2017 IEEE International Conference on Data Mining Workshops

Exploring Transfer Learning for Crime Prediction

Xiangyu Zhao
Data Science and Engineering Lab
Michigan State University
Email: zhaoxi35@msu.edu

Jiliang Tang
Data Science and Engineering Lab
Michigan State University
Email: tangjili@msu.edu

***Abstract*—Crime prediction plays a crucial role in addressing crime, violence, conflict and insecurity in cities to promote good governance, appropriate urban planning and management. Plenty efforts have been made on developing crime prediction models by leveraging demographic data, but they failed to capture the dynamic nature of crimes in urban. Recently, with the development of new techniques for collecting and integrating fine-grained crime-related datasets, there is a potential to obtain better understandings about the dynamics of crimes and advance crime prediction. However, for a city, it is hard to build a uniform framework for all boroughs due to the uneven distribution of data. To this end, in this paper, we exploit spatio-temporal patterns in urban data in one borough in a city, and then leverage transfer learning techniques to reinforce the crime prediction of other boroughs. Specifically, we first validate the existence of spatio-temporal patterns in urban crime. Then we extract the crime-related features from cross-domain datasets. Finally we propose a novel transfer learning framework to integrate these features and model spatio-temporal patterns for crime prediction.**

***Index Terms*—Crime Prediction, Transfer Learning, Spatio-Temporal Patterns.**

I. Introduction

Recent studies have shown that crime prediction is closely related to address crime, violence, conflict and insecurity in cities to promote good governance, appropriate urban planning and management[1]. Thus there is an increasing and urgent demand for accurate crime prediction. Efforts have been made on understanding crime prediction model based on demographic data [2], [3], [4], i.e., statistical socioeconomic characteristics of a population, but it is still challenging for researchers to accurately predict crime number due to the following facts (1) most regions in a city share similar demographic features that cannot capture the differences between different regions, and (2) demographic features are stable over a long-term period that cannot capture the dynamics within a region[5].

Recently, with the development of new techniques for collecting and integrating fine-grained urban data, a large amount crime-related datasets are recorded such as public safety data, meteorological data, point of interests data, human mobility data and 311 public-service complaint data. These datasets contain fine-grained information about where and when the data is collected and provide helpful context information about crime. Such information allows us to better understand the dynamics of crime and enables us to study spatial factors of crime such as geographical influence. Meanwhile, criminal theories[6], [7] suggest that crime distribution is highly determined by time and space, thus spatio-temporal patterns play a crucial role in crime analysis and have great potential to help us build crime prediction model.

In this paper, we explore spatio-temporal patterns for crime prediction with urban data. To be specific, for temporal-spatial patterns, we focus our investigation on (a) *intra-region temporal patterns* that help us to understand how crime evolves over time for a region in a city and (b) *inter-region spatial patterns* that suggest the geographical influence among regions in the city. However, for a city, it is hard to build a uniform framework for all boroughs due to the uneven distribution of data, e.g., the data of Brooklyn borough is much sparser than Manhattan. Motivated by the existence of movement of citizens and commuting of public transportations between different boroughs, there is a potential to exploit transfer learning to make accurate crime prediction for all boroughs. To this end, in this paper, we exploit spatio-temporal patterns in urban data in one borough in a city, and then leverage transfer learning techniques to reinforce the crime prediction of other boroughs.

II. Data Analysis

In this section, we will first introduce the dataset for this study, and then perform preliminary analysis about spatio-temporal patterns in crime data.

A. Data

We collect crime-related data from July 1, 2012 to June 30, 2013 in New York City. We divide NYC into 133 disjointed regions, and each region is a $2km \times 2km$ grid.

- **Public Security Data**: We collect (1) crime complaint data that contains the complaint frequencies of multiple types of offenses, and (2) Stop-and-Frisk data, which includes a NYC Police Department practice of temporarily detaining, questioning, and searching weapons.
- **Meteorological Data**: Meteorology and crime have been found to be correlated[8]. Hence, we collect meteorological data, consisting of weather, temperature, wind strength, precipitation, etc. In total, 30 features are collected from NYC meteorological stations every day.
- **Point of interests (POIs)**: The density of POIs can characterize the neighborhood functions, which could be helpful for crime prediction. We crawled point of interests from FourSquare. In total, 11 categories of POIs are obtained.

2375-9259/17 $31.00 © 2017 IEEE
DOI 10.1109/ICDMW.2017.165

- **Human Mobility**: Human mobility provides useful information, such as residential stability, which is related to urban crime. We extract three features from this source, i.e., check-ins from the POI dataset, and pick-up & drop-off points from the taxi trajectories dataset, which denote the number of people arriving at or departing from the target region.
- **311 Public-Service Complaint Data**: 311 is NYC's governmental non-emergency service number, allowing people to complain about things by making a phone call, which shows the citizens' dissatisfaction with government service, thus it is highly related with crime.

B. An Analysis on spatio-temporal Pattern

In this subsection, we investigate spatio-temporal patterns in crime data. To be specific, we focus on: (i) intra-region temporal patterns and (ii) inter-region spatial patterns. We could summarize the observations from our preliminary study as follows:

For a region, we observe intra-region temporal patterns: (1) for two adjacent time slots, they are likely to share similar crime numbers; and (2) with the increase of differences between two time slots, the crime difference has the propensity to increase.

For different regions within a borough, we note inter-region spatial patterns: (1) two spatially close regions have similar crime numbers; and (2) with the increase of spatial distance between two regions, the crime difference tends to increase; and (3) for regions from different boroughs, they do not follow above mentioned two inter-region spatial patterns.

The above observations provide the groundwork for our proposed transfer learning framework for crime prediction.

III. Framework Overview

Figure 1 shows that the framework of our method comprises of three major components: (i) feature extraction, (ii) transfer learning based framework, and (iii) crime prediction, as follows.

Step 1: Feature Extraction. We first extract features from multiple datesets, such as crime complaint dataset, stop-and-frisk dataset, meteorology, Point of Interests (POIs), human mobility and 311 complaint dataset. Then we fuse these features into feature matrices.

Step 2: the proposed strategy STF. Based on feature matrices and the historical crime numbers, we propose an approach to learn the model parameters for each region in each time slot for one borough. We exploit a spatio-temporal multi-task learning strategy to develop the predictive model, which includes (1) intra-region temporal patterns that the crimes change smoothly over adjacent time and change over consecutive weeks periodically within a region, and (2) inter-region spatial patterns that two spatially close regions tend to have similar crime numbers. Then, based on the parameters of one borough, we leverage transfer learning techniques to train the parameters $\mathbf{W}$ of other boroughs in the city.

Step 3: Crime Prediction. Based on the well trained parameters $\mathbf{W}$, our framework provides crime prediction of each region in the near future of other boroughs in the city to police departments, and then assists them take actions to prevent crimes.

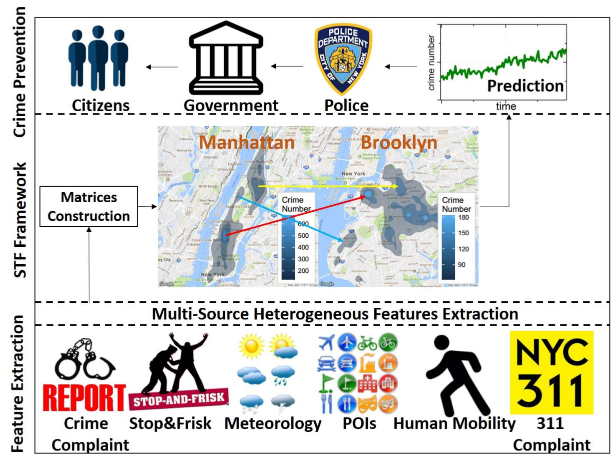

Fig. 1. The Overall of the crime prediction system.

IV. Conclusion

In this paper, we propose a novel framework STF, which captures temporal-spatial patterns and leverages transfer learning for crime prediction. STF leverages cross-domain urban datasets, e.g., public security data, meteorological data, point of interests (POIs), human mobility data and 311 complaint data.

There are several interesting research topics, such as (1) Where: mining where is the hotspot for a specific category of crime such as robbery, (2) When: knowing which hours are safe or unsafe for certain crimes, (3) Who: mining who are likely be criminals through user portrait on online social network, (4) How: identifying the process of how an offense happens, and (5) Why: exploring why an offense happens at a specific time in a specific region. We will leave these as future investigation directions.

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