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URBAN COMPUTING WITH MOBILITY DATA: A UNIFIED APPROACH

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Abstract

With the advent of information age, various types of data are collected in the context of urban spaces , including taxi pickups/drop-offs, tweets from users, air quality measure, noise complaints, POIs, and many more. It is crucial to use these data to solve urban issues, such as traffic congestion, crime prediction, and pollution. Two immediate questions are “Are those different data correlated?”, “How do we employ their correlation to infer one from the other?”

Urban computing has gained increasing popularity as an active research topic. These studies include profile city functions, detect traffic anomalies, predict air qualities, and location recommendation. The common challenges we face include 1) dealing with sparse and noisy data sources, and 2) handle implicit and complicated correlations. While various approaches are proposed, they still have the following drawbacks. 1) The partition of spatial-temporal space is over-simplified. Partition space into regions with road network or administrative division is widely used. However, these partitions does not always align with the data distribution. 2) Most models assume uniform correlation among different spatial regions. As a matter of fact, in my preliminary study I have observed that when training separate models on Chicago south and north, two models are different and the estimation results will be better. 3) The feature construction from different data sources is ad-hoc.

The goal of this thesis will be to develop a unified framework to capture the correlations of heterogeneous data in the urban context. Starting from a preliminary study on estimating the Chicago community level crime with POI and taxi flow. The intuition is that the POI complements the demographics features, and the taxi flow acts as a hyperlink to connect non-adjacent community areas. The results suggest that both newer type of features correlates with the crime and improves the estimation significantly. Next, I am trying to model spatial variations. Namely, the same features in different regions correlate differently. Meanwhile, a smart partition based on observed urban data is also a key component in this framework. Finally, the urban data are classified as nodal feature and dyadic feature, which belong to a spatial unit and a pair of units respectively. In my future work, I plan to build a

unified probabilistic graphical model to capture the complicated interactions among spatial units.

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Acknowledgments

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Lastly i would also like to thank my parents and friends who helped me a lot in finalizing this project within the limited time frame.

Chapter 1 Introduction – Urban Computing

With the advent of information age, more and more data are collected in the urban space. Using various urban data to solve real urban problem is called urban computing.

1.1 The Challenges and Opportunities from Urban Data

Urban data have the following three main properties.

Variety refers to the heterogeneous data sources. As shown in Figure 1.1, there is various types of data in the urban space. In the city, we can collect traffic data, Point-of-interest (POI), air quality measure, weather, city noise complaints, and many more. Different types of data lead to different format in the data. For example, the air quality measure and weather is global over the city. Meanwhile, the crime incidents and taxi trip data have specific location information.

Volume of urban data is generally large. For example, there are more than $380,000$ POIs in New York City and $112,000$ POIs in Chicago. According to the Chicago public crime incidents record, there are over 5.8 millions of records in the past 15 years. Each of the crime records have detailed information on the date, location, and crime description.

Velocity refers to the speed that new data is generated, which is also huge in the urban space. For example, there are almost half million taxi trips are generated in New York City each day, and there are 621 millions of tweets posted each day.

All the large volume and heterogeneity of urban data poses a challenge for us to study. At the same time, those data enables the opportunities to look into many urban problems, such as traffic anomaly detection, travel time estimation, city noise diagnosing, from a new angle.

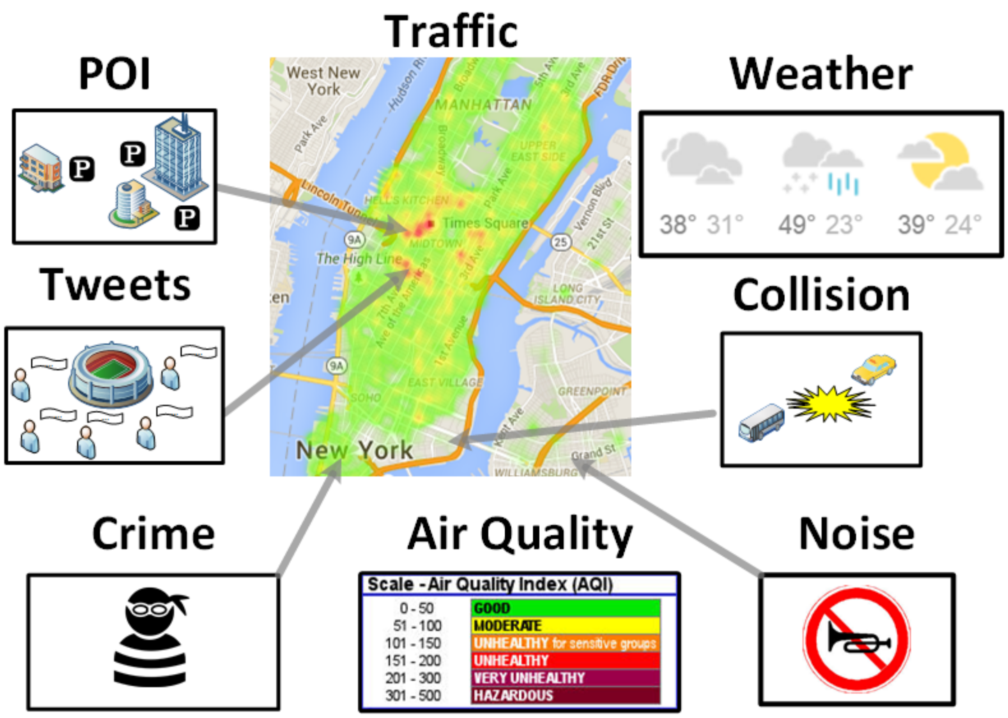


Figure 1.1. Use data collected in the urban space to address real urban problems.

1.1.1 A New Type of Data: Mobility Flow

As the advance to positioning technology, we are able to collect more and more mobility data. In the urban space, the trajectories of massive public transportation vehicle are recorded at minute intervals; the taxi/urban trips are recorded by pickup/drop-off locations and time; personal trajectories are tracked by health related mobile App, people's home and office location are surveyed by US Census Bureau.

The mobility data is a new type of data, because it is not attached to one specific point as most of other urban data. The mobility data tracks the movement of people among two or several locations. The ability to connect various locations make the mobility data unique and important [1].

1.2 Model Interactions In Urban Space

1.2.1 Traditional Approach: Space Continuity

City is a huge and complicated system, where everything might be connected. Building a new transportation center may incur more traffic as well as crime incidents in the nearby areas. When a big event happens and a lot of people accumulate at the venue, the traffic volumes at nearby regions increase as well. From the example above, we see that various interactions are undergoing among different regions in the city.

In the traditional urban computing research literature, the most widely used and accepted assumption is **space contiguity**, which assumes that spatially adjacent regions tend to have similar properties. In urban space, most data reflect the properties of human beings, such as the traffic volume, crime count, and geo-tagged tweets. Therefore, these data are attached to human crowd instead of a specific location. In the urban space, the intuition behind the **space continuity** is that human movement is regular, and most of our daily activities are conducted in a limited area. Based on the space continuity assumption, when studying the interactions among regions, it is naturally to assume that geographically adjacent regions tend to be more alike. Examples are high-crime community tend to have bad influence on its neighboring community, and vice versa.

1.2.2 New Approach: Flow as Hyperlink

When the human mobility data is not widely available, the space continuity makes a lot of sense. However, the new mobility flow data enables us to build better model of **region interactions** with the real human movement. *In my proposal, my research focus is to capture the complicated interactions in the urban space with the new flow data.*

Take crime inference as an example. Understanding how to control crime is important because exposures to violence and crime have been unusually high in

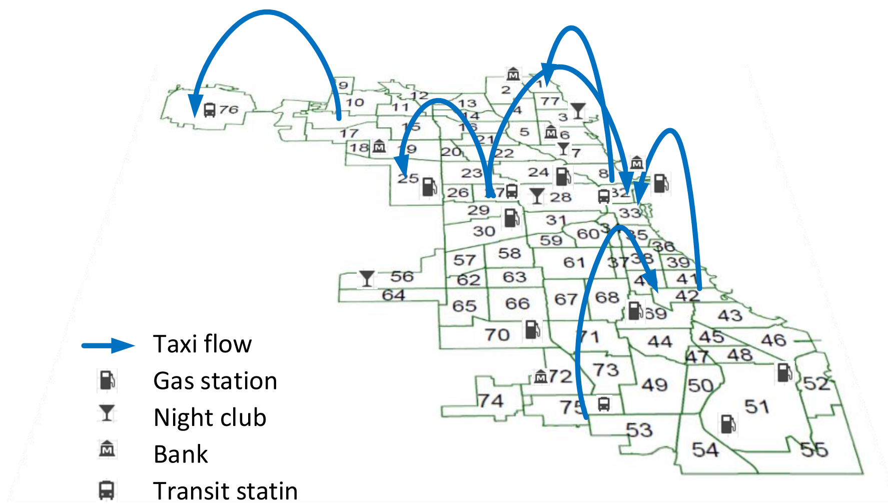


Figure 1.2. An illustration of various types of features we used in Chicago. The POI distribution across community areas reflects profiles of the region functionality. The taxi flow connects nonadjacent regions and act as a "hyperlink".

the U.S. for several decades and, while declining, they remain high [2, 3].Over half a million children and youth aged 10-24 years were treated in 2012 in emergency departments for nonfatal physical assault injuries related to gun shots, cuts and stabbings, among others [4]. Understanding the neighborhood context of crime is particularly important because victimization and other forms of crime exposures have many severe consequences. Beyond the high medical bills and violent death, consequences include behavioral and mental health problems, aggression, substance abuse, post-traumatic stress disorder, and suicide, lower academic achievement, and engaging in further violence [5].

Traditionally, researchers have used demographic information (e.g., population poverty level, socioeconomic disadvantage, racial composition of population) to estimate the crime rate in a community [6]. However, such demographic information only contains partial information about the neighborhoods and does not dynamically reflect the changes in the community (demographic survey is conducted by census bureau every 10 years). Using only demographic information will result in a relative error of at least 30% for crime rate estimation in Chicago (refer to experiment section in the paper). Existing studies also use the geographical influence [7] to estimate the crime rate, i.e., the crime in the nearby communities can be propagated to the focal community. But this geographical influence is of little help in improving the crime inference on top of demographic feature, with at most 0.4% relative improvement in our experiments. This is probably because the nearby communities also share similar demographics, which limits the additional benefit of geographical influence.

In Figure 1.2, we show that taxi flow as a newer type of big data could provide us new insights to understand some traditional socioeconomic urban problems. A huge amount of taxi flow data reflect how people commute in the city. In previous studies, when using geographical influence [7], people assume that a community is affected by the spatially nearby communities. However, communities are not only affected by spatially-close communities. Even if two communities are distant in geographical space, they could have a strong correlation if there are many people frequently travel between these two communities [8]. We hypothesize that taxi flows may be considered as "hyperlinks" in the city that connect the locations and we use such data to estimate crime rates. Our experiments show very promising results – adding taxi flow data on top of all other features can further decrease the error by 5%.

1.3 Proposed Research Questions

In the urban space, **region interactions** bring solutions to the following several fundamental data mining questions. We propose to view the city as a spaital network of communites linked by "hyperlink" flow.

- Understand nodes using links. Estimate an unobserved property of focal community, given the observations on other communities and other types of data. For example, the crime rate in a residential neigborhood could be impacted by non-adjacent but flow-connected neighborhoods, because the residents in the neighborhoods are also exposed to and influenced by the environment in the workplace.

- Understand links using nodes. Are certain properites of two connected nodes associated with the type and volume of the flow connections? For example, given the crime profiles of two connected communities, which type of interactions (taxi, LEHD, or space continuity) is more important in forming the crime properties?

- Identify the fundamental dependency structure among properties of nodes. For example, the crime rate of two connected communities may show a strong correlation. However, this does not necessarily mean that high crime rate in one community lead to the high crime in another. The crime is very likely to be caused by other properties.

Chapter 2
Understand Nodes Using Links

In this chapter we address the first proposed research question. Namely, we use the observations in other regions and other types of data to estimate one unobserved property in focal region. We call this problem **inference problem**. At the very beginning, we give a generalized inference problem definition. Following the general definition, we look at one example of crime inference.

2.1 General Problem Definition

In this section, we give a generalized definition of the inference problem. Suppose we have a set of regions $r_1, r_2, \cdots, r_n$, and we are interested in one property y_i for region r_i. In addition to $\vec{y}$, we also have other properties $\vec{x}_i$ observed on region r_i, and the set of all auxiliary properties are denoted as X. It is noteworthy that both $\vec{y}$ and X are nodal properties. The spatial adjacency among all regions are known as W^0, where W^0 is spatial adjacency matrix. The hyperlink mobility flow is also observed as W^k for type $k = \{1, 2, \cdots\}$. The entry w_{ij}^k in W^k refers to the quantity flow from r_i to r_j of type k.

The inference problem is that for a given region r_t, whose y_t is unobserved, we try to use $\{y_i\} \backslash y_t$ together with X and $W^k, k \in \{0, 1, 2, \}$ to estimate y_t. Mathematically, we have

$$\hat{y_t} = f(\{y_i\} \backslash y_t, X, W^k), \tag{2.1}$$

where f is the estimation model of any choice.

In the next section, we will use the crime inference as an example to show

how this inference problem is solved in the literature, and how do we enhance the existing model.

2.2 Crime Inference as One Example

2.2.1 Related Work

In the criminology literature researchers have studied the relationship between crime and various features. Examples are historical crime records [9, 10], education [11], ethnicity [12], income level [13], unemployment [14], and spatial proximity [7]. In data mining field, newer type of data are used in the study. For example, there are works using twitter to predict crime [15, 16], and works using cellphone data [17, 18] to evaluate crime and social theories at scale.

Overall, the existing work on crime prediction can be categorized into three paradigms.

Time-centric paradigm. This line of work focuses on the temporal dimension of crime incidents. For example, in a study [9], the authors propose to use a self-exciting point process to model the crime and gain insights into the temporal trends in the rate of burglary. In another study [19], the authors investigate the temporal constraints on crime, and propose an offender travel and opportunity model. This paper validates the claim that a proportion of offending is driven by the availability of opportunities presented in the offender's routine lives.

Place-centric paradigm. Most existing work adopt a place-centric paradigm, where the research question is to predict the location of crime incidents. The predicated crime location is usually refereed by the term *hotspot*, which has various geographical size. There are plenty of works on exploration of the crime hotspots. For example, in a study [20] the authors use criminal offense records to identify spatio-temporal patterns at multiple scales. They employ various quantitative tools from mathematics and physics and identify significant correlation in both space and time in the crime behavioral data. Short *et al.* [21] use a simple model to study the dynamics of crime hotspots and identify stable hotspots, where criminals are modeled as random walkers. Bogomolov *et al.* [18] use human behavioral data derived from mobile network and demographic sources, together with open crime data to predict crime hotspots. They compare various classifiers and find random forest has the best prediction performance. The paper [15] bases on automatic semantic analysis to understand natural language Twitter posts, from which the crime incidents are reported. Some other work [22, 23] employ the kernel density estimation (KDE) to identify and analyze crime hot spots. Those works form another form of crime prediction, which relies on the retrospective crime data to identify areas of high concentrations of crime. In [24], the authors extend the crime cluster analysis with a temporal dimension. They employ the space-time variants of KDE to simultaneously visualize geographical extent and duration of crime clusters.

Population-centric paradigm. In the last paradigm, research focuses on the criminal profiling at individual level and community level. At the individual level, [10] aim to automatically identify crimes committed by same individual from the historical crime database. The proposed system called *Series Finder*, is designed to find and classify modus operandi (M.O.) of criminals. At the community level, Buczak *et al.* [25] use fuzzy association rule mining to find crime pattern. The rules they found are consistently held across all regions. The paper constructs association rules from population demographics in community. In another paper [17], the authors use computation method to validate various social theories at a large scale. The data they used is mobile phone data in London, from which they mine the people dynamics as features to correlate with crime.

Our problem is different from the first two categories of work, mainly because our innovation mostly lies in using newer type of data to enhance the commonly used traditional counterpart. More specifically, we use POI to enhance the demographics information, and use taxi flow as hyper link to enhance the geographical proximity correlation. Although our problem does not consider the temporal dimension of crime in depth, it could be a promising supplement to better profile crime. Our problem dose not predict the location of any particular crime incident. Therefore the methods proposed in place-centric method are not applicable in our problem. However, the features we proposed may be incorporated in those crime prediction model. Our problem falls into the third paradigm, because we are trying to profile the crime rate for Chicago community areas. In our problem, the community areas are well-defined and stable geographical regions. The newly proposed POI feature and taxi hyper link provide a unique perspective in profiling the crime rate across community areas.

2.2.2 Data Description and Feature Extraction

The crime dataset in Chicago has detailed information about the time and location (i.e., latitude and longitude) of crime and the types of crime. In our problem, when we use term crime count, we often refer to crime count in a region (i.e., community area) in a year. The *community area* is used as our geographical unit of study, since it is well-defined, historically recognized and stable over time [26]. In total, there are 77 community areas in Chicago. Crime rate is the crime count normalized by the population in a region. We use vector $\vec{y} = [y_1, y_2, \ldots, y_n]$ to denote the crime rate in region i.

The crime data of Chicago are obtained from City of Chicago data portal [27]. Chicago is the city with most complete crime data that are made public online. The crime dataset contains the incident date, location (strict name and GPS coordinates), and primary type from year 2001 to 2015. In total there are $5,856,414$ recorded crime incidents over 15 years, which is an average $390,417$ crimes incidents per year. We visualize the crime normalized by population in Figure 2.1, from which we can see that the downtown area has the highest crime rate.

In this example we study the crime rate inference problem. More specifically, we estimate the crime rate of some regions given the information of all the other regions. Without loss of generality, we assume there is one community area t with crime rate y_t missing, and we use the crime rate of all the other regions $\{y_i\} \backslash y_t$ to infer this missing value. Our problem is mathematically formalized as follows

$$\hat{y_t} = f(\{y_i\} \backslash y_t, X), \tag{2.2}$$

where X refers to observed extra information of all those community areas.

We consider two types of features X for inference:

- Nodal feature. Nodal features describe the characteristics of the focal region. Such features include demographic information and Point-of-Interest (POI) distribution. Demographics are frequently used in literature, but POI is a newer type of big data, which we find significantly improve the crime inference accuracy.

- Edge feature: (1) Geographical influence. Geographical influence considers the crime rate of the nearby locations. This feature has been extensively used

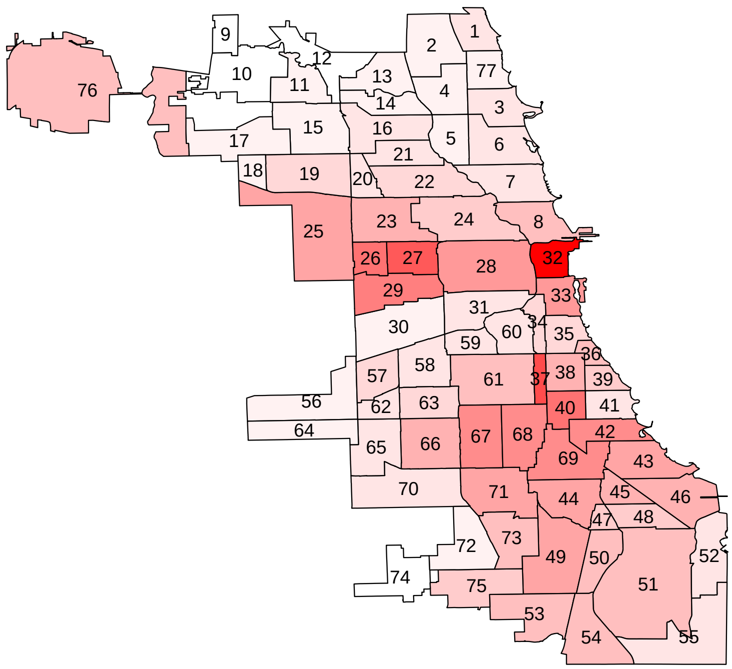


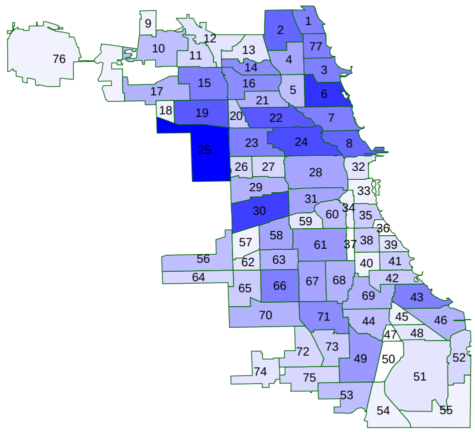
Figure 2.1. Crime rate of Chicago by community areas. The community area #32 is Chicago downtown, which has the highest crime rate.

in literature as well. To estimate the focal region, the crime rate of nearby regions are weighted according to spatial distances. (2) Hyperlink by taxi flow. Locations are connected through the frequent trips made by humans, which can be considered as the hyperlinks in space. This type of feature has never been studied in literature. We propose to use taxi trips to construct the social flow. Our hypothesis is that similarity in the crime rate of two regions should correlate with the social flow strength between these two regions.

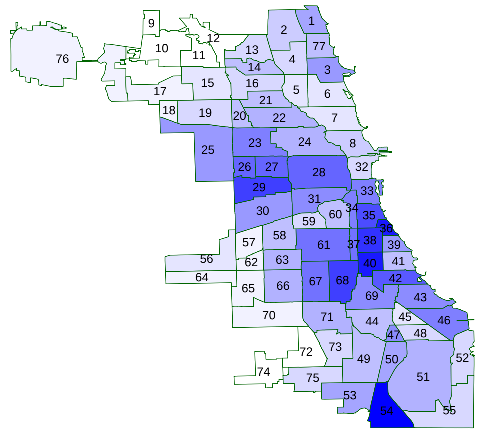
Below we will describe the datasets used to construct features and the characteristics of these features.

Nodal Feature: Demographics

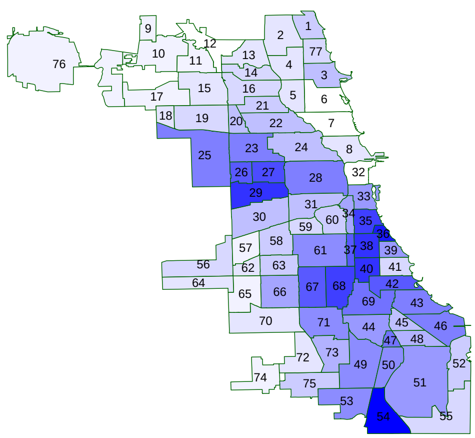
Socioeconomic and demographic features of neighborhoods have been widely used to predict crime [18, 28–30]. Previous studies have shown that crime rate correlates with certain demographics. For example, [6, 31] suggests that population diversity leads to less crime in certain neighborhoods. In our study, we include demographic



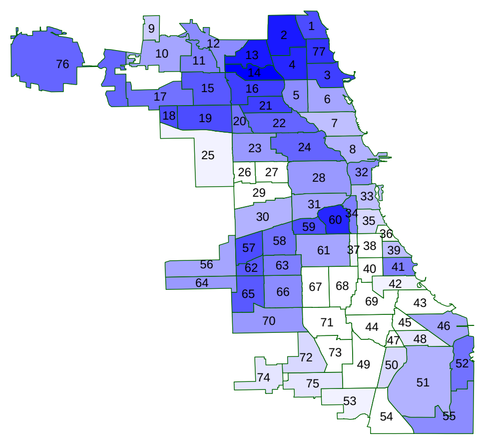
(a) Total population



(b) Poverty index



(c) Disadvantage index



(d) Ethnic diversity

Figure 2.2. (a)-(d) Demographics in Chicago by community areas. Darker colors indicate higher values.

information from the US Census Bureau's Decennial Census of 2010 [32] and American Community Survey's five-year average estimates between 2007 and 2011. We use year 2010 data because we are evaluating crime rates in 2010-2013. The demographics include the following features:

total population, population density, poverty, disadvantage index, residential stability, ethnic diversity, race distribution.

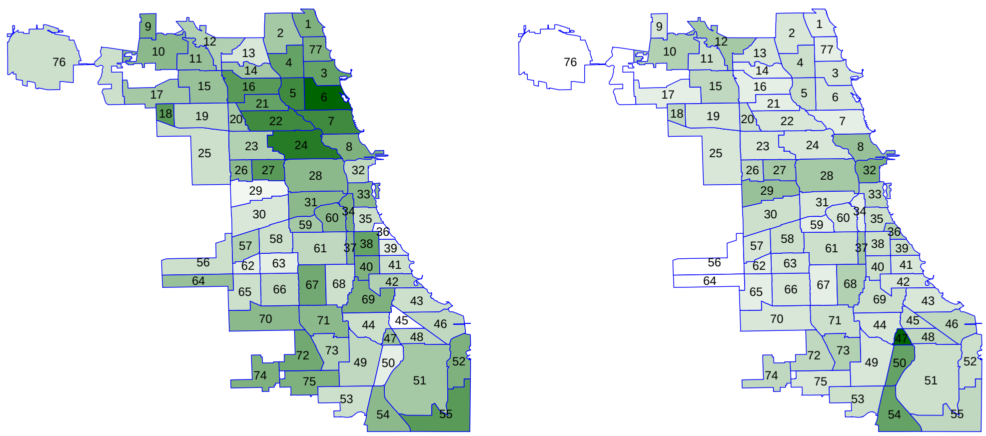
The poverty index measures the proportion of community area residents with income below the poverty level. The disadvantage index is a composite scale based on prior work [33], a function of poverty, unemployment rate, proportions of families with public assistance income, and proportion of female headed households. The residential stability measures home ownership and proportion of residents who lived in the neighborhood for more than one year. Racial and ethnic diversity is an index of heterogeneity [6] based on six population groups, including: Hispanics, non-Hispanic Blacks, Whites, Asians, Pacific Islanders and others.

Figure 2.2 visualizes the crime rate and demographics features in Chicago by community areas. Comparing with Figure 2.1, it is clear that the crime rate and poverty index and disadvantage index are consistent, the ethnic diversity shows an inverse correlation, and the total population has little correlation with crime.

Table 2.1 shows the Pearson correlation coefficient between various demographics features and the crime rate at community area level. The corresponding p-value is also calculated and shown in the table to indicate the significance of the correlation coefficient. There are in total 77 community areas in Chicago. Table 2.1 shows such correlation with several most correlated features. We can see that the poverty index and disadvantage index positively and strongly correlate with crime, while the ethnic diversity negatively correlates with crime. Other features such as total population, population density, and residential stability have weaker correlations. One counter-intuitive observation is that the total population has a weak and negative correlation with crime. The reason is that we use crime rate in each community area, which is already normalized by the population, and therefore the total population and population density have less impact.

Table 2.1. Pearson correlation between demographic features and crime rate (***** indicates significant correlations with p-value less than 5%).

Feature	Correlation	p-value
Total Population	-0.1269	0.2716
Population Density	-0.1972	0.0855
Poverty Index	**0.5573***	1.403e-07
Disadvantage Index	**0.5959***	1.082e-08
Residential Stability	-0.0453	0.6965
Ethnic Diversity	**-0.5545***	1.678e-07
Percentage of Black	**0.6696***	2.779e-11
Percentage of Hispanic	**-0.3820***	0.0006



(a) Nightlife (b) Professional

Figure 2.3. Plot the POI ratio per neighborhood. The saturation of color is proportional to the ratio value. The “professional” category distribution is more consistent with the crime distribution, and therefore it is the most correlated with crime. Meanwhile, the “nightlife” category is not positively correlated with Chicago crime.

Nodal Feature: Point-of-Interest (POI)

While demographics are traditional census data, POI is a type of modern data that provide fine-grained information about locations. We collect POI from FourSquare [34]. POI data from FourSquare provide the venue information including venue name, category, number of check-ins, and number of unique visitors. We mainly use the major category information because categories can characterize the neighborhood functions. There are 10 major categories defined by FourSquare:

food, residence, travel, arts & entertainment, outdoors & recreation, college & education, nightlife, professional, shops, and event.

In total, we have crawled $112,000$ POIs from FourSquare for Chicago. Most of these POIs are in downtown area of Chicago. We normalize the POIs count per category by the total POI count in a neighborhood and plot two selected category, i.e. nightlife and professional, in Figure 2.3. The darker colored neighborhoods in Figure 2.3 are the ones with a higher portion of residence POIs.

In Table 2.2 we show the Pearson correlation between POI category and crime rate. The category “professional” is most significantly correlated with the crime rate. Under the professional POI category, there are some venues with a large population concentration, such as transportation center, convention center, community center,

Table 2.2. Pearson correlation between POI category and crime rate (* indicates significant correlations with p-value less than 5%).

POI category	Correlation	p-value
Food	-0.1543	0.1803
Residence	-0.0610	0.5984
Travel	-0.0017	0.9883
Arts & Entertainment	-0.0049	0.9661
Outdoors & Recreation	0.0668	0.5637
College & Education	-0.0078	0.9473
Nightlife	-0.1553	0.1775
Professional	**0.3221***	0.0043
Shops	-0.1676	0.1450
Event	0.2196	0.0549

and coworking space. In those venues, the population volume is high and residential stability is low, therefore the professional POI counts positively correlates with crime rate. One counter-intuitive observation is that "nightlife" category is not positively correlated with crime (-0.1553). This can be explained through Figure 2.3(a). The majority of nightlife venues in Chicago locate in northern area, while most crime incidents occur in downtown area.

Edge: Geographical Influence

Together with the US census demographics data, we also collected the boundary shape files of Chicago, which are used to calculate the geographical influence feature.

Previous studies have also shown that the crime rate at one location is highly correlated with nearby locations [35, 36]. Such geographical influence is also frequently used in the literature [37, 38], which is calculated as:

$$\vec{F^g} = W^g \cdot \vec{Y}, \tag{2.3}$$

where W^g is the spatial weight matrix. If region i and j are not geospatially adjacent, $w^g_{ij} = 0$; otherwise, $w^g_{ij} \propto distance(i, j)^{-1}$.

In Figure 2.4, we plot crime rate with respect to geographical influence calculated in Eq. 2.3. We observe an obvious positive correlation, which means if nearby neighborhoods have a high crime rate, the focal neighborhood is more likely to have a high crime rate. We also do observe a few outliers in Figure 2.4. These neighborhoods show different crime rate in their nearby neighborhoods compared

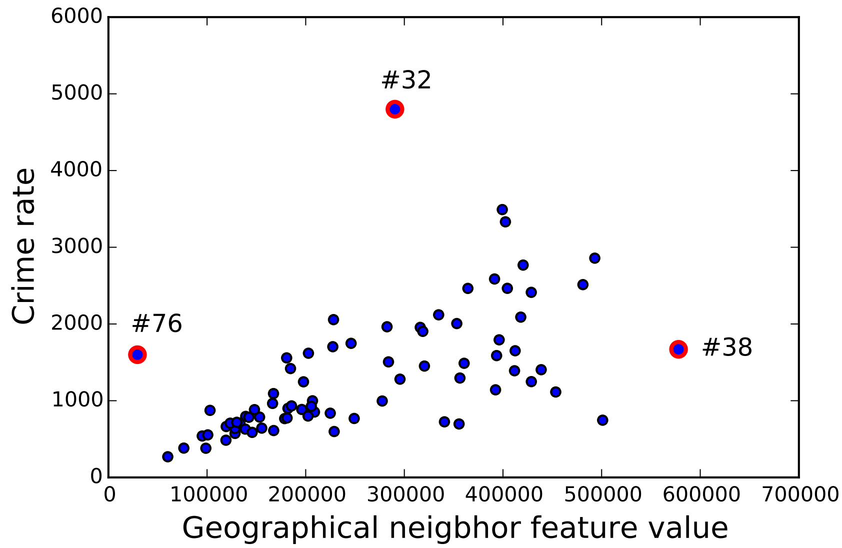


Figure 2.4. The geographical influence feature correlation with crime. In the plot we marked out three outliers and their corresponding community area ID.

to their own. For example, as we can also see in Figure 2.1, community area #38 locates in an area where the the neighbors have high crime rates but its crime rate is relatively low; in contrast, neighborhood #32 has a high crime rate even though its neighbors have relatively low crime. The community area #76 home of the O'Hare International Airport is far from most of other community areas, however its own crime rate is relative high.

Edge: Hyperlinks by Taxi Flow

In our Chicago taxi dataset, there are $1,048,576$ taxi trips in total during the October to December in 2013. For each trip the following information are available: pickup/dropoff time, pickup/dropoff location, operation time, and total amount paid. We requested the taxi trip records from Chicago taxi commission pursuant of the Freedom of Information Law. Figure 2.5 shows a visualization of the major flows at community level.

One of our hypothesis is that the social interaction among two community areas propagates crime from one region to another. The Chicago taxi data captures the social interactions among various community areas. To calculate this first, we first map all taxi trips to community areas to get the taxi flow w_{ij} $\forall i, j \in \{1, 2, \cdots n\}$. Then the taxi flow lag is constructed by the product of social flow and the crime

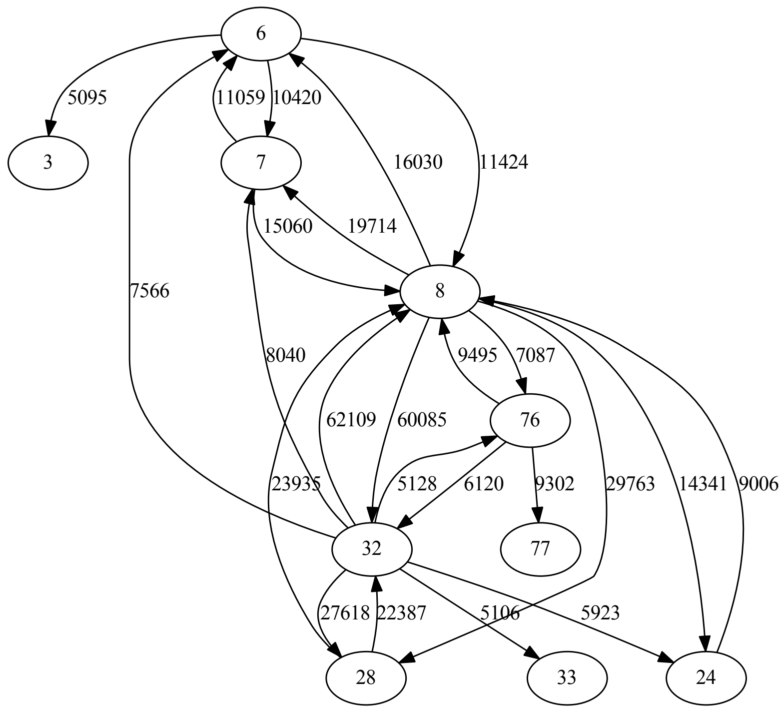


Figure 2.5. Major taxi flows between neighborhoods. We set a threshold ($> 5,000$) on the flow and only plot the high volume flow. The label on the node is the ID of the corresponding community areas. We can see that there are several hub community areas, such as #6, #8, #32, which are all in the downtown areas. The label on the edge shows how many taxi trips are commuting through the two community areas for three months in 2013.

rate of neighboring regions as follows

$$\vec{F^t} = W^t \cdot \vec{Y}. \tag{2.4}$$

The taxi flow W^t is a matrix with entry w_{ij} denoting the taxi flow from i to j. Note that $\forall i$, $w_{ii}^s = 0$ in matrix W^t, because we have to exclude the crime in focal area from its own predictor. The semantic of this taxi flow feature is how many crime in the focal area is contributed by its neighboring areas through social interaction.

The correlation between taxi flow and crime rate is shown in Figure 2.6. From the scatter plot, we can see that overall the crime rate is positively correlate with the taxi flow. There are two outliers clearly shown in Figure 2.6. The community area #32 is the downtown Loop, which has the highest crime rate and is hard to predict by taxi flow. Another anomalous community area #47 has relatively low crime rate by itself. However, this area has a lot of in flows from high-crime communities.

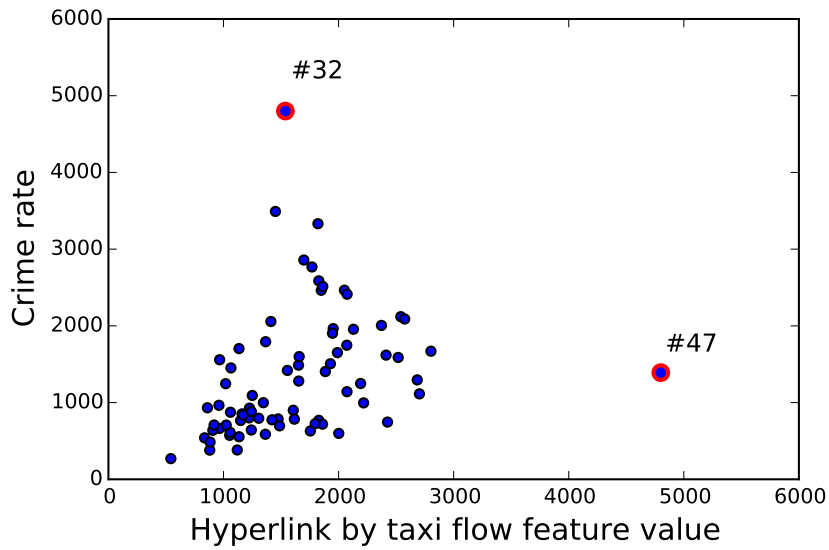


Figure 2.6. Correlation between taxi flow and crime rate. In the plot, we marked out three outliers and their corresponding community area ID.

2.2.3 Spatial AutoRegressive Inference Model

Linear Regression

The most straightforward prediction is linear regression model. This model assumes the error terms follow a Gaussian distribution $\epsilon \sim \mathcal{N}(0, \sigma^2)$. As a result the parameter distribution also follows a Gaussian distribution. This assumption makes the model less generative, since in real applications, there is no way to ensure the dependent variable has a Gaussian error term.

Equation 2.5 gives the linear regression formulation of our problem.

$$\vec{y} = \vec{\alpha}^T \vec{x} + \beta^f W^f \vec{y} + \beta^g W^g \vec{y} + \vec{\epsilon}, \tag{2.5}$$

where $\vec{x}$ represents the nodal features including demographics and POI distribution, W^f is the flow matrix of taxi flow, and W^g is the spatial matrix representing the geographical adjacency. On the right-hand side, ϵ is the only stochastic variables, and all other terms are fixed observation values. Therefore, we incorporate all the fixed observations into one term X, and we get the standard regression problem

$$E(y) = Xw + \epsilon.$$

In order to learn the regression parameter w, we can use a maximum likelihood estimator. Since $\epsilon = y - Xw$, the joint probability of error term is

$$P(\epsilon|w) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{(y-Xw)^2}{2\sigma^2}}. \tag{2.6}$$

Maximizing the joint probability gives us the optimal solution.

Linear regression gives negative prediction

One obvious drawback is that the linear regression is not a count prediction model, since it will give negative number as prediction. For example, we find the suspicious community #32 case. Refer to Figure 2.1, we know this community is the downtown. The crime count for community #32 is $7,709$ in 2010. However, the linear regression base model gives $-1,448$ as prediction. This result is not acceptable in a count prediction model. We further look into the features of community #32 to figure out why it has negative crime count estimation. It turns out that community #32 has $12,175$ venues in total, which is 10 times more than the average of other communities $(1,011)$. In our learned model, the venue count feature has a negative coefficients, which indicates that popular places tend to have less crime incidents. The big difference in the venue count feature lead to a negative prediction for community # 32.

Poisson regression as a count prediction model

To address this issue, a count prediction model is a natural selection. The *Poisson regression* is another form of regression, more appropriate for count data than linear regression [39] [40]. With shortened notation X, Poisson regression model has the exponential function as link function

$$E(y) = e^{Xw}. \tag{2.7}$$

This comes from the assumption that y follows Poisson distribution with mean λ. Additionally, the mean *lambda* is determined by observed independent variables X, with the link function $\lambda = e^{Xw}$. Adding all together, the joint probability of y is

$$P(y|w) = \frac{e^{-e^{Xw}}(e^{Xw})^y}{y!}. \tag{2.8}$$

Compared with the linear regression, the negative log-likelihood function of Poisson regression is derived from the dependent variable itself, unlike linear regression, which is derived from the joint distribution of error term.

However, Poisson regression enforces the mean and variance of dependent variable y to be equal. This restriction leads to the "over-dispersion" issue for some real problems, that is the presence of larger variability in data set than the statistical model expected. In our crime dataset, the mean of crime count for all communities is $4,787$, while the variance is 1.6×10^7. The variance is almost the square of the mean, which significantly violate the Poisson distribution assumption. Therefore, we should look for other count prediction model.

Negative binomial regression addresses over-dispersion

To allow larger variance in the predicted value, we introduce the Poisson-Gamma mixture model, which is also known as *negative binomial regression.* The negative binomial regression has been used in similar work [41].

Given that the crime rate y follows Poisson distribution with mean λ. In order to allow for larger variance, now the λ itself is a random variable, distributed as a Gamma distribution with shape $k = r$ and scale $\theta = \frac{1-p}{p}$. The probability function of y becomes

$$\begin{aligned} P(y|r,p) &= \int_0^\infty P_{Poisson}(y|\lambda) \cdot P_{Gamma}(\lambda|r,p) d\lambda \\ &= \int_0^\infty \frac{\lambda^y}{y!} e^{-\lambda} \cdot \lambda^{r-1} \frac{e^{-\lambda(1-p)/p}}{(\frac{p}{1-p})^y \Gamma(r)} d\lambda \\ &= \frac{\Gamma(r+y)}{y!\Gamma(r)} p^k (1-p)^y \end{aligned} \tag{2.9}$$

This is exactly the probability density function of negative binomial distribution.

In negative binomial regression, the link function is

$$E(y) = e^{Xw+\epsilon}. \tag{2.10}$$

The error term e^ϵ is the mixture prior, and we assume it follows Gamma distribution with shape parameter $k = \frac{1}{\theta}$, so that it has mean $E(e^{\epsilon}) = k\theta = 1$ and variance $Var(e^{\epsilon}) = k\theta^2 = \theta$. This setting ensures the $E(y) = e^{Xw} \cdot e^{\epsilon} = e^{Xw}$.

2.2.4 Evaluation of negative binomial regression model

Evaluation Settings

We adopt the leave-one-out evaluation to estimate the crime rate of one geographic region given all the information of all the other regions. When we construct the spatial/social lag variable for the training data, the effect of testing region is completely removed. For example, if region y_t is the testing region, the remaining $\{y_i\} \backslash y_t$ become the training set. For any y_j in the training set, its geographical influence feature and taxi flow feature are constructed from $\{y_i\} \backslash \{y_t, y_j\}$.

In the evaluation, we estimate the crime rate for testing community area. The accuracy of estimation is evaluated by mean absolute error (MAE) and mean relative error (MRE).

$$MAE = \frac{\sum_i^n |y_i - \hat{y}_i|}{n} \tag{2.11}$$

$$MRE = \frac{\sum_i^n |y_i - \hat{y}_i|}{\sum_i^n y_i} \tag{2.12}$$

Performance Study: Negative Binomial Regression vs. Linear Regression

We evaluate the estimation accuracy under various feature combinations. The leave-one-out evaluation results are shown in Table 2.3. We run both linear regression model and negative binomial model on five consecutive years, 2010 – 2014. Both MAE and MRE are shown in the table. We have four types of features, demographics, POI, geographical influence and taxi flow. We test the various settings of feature combinations.

We compare the estimation error of negative binomial model with the linear regression base model. We use a incremental settings, where new features are added on top of previous one. The results are shown in Figure 2.7.

It is clear that the negative binomial model significantly outperform the linear regression model. Meanwhile, the negative binomial model captures our intuition well. Namely, adding new features will effectively improve the estimation accuracy.

Table 2.3. Performance evaluation. Various feature combinations are shown in each column. The linear regression model and negative binomial results are compared by year group.

			Settings							
Column ID			1	2	3	4	5	6	7	8
Features[1]		D	✓	✓	✓	✓	✓	✓	✓	✓
		G					✓	✓	✓	✓
		P		✓		✓		✓		✓
		T			✓	✓			✓	✓
Year	Model[2]	Error								
2010	LR	MAE	394.41	416.98	408.09	406.93	394.78	432.45	402.25	416.41
		MRE	0.294	0.311	0.304	0.304	0.295	0.323	0.300	0.310
	NB	MAE	391.53	333.14	395.64	323.47	389.55	350.06	387.43	**320.75**
		MRE	0.292	0.249	0.295	0.241	0.290	0.261	0.289	**0.239**
2011	LR	MAE	380.22	409.30	396.97	401.11	379.61	422.94	389.39	408.91
		MRE	0.295	0.318	0.309	0.312	0.295	0.328	0.302	0.320
	NB	MAE	381.11	332.62	388.81	328.94	378.84	345.24	381.33	**335.97**
		MRE	0.296	0.259	0.302	0.256	0.294	0.268	0.296	**0.253**
2012	LR	MAE	378.91	412.95	401.54	412.20	376.53	423.88	399.25	419.93
		MRE	0.306	0.334	0.325	0.333	0.304	0.343	0.322	0.339
	NB	MAE	386.31	337.24	389.58	331.41	384.23	352.22	381.67	**345.49**
		MRE	0.312	0.273	0.315	0.268	0.310	0.284	0.308	**0.279**
2013	LR	MAE	367.89	420.81	390.75	402.75	369.24	433.48	388.92	412.31
		MRE	0.324	0.370	0.344	0.354	0.325	0.381	0.342	0.362
	NB	MAE	376.08	333.92	373.08	312.63	377.57	350.33	368.49	**319.86**
		MRE	0.331	0.294	0.328	0.275	0.332	0.308	0.324	**0.281**
2014	LR	MAE	331.28	375.53	349.00	350.31	329.93	386.90	345.79	361.28
		MRE	0.326	0.369	0.343	0.345	0.324	0.380	0.340	0.355
	NB	MAE	340.73	293.52	339.17	274.45	336.09	308.18	326.07	**273.27**
		MRE	0.335	0.289	0.334	0.270	0.331	0.303	0.321	**0.269**

[1] D – demographic features, G – geographical influence, P – POI features, T – taxi flow feature.
[2] LR – Linear Regression, NB – Negative Binomial Regression.

In Table 2.3, we can see that in different years and under most settings, the negative binomial regression significantly outperforms the linear regression (with only a few exceptions when using only demographic feature). When using all the features, NB is significantly better than LR with at least 6% improvement in relative error. One reason is that the negative binomial is a count prediction model, which assumes some distribution for the predicted variable and guarantee its positivity. Another reason is that it is difficult to get very precise estimation of crime rate,

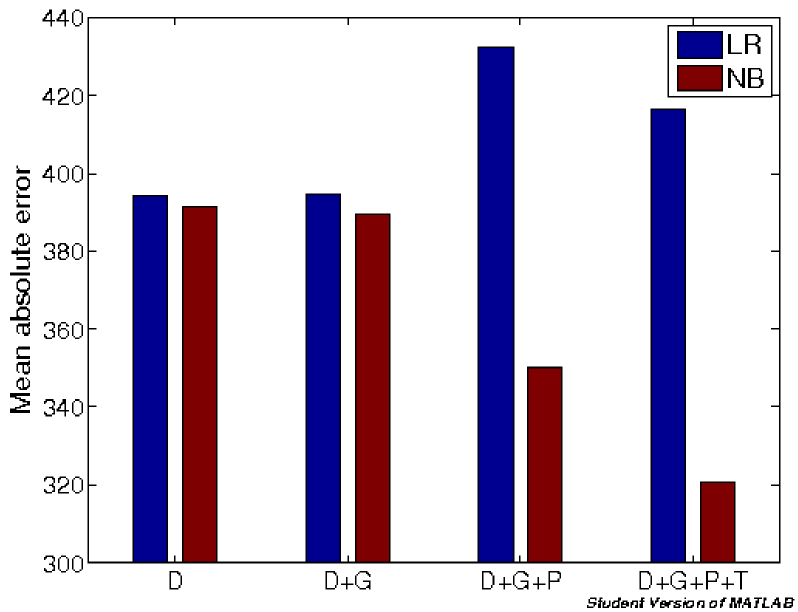


Figure 2.7. The inference error for linear regression base model. *D – demographic features, G – geographical influence, P – POI features, T – taxi flow feature

and negative binomial model allows a large variance in the estimated crime rate. Therefore negative binomial is more appropriate for crime rate estimation than linear regression.

Chapter 3
Understanding Links Using Nodes

3.1 Capture spatial non-stationarity (Proposed problem 1)

3.1.1 Dynamic spatial model

We use various types of data to estimate the crime count in community area (CA) of Chicago. For each CA we have observations on crime count and demographics. For each pair of CAs we also have observations on the taxi flow and spatial distance. One straightforward method is to build a regression model from all the features we observed to the crime counts.

We have one interesting observations is that in the south and north part of Chicago, the significance of different features are different. Therefore, the idea is to learn a dynamic weights for different spatial region.

Suppose we have n regions in total, $R = \{r_1, r_2, \cdots, r_n\}$. The following notations are used

crime count at r_i	y_i
demographics at r_i	$\mathbf{d}_i$
taxi flow between r_i and r_j	f_{ij}
taxi flow weight matrix for r_i	$\mathbf{f_i}$
spatial weight matrix for r_i	$\mathbf{g_i}$
social flow lag variable for r_i	$s_i = \mathbf{f}_i^T \mathbf{y}$
spatial flow lag variable for r_i	$p_i = \mathbf{g}_i^T \mathbf{y}$

Table 3.1. Symbols for the dynamic coefficient model.

3.1.1.1 Dynamic linear regression model

For simplicity we use linear regression model

$$y_i = \mathbf{w}_1^T \mathbf{d}_i + w_2 s_i + w_3 p_i + w_4,$$

where $\{w\}$ are the coefficients.

To simplify notations, we use $\mathbf{x}_i$ denote all the available predictors for region r_i,

$$\mathbf{x}_i = [\mathbf{d}_i, s_i, p_i, 1].$$

Then the model becomes

$$y_i = \mathbf{w}^T \mathbf{x}_i.$$

Now we use a dynamic model, where $\mathbf{w}$ is different for various regions. This leads to

$$y_i = \mathbf{w}_i^T \mathbf{x}_i.$$

The problem with formulation is that there are too many parameters to learn. To address this issue, we use the constraint that **spatially adjacent regions share similar coefficients**.

We use S_{ij} to denote the adjacency of r_i and r_j. And the aforementioned constraint is formulated as

$$\min \sum_{i,j} S_{ij} ||\mathbf{w}_i^T - \mathbf{w}_j^T||_2^2$$

The several choice of S_{ij}

- Binary indicator. $S_{ij} = 1$ if two regions are contiguous, otherwise $S_{ij} = 0$.
- The reverse distance between r_i and r_j.

The overall objective is

$$\min_{\mathbf{W}} \sum_i ||y_i - \mathbf{w}_i^T \mathbf{x}_i||_2^2 + \eta \sum_{i,j} S_{ij} ||\mathbf{w}_i^T - \mathbf{w}_j^T||_2^2 + \theta ||\mathbf{W}||_F^2 \tag{3.1}$$

3.1.1.2 Optimization

Rewrite the Frobenius norm in the last term

$$||\mathbf{W}||_F^2 = \sum_i ||\mathbf{w}_i - \mathbf{0}||_2^2.$$

Therefore the Equation 3.1 is rewritten as

$$\min_{\mathbf{W}} \sum_i ||y_i - \mathbf{w}_i^T \mathbf{x}_i||_2^2 + \eta \sum_{i,j \in 0, \cdots, N} S_{ij} ||\mathbf{w}_i - \mathbf{w}_j||_2^2, \tag{3.2}$$

where $\mathbf{w}_0 = \mathbf{0}$ and $S_{0i} = 1$ for $\forall i$.

To solve the objective in Equation 3.2, we use variable splitting. Namely, when optimizing for $\mathbf{w}_i$, we assume all other $\mathbf{w}_{j,j \neq i}$ are fixed. The sub-problem is

$$\min_{\mathbf{w}_i} ||y_i - \mathbf{w}_i^T \mathbf{x}_i||_2^2 + \eta \sum_j S_{ij} ||\mathbf{w}_i - \mathbf{w}_j||_2^2. \tag{3.3}$$

The update on $\mathbf{w}_i$ is

$$\mathbf{w}_i = \min_{\mathbf{w}_i} ||y_i - \mathbf{w}_i^T \mathbf{x}_i||_2^2 + \eta \sum_j S_{ij} ||\mathbf{w}_i - \mathbf{w}_j^{(t)}||_2^2.$$

The closed-form solution is

$$\mathbf{w}_i = (\mathbf{x}_i^T \mathbf{x}_i + \eta \sum_j S_{ij} \mathbf{I})^{-1} (y_i \mathbf{x}_i + \eta \sum_j S_{ij} \mathbf{w}_j) \tag{3.4}$$

3.1.1.3 Inference

We use the **leave-one-out** setting to infer and evaluate the crime rate of new community area.

Suppose the we want to estimate the crime rate y_i of CA_i. During the training process, we hold everything about CA_i out (including y_i, flow coming in and leaving from CA_i). Then training the model on CA_j, $\forall j \neq i$, which gives us w_j, $\forall j \neq i$. To infer the y_i, we need estimate the model coefficient w_i first. Follow the same intuition that model on CA_i is only similar to all its neighboring models, we have

$$\min_{\mathbf{w}_i} \sum_{j, \forall j \neq i} S_{ij} ||\mathbf{w}_i - \mathbf{w}_j||_2^2 + ||\mathbf{w}_i||_2^2 \tag{3.5}$$

After getting $\mathbf{w}_i$, we infer y_i by

$$\hat{y}_i = \mathbf{w}_i^T * \mathbf{x}_i \tag{3.6}$$

3.2 Consider complicated interaction (Proposed problem 2)

3.2.1 Problem Formulation

We want to predict the crime rate y_i of each geographical grid (tract/community area) g_i. The available observations are demographics features $\vec{\mathbf{x}}_i$ of each g_i from census, and the interactions among grids. We denote the interactions as $\vec{\mathbf{f}}_{ij}$ for grid pair g_i, g_j, and examples of such interactions are social flow and geospatial distance.

3.2.2 Conditional random field model

The first model comes to mind.

3.2.2.1 Potential Function

Each grid is a node, and its crime rate y_i is the hidden variable that we want to estimate. Two kinds of fixed parameters are observed for each grid g_i. The first one is the demographic features $\vec{\mathbf{x}}_i$. The second is the interactions among grids, such as social flow and geospatial distance, denoted by $\vec{\mathbf{f}}ij$.

We use Conditional Random Field (CRF) shown in Figure 3.1 to model the dependency of nodal features. The learning goal is to estimate the conditional probability of y given $\vec{\mathbf{x}}$ and $\vec{\mathbf{f}}$

$$P(y|\vec{\mathbf{x}}, \vec{\mathbf{f}}) \tag{3.7}$$

In the CRF model, we factorize the probability distribution of y to a series of potential functions ψ on the clique.

$$P(Y) = \frac{1}{Z} \prod_{c \in C} \psi(c) \tag{3.8}$$

Use C_1 to denote the set of cliques of size 1 with the form $\langle y_i \rangle$, and C_2 to denote size-2 clique. We define the potential function as follows:

$$\psi_{C_1} = exp(-|y_i - \vec{\alpha}^T \cdot \vec{\mathbf{x}}_i|) \forall i \in [1, n], g_i \in C_1, \tag{3.9}$$

$$\psi_{C_2} = exp(-|y_i - y_j - \vec{\mathbf{w}}^T \cdot \vec{\mathbf{f}}_{i,j}|) \forall i, j \in [1, n], g_i, g_j \in C_2, \tag{3.10}$$

where $\vec{\alpha}$ and $\vec{\mathbf{w}}$ are all positive coefficients.

The distribution of Y is given by

$$P(Y) = \frac{1}{Z} \left[\prod_{i=1}^{n} \psi_{C_1}(y_i) \times \prod_{i=1}^{n} \prod_{j=i}^{n} \psi_{C_2}(y_i, y_j) \right] \tag{3.11}$$

$$P(Y) = \frac{1}{Z} exp \left(-\sum_{i=1}^{n} |y_i - \vec{\alpha}^T \cdot \vec{\mathbf{x}}_i| - \sum_{i=1}^{n} \sum_{j=i}^{n} |y_i - y_j - \vec{\mathbf{w}}^T \cdot \vec{\mathbf{f}}_{i,j}| \right) \tag{3.12}$$

A large value of potential function ψ implies the high probability of $P(Y)$. The goal is to find a set of Y maximizing $P(Y)$.

3.2.2.2 Inference

Estimate CRF Parameters

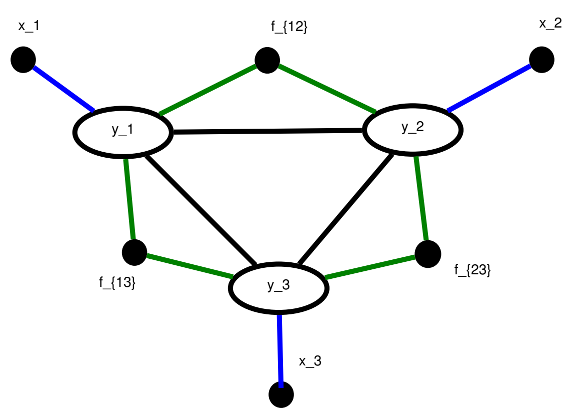


Figure 3.1. The CRF model of the crime rate y_i for each grid g_i.

We solve the Equation (3.12) by minimizing the negative log-likelihood function

$$\min_{\vec{\alpha},\vec{\mathbf{w}}} - \log P(Y|\vec{\alpha},\vec{\mathbf{w}}) = \min_{\vec{\alpha},\vec{\mathbf{w}}} \Bigg[\log Z + \sum_{i=1}^{n} |y_i - \vec{\alpha}^T \cdot \vec{\mathbf{x}}_i| + \sum_{i=1}^{n}\sum_{j=i}^{n} |y_i - y_j - \vec{\mathbf{w}}^T \cdot \vec{\mathbf{f}}_{i,j}|\Bigg] \quad (3.13)$$

Use matrix form

$$\min_{\vec{\alpha},\vec{\mathbf{w}}} ||X\vec{\alpha} - \vec{\mathbf{y}}||_1 + ||F \cdot \vec{\mathbf{w}} - \vec{\mathbf{y}_p}||_1,$$

where X is demographics matrix with n rows, $\vec{\mathbf{y}}$ is the n-dimension crime rate vector, F is the pairwise features matrix with $(n^2+n)/2$ rows, and $\vec{\mathbf{y}_p}$ is the $(n^2+n)/2$-dimension pairwise crime rate difference vector $\{y_i - y_j\}$.

We can minimize separably.

Minimize $\vec{\alpha}$

$$\min_{\vec{\alpha}} ||X\vec{\alpha} - \vec{\mathbf{y}}||_1$$

Take $X\vec{\alpha} - \vec{\mathbf{y}} = \vec{\mathbf{z}}$, and use ADMM.

$$\min_{\vec{\mathbf{z}},\vec{\alpha}} ||\vec{\mathbf{z}}||_1 + \rho/2||\vec{\mathbf{z}} - X\vec{\alpha} + \vec{\mathbf{y}}||_2^2, \quad s.t. \quad \vec{\mathbf{z}} - X\vec{\alpha} + \vec{\mathbf{y}} = 0 \quad (3.14)$$

$$L(\vec{\theta_1},\vec{\mathbf{z}},\vec{\alpha}) = \max_{\vec{\theta_1}} \min_{\vec{\mathbf{z}},\vec{\alpha}} ||\vec{\mathbf{z}}||_1 + \rho/2||\vec{\mathbf{z}} - X\vec{\alpha} + \vec{\mathbf{y}}||_2^2 + \vec{\theta_1}(\vec{\mathbf{z}} - X\vec{\alpha} + \vec{\mathbf{y}}) \quad (3.15)$$

$\vec{\alpha}$ **update**

$$\vec{\alpha}^{k+1} \leftarrow \arg\min_{\vec{\alpha}} \rho/2||\vec{\mathbf{z}}^{k+1} - X\vec{\alpha} + \vec{\mathbf{y}} + \vec{\theta_1}^{k+1}||_2^2$$

Take derivative we have

$$\frac{\partial}{\partial \vec{\alpha}} = \rho X^T (X\vec{\alpha} - \vec{\mathbf{z}}^{k+1} - \vec{\mathbf{y}} - \vec{\theta}_1^{k+1})$$

Make it 0, $\vec{\alpha}^{k+1} = (X^T X)^{-1} X^T (\vec{\mathbf{z}}^{k+1} + \vec{\mathbf{y}} + \vec{\theta}_1^{k+1})$.

$\vec{\mathbf{z}}$ update

$$\vec{\mathbf{z}}^{k+1} \leftarrow \arg\min_{\vec{\mathbf{z}}} ||\vec{\mathbf{z}}||_1 + \rho/2||\vec{\mathbf{z}} - X\vec{\alpha}^{k+1} + \vec{\mathbf{y}} + \vec{\theta_1}^{k+1}||_2^2$$

So, $\vec{\mathbf{z}}^{k+1} = S_{1/\rho}(X\vec{\alpha}^{k+1} - \vec{\mathbf{y}} - \vec{\theta}_1^{k+1})$.

$\vec{\theta}_1$ update

$$\vec{\theta}_1^{k+1} = \vec{\theta}_1^{k} + \vec{\mathbf{z}}^{k+1} - X\vec{\alpha}^{k+1} + \vec{\mathbf{y}}$$

Minimize $\vec{\mathbf{w}}$

$$\min_{\vec{\mathbf{w}}} ||F \cdot \vec{\mathbf{w}} - \vec{\mathbf{y}_p}||_1$$

It has exactly the same form as previously. Therefore,

$$L(\vec{\theta_2}, \vec{\mathbf{z}}', \vec{\mathbf{w}}) = \max_{\vec{\theta}_2} \min_{\vec{\mathbf{z}}', \vec{\mathbf{w}}} ||\vec{\mathbf{z}}'||_1 + \rho/2||\vec{\mathbf{z}}' - F\vec{\mathbf{w}} + \vec{\mathbf{y}_p}||_2^2 + \vec{\theta_2}(\vec{\mathbf{z}}' - F\vec{\mathbf{w}} + \vec{\mathbf{y}_p}) \quad (3.16)$$

$\vec{\mathbf{w}}$ update

$$\vec{\mathbf{w}}^{k+1} = (F^T F)^{-1} F^T (\vec{\mathbf{z}}'^{k+1} + \vec{\mathbf{y}_p} + \vec{\theta}_2^{k+1})$$

$\vec{\mathbf{z}}'$ update

$$\vec{\mathbf{z}}'^{k+1} = S_{1/\rho}(F\vec{\mathbf{w}}^{k+1} - \vec{\mathbf{y}_p} - \vec{\theta}_2^{k+1})$$

$\vec{\theta}_1$ update

$$\vec{\theta}_2^{k+1} = \vec{\theta}_2^{k} + \vec{\mathbf{z}}'^{k+1} - F\vec{\mathbf{w}}^{k+1} + \vec{\mathbf{y}_p}$$

Infer New y_i

To infer new y_i, we want to maximize the following probability

$$P(y_i | \vec{\mathbf{x}}_i, F, \vec{\mathbf{y}}, \vec{\alpha}, \vec{\mathbf{w}}),$$

where $\vec{\alpha}$ and $\vec{\mathbf{w}}$ are estimated using previous section, $\vec{\mathbf{y}}$ denote the crime rates of other observed geographical units, and F is the pairwise feature matrix.

Take negative log of the probability, we have

$$\begin{aligned}
&\min_{y_i}\left[\log Z + |y_i - \vec{\alpha}^T \cdot \vec{\mathbf{x}}_i| + \sum_{j\neq i}^{n} |y_i - y_j - \vec{\mathbf{w}}^T \cdot \vec{\mathbf{f}}_{i,j}|\right] \\
&\min_{y_i}\left[|y_i - \vec{\alpha}^T \cdot \vec{\mathbf{x}}_i| + \sum_{j\neq i}^{n} |y_i - y_j - \vec{\mathbf{w}}^T \cdot \vec{\mathbf{f}}_{i,j}|\right]
\end{aligned} \tag{3.17}$$

In Equation 3.17, we have $n+1$ ℓ_1-norm terms, which have exactly the same form $|y_i - b_j|$. The objective becomes

$$\min_{y_i} \sum_{j}^{n} |y_i - b_j|, \tag{3.18}$$

where $b_1 = \vec{\alpha}^T \cdot \vec{\mathbf{x}}_i$ and $b_j = y_{j-1} + \vec{\mathbf{w}}^T \cdot \vec{\mathbf{f}}_{i,j-1}$ for $j > 1$.

Notice that the optimal solution must take value on $\{b_j\}$. We solve this by sorting all the b_j and then calculate the result segment by segment.

Chapter 4
Research Plan and Schedule

The first part of improvement on the base model is already finished and under review now. Solve two proposed problems: 1) develop a dynamic spatial model and 2) develop a unified probabilistic graphical model in the next two years. Specifically,

Fall 2016

- Work on the dynamic spatial model on top of negative binomial regression.
- Look for other geospatial local model to compete.
- By the end of semester have a paper ready to submit.

Spring 2017

- Submit the dynamic spatial model paper to KDD. Prepare for revision.
- Develop a unified model starting from CRF for the crime inference.
- Look into other urban problems to see whether the model can be easily generalized.

Fall 2017

- Evaluate the unified CRF model on crime inference problem, and hopefully another real problem.
- Start drafting the paper.

Spring 2018

- Submit the unified model to KDD. Prepare for revision.
- Write my thesis and prepare for final defense.

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Publications

- **Hongjian Wang**, Zhenhui Li, Daniel Kifer, Corina Graif. Crime Rate Inference with Big Data. ACM SIGKDD, 2016. (Under review)
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