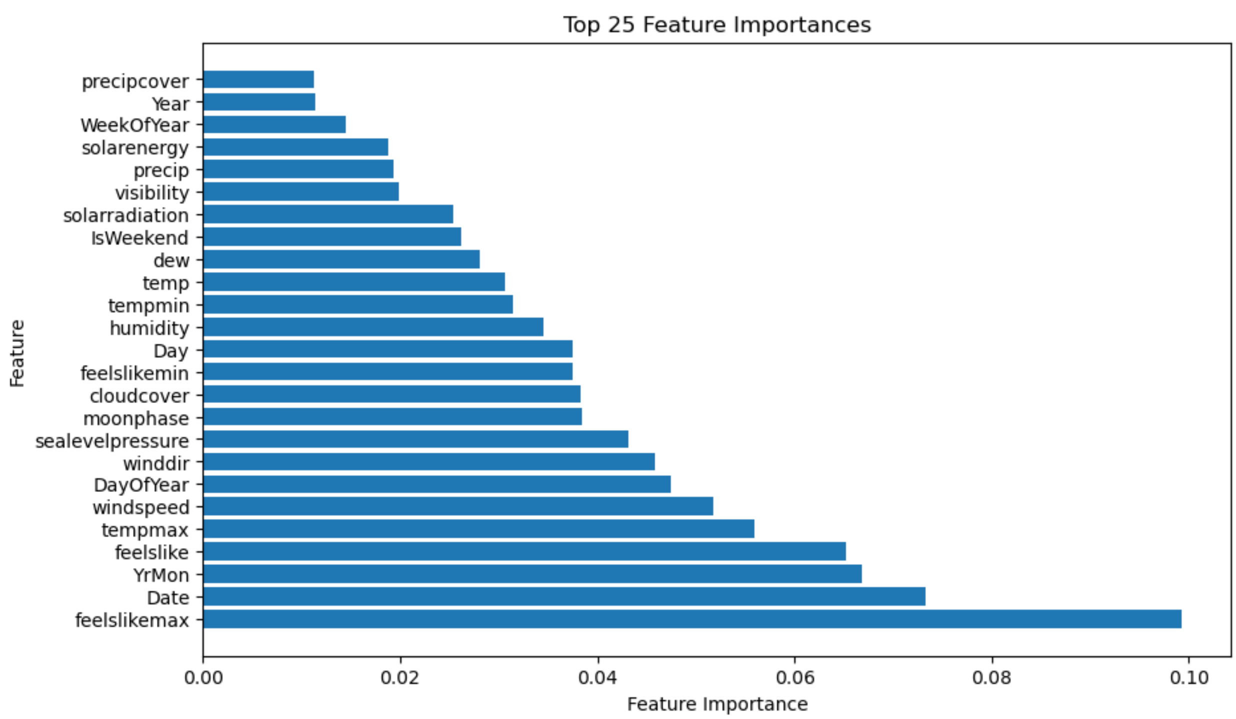


Figure 5: Image Description

To corroborate the effect that we saw from the generalized linear regression models, we used SHAP as well to understand the impact of the features on our model predictions. We anticipated that temperature would be an important factor just as we saw previously.

```
#Fitting the model
rf = RandomForestRegressor(n_estimators=200, random_state=42)
rf.fit(X_train, y_train)

#Getting SHAP values and plotting them
explainer = shap.Explainer(rf, X_train)
shap_values = explainer.shap_values(X_test[:100])
shap.summary_plot(shap_values, features=X_test[:100], feature_names=X_train.columns)
```

In summary, in accordance with the SHAP values analysis, it seems that the model seems to be influenced significantly by perceived temperature (`feelslike`) and actual temperature measures, with time-related features also playing a key role. Lower on the importance scale are some other weather-related features and atmospheric conditions.

Cluster Analysis and Anomaly Detection

We wanted to apply cluster analysis to understand patterns or groups in how these factors correlated with crime rates.

```
#Starting clustering analysis
kmeans = KMeans(n_clusters=3, n_init='auto')
kmeans.fit(X)
y_kmeans = kmeans.predict(X)

hc = AgglomerativeClustering(distance_threshold=None, n_clusters=3)
hc.fit(X)
linkage_methods = ['single', 'complete', 'average', 'ward']

# Plotting
plt.figure(figsize=(12, 8))
for i, method in enumerate(linkage_methods, 1):
    plt.subplot(2, 2, i)
    Z = linkage(X, method=method)
    dendrogram(Z)
    plt.title(f'Dendrogram ({method.capitalize()} Linkage)')
    plt.xlabel('Samples')
    plt.ylabel('Distance')

plt.tight_layout()
```

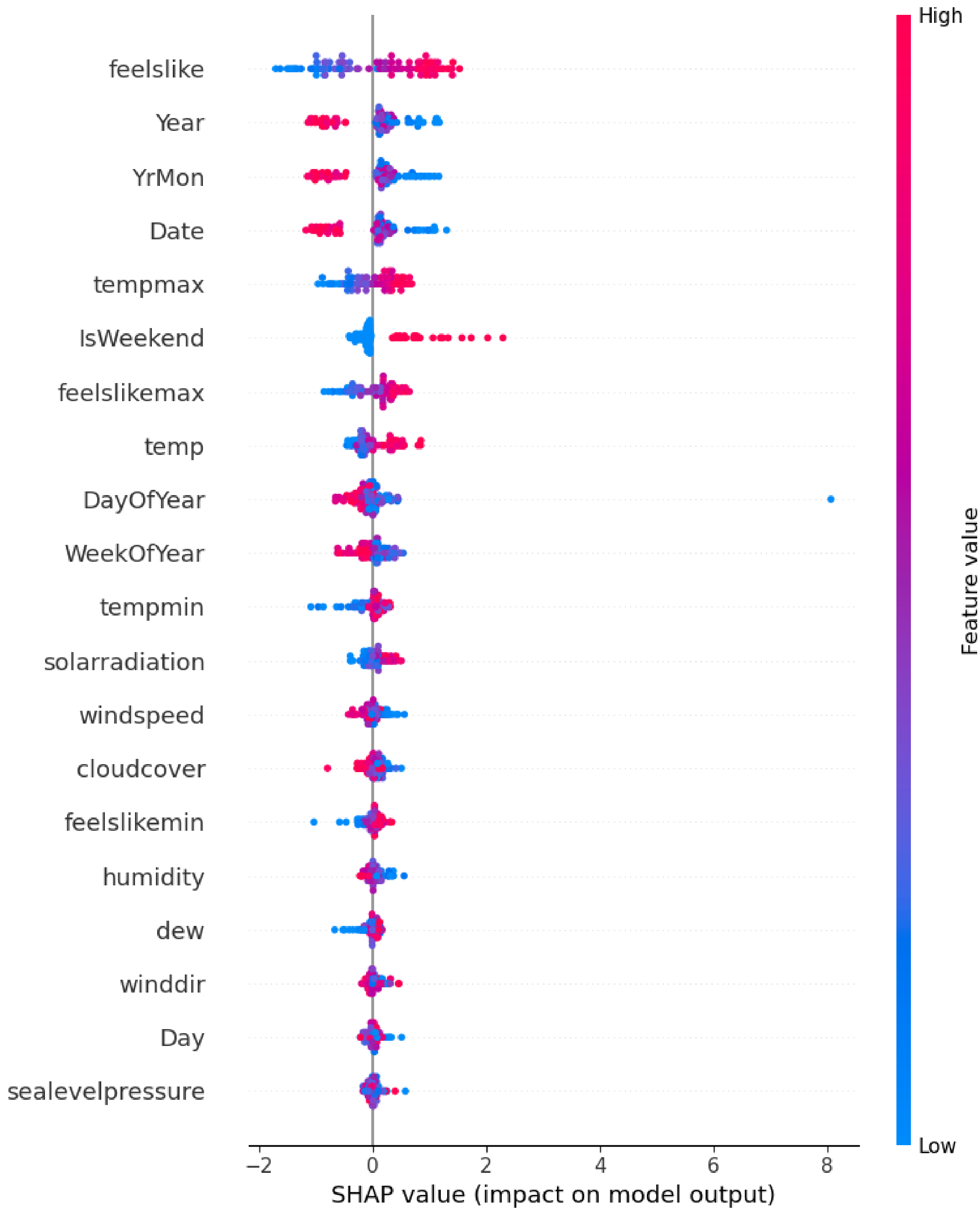


Figure 6: Image Description

```
plt.show()
```

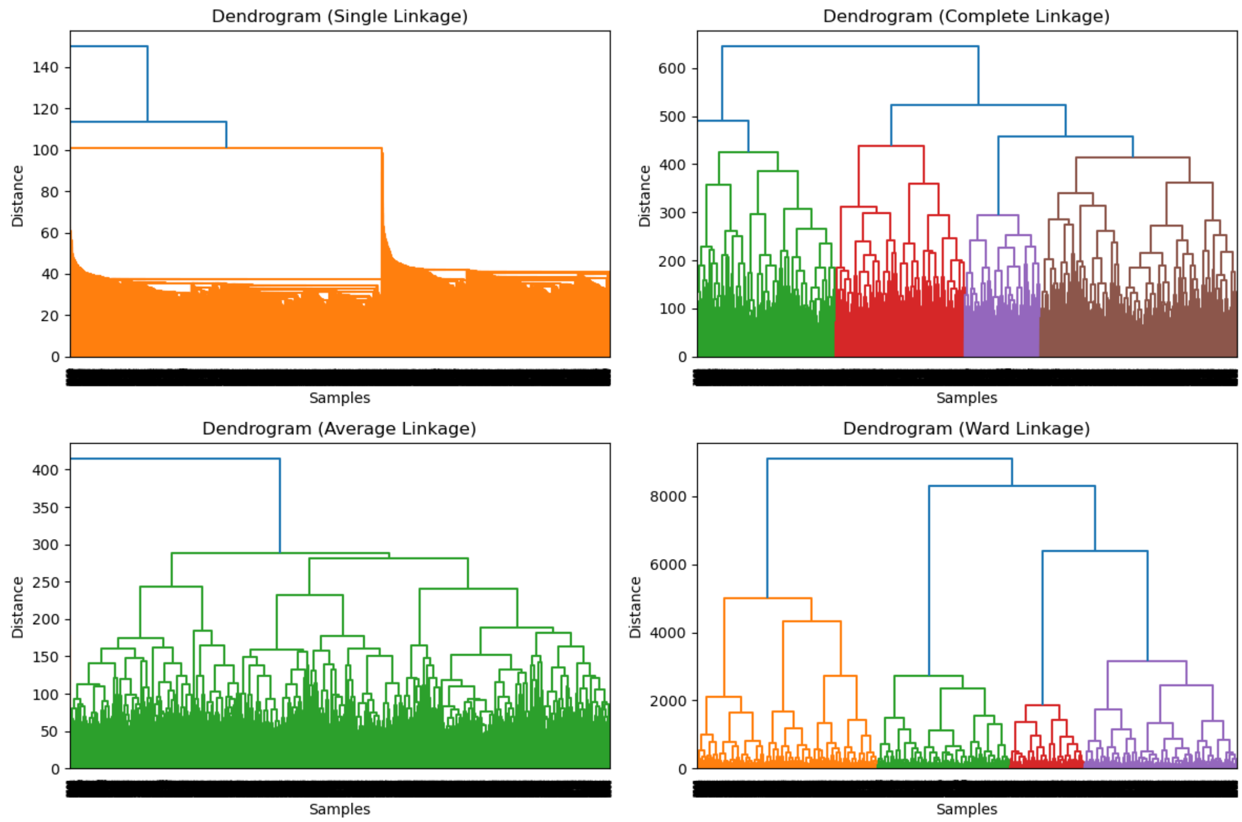


Figure 7: Image Description

It seems that they're 3 main clusters in the data. This is confirmed with the "elbow method" technique, since it seems to be around 3 or 4 where the rate of decrease in WCSS slows down significantly.

```
# Calculating WCSS by K number of clusters for plot
kmeans_per_k = [KMeans(n_clusters=k, n_init='auto', random_state=42).fit(X)
                for k in range(1, 10)]
inertias = [model.inertia_ for model in kmeans_per_k]


#Plotting WCSS by number of clusters
plt.figure(figsize=(10,4))
plt.plot(np.arange(len(inertias))+1,inertias,marker="o")
plt.xlabel('Number of Clusters, K')
plt.ylabel('WCSS')
```

After defining the number of clusters, we can start analyzing the major factors with these 3 clusters.

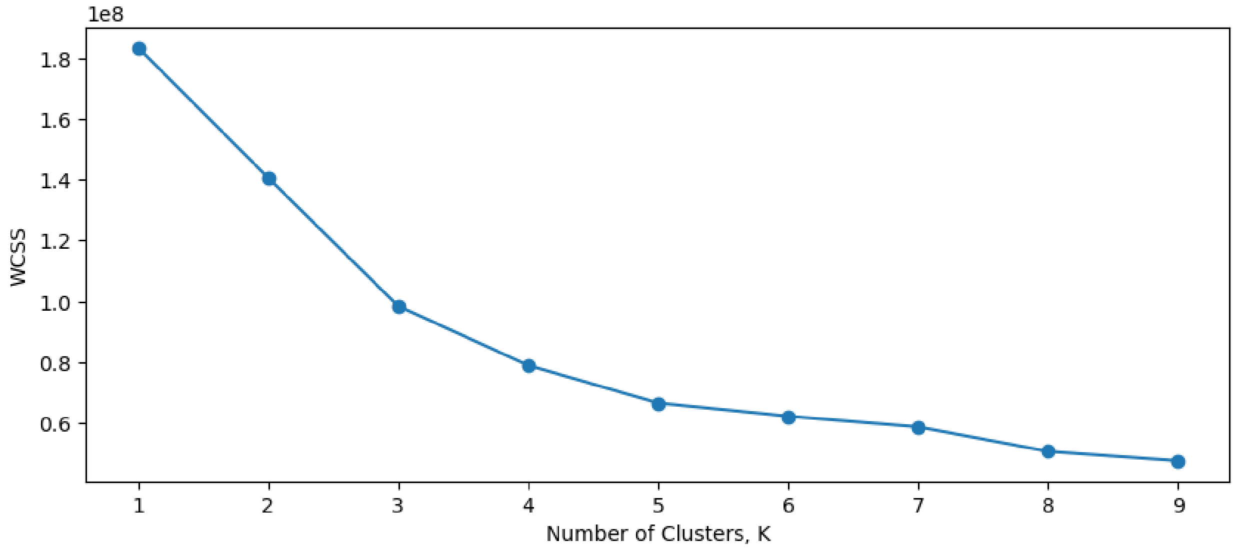


Figure 8: Image Description

```
#Selecting factors to see
plot_df = pd.DataFrame(X[['feelslike', 'Year', 'YrMon', 'Date', 'tempmax',
  'IsWeekend', 'feelslikemax', 'temp', 'DayOfYear', 'WeekOfYear']])

#Plotting
plot_df['clusters'] = y_kmeansf Clusters, K')
plt.ylabel('WCSS')
sns.pairplot(plot_df, hue='clusters', palette='Dark2')
```

From our clustering analysis, we learn about the feature relationships, distribution, and seasonality.

Conclusion

Our investigation into the factors influencing violent crime rates in Chicago's District 11 from 2010 to 2024 employed various machine learning models. Experimentation with generalized linear regression models, Random Forest Regression, Decision Tree Regression, and K-Nearest Neighbors Regression revealed that Random Forest Regression yielded the most accurate predictions for violent crime counts.

The incorporation of cyclical features for month and day significantly enhanced the model's ability to capture seasonal patterns that might be linked to weather or other external factors. Examining feature importance through Random Forest analysis validated our initial hypothesis regarding the significant influence of temperature (both perceived and actual) on crime rates. Time-based features were also identified as impactful.

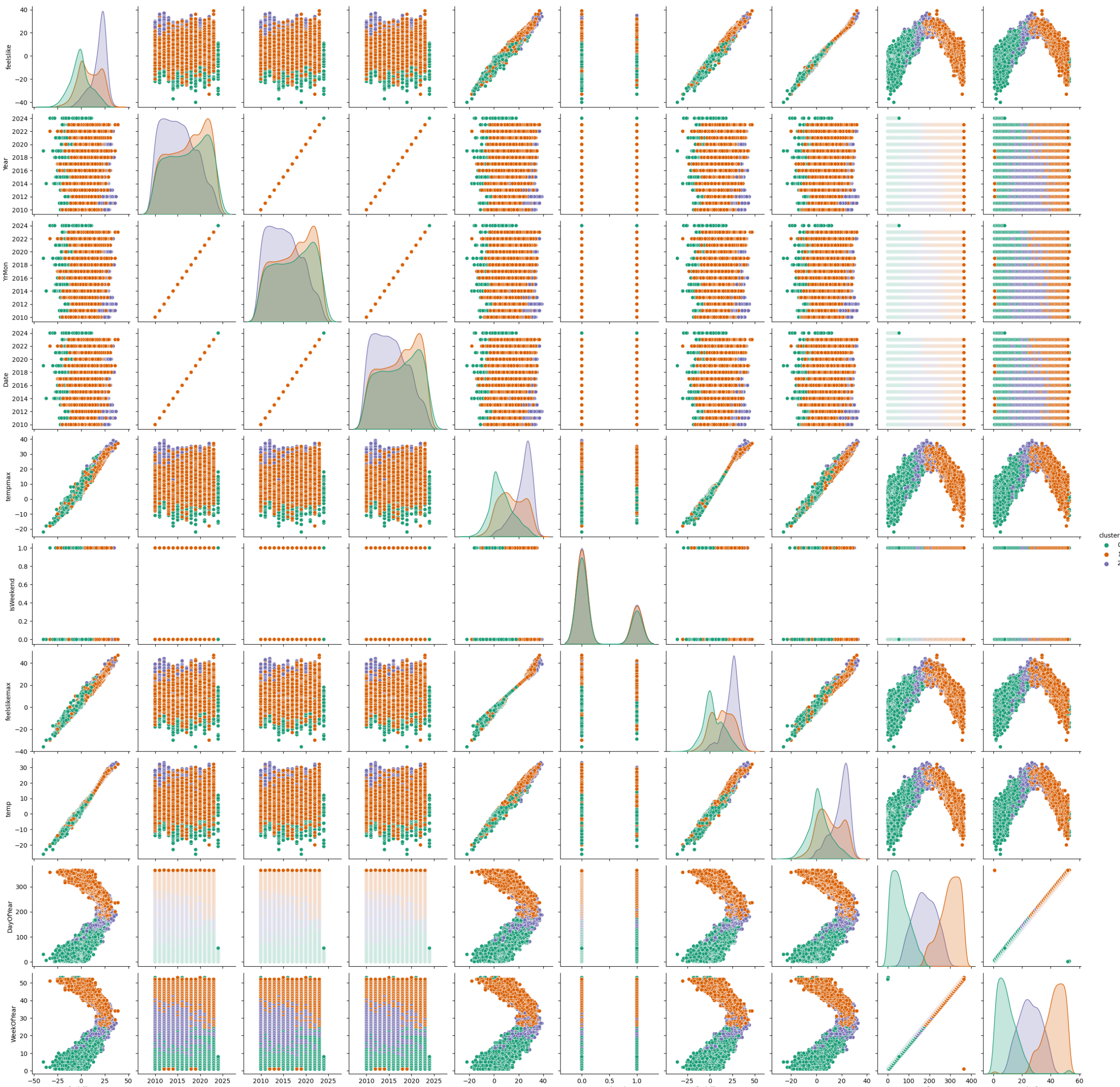


Figure 9: Image Description

Cluster analysis provided further insights, revealing three distinct data clusters that potentially represent unique underlying dynamics influencing crime rates. Pair plots across these clusters suggested variations in feature distribution and seasonality.

Future Exploration

While this study offers valuable insights, opportunities for further exploration exist:

- Model Exploration: Our focus was on common regression models. Investigating more advanced techniques, such as deep learning or geospatial analysis, could potentially improve prediction accuracy and uncover more intricate relationships within the data.
- Feature Engineering: Investigating additional features, such as further social or economic indicators, could provide a more comprehensive understanding of the factors influencing crime rates.
- Random Forest Model Optimization: Hyper parameter optimization within the chosen Random Forest model could potentially enhance its performance.
- Predictive Policing Applications: While this study focused on understanding the factors influencing crime, the insights gained could be used to develop a framework for predictive policing applications. However, careful consideration would need to be given to ethical considerations and potential biases within the data.

By pursuing these areas, we can gain a deeper understanding of the complexities surrounding violent crime and develop more effective prevention strategies.