CIS 635 Final Project Report

Crime Forecasting Using Long Short-Term Memory Network

Ian Mbaya & Irene Kibet

Abstract

Crimes have detrimental effects on the social and economic welfare of any society. Law enforcement officers are faced with numerous challenges in their efforts to curb crime. In this project, we propose a crime-predicting model that will assist in forecasting crime rates within the Portland Police District. We will employ different machine-learning models and data mining techniques for crime analysis and prediction to come up with a model that will predict the crime locations with the highest level of accuracy. The model's predictive capabilities are demonstrated by measuring its performance against the test data from previous years.

This project focuses on providing the law enforcement officers in the Portland Police District with proper crime forecasting to better delegate their resources in response to future crime hotspots. In a world where crime rates continue to soar with each passing day, it is crucial to implement computational crime prediction and forecasting that will help curb crime.

Introduction

Our project explores the application of Long Short-Term Memory (LSTM) networks in predicting crime hotspots, focusing on the spatiotemporal dynamics of crime occurrence. With the increasing availability of detailed crime data, including time, location, and type of crime, developing accurate prediction models offers crucial insights for crime prevention and resource allocation.

We propose an LSTM-based model that captures both temporal dependencies, learning from historical crime patterns, and spatial correlations, considering the geographical distribution of crime incidents. For this project, we utilized the crime dataset acquired from the National Institute of Justice which spans from the year March 2012 to December 2016. We chose three features for our analysis, the crime category, occurrence date, and the coordinates of the locations where the crimes occurred.

The main aims of this project were to:

- Develop an LSTM-based model for predicting crime hotspots with high accuracy. This will involve exploring different LSTM architectures and hyperparameter tuning to optimize the model's performance.
- Analyze the impact of various spatiotemporal features on the model's prediction accuracy. By identifying the most influential features, we can gain deeper insights into the factors driving crime patterns.
- Visualize the predicted crime hotspots to provide actionable insights for law enforcement agencies. This will involve developing interactive maps that present the predicted risk levels in different geographical areas.

The successful implementation of this project has the potential to significantly improve crime prevention strategies by allowing law enforcement to proactively allocate resources and implement targeted interventions in areas with high predicted crime risk. Furthermore, the extracted spatiotemporal insights can inform broader policy decisions aimed at addressing the root causes of crime and creating safer communities.

Related Work

In this section, we examine existing research that has been implemented through the application of several machine learning models and data mining to predict and forecast crime. A vast amount of work related to spatiotemporal forecasting has been carried out globally as a means of analyzing crime patterns to anticipate crime occurrences.

During our exploration, we encountered some notable studies related to crime prediction that we will explore in this section.

In 2017, Yong Zhuang and his team[1] at the University of Massachusets in Boston, used Spatio-Temporal Neural Network(STNN) to forecast hot spots by incorporating spatial information. The evaluation based on the Portland Police Bureau's call-for-service data, demonstrates the exceptional performance of the STNN model compared to the classical machine learning approaches and alternative neural network architectures applied in the past.

Another study was done by Umair Muneer et al. 2016[2] came up with a study to investigate crime forecasting in different cities. Their main focus was to examine the Hierarchical Density-based Spatial Clustering of Applications with Noise to detect high-risk zones based on spatial density and noise-aware clustering. Additionally, in each dense crime location, the Periodic Auto-Regressive Intergrated Moving. Outperforming existing methods, the model delivers superior accuracy across various timeframes, from individual years to the entire ten-year span.

The study done by Chung-Hsien and his team in 2011 [3] focused on enhancing the predictability of crime, which had been deemed unpredictable in the past by developing a crime forecasting model which was done in collaboration with the Northwestern Police Department. Their approach involved constructing datasets from original crime records by incorporating aggregated counts of crime events by the police department and extracting location and time information. An ensemble of data mining classification techniques was used to conduct crime forecasting. These classification methods were then analyzed to determine which best predicted the crime hotspots, which was then used to select the best classification model with the highest accuracy.

Method

We used data that is publicly available from the NIJ website. We downloaded the data and uploaded the data to our computers. We decided to conduct exploratory data analysis on our data that would help us gather insights and patterns within the data.

After data analysis and exploration, we opted to use the LSTM model. We selected this model because it is optimized for learning patterns in sequence data and exploring long-term dependencies. The architecture of our data was influenced by the data we had at hand and our expected results. We opted to use Python's open-source library Keras. Since we were only interested in finding the predicted crime locations for the next 14 days we only decided to include the data and location coordinates for computation efficiency. Our outputs from the model were coordinates for the most likely crime locations.

Results and Discussion

Exploratory Analysis Results

Our exploratory Data Analysis yielded some important patterns and insight that could help improve crime detection and prevention in Portland City. The first insight was that crime rates had a cyclical pattern throughout the year, with the summer months of May, June, & July seeing the largest number of crime reports. The winter months of November, December, January, and February saw the lowest crime reports. It is also notable that the number of crimes reported increased significantly from 2013 to 2014, to 2015. We also noticed that the number of Crimes reported on Friday and Saturday was slightly above other days of the week.

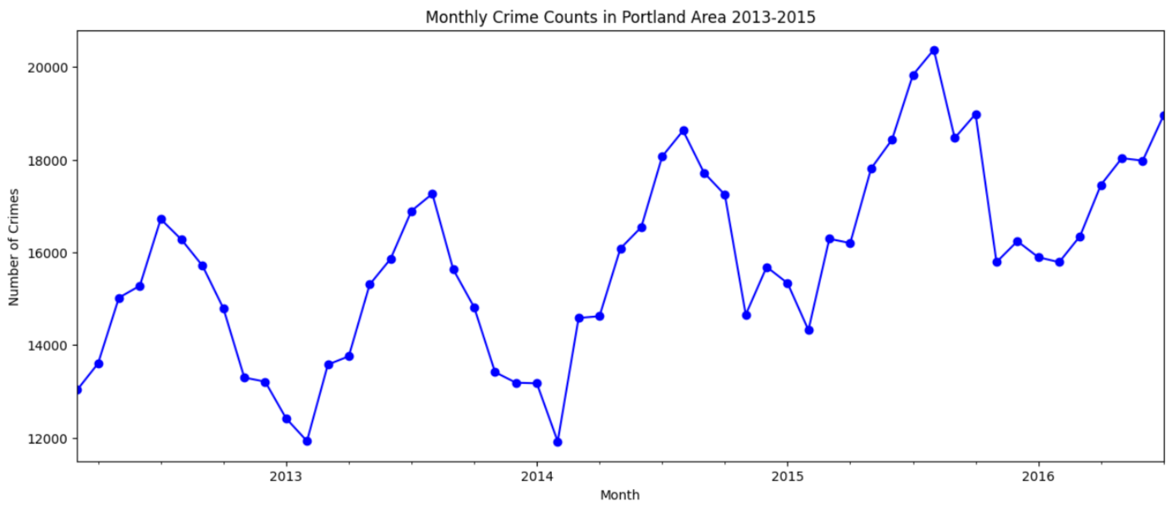
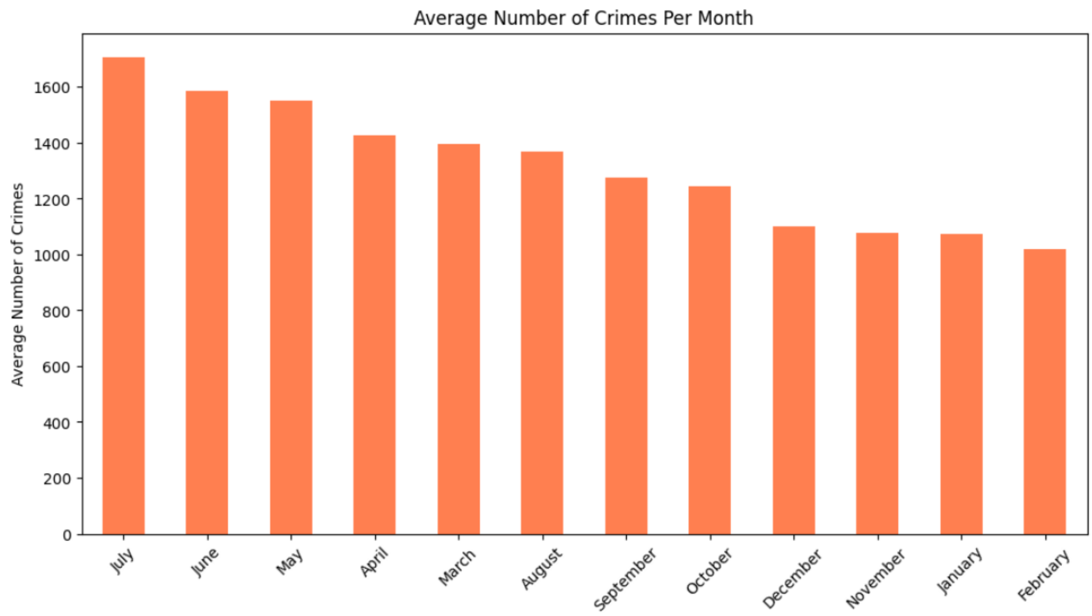


Figure 1: Line chart of the Historical crime reported between June 2012, to July 2016. *Notice the increasing peaks for 2013, 2014, and 2015.*



Our exploratory analysis also showed us the Police district with the highest number of crimes reported. Districts around the Northeast and central-midwest of the city saw the highest rates of reported crimes. Police Districts 941, 810, and 842 reported the highest number of crimes.

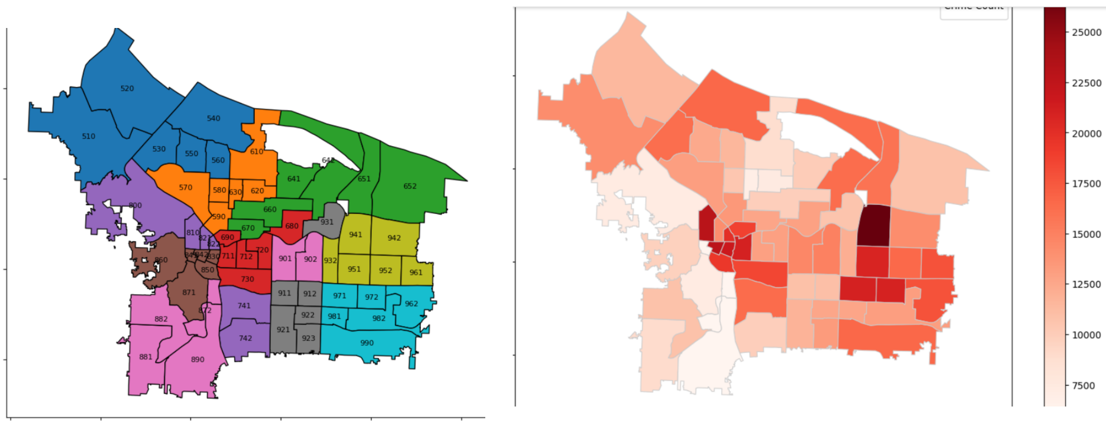


Figure 2: Left: map of Portland with color-coded police districts and numbers. Right: density map of reported crimes grouped by districts.

LSTM Prediction Results

The results from our LSTM model predictions gave as a mean squared error of 8,678 for our best-performing iteration. This was not a good performance but upon looking at the predicted locations we learned what needed to be fixed with our model. The model seemed to be biased towards locations with the highest numbers of reported crimes.

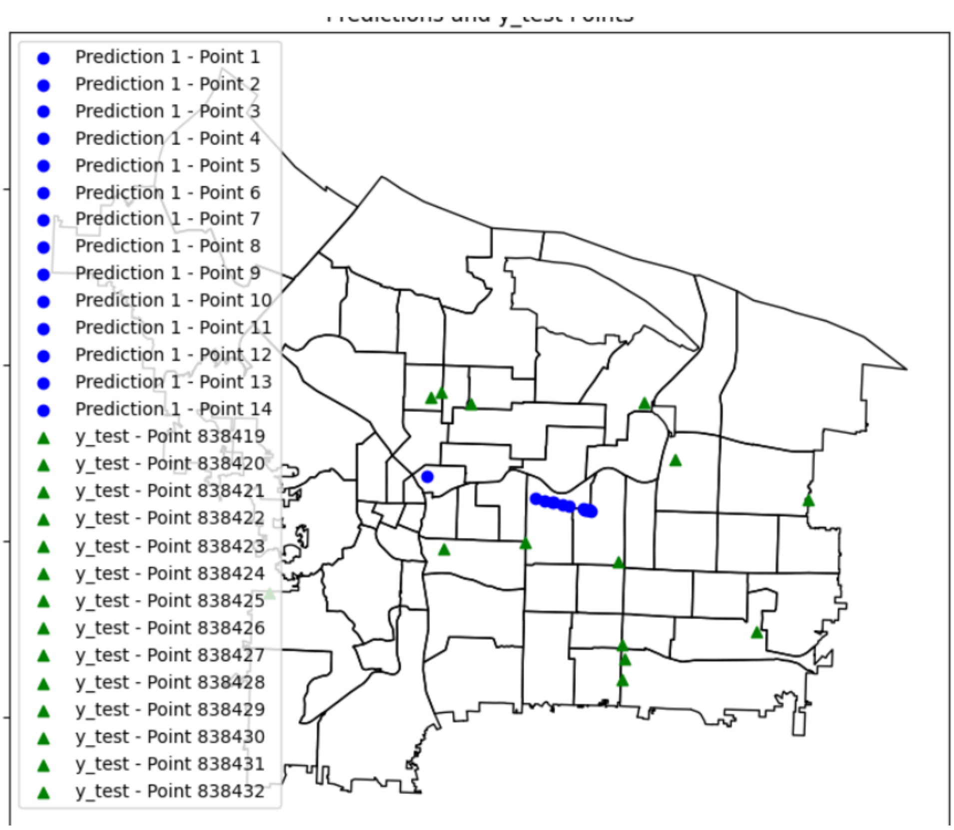


Figure 3: Map of Portland with predicted crimes in blue and actual reported crimes in blue. *Note the actual crimes are spread out while the predictions are concentrated in the middle.*

Our thoughts on how to rectify this problem with the model was to make predictions for each district instead of predicting for the whole city together. Predicting for each district would prevent the model from being biased in predicting locations with a high density of crime reports.

Grid View

Our initial plan for our model was to use 600 sq ft to represent the entire space. And then use those grids to make predictions. However, this plan was abandoned due to a lack of agreement on the way forward and the lack of sufficient computing power to make predictions for each grid.

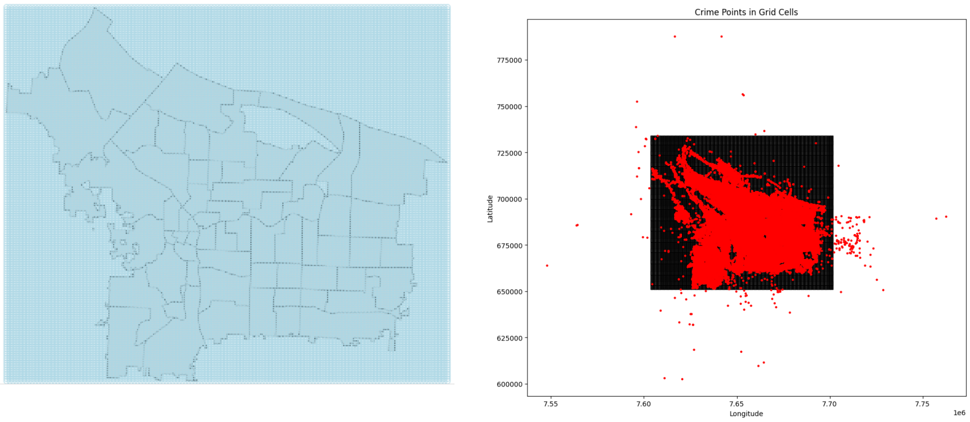


Figure 4: Left: A grid view of the map of Portland with districts overlaid. Right:Left: A grid view of the map of Portland with crimes plotted.

Conclusion

Overall, the project helped us to discover some interesting patterns hidden within the data like cyclical patterns and crime report density. While our prediction did not output the intended results it helped us learn how to implement models like LSTM in real-life cases. The primary suggestion for this project is to attempt to fine-tune it to make better predictions, perhaps by making predictions based on district crime reports rather than the entire dataset. Further projects could also explore the use of other models like CNN to solve this challenge.

Data and Software Availability

The data used in this project was derived from the official website of the National Institute of Justice (NIJ), it is a call-for-service data provided by the Portland,

Oregon Police Bureau (PPB) for 5 years from March 2012 through the end of December 2016.
https://nij.ojp.gov/funding/real-time-crime-forecasting-challenge-posting#data

All the materials and the code have been made available on our GitHub Repository as well as the data.
https://github.com/GVSU-CIS635/gvsu-cis635-term-project-team-i-k-i-m

References

[1] Y. Zhuang, M. Almeida, M. Morabito, W. Ding, Crime hot spot forecasting: a recurrent model with spatial and temporal information, in 2017 IEEE International Conference on Big Knowledge (ICBK), 2017.
https://ieeexplore.ieee.org/document/8023406

[2] U.M. Butt, S. Letchmunan, F.H. Hassan, M. Ali, A. Baqir, T.W. Koh, H.H. Sherazi, Spatio-temporal crime predictions by leveraging artificial intelligence for citizens' security in smart cities (2021).
https://www.preprints.org/manuscript/202102.0172/v1

[3] C. Yu, M. W. Ward, M. Morabito, and W. Ding, "Crime forecasting using data mining techniques," 11th IEEE Intl. Conf. on Data Mining Workshops, pp.779–786, 2011. https://ieeexplore.ieee.org/document/6137459