# Crime Analysis And Hotspot Prediction

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**Abstract**

*Crime is a major social and economic problem in almost every country, which threatens the safety of its citizens and also disrupts the economy of that nation. Understanding patterns in criminal activity will allow us to predict the crimes that may occur in the future and also predict their "hot spots" (the areas where they are most prominent to occur) and enables the authorities to more effectively and efficiently allocate manforce and resources to prevent or respond to incidents. Day by day crime is increasing, as there is an increase in unemployment, population density and other such factors. Crime has always been a problem for civilians as well as the authorities. The authorities are collecting and storing detailed data tracking crime occurrences. This data contains spatial and temporal data, which can be used to precisely predict the regional crime rates, detect and predict Crime Hotspots. Deep Learning and Neural Networks has been widely proven effective for detecting temporal patterns in a time series . We aspire to use the power of Deep Learning to help the authorities battle crime to provide a safer society for the civilians to live in.*

## 1. INTRODUCTION

### 1.1. Motivation

Machine learning and Artificial Intelligence have gained immense popularity, starting from the end of the previous decade. Their shere, almost unlimited scope and areas of application has taken over the decade by storm. To humans research and analytics for predicting the chance of some event occurring has always been one of the top priority. Such type of analysis is broadly classified as predictive analysis. This predictive analysis helps us gain a possible insight in the future. This insight in predicting storms, natural calamities, crimes, etc can mean the difference between losing and saving millions.

### 1.2. Relevance

Pervasive criminal activity research suggests that setting focus on specific areas with high crime rates or criminal activity is an effective crime prevention strategy, and with the help of an accurate prediction model authorities will be able to identify timings and areas of elevated crime rates in certain localities of a town. The authorities would be able to allocate their resources to that particular locality which is termed as a hotspot (an area with high crime rate) more efficiently to either prevent or effectively and quickly respond to criminal activity. Absorbing this model into the system will help authorities take appropriate measures that allows for an effective deployment of manforce and other resources at the crime hotspots and removing resources from areas seeing a decrease in crime levels. But, the real challenge is the sheer volume of data and number of variables that criminal activity and crime depends on. This presents a challenging task in formulating, analyzing, predicting criminal activities and hotspots and even more while developing a model to do so.

This paper aims to use the power of algorithms like RNN (Recurrent Neural Networks) and STNN(Spatio Temporal Neural Networks) and predict crime hot spots. RNN have proved very efficient in predicting textual and numeric data in stock markets and predictive fields and on the other hand STNN have proved very efficient in space and time series predictions.

This type of predictive analysis will identify the future hotspots(locations) for a crime and what crime is more likely to occur there. This analysis is done on past crime data of that particular location. Traditionally the local authorities use simple graph based methods to look at which crime is occurring more and in which area. The pin that is on the map and starts focusing more on that area, increasing their patrol frequencies and so on.

## 2. LITERATURE SURVEY & RELATED WORKS

Various methods and suggestions have been made by researchers and authorities for the prediction of crime. However every system has its own lacunas.

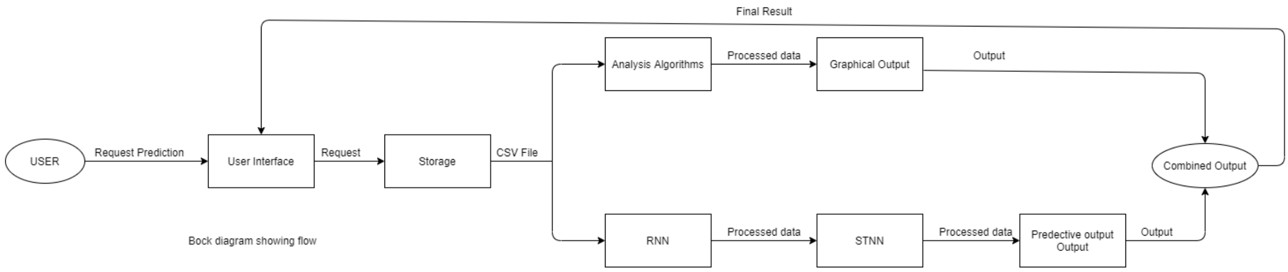


**Figure 1:** Block diagram

Dev Naomi.G Karthigaa.M Keerthana.B and Janani A [1] have proposed a big data analysis approach in which they have amassed massive amounts of crime data and provided analysis based on graphical plotting. They have used the hadoop ecosystem for storage retrieval and analysis of crime data.

Anish Krishnan, Aditya Sarguru and A. C. Shantha Sheela [2] have proposed the use of Recurrent Neural Networks, LSTM and BPTT for analysis and prediction of crime data.

Panagiotis Stalidis, Theodoros Semertzidis and Petros Daras [3] has suggested deep learning methods CNN's, kNN's, SVM's, MLP's Decision Trees, Naive Bayes, CCRBoost and ST-ResNet models for clustering, classification and prediction of crime.

Yong Zhuang, Matthew Almeida, Melissa Morabito and Wei Ding [4] have proposed a method in which they use RNN with spatio-temporal information to analyse and predict crime.

## 3. PROPOSED MODEL

### 3.1. Factor Related to Crimes

#### *3.1.1. Mobility Of The Hotspots*

The major problem that presented itself during our development of a predictive model was about the mobility of the hot spots. The question that presented itself was "How likely is it that in an area with a high crime rate would have a high crime rate or similar crime rate every month or every year? If social and economic factors remain largely the same. over the course of the data and time, it may be difficult for these patterns to change.

But, with changing socioeconomic factors the hotspots mobility is also possible. Thus, Hotspot mobility should also be considered as an important factor.

#### *3.1.2. Crimes influenced by other crimes*

During our analysis, we have seen that two crimes can be related if they occurred with less distance between their locations or less difference in time interval between their occurrences i.e, spatially and temporally.

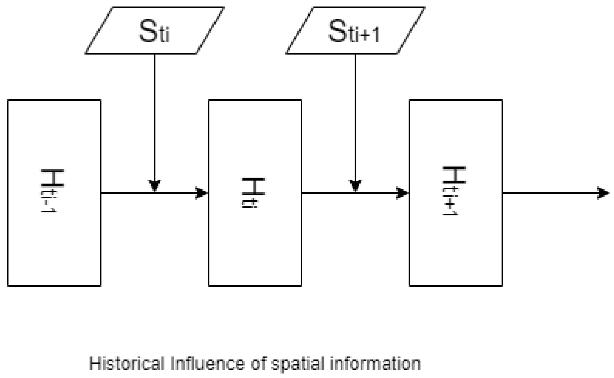


**Figure 2:** Historical influence of spatial information

### 3.2. Problem Description

Let S be a set of cells, n be the number of crimes, M be a set of n, and C be the crime rate. For each cell, its location information is associated with its coordinate { latitude ,longitude }, its crime rate at a specific time t is denoted as $C_t^s$, and its historical crime information is given as $M_s = \{n_{t_1}^s, n_{t_2}^s, ...\}$ , where $n_{t_i}^s$ presents the number of crimes occurred in the cell s in time interval $t_i$. And the history of all cells is denoted as $M_s = \{M_{s_1}, M_{s_2}, ...\}$ . Then the crime hot spots forecasting problem can be formulated as to predict $C_t^s$, based on the history $M_s$.

### 3.3. Recurrent Neural Network

Generally, a recurrent neural network is able to combine the input and the hidden state of one step with the inner weight matrices to generate the hidden state on the next step. The hidden state can be computed as follows:

$$h_{t_i}^s = \mathrm{f}\{\mathrm{a} \cdot m_{t_i}^s + \mathrm{b} \cdot h_{t_{i-1}}^s\}$$

where $h_{t_i}^s$ presents the historical information of a cell s in the time interval $t_i$, $m_{t_i}^s$ denotes the number of crimes occurred in s at time interval $t_i$. a and b are the weights. And the activation function f(x) is chosen as a rectifier function as follows:

$$h_{t_i}^s = \max\{\mathrm{a} \cdot m_{t_i}^s + \mathrm{b} \cdot h_{t_{i-1}}^s, 0\}$$

### 3.4. Spatio Temporal Neural Network

In order to construct an accurate time-space series analysis model, we need to consider both the temporal as well as the spatial influence. To predict the crime count of a cell it is essential that we consider that cell's own crime

 

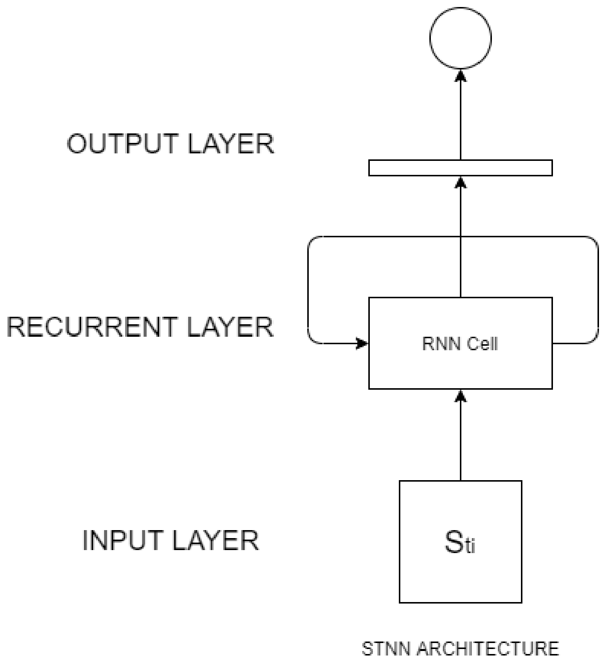


**Figure 3 :** STNN architecture

count as we as the crime count of the cells surrounding it, therefore it is mandatory to include all of this information for the model. Hence the historical spatial influence can be considered as the aggregation of the short-term influences of current, recent, neighbouring events. Since influence of a certain event will decrease with the passage of time , the historical and spatial influence of a cell s, can be limited to only those events that have an influence which can "reach" the particular cell in focus and those that are in a particular space-time window $S_t \subset S$. where, $S_t$ is the set of neighbouring cells in the time window $\{t\text{-}\Delta t,\ t\}$.As shown in Figure 4, given a cell s, its crime level at a specific time t can be denoted as follows:

$$h^s_{t_i} = \mathrm{f}\{\mathrm{a} \cdot M^{S_{t_i}} + \mathrm{b} \cdot h^s_{t_{i-1}}\}$$

Here, $M^s_{t_i}$ computes the total spatial influence at cell s in time interval $t_i$ . In this study, we formulate the crime level as a binary classification ( Q = 2 ) where hot =0 or non-hot =1. $W_i$ are the weights of $C_i$. Below figure shows the architecture of STNN.

## 4. METHODOLOGY

The block diagram in figure illustrates the flow of the proposed model (Figure 1).The proposed model works in the following phases:

### 4.1. Sources Of Data

We use the Data provided by the Chicago Police Department on the City of Chicago Data Portal from 2001 to 2017 in csv file format. The Dataset contains millions of records. This data contains all the crimes that happened in Chicago city from 2001 to 2017 and we have longitude and latitude of the locations and their time-stamps with their ward, community areas, crime type, description, arrests,etc. We have gathered the geographical data of chicago city i.e the shapefiles of chicago city. These shapefiles contain geometry and area of the community areas, wards of chicago city. We have converted the geography of chicago city into a grid community areas as cells, in such a way that the community areas are given their numbers and the dataset is divided based on community areas. Thus , we have 77 cells in this grid and each cell is a community area.The satellite view of chicago city is shown in figure 4. The geographical view of chicago city divided into community areas (cells) is shown in figure 5. (https://data.cityofchicago.org/)

### 4.2. Data Preprocessing

The preprocessing of data is done by using python libraries like numpy and pandas. In Preprocessing, the removal of duplicate records and filling of missing places is done. Then the data is sorted based on their timeline, so that they will be in a time series. This dataset is used for the following purposes:

- This dataset is used for crime analysis thus it is preprocessed to analyze the crime patterns and the correlation between them.
- This dataset is used for Crime Hotspot detection based on the Crime Rate of the cell, and also used to predict the Crime Hotspots Prediction with the help of spatial and temporal crime data.

This dataset is classified based on community areas, Crime type and year of occurence. This dataset is used to create a new dataset which contains the Crime Rate of the cell s, for a given interval of time t, in the time series.

### 4.3. Space-time Window Selection

Determining and selecting an appropriate space-time window over which we can calculate . The overall historical impact on a particular cell is extremely crucial for the performance of the model . While accumulating the events of a small time period (i.e- a single day) enables us to show intricate details and variation in the temporal pattern. Using such a small interval introduces a large amount of noise in the number of crimes in a particular time period .In fig.4, We compare choices of selected time periods by looking at the entire city, such that we examine the time periods thoroughly. The first row considers just the monthly arrests of the year 2012 to 2017, the next row displays the weekly arrests made and the last row displays daily arrests made. The last three rows show a total number of crimes in the city for purposes of examining the time windows. When actually training the model, the network input contains the actual crime count for each cell in the

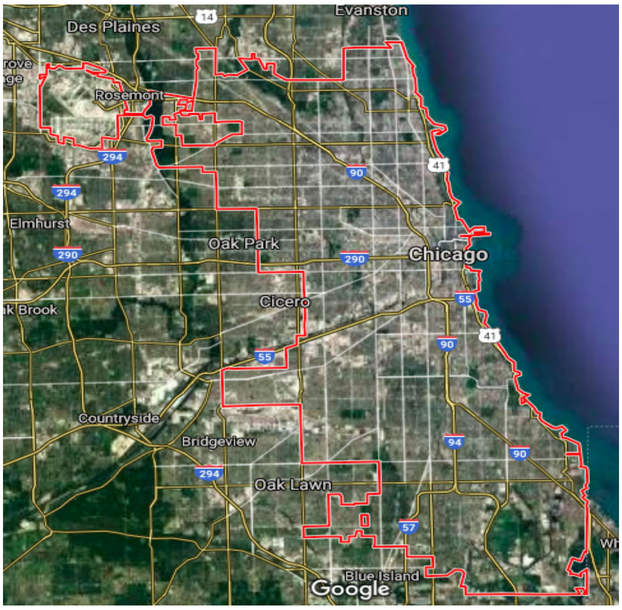


**Figure 4:** Satellite image

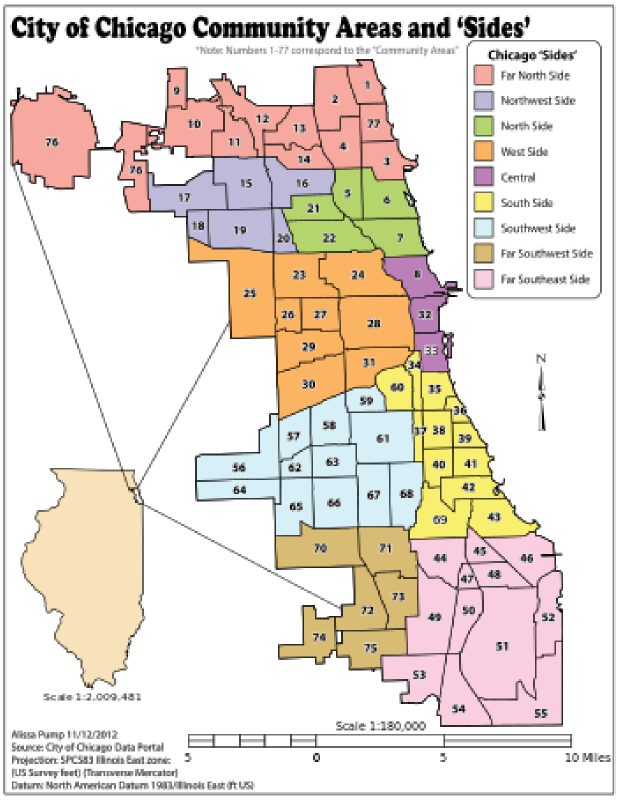


**Figure 5 :** chicago city map.

city. Increasing the spatial region we look at it and observe it has a smoothing effect on the number of crimes, as does increasing the size of the time period taken. For a single day the plots are noisy. Using monthly crime counts has a high smoothing effect and removes too much temporal

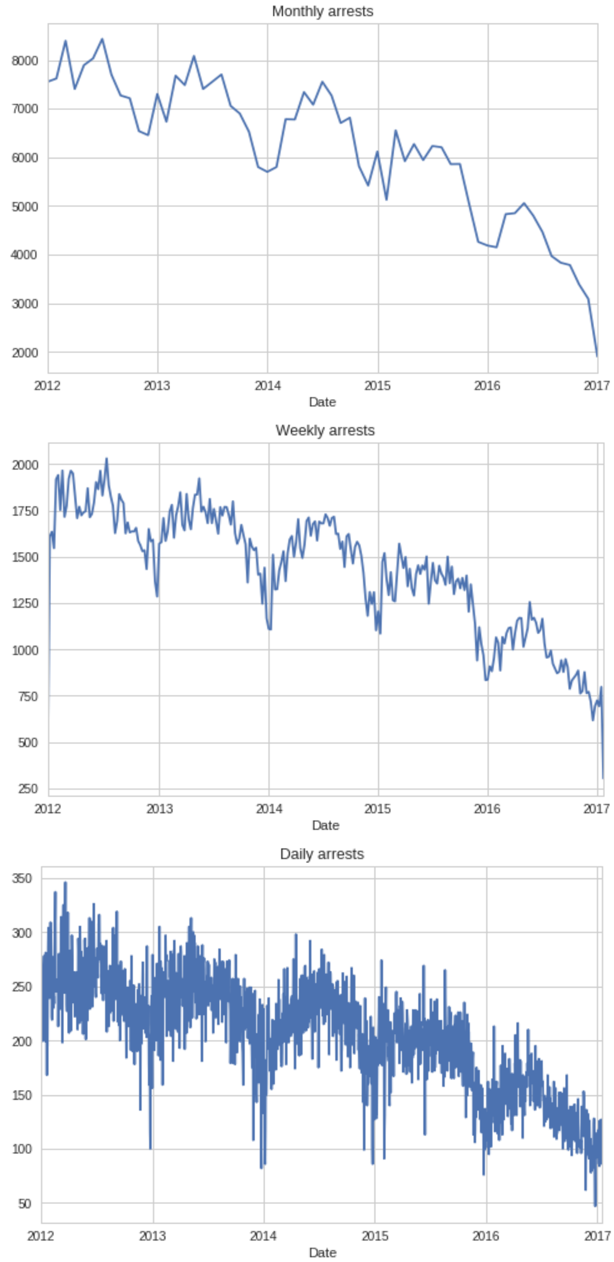


**Figure 6:** Analysis graphs

information and reduces the overall number of training samples by a significant amount. Thus, using the weekly crime counts has an adequate smoothing effect and removes adequate temporal noise while maintaining the required temporal information. In this study, we selected to use the space-time window with = 7 for each cell.

### 4.4. Train Model

The preprocessed data is then used as input for the Deep Learning Model. This Deep Learning model consists of a RNN, STNN and Binary Classifier, which will be used for prediction of Crime Hotspots.In RNN, the input data is the crime rate of each cell for a given time interval and the output is the predicted crime rate of each cell . The relu function has been used as the activation function. Finally, the obtained output and compare it with the expected output. Training is carried out until the loss is considerably low with model weights stored at regular intervals. In STNN, the input data is the crime rate of the neighbouring cells of each cell as well as its historical crime rate is used to train the STNN. The STNN is trained until the loss is considerably low. After this, the crime rate of each cell will undergo a Binary Classification to predict whether the cell is a 'Hotspot' or not.

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