Crime Rate Prediction with Region Risk and Movement Patterns

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Abstract—The location-based social network, FourSquare, helps us to understand a city’s mass human mobility. It provides data that characterises the volume of movements across regions and Places of Interests (POIs) to explore the crime dynamics of a city. To fully exploit human movement into crime analysis, we propose the region risk factor which combines monthly aggregated crime and human movement of a region across different time intervals. We then derive a number of features using the region risk factor and conduct extensive experiments with real world data in multiple cities that verify the effectiveness of these features.

I. INTRODUCTION

One of the basic demands for every person in society is a safe and secure living space. Therefore, it is important to find ways to control a city’s crime rate, which hinders economic development. Understanding the root causes of what increases the likelihood of crime occurring at any time has great benefits for law enforcement to coordinate response and prevention strategies. According to criminology theory, the surrounding environment, including neighbourhood regions, and the movement of people play a crucial role in crime event prediction. The widespread use of location-based social networks such as FourSquare open up a door of opportunities to analyse crime events in a timely manner. In this paper, we study crime rate prediction with the help of urban mobility data.

Recently, there has been research linking crime events with urban dynamics using FourSquare data [1]. However, this study focused on a region’s check-in information to predict crime events. There has been no focus on linking human movement between two regions. In [2], the authors considered the movement between regions using taxi flow data for crime inference, however, did not account for the variation of movement in different time periods of day. For example, the people who move from their home to work will move in the opposite direction in the afternoon. In this paper, we analyse crime inference with human mobility at different periods of the day. In Figure [1], we observe the difference in the number of people moving in the morning and afternoon for New York City. The changes of human movements between the two periods of the day are highlighted with different colour. To fully exploit the human dynamics in crime inference, we further introduce Region Risk, which associates crime with people moving in that region over a time interval. The hypothesis is that human mobility from a high crime risk area implies a high crime risk in the arrival area. We derive numerous features with the assistance of Region Risk. The significance of this and other features are verified for Chicago and New York City at different times of the day.

The contributions of this paper are summarized as follows:

• This is the first work that predicts the crime rate based on the dynamic features that associate Region Risk and movement patterns between regions.
• New features associated with Region Risk and human mobility are crafted.
• This work verifies the effectiveness of different features in the crime inference problem using correlation and regression analysis. Real-world crime data and FourSquare movement data are used for evaluation. The experimental results show that the Region Risk features are highly correlated with crime count of a region.

II. RELATED WORK

Previous data mining studies were conducted to verify the impact of human mobility onto crime. In [3], the authors extracted human behavior from mobile network activities and demographic features of people connected to the network over different regions and times. The study showed that the combination of mobile activity data and demographic data can be used to predict crime events with better accuracy. FourSquare check-in data measures the ambient population of a region and is used to understand the long-term crime...
event occurrences \cite{4, 5}. In \cite{1} the authors proposed several dynamic features using FourSquare data to measure the social diversity of a region, and predict short-term crime event occurrences. Furthermore, it is important to explore the correlation of crime events between places. The mobility data represented by taxi flows and Points of Interest (POIs) can improve crime rate inference \cite{2}. Here, the authors’ hypothesis is that the social interaction between two places can be inferred through taxi trips, and crime propagates based on these connections. In \cite{6}, the authors proposed crime-specific dynamic features by analyzing the individual risk factor of the users and extracted multiple features based on the risk analysis.

However, none of these works correlates the large scale human movement in different times of the day with crime in a region. Our work attempts to fill this gap.

III. DATASET DESCRIPTION

The datasets are collected for Chicago and New York City. We collect different types of data including check-ins and crime events for each city. We segment each city into a 400 × 400 grid.

A. POI and Check-in Data

The POI and check-in information is collected from FourSquare. This dataset is provided as part of the Future Cities Challenge at Netmob \cite{1}. The check-in information describes an aggregated count of all movements from one venue to another, separated by month and five time intervals: Morning, Midday, Afternoon, Night and Overnight. In the collected data, we focus on the two cities mentioned above for the year of 2018. The aggregated number of venues and number of total venue movements are summarised in Table \ref{table:1}.

\begin{table}[!h]
\centering
\begin{tabular}{|c|c|c|}
\hline
City & Venues & Unique Movements \\
\hline
Chicago & 13,904 & 5,396,723 \\
New York & 32,971 & 5,296,809 \\
\hline
\end{tabular}
\caption{Number of Venues and Venue Movements for each city}
\end{table}

B. Crime Data

We collect the 2018 crime event records for Chicago and New York from the Open Data Portals of the respective city councils \cite{2, 3}. Each dataset consists of the longitude, latitude, and the time and date of crime event occurrences. The total number of crime event occurrences are 263,515 and 452,958 for Chicago and New York respectively.

IV. FEATURE DESCRIPTION

This section presents the detailed description of the features. Over a time period, \( t \), we consider each city as a weighted directed graph, \( G_t = (V, E, W) \), where \( V \) is the set of grids on the graph, \( E \) represents the set of edges between two grids. \( W \) represents the weighted adjacency matrix of \( G_t \), where if two nodes, \( i, j \in V \), share a directed edge, \( (i, j) \in E \), it will have weight \( W(i, j) \). Time periods are separated by month and time of day (previously mentioned in Section 3A). The weight of each edge is the aggregated number of check-ins over \( t \). For each node \( v \in V \) in a time interval, \( t \), the following nodal and edge features are calculated.

A. Nodal Features

Nodal features describe the characteristics of the focal grid only.

1) Historical Features: To retain the historical knowledge about crime event occurrence, we calculate the following feature:

\textbf{Crime Event History:} We analyse Crime Event History, \( C_{r_j}(v, t) \) denotes the number of crime events that happened on \( j \)-th day in node, \( v \), during time interval \( t \). The variable, \( m \), represents the day in the past month. This is denoted as:

\begin{equation}
NH(v, t) = \sum_{j \in m} Cr_{j}(v, t). \tag{1}
\end{equation}

2) POI Features: The regional information of a node is described using the following features.

\textbf{POI Density:} For each node, \( v \in V \) the POI density is calculated as follows:

\begin{equation}
NP(v) = \frac{N(v)}{N(V)}. \tag{2}
\end{equation}

The total POI of the city is represented as \( N(V) \). \( N(v) \) denotes the number of POI in focal node, \( v \).

\textbf{Venue Category Distribution:} Each type of venue has different impact on crime. Hence, it is important to extract the distribution of venue types in a node. It is calculated as:

\begin{equation}
ND_i(v) = \frac{N_i(v)}{N(v)}. \tag{3}
\end{equation}

Here, \( N_i(v) \) is the number of \( i \)-th category venues in node, \( v \).

\textbf{Venue Diversity:} Shannon’s entropy \cite{7} measurement is applied to determine the diversity of venue types, \( P \), in node, \( v \). Thus, Venue Diversity is modelled as:

\begin{equation}
NE(v) = -\sum_{i \in P} \frac{N_i(v)}{N(v)} \log_2 \left( \frac{N_i(v)}{N(v)} \right). \tag{4}
\end{equation}

3) Movement Features: The human dynamics of region in a time interval is represented using the following features:

\textbf{Incoming Movement:} The density of incoming movement into node, \( v \), in time interval, \( t \), is measured here. If a check-in is performed from other nodes to node, \( v \), then it is considered as incoming movement. This we obtain the density of incoming movement as,

\begin{equation}
NI(v, t) = \frac{C_i(v, t)}{C(v, t)}. \tag{5}
\end{equation}

where \( C(v, t) \) and \( C_i(v, t) \) denote total check-in and incoming check-ins respectively.
### Table II: Feature Correlation Analysis for the New York and Chicago

| Feature Name               | Chicago          | New York         |
|----------------------------|------------------|------------------|
| Check-in Entropy           | Morning, Midday, A’noon, Night, O’Night | Morning, Midday, A’noon, Night, O’Night |
| In Check-in Density        | 0.365, 0.277, 0.273, 0.360 | 0.264, 0.304, 0.309, 0.309 |
| Out Check-in Density       | 0.051, 0.056, 0.027, 0.048 | 0.019, 0.075, 0.055, 0.017 |
| Stationary Density         | -0.064, -0.047, -0.056, -0.047 | -0.158, -0.025, -0.089, -0.157 |
| Mean                       | 0.133, 0.025, 0.021, 0.088 | 0.058, 0.022, 0.053, 0.158 |
| Median                     | 0.124, 0.015, 0.015, 0.079 | -0.007, -0.026, 0.017, 0.112 |
| Risk Count                 | 0.210, 0.088, 0.077, 0.095 | 0.402, 0.424, 0.512, 0.282 |
| Risk Ratio                 | 0.113, -0.001, 0.002, 0.042 | -0.018, -0.036, 0.000, 0.037 |
| Self Risk                  | 0.154, 0.095, 0.070, 0.116 | 0.113, 0.050, 0.076, 0.225 |
| Neighbourhood Crimes       | 0.001, 0.039, -0.026, 0.035 | 0.357, 0.074, 0.053, 0.309 |
| Historical Density         | 0.637, 0.867, 0.872, 0.671 | 0.936, 0.983, 0.723, 0.961 |
| Arts & Entertainment        | -0.018, -0.030, -0.021, 0.005 | 0.161, 0.137, 0.174, 0.149 |
| College & University       | -0.072, -0.063, -0.054, -0.042 | 0.054, 0.058, 0.066, 0.049 |
| Event                      | -0.059, -0.023, -0.012, -0.009 | -0.02, -0.028, -0.024, -0.035 |
| Food                       | 0.175, 0.116, 0.119, 0.228 | 0.262, 0.203, 0.164, 0.233 |
| Nightlife Spot             | 0.047, 0.007, -0.069, 0.120 | 0.086, 0.149, 0.146, 0.153 |
| Outdoors & Rec.            | -0.072, -0.087, -0.071, -0.117 | -0.128, -0.128, -0.131, -0.128 |
| Professional & Other       | -0.038, 0.017, 0.007, -0.061 | 0.107, 0.077, 0.148, 0.105 |
| Residence                  | 0.068, 0.016, -0.010, -0.021 | 0.180, 0.183, 0.154, 0.185 |
| Shops & Service            | 0.050, 0.031, 0.047, 0.077 | -0.045, 0.022, 0.019, -0.031 |
| Travel & Transport         | -0.086, -0.056, -0.059, -0.165 | -0.016, -0.103, -0.122, -0.087 |
| Total POS                  | 0.517, 0.651, 0.631, 0.638 | 0.509, 0.655, 0.673, 0.586 |
| Venue Diversity            | 0.318, 0.287, 0.255, 0.366 | 0.428, 0.367, 0.356, 0.375 |

**Outgoing Movement:** If a check-in is performed from a node to other nodes, it is considered as outgoing movement. The density of outgoing movement is represented as,

\[
NC(v, t) = \frac{|C_o(v, t)|}{|C(v, t)|},
\]

where \(C_o(v, t)\) represents outgoing check-ins performed in node, \(v\), during time interval, \(t\), in each month.

**Stationary Movement:** When the origin and destination of a check-in is the same node, it is denoted as stationary movement. The density of stationary movement for \(C_s(v, t)\) stationary check-ins in node, \(v\), in time interval, \(t\), is:

\[
NS(v, t) = \frac{|C_s(v, t)|}{|C(v, t)|}.
\]

**Diversity of Movement:** The heterogeneity of movement type is measured using:

\[
NM(v, t) = -\sum_{i \in M} \frac{|C_i(v, t)|}{|C(v, t)|} * \log_2 \left( \frac{|C_i(v, t)|}{|C(v, t)|} \right).
\]

The set, \(M\), consists of three movement types: incoming, outgoing and stationary.

**B. Edge Features**

Edge features determine how the crime rate of a region is influenced by its connected region. Two types of features have been crafted. One is based on the crime rate in the neighbourhood region and the other is based on the risk analysis of a region based on movement data.

1) **Neighbourhood Crime:** The number of crime events for each adjacent node of focal node, \(v\), is computed in each time interval. It reflects the situation of the surroundings.

2) **Region Risk:** To compute Region Risk, we analyse the risk associated with each node to support the following intuition. If the incoming check-ins of a node in a time interval are from high risk area, it imposes high risk of crime event occurrence in that node in that time interval. The Region Risk of node, \(v\), for time interval, \(t\), is:

\[
RR(v, t) = \frac{|Cr(v, t)|}{|C(v, t)|},
\]

where \(Cr(v, t)\) denotes the crime events that happened in node, \(v\), in time interval, \(t\). Several edge features are crafted which consider Region Risk, \(RR(v, t)\).

**Risk Distribution:** The risk distribution consists of the mean and median of the Region Risk associated with the regions \(r \in R(v, t)\) from where people are moving to focal node, \(v\), in time interval \(t\).

**Risk Count:** The risk count in node, \(v\), in time interval, \(t\), determines the number of regions with high risk than average from where incoming movement occur in node, \(v\), in that time interval. The risk count is denoted by,

\[
RC(v, t) = |\{r : r \in R(v, t) \text{ and } RR(r) > \frac{1}{|R|} \sum_{n \in V} RR(n, t)\}|
\]

Here, \(R(v, t)\) denotes the regions which are origin of check-ins to node \(v\), and \(|R|\) is the total number of regions.

**Risk Ratio:** Risk count determines the absolute number of regions with high risk. We normalise this feature based on total regions with incoming movement. The risk ratio is modelled using,

\[
RT(v, t) = \frac{RC(v, t)}{|R(v, t)|}.
\]
**Self Risk:** This feature represents absolute value of region risk that is associated to the focal node, $v$ in time interval, $t$, $RR(v, t)$

### C. Feature Correlation Analysis

We conduct a Pearson correlation analysis to see how the proposed features are individually correlated with the monthly crime count of a region in a certain time interval of day. The correlation values between the features and crime count are illustrated in Table II for Chicago and New York City across different periods of a day. We observe that crime count is highly correlated with Crime Event History in both cities over many time intervals. According to the Near Repeat theory [8], crime tends to happen in the vicinity of past crime events. The features derived from region risk analysis also have good correlation with crime count for both cities, especially overnight. Such positive correlation highlights the importance of such features in crime count. Surprisingly, many POI densities are negatively correlated with crime count. However, venue diversity has good correlation with crime which verifies that mixed land use has good impact on crime.

### V. Model Description

The main purpose of this paper is to show the effectiveness of the features derived from human movement in crime inference. To do so, we apply Linear Regression (LR), Negative Binomial Regression (NB), and Random Forests (RF) to count crime events. The features derived from region risk analysis also have good correlation with crime count for both cities, especially overnight. Such positive correlation highlights the importance of such features in crime count. Surprisingly, many POI densities are negatively correlated with crime count. However, venue diversity has good correlation with crime which verifies that mixed land use has good impact on crime.

### VI. Experiments

In this section, we describe about the experimental results followed by the data pre-processing method.

#### A. Settings

The dataset used in this experiment is introduced in Section III. Each day is segmented in five intervals and for each interval the data is aggregated in monthly level. To prevent extreme sparsity situations, we only include check-in movement data with ten or more unique movements in a month. The aim of the experiment is to examine the effectiveness of the proposed features in crime inference model for a month in a certain period of day.

We partition the data between January 2018 and September 2018 (inclusive) as the training data and the data between October 2018 and December 2018 (inclusive) as the test data. If new regions are found with check-in movement greater than, or equal to 10 in test data for a time interval, the risk value for that region is set 0.

Two performance metrics, Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE), are used to verify the effectiveness of the crime inference model.

### TABLE III: MAE and RMSE for different times of the day for Chicago and New York after applying Linear Regression

| Time of Day | Error | Chicago | New York |
|------------|-------|---------|----------|
|            | 1     | 2       | 1        | 2        |
| Morning    | MAE   | 1.068   | 7.755    | 7.649    |
|            | RMSE  | 1.557   | 11.109   | 10.736   |
| Midday     | MAE   | 1.764   | 12.376   | 12.399   |
|            | RMSE  | 2.791   | 16.362   | 15.764   |
| Afternoon  | MAE   | 1.846   | 21.287   | 22.021   |
|            | RMSE  | 3.074   | 42.552   | 44.461   |
| Night      | MAE   | 1.961   | 12.628   | 13.986   |
|            | RMSE  | 2.946   | 16.558   | 17.515   |
| Overnight  | MAE   | 1.821   | 13.390   | 18.104   |
|            | RMSE  | 2.772   | 17.509   | 21.933   |

1. All Features Present  
2. Region Risk Features Omitted

### TABLE IV: MAE and RMSE for different times of the day for Chicago and New York after applying Negative Binomial Regression

| Time of Day | Error | Chicago | New York |
|------------|-------|---------|----------|
|            | 1     | 2       | 1        | 2        |
| Morning    | MAE   | 1.496   | 19.978   | 19.958   |
|            | RMSE  | 2.128   | 31.304   | 31.287   |
| Midday     | MAE   | 2.496   | 43.324   | 43.316   |
|            | RMSE  | 5.458   | 71.069   | 71.083   |
| Afternoon  | MAE   | 2.625   | 45.709   | 45.712   |
|            | RMSE  | 6.049   | 74.188   | 74.173   |
| Night      | MAE   | 2.706   | 46.746   | 46.693   |
|            | RMSE  | 4.507   | 71.499   | 71.487   |
| Overnight  | MAE   | 2.754   | 41.719   | 41.616   |
|            | RMSE  | 4.973   | 56.823   | 56.778   |

1. All Features Present  
2. Region Risk Features Omitted

### B. Performance Study

We evaluate the performance of the proposed Region Risk based edge features for monthly crime count. We build two regression models to show the effectiveness of that set of features. The first model is trained with Region Risk based edge features and the second model is trained without Region Risk based edge features. Finally, MAE and RMSE value is calculated using test test for both models. If the MAE and RMSE increase for second model compared to the...
first one, Region Risk features are considered important in monthly crime count. The experimental results using different regression algorithms including LR, NB and RF are shown in tables III to V respectively. The experimental results show that the model with Region Risk based features has less error compare to the model without Region Risk based features in most of the time intervals. Among three different regression algorithm, RF shows the consistent and better performance result.

C. Feature Importance

As RF shows the consistent performance, We measure the importance of each group of features using the RF regression method. We build a regression-based RF model and apply the ‘ablation study’ to measure the performance of a set of features. First, we train a model with all the features. Next, we train another model without a set of features to identify the effectiveness of that set of features. If the MAE and RMSE is higher without a set of features, it verifies the importance of that feature set. The importance of each feature set is illustrated in Figures 2 for New York City and Chicago. In New York, we observe that the most dominant set of features are primarily POI features. The other features show more or less importance across different time intervals. In Chicago, we also observe that POI features are the most dominant features.

VII. Conclusion

This work provides new perspectives to understand crime dynamics with the help of human mobility. It captures the relationship between the monthly aggregated crime data and the movement of people in a region across different periods of the day. The experiments verify that a group of people from high risk areas increase the crime risk of their destination.

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