Chicago Crime Rates Prediction

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May 31, 2022

Abstract

TODO

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1 Introduction

Crime has always been a major problem in small and big cities around the world. Throughout the years, society has been trying to reduce the number of unlawful acts committed by people. By establishing new rules and punishments for those who do not obey the law, people have found a way to reduce the crime rate. Nations have evolved their legal systems during thousands of years of trial and error, but that still does not stop citizens from commiting a crime.

There are many reasons why people still tend to participate in unlawful activities. Whether it be because of poor living conditions, psychological disorders or other, the world is always going to be a witness of crimes, no matter how scary the consecuenses of committing them are. For this reason the safety of each city is handed over to the police departments.

Police departments are another tool for lowering the amount of crimes. They operate by answering to people's calls for help and by patrolling around the city, split into designated areas. Sometimes, however, there are not enough patroling cars in the area to react quickly to the amount of crimes happening at the same time.

2 Research Question

By collecting data from one of the U.S's largest cities - Chicago, where the murder rate has remained persistently high troughout the years[3], this reasearch is going to use a data-driven approach to examine if:

- Crime is influenced by the date and time;

- Crime is influenced by the districts.

Using the analysis the reasearch is going to try to answer the question:

- Can crime rate be predicted based on the date, time and disctrict?

3 Methods

This research objectives necessitate a multi-methodological approach that integrates theory building, systems development, observation and experimentation, as described by Nunamaker et al[5]. Rather than a linear research method, this approach can be considered an agile research model, due to the continuous going back and forth between theory building, systems development, observation, and experimentaion.

3.1 Theory building

Starting with the dataset[1], the research is going to begin with data exploration, in order to see how the data looks like. Viewing the different features the dataset has and the missing values, it will help to formulate a theory that will need to be proven. After removing or extrapolating the missing values, different parts of the data can be plotted in order to gain more insight into how the data is looking.

3.2 System development

Next part is the System development, which involes createing new features to the dataset (feature engineering), converting the one type of data to another (for example date and time to UNIX timestamp). After that models are selected for experimantation with the newly build data.

3.3 Observation

The Observation happens after each model is trained. By examining the result a decision needs to be made to choose which model performs the best in the given conditions with the given parameters.

3.4 Experimentation

After observation the research is continued by making small adjustments to the model parameters and the dataset in order to see what changes will take place and how will they influence the results.

4 Analysis

4.1 Data Cleanup and data exploration

With the process described in section 3.1 the research started by analyzing the content of the
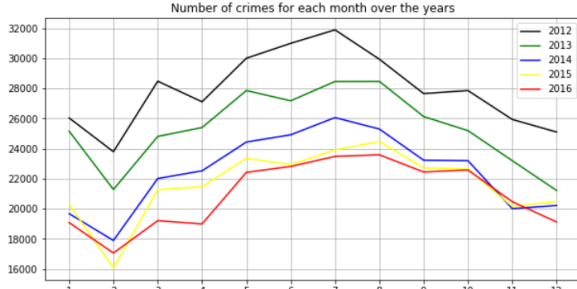
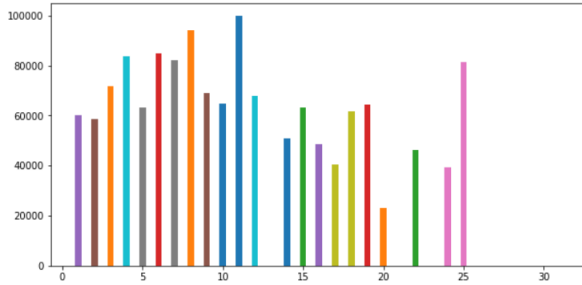Figure 1: Number of Crimes throughout the years

Figure 2: Number of crimes for each district

dataset. Non-relevant rows were dropped in order to gain more focus on data related to place and time. There are some specific days during which the crime rate is significantly higher, which mostly corresponds to most popular national holidays. During the day, the crime rate in Chicago is lower and the number of the most dangerous crime types tend to increase during the night. As can be seen in Figure 1, there is a specific pattern for each year for how the number of crimes changes every month. The number of crimes is decreasing every year.

The city is divided into 22 police districts, the value which was decided to be taken as parameter for the location of the crime. After the graphical representation of the number of crimes in each district in Figure 2 it is possible to identify that there are districts with a higher number of crimes. It still doesn't mean that a specific district got a higher level of alarm as each district is of a different size with different number of population. test

4.2 Time Series Analysis

For the the timeseries analysis and forecasting some aditional cleanup steps were implemented. The date and time was converted to a UNIX timestamp. Each timestamp represents an hour of the day for the specific day. By counting the number of crimes for each hour in a specific district, a new feature is created holding the count of crimes(Section 3.2).

One can see the daily and weekly crime count for the peak months of Spring and Summer 2015 in Figure 3 of Appendix A.2. It is noticeable that there are outliers on the first day of each month. It is uncertain if that is a systematic error, or an actual occurence so this poses an interesting problem. By choosing a weekly forecasting period, the outlier values of the first day were spread over the whole first week of the month (Figure 4 of Appendix A.3).

4.3 Splitting the set in training, validation and testing sets

In order to train the models, tune their hyperparameters and test the result on unseen datathe dataset is split and cleaned in 3 sub sets. The data is split in chronological order, where the training set is chronologically first, the validation set comes next and the test data is the last. The reason for this is that this research is trying to get answers about unknown future values – extrapolation. So the aim is to train and evaluate the models in a chronological order, by learning on previous data and forecasting future uknown data. For the timeseries ARIMA model, the data is split in 75% train/validation and 25% test data, and further split the train/validation in 75% train and 25% validation. For the rest of the machine learning models, the split is 60% training, 20% validation and 20% testing.

Timeseries Dataset:	
Size of Training set	: (147)
Size of Validation set	: (49)
Size of Test set	: (65)
Machine Learning Dataset :	
Size of Training set X	: (24147, 2)
Size of Training set Y	: (24147,)
Size of Validation set X	: (8049, 2)
Size of Validation set Y	: (8049,)
Size of Testing set X	: (8049, 2)
Size of Testing set Y	: (8049,)

4.4 Implementation and Parameter tuning for ARIMA

Following the methods in Section 3.2 the choice to include a classical forecasting model for timeseries seems natural, as these models are known in may cases to perform better and needing less data, as observed by Parmezanet al. [7] The Autoregressive Integrated Moving Average (ARIMA) model is a good fit for this purpose due to the observed trend in the dataset A.3. The ARIMA model is a common choice for this type of datasets, as seen in similar works - Al Balamesh et al and Eymen et al. [6] [2] The ARIMA model is expecting monodimentional periodic series of data with a trend and three hyperparameters. The hyperparameters are initialising the three different aspects of the model, p for autoregression, d integration and q for the moving average. The Grid Search method was used, as described by LaValle et al, [4] and executed walk-forward train/validation steps for each combination of the selected hyperparameter values. The Mean Square Error was used in order to evaluate and compare the predictions of each hyperparameter set (Section 3.3).

4.5 Implementation and Parameter Tuning for Decision Tree Classifier

Further in the analysis it was found that the existing data is very clustered, as can be seen in Figure 3
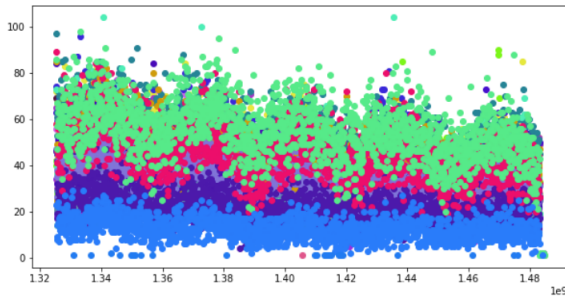

Figure 3: All crimes for each Disctict during the years 2012-2016

This type of data would indicate that using a regression model to predict the amount of crimes

would not be a good fit. For this reason a classifier model would be a better fit for this dataset In order to create and use a Decision Tree Classifier a new feature needed to be created for the dataset which would classify the amount of crimes for each day into 3 groups:

1. **Low Crime Rate - 0**

2. **Medium Crime Rate - 1**

3. **High Crime Rate - 2**

By observing the dataset it was found that the median value for the amount of crimes is 35 which will be the border between the **Low Crime Rate** and **Medium Crime Rate**. The next partition will be at 50. Every crime rate that is above 35 and below 50 will be classified as **Medium Crime Rate**. Everything above 50 and below 104(the maximum amount of crimes recorder) is classified as **High Crime Rate**.

Using the methods in Section 4.3 the new train, test and validation sets were created in order do train a Decision Tree Classifier. An exhaustive search over specified parameter values for the decision tree was implemented in order to tune the model to the best performance. The hyperparameters used for the search were:

1. **Maximum Depth - 2, 3, 5, 10, 20**

2. **Minimun Samples per leaf - 5, 10, 20, 50, 100**

3. **Criterion - gini, entropy**

This way the model will be tested with each of the parameters provided and increase the accuracy of the predictions.

5 Findings

The results of the Grid Search method for selecting hyperparemeter values resulted to an ARIMA(4, 0, 0) with Mean Square Error of 136 179 for the train/validation sets and 84 182 for the test set. This means that according to this research a simple Auto Regressive model with a lag order of 4 is enough, as values of 0 for the Integration and Moving Average are disabling these last two models. In Figure 4 of Appendix A.1 the results of the tuned

model can be seen on the test data, and the actual observations.

The result from the decission tree classifier before the tuning was an accuracy of 64.02%. The following confusion matrix:

Predicted Rate	0	1	2
Actual Rate			
0	4610	651	45
1	1695	406	191
2	273	41	137

shows that the model guessed correctly moslty the crime rate classified as **Low**. Further analysis in the classification report shows:

	precision	recall	f1-score	support
0	0.70	0.87	0.78	5306
1	0.37	0.18	0.24	2292
2	0.37	0.30	0.33	451
accuracy			0.64	8049
macro avg	0.48	0.45	0.45	8049
weighted avg	0.59	0.60	0.60	8049

That The precision is not so high for the Medium and High Alarm which are more important for prediction.
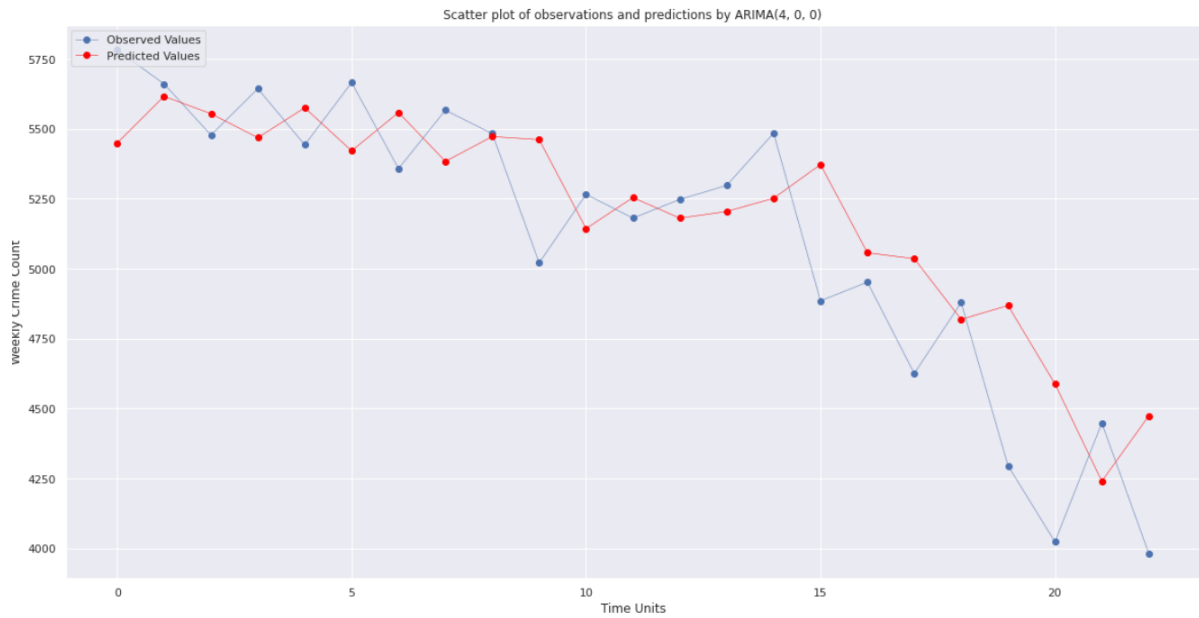
A Appendix

A.1 Figure 4 - ARIMA results

Figure 4: Spring and Summer Crime count

A.2 Figure 5 - Spring and Summer Crime count
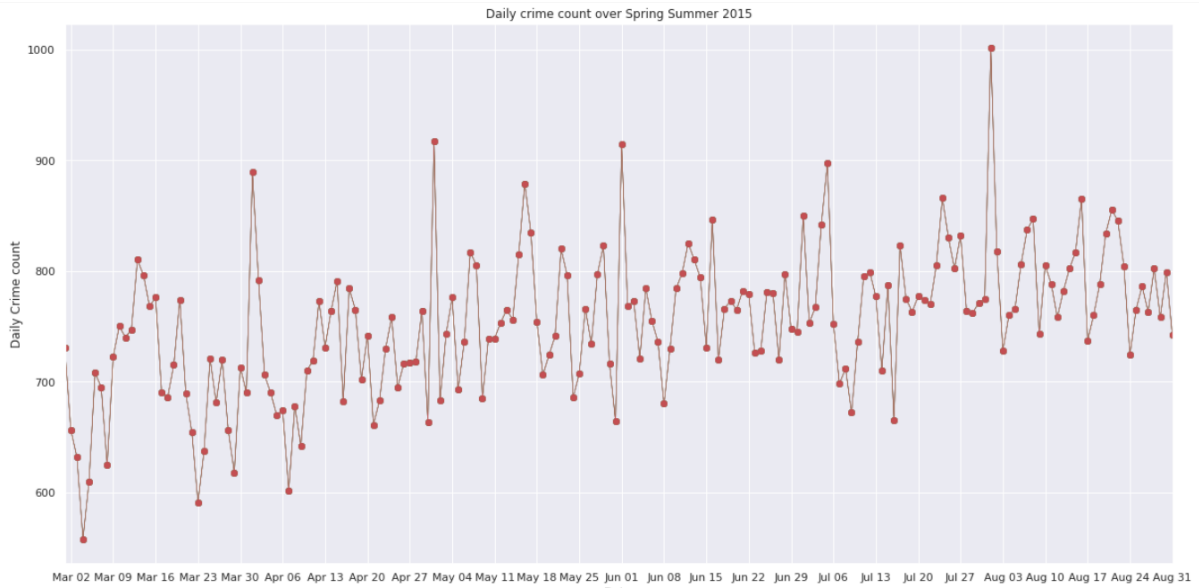
A.3 Figure 6 - Weekly Crime count

Figure 5: Spring and Summer Crime count

References

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[3] Matthew Friedman, Ames C Grawert, and James Cullen. *Crime Trends, 1990-2016.* Brennan Center for Justice at New York University School of Law New York, NY, 2017.

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[5] Jay F Nunamaker Jr, Minder Chen, and Titus DM Purdin. "Systems development in information systems research". In: *Journal of management information systems* 7.3 (1990), pp. 89–106.

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[7] Antonio Parmezan, Vinícius Alves de Souza, and Gustavo Batista. "Evaluation of statistical and machine learning models for time series prediction: Identifying the state-of-the-art and the best conditions for the use of each model". In: *Information Sciences* (Jan. 2019). DOI: 10.1016/j.ins.2019.01.076.
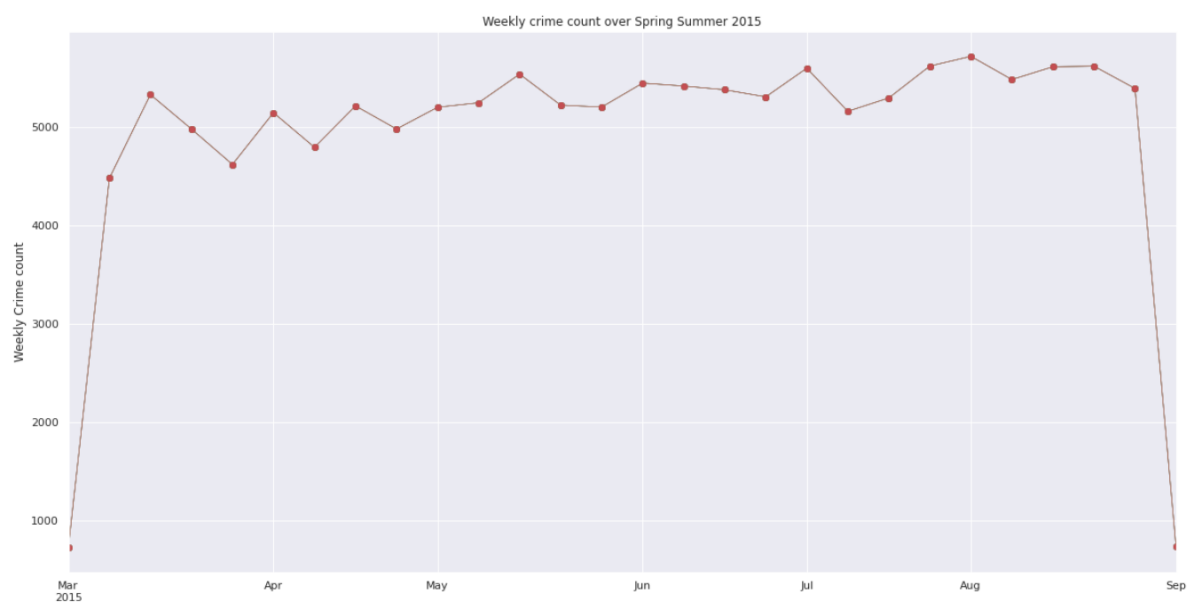
Figure 6: Weekly Crime count