

## ANALYSIS ON DETECTION AND PREVENTION OF CRIME PATTERNS USING MACHINE LEARNING ALGORITHMS

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### ABSTRACT

The development of policing strategies and the implementation of crime prevention and control depend greatly on crime prediction. The most popular prediction technique right now is machine learning. Few research, however, have rigorously contrasted various machine learning approaches for crime prediction. This study compares the predicting abilities of various machine learning algorithms using historical data on public property crime from a significant coastal city in southeast China from 2015 to 2018. The LSTM model appears to perform better than KNN, random forest, support vector machine, naive Bayes, and convolution neural networks, according to results based solely on historical crime data. Therefore, historical crime data and factors related to criminological ideas should both be used in future crime prediction. Not all machine learning algorithms are equally effective in crime prediction.

Keywords: naïve bayes, convolution neural networks, KNN and RNN algorithms, crime prediction

### INTRODUCTION

Public security-related spatiotemporal data have been expanding at an exponential rate in recent years. Not all data, nevertheless, have been successfully applied to solve problems in the actual world. Many academics have created crime prediction models to aid in crime prevention. The majority of them only calibrated their predictive models using past crime data. The two main areas of crime prediction study at the moment are the prediction of crime hotspots and crime risk. The crime risk area prediction, based on the relevant influencing factors of criminal activities, refers to the correlation between criminal activities and physical environment, which both derived from the “routine activity theory”. Traditional crime risk estimation methods usually detect crime hotspots from the historical distribution of crime cases, and assume that the pattern will persist in the following time periods. For example, considering the proximity of crime places and the aggregation of crime elements, the terrain risk model tends to use crime-related environmental factors and crime history data, and is relatively effective for long-term, stable crime hotspot prediction. Many studies have carried out empirical research on crime prediction in different time periods, combining demographic and economic statistics data, land use data, mobile phone data and crime history data. Crime hotspot prediction aims to predict the likely location of future crime events and hotspots where the future events would concentrate. A commonly used method is kernel density estimation. A model that considers temporal or spatial autocorrelations of past events performs better than those that fail to account for the autocorrelation. Recently machine learning algorithms have gained popularity. The most popular methods include K-Nearest Neighbor (KNN), random forest algorithm, support vector machine (SVM), neural network And Bayesian model etc.. Some compared the linear methods of crime trend prediction, some compared Bayesian model and BP neural network and others compared the spatiotemporal kernel density method with the random forest method in different periods of crime prediction.

Among these algorithms, KNN is an efficient supervised learning method algorithm SVM is a popular machine learning model because it can not only implement classification and regression tasks, but also detect outliers. Random forest algorithm has been proven to have strong non-linear relational data processing ability and high prediction accuracy in multiple fields. Naive Bayes (NB) is a classical classification algorithm, which has only a few parameters and it is not sensitive to missing data. Convolution neural networks (CNN) have strong expansibility, and can enhance its expression ability with a very deep layer to deal with more complex classification problems. Long Short-Term Memory (LSTM) neural network extracts time-series features from features, and has a significant effect on processing data with strong time series trends. This paper will focus on the comparison of the above six machine learning algorithms, and recommend the best performing one to demonstrate the predictive power with and without the use of covariates.

## **II. LITERATURE SURVEY:**

### **PRINCIPLES OF THEORETICAL CRIMINOLOGY IN PREDICTION OF**

**CRIME HOTSPOTS:** The focus of crime hotspot prediction is to forecast future concentration of criminal events in a geographical space. Theoretical criminology provides the necessary theoretical basis. Specifically, several related criminological theories not only provide guidance for us to understand the important influence of location factors in the formation and aggregation of criminal events, but also provide a basic mechanism for the police to use information of crime hot spots for crime prevention or control. It mainly includes routine activity theory, rational choice theory, and crime patterns theory. These three theories are generally considered as the theoretical basis of situational crime prevention. Routine activity theory was jointly proposed by Cohen and Felson in 1979, and has now been further developed through integration with other theories. This theory believes that the occurrence of most crimes, especially predatory crimes, needs the convergence of the three elements including motivated offenders, suitable targets, and lack of ability to defend in time and space. Rational choice theory was proposed by Cornish and Clarke. The theory holds that the offender's choices in terms of location, goals, methods be explained by the rational balance of effort, risk and reward. Crime pattern theory integrates the routine activities theory and the rational choice theory, which more closely explains the spatial distribution of criminal events. People form "cognitive map" and "activity space" through daily activities. At the same time, potential offenders also need to use their cognitive maps and choose specific locations for crimes in a relatively familiar space. When committing a crime, the offender tends to avoid those places they don't know but to choose the places where the "criminal opportunity overlaps with cognitive space" based on their rational ability. The reason why these places become crime hotspots is that they have the obvious characteristics of "producing" or "attracting" crime. Therefore, the environmental factors of the places need to be considered besides historical crime data for the prediction of crime hotspots.

### **BUILT ENVIRONMENT DATA :**

At present, a large number of studies show that the urban built environment has a significant impact on urban criminal behavior, through the impact of crime opportunities to reduce and prevent crime. In the 2007 Global Habitat Report, it was pointed out that the elements of the built environment have an important impact on the occurrence of criminal acts. Point of interests (POIs) data and road network density data are considered as covariates in the crime prediction model.

#### **1) POI DATA :**

The urban infrastructure data POI includes the location information and attribute information of various urban facilities. Catering facilities, shopping malls and stores are usually

located in places with convenient transportation and large flow of people, gathering a large number of different groups of people to generate the targets for the criminals, while entertainment places attract criminals. These POIs are selected as covariates of the prediction model.

## 2) ROAD NETWORK DENSITY:

The conventional definition of road network density refers to total length of roads divided by the size of an areal unit. The area with a denser road network attracts greater flow of people, including potential victims and criminals. Previous studies have shown that the density of road network has an impact on crime rate, especially in public space.

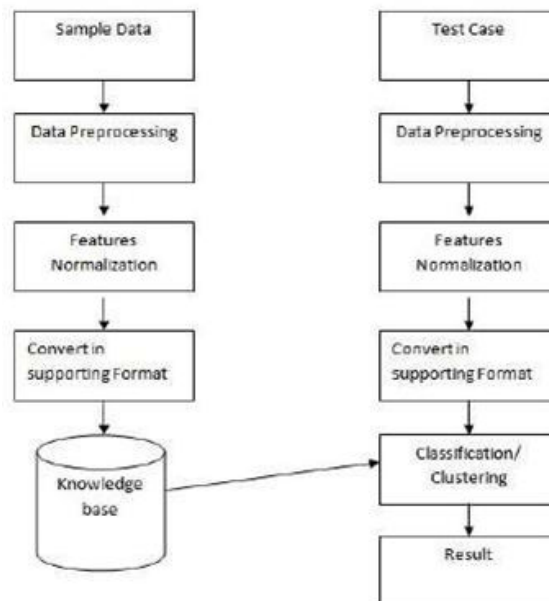
## III. EXISTING SYSTEM

The focus of crime hotspot prediction is to forecast future concentration of criminal events in a geographical space. Theoretical criminology provides the necessary theoretical basis. Specifically, several related criminological theories not only provide guidance for us to understand the important influence of location factors in the formation and aggregation of criminal events, but also provide a basic mechanism for the police to use information of crime hotspots for crime prevention or control. It mainly includes routine activity theory, rational choice theory, and crime patterns theory. Datasets are available in Kaggle.com

## IV. PROPOSED SYSTEM

In this paper, random forest algorithm, KNN algorithm, SVM algorithm is used for crime prediction. First, historical crime data alone are used as input to calibrate the models. Comparison would identify the most effective model. Second, built environment data such as road network density and poi are added to the predictive model as covariates, to see if prediction accuracy can be further improved.

## V. SYSTEM ARCHITECTURE:



### 5.1 IMPLEMENTATION: PREDICTION MODEL:

In this paper, random forest algorithm, KNN algorithm, SVM algorithm and LSTM algorithm are used for crime prediction. First, historical crime data alone are used as input to calibrate the models. Comparison

would identify the most effective model. Second, built environment data such as road network density and poi are added to the predictive model as covariates, to see if prediction accuracy can be further improved.

#### **A.KNN:**

KNN, also known as k-nearest neighbor, takes the feature vector of the instance as the input, calculates the distance between the training set and the new data feature value, and then selects the nearest K classification. If  $k = 1$ , the nearest neighbor class is the data to be tested. KNN's classification decision rule is majority voting or weighted voting based on distance. The majority of k neighboring training instances of the input instance determine the category of the input instance.

#### **B.RANDOM FOREST:**

The random forest is a set of tree classifiers

$\{h(x, \beta_k), k = 1, \dots\}$ , in which the meta classifier  $h(x, \beta_k)$  is an uncut regression tree constructed by CART algorithm;  $x$  is the input vector;  $\beta_k$  is an independent random vector with the same distribution, and the output of the forest is obtained by voting. The randomness of random forest is reflected in two aspects: one is to randomly select the training sample set by using bagging algorithm; the other is to randomly select the split attribute set. Assuming that the training sample has  $M$  attributes in total, we specify an attribute number  $F \leq M$ , in each internal node, randomly select  $F$  attributes from  $M$  attributes as the split attribute set, and take the best split mode of the  $f$  attributes Split the nodes. The multi decision tree is made up of random forest, and the final classification result is determined by the vote of tree classifier.

#### **C.SVM :**

SVM, based on statistical learning theory, is a data mining method that can deal with many problems such as regression (time series analysis) and pattern recognition (classification problem, discriminant analysis) very successfully. The mechanism of SVM is to find a superior classification hyperplane that meets the classification requirements, so that the hyper plane can ensure the classification accuracy and can maximize the blank area on both sides of the hyperplane. In theory, SVM can realize the optimal classification of linear

#### **D.NB :**

In the field of probability and statistics, Bayesian theory predicts the occurrence probability of an event based on the knowledge of the evidence of an event. In the field of machine learning, the naïve Bayes (NB) classifier is a classification method based on Bayesian theory and assuming that each feature is independent of each other. In abstract, NB classifier is based on conditional probability, to solve the probability that a given entity belongs to a certain class.

#### **E.CNN:**

CNN uses one-dimensional convolution for sequence prediction, which is the convolution sum of discrete sequences. To convolve the sequence, CNN first finds a sequence with a window size of `kernel_size`, and perform convolution with the original sequence to obtain a new sequence expression. The convolutional network also includes a pooling operation, which is to filter the features extracted by the convolution to get the most useful characteristics.

#### **F.LSTM:**

LSTM is a kind of deep neural network based on RNN. The core of LSTM is to add a special unit (memory module) to learn the current information and to extract the related information and rules between the data, so as to transfer the information. LSTM is more suitable for deep neural network calculation because of memory module to slow down information loss. Each memory module has three gates, including input gate (it), forget gate (ft), and output gate (ot). They are used to selectively memorize the correction parameters of the feedback error function as the gradient decreases. The specific structure is shown in the figure .

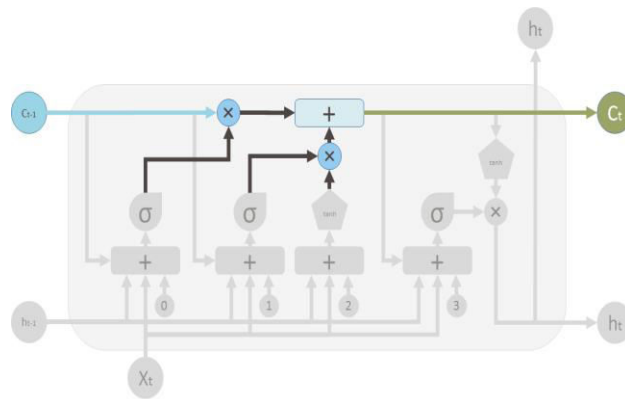


FIGURE 1. The structure chart of LSTM cell

In the figure above, LSTM has two state chains (hidden layer state) and C (cell state) that are passed over time, only cell state C of RNN is transmitted over time.  $h_{t-1}$  is the value of the current time transmitted from the hidden layer at the previous time,  $x_t$  is the input value at the current time,  $C_{t-1}$  is the state value of the LSTM memory cell at the previous time, and  $C_t$  is the state value of the memory cell at the current time. When  $h_{t-1}$  and  $x_t$  pass through the forgetting gate, the information to be discarded is calculated. The value of output to the cell state is between 0 and 1, 0 means all forgetting, and 1 means all information is reserved. Forgetting gate  $f_t$  is given by the following equation:

$$f_t = \sigma(w_f \cdot [h_{t-1}, x_t] + b_f)$$

where  $w$  and  $b$  are weight matrix and bias vector in forgetting gate respectively;  $\sigma$  is activation function Sigmoid. There are two processes for updating new information into a cell. First, the input gate of Sigmoid function is used to calculate the information to be updated, and then a new value  $k_t$  created by tanh layer is added to the cell state:

$$i_t = \sigma(w_i \cdot [h_{t-1}, x_t] + b_i)$$

$$k_t = \tanh(w_k \cdot [h_{t-1}, x_t] + b_k)$$

The results obtained from equation (2) and equation (3) are multiplied and added to the results obtained from the forgetting gate of the previous time cell state value to obtain the current time cell state value, as follows:

$$C_t = f_t * C_{t-1} + i_t * k_t \quad (4)$$

The final output depends on the cell state. First of all, Sigmoid classifies the output results, selects the data to be output, processes the cell state with tanh function, and obtains the state value  $h_t$  that the hidden layer transfers to the next time. After being processed by sigmoid,  $h_t$  can obtain the pre output value  $y$  at the current time, as shown in equation (5) - equation (7):

$$O_t = \sigma(w_o \cdot [h_{t-1}, x_t] + b_o) \quad h_t = O_t * \tanh(C_t)$$

$$y = \sigma(w_o \cdot h_t)$$

## VI. Results



CONCLUSION

Six machine learning methods are used in this study to forecast the emergence of crime hotspots in a city along China's southeast coast. The conclusions are as follows: 1) The LSTM model has higher prediction

accuracy than the other models. It is more effective in identifying patterns and regularities in past crime data.

2) The prediction accuracy of the LSTM model is further enhanced by the inclusion of covariates related to the urban built environment. The prediction outcomes utilizing historical crime data alone are superior to those of the original model. Compared to other models, our models' forecast accuracy has increased. Rummens et al.'s study on predicting crime hotspots used historical crime data at a grid unit scale of 200 m × 200 m, using three models of logistic regression, neural network, and the combination of logistic regression and neural network. In the biweekly forecast, the highest case hit rate for the two-robbery type is 31.97%, and the highest grid hit rate is 32.95%; Liu et al. Used the random forest model to predict the hot spots in multiple experiments in two weeks under the research scale of 150 m × 150 m. The average case hit rate of the model was 52.3%, and the average grid hit rate was 46.6%. The case hit rate of the LSTM model used in this paper was 59.9%, and the average grid hit rate was 57.6%, which was improved compared with the previous research results. For the future research, there are still some aspects to be improved. The first is the temporal resolution of the prediction. Felson et al. revealed that the crime level changes with time. Some studies have shown that it is useful to check the variation of risks during the day. We chose two weeks as the prediction window. It does not capture the impact of crime changes within a week, let alone the change within a day. The sparsity of data makes the prediction of crime event difficult if the prediction window is narrowed down to day of a week or hour within a day. There is no viable solution to this challenging problem at this time. The second is the spatial resolution of the grid. In this paper, the grid size is 150m × 150m. Future research will assess the impact of changing grid sizes on prediction accuracy. Third, the robustness and generality of the findings of this paper needs to be tested in other study areas. Nonetheless, the findings of this research have proven to be useful in a recent hotspot crime prevention experiment by the local police department at the study size.

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