Hindawi
Discrete Dynamics in Nature and Society
Volume 2022, Article ID 1217627, 18 pages
https://doi.org/10.1155/2022/1217627

Research Article

Characterizing the Temporal Regularities of Crime

Xiaohua Luo,[1] Jiaruo Peng ,[2] and Mingsong Mao[3]

[1]*School of Taxation and Public Administrations, Jiangxi University of Finance and Economics, Nanchang, Jiangxi, China*
[2]*Department of Computer Science, University of Exeter, Exeter, UK*
[3]*School of Information Management, Jiangxi University of Finance and Economics, Nanchang, Jiangxi, China*

Correspondence should be addressed to Jiaruo Peng; 752422110@qq.com

Received 10 November 2021; Accepted 16 December 2021; Published 12 January 2022

Academic Editor: Daqing Gong

There are a lot of studies that show that criminal activities exhibit certain temporal and spatial regularities. However, they often focus on either specific cities or types of crime and cannot clearly explain the patterns for the crime. What are the temporal patterns at the microlevel spatial scale? How general? Understanding the regularities of urban crime is important because it can help us improve the economy and safety of the cities and maintain harmony. This study analyzes the theft and burglary crime data from five cities in the United States. We successfully find the spatiotemporal patterns of two types of crime in different time series across cities.

1. Introduction

Crime is a human activity that is detrimental to social development, and it brings a heavy burden to the city's economy [1]. The UK Peace Index (2013) technical report pointed out that criminal activities can cause a 7.7% loss of GDP of the United Kingdom every year. It is undoubtedly a heavy blow to the British economy. The loss of this part will indirectly increase people's tax pressure.

Not only that, but it also affects city security. Sherman and Lawrence pointed out that police actions can impact crime [2]. The police have tried to adjust the distribution of the police force in each region by paying attention to the concentration of crime to protect more people [3]. In this method, the police will arrange more police forces in areas where crime accidents occur to ensure the safe life of the people who live in these places [3].

Although this decision is based on past crime data, this approach is unreasonable to a certain extent. Because the research shows this approach can only cause a regional migration of the crimes, but the number has not decreased. However, the police wasted a lot of energy and money on the police force schedule. Some people claimed that police have only minimal contributions to crime prevention [4].

The number of crimes will change over time. With the total number of crimes in a city or the number of crimes in each region, there will be a specific time pattern [5]. For example, the number of crimes in some areas always rises on weekends or has other changes. Not only that, but we also want to know whether the number of crimes has different laws in different time series. Whether the time patterns of diverse regions are similar? Through such a clear understanding of the crime model, we can better protect the safety of people and property.

In this study, we divide each city into the same number of equal area grids and locate two representative criminal events, namely, theft and burglary. We will change the time series to explore the urban space-time crime model to find the temporal patterns at the microlevel spatial scale. Finally, we find out that some regions of one city share similar regularities and two types of crimes in some cities also share similar patterns.

2. Background

Criminal activities are defined as illegal activities for society. As early as decades ago, Cohen and Felson declared that the crime trends have changed with the development of the world in their research [6]. It is similar to what Gomez et al.

found in recent years that crime regularities have some related social elements such as economic complexity, cultural evolution, and population size [7].

Moreover, their results have shown that crimes would have grown with the increasing population. Except for these social factors, there are other factors like spatial and temporal. In recent years, increasing studies have focused on the regularity of crime in spatial and temporal patterns.

2.1. Crime Temporal Patterns. Some studies only focused on the relationship crimes with time. Tennenbaum and Fink paid attention to homicides finding the relationship between crime and time [8]. They discovered some seasonal regularities. Some people chose to focus on other crime types to find their temporal patterns. However, Farrell has successfully found that crimes have a close relationship with both time and space by studying repeat crime patterns [9]. He did not get any particular temporal regularity in them, but it is a good start for further study.

For the time factor, Oliveira et al. studied the different time patterns of crime in 12 cities in the United States in 2018, such as the annual cycle and the seasonal cycle [10]. However, the crime curve in most grids shows an unstable state.

Oliveira et al. also used the method of increasing the number of divided areas to increase coverage and reduce data instability [10]. It is a feasible measure to increase the number of divided regions to obtain a stable cyclic curve of criminal activities. However, this division method relies on the urban population that would change every year.

2.2. Crime Spatial Patterns. There are also many studies only talking about the spatial factor. Ruiter has written in his study that for different types of offenders, their choice of crime location is regular [11]. Jeong et al. also found out that robbery in Korea has a spatial continuity [12].

Moreover, Oliveira and Menezes have described the tendency of crime to spatially concentrate in their study published in 2019 [13]. The analysis method based on the spatial factors of crime is regarded as the most commonly used theoretical strategy to strengthen crime defense [14]. However, there is a limitation to analyze crime patterns only by using a single factor of space or time.

Oliveira et al. used two-part data in their study of 2017. One part is from 19 cities in the United States. Another part is from six police forces from the United Kingdom. Although using data from two countries increases the data complexity, they still found that the concentration of criminal activities has nothing to do with the regional differences but will change over time [15].

However, these two countries have different classification standards about crime types. There is no evidence that the new definition of crime type has affected the results. It is useless to analyze the results between two countries because of too many social elements. Instead, the focus should be on comparing the changes in different cities from the same country.

2.3. Crime Clustering Patterns. Undoubtedly, for the crimes, the space factor has some interaction with the time factor. In the latest study of van Sleeuwen et al., they have presented an extended crime pattern theory that contains space and time factors, and it can better explain crimes [16].

Grubesic and Mack have also tried to use space-time tests for the analysis of crime activities in their study [17]. They introduced time geography when discussing changes in crime patterns and tried to decompose crime incidents at the time and space levels [17].

There is similar research from Asia. Ye et al. also used a similar spatial-temporal clustering method to study crime in Wuhan, China [18]. Although these research studies have a similar result that the concentration of crime will change over time, none have more specific regularities. However, they are still demonstrations of successful research on crime using the spatial-temporal clustering method.

Oliveira and Menezes paid attention to analyzing the latent regularity of the time of the crime data in different regional levels in their latest research [13]. At the city level, the crime curve has an obvious time pattern. Oliveira et al. raised the spatial aggregation unit to the local level.

However, they also found that the curve in some areas would suddenly lose stability in one year, and this kind of phenomenon will not expose to the curves of the city level [13]. But they only use data from cities with more crime and did not use other cities with less crime. Therefore, the result is not universal. But in some way, it did reflect that the concentration of crime is related to the size of cities.

Recently, Prieto et al. have described changes in criminal activity as the heartbeat of the city [19]. Considering the number of deaths caused by traffic accidents is far greater than that of crimes, they have studied traffic accidents and criminal activities together. By studying the data from Mexico, Prieto et al. obtained a repetitive pattern in the distribution of crimes and found that nearby regions have similar patterns [19].

In terms of time, they reduced the research period to weekly. In terms of space, based on its public transportation system, they divided the city into many grids. In this study, the basis for dividing the city is the city's public transportation system, which leads the model too special. Moreover, some cities' transportation system data are not easy to obtain. Therefore, it is unrealistic to divide the cities according to the public transportation system.

3. Aims and Objectives

The main objective of the project is to describe the latent spatiotemporal patterns of crimes. It needs us to analyze the public crime datasets in different cities. The project is divided into three parts: temporal regularities in cities are characterized, regularity differences across crime types are compared, and regularity differences across cities are compared.

First, we will observe how the number of crimes in each city changes while time and its type change. It means we want to see how two types of crimes increase or decrease over time in each particular location and time series. Then, we use the spatial location to examine how patterns distribute in the grid that we create for each city. We will answer the following questions:

Q1 What are the temporal regularities of crime in a city?

Q2 How are these temporal regularities distributed in a city?

The first part of the project enables us to understand the time and space factors of the crime regularities in different regions across cities.

In the second part of the project, we want to find the differences between regularities by comparing the two crime types. We will also investigate whether these regularities are general across cities. Here, we want to answer the following questions:

Q3 How different are the temporal regularities across different types of crime?

Q4 How different are the temporal regularities across cities?

These questions can help us understand the differences across crime types and whether regularities are stable over time. Finally, we will compare the regularity differences across cities. We note that the method in the second part of the project can also be used in other cities. Thus, we will create a universal function that can analyze the crime data of all cities. Once it is complete, we can use the data of other cities to test it. Then, we can obtain all regularities across cities and analyze them.

4. Experiment Design and Methods

In this study, we decide to focus on theft and burglary. As Shover pointed out in his study, burglary is one of the most common types of crimes in the United States and other countries [20]. Not only that, according to the Crime in the U.S. (2019) report, released by the FBI, the part of property crime showed that theft and burglary accounted for the first and second places, accounting for 73.4% and 16.1%, respectively. It means that these two crimes are the most common and typical types of crime.

4.1. Data Resources. To study the spatial and temporal characteristics of the crime, we need to get the (i) types of crimes, (ii) locations of crimes, and (iii) times of crimes. These three attributions are all we need in each dataset. The locations of crimes made up of the longitude and the latitude of the crimes.

In this study, we will use public data from 10 cities in the United States. Each of them will record crimes from previous years to the year 2019. We need to at least acquire five years' records to keep the results stable and reliable. We do not need the crime in the 2020 and the 2021 years because they were affected by COVID-19. So patterns of these two years will be different from other years. Therefore, we first decide to remove these data from each original data.

These data are available on the official website of the cities. Although these cities belong to the United States, they have different names for theft and burglary. Thus, we use a flexible list to find them in the original data. Then, we also need to obtain latitude and longitude to describe the location of the crime. Moreover, we also need the times of crimes. Thus, the data after data processing for further analysis should have the following attributions:

(i) Date—the time of the crime.

(ii) Latitude—the latitude of the crime location.

(iii) Longitude—the longitude of the crime location.

(iv) Type—the type of the crime. In this study, this attribute only involves two main types of crimes: theft and burglary. But they have different names in different cities, as shown in Table 1.

4.2. The Crime_Analysis Library. We create a general library that contains all functions we need to use in the experiment. Here are explanations of the usage of functions:

(i) Get the attributions we need: in this part, we select the attributions we need from the original data: date, latitude, longitude, and type.

(ii) Divide them into two types and find which year of crime you need: we select the crimes in the year when we want to analyze and separate data into two types. In this function, we will acquire three data frames: one-year crime, theft in one year, and burglary in one year.

(iii) Plot all crime in the city: all crimes in one year are shown.

(iv) Grid city and move useless grids: we create the same number of grids for each city and divide the crimes into each grid. Then, we remove empty grids.

(v) Get the boundary of each grid: we save the boundaries of crime sets in each effective grid.

(vi) Group and normalize the data: in this function, we calculate the crime that happened in one day and make a data frame for the daily crime in each grid. To further make the average line of the crime, we should normalize the data. Only in this way, we could see the trends of the crimes around 0, which can make the curve clearer.

(vii) Group data in the average of the week: we group daily data into each day of the week and use the mean value of them.

(viii) Group data in each month: we group daily data into each month.

Table 1: Two types in each considered dataset.

City	Theft	Burglary
Chicago	"THEFT"	"BURGLARY"
New York	"LARCENY"	"BURGLARY"
Philadelphia	"Thefts"	"Burglary"
San Francisco	"Larceny theft"	"Burglary"
Santa Monica	"Larceny"	"Burglary"

(ix) Elbow method: it can help us to find the best k value for K-means.

(x) K-means: it can help us find the number of clusters for each grid.

(xi) The average line: it uses the standard value and the mean value of the data frame to draw the average line for the trends of each cluster.

4.3. Methods. We also decide to use some simple methods to remove too many curves from the original data.

4.3.1. Normalization. Data normalization is to scale the data to a small specific interval like from −1 to 1. It is often used in the processing of some comparison and evaluation indicators. The unit limit of data is removed and it is converted into pure values to keep indicators of different units or orders of magnitude that can compare and weigh; we use the "StandardScaler" utility class, in which the "preprocessing" module is provided to standardize the data.

4.3.2. K-Means. K-Means can divide n samples into k clusters, and it will let each one to belong to the cluster, which is most similar or closest to the central sample; parameters are as follows: we set n_clusters as the same as k, which from the elbow method; we use the k from elbow method as the best k value. "K-means++" is used to select initial cluster centers for K-means clustering. Then, we use the "fit-predict" function to compute cluster centers and predict cluster index for each data;

4.3.3. Elbow Method. In the K-means method, parameter "distortions" can be used as the standard to test clustering performance. It will decrease with the increase in class (k). For the data with certain differentiation, with the increase in k, it will greatly change and slow down after then. This k will be the best one for the data tested; we use the "KneeLocator" class from the "kneed" module to find the best k for K-means.

5. Results

In this part, we use the crime in Chicago city as an example to show the results.

5.1. Data Processing. First, we get all the attributions of the data that we need. Then, we locate them on the map of the city. For analyzing data in different time series, we should use data in a year. The left one in Figure 1 describes the distribution of the crime of Chicago in 2018. Each blue point means a crime and its location in the city. The right one in Figure 1 describes the effective grids. After creating grids, we locate each data to each grid. Then, we should remove these empty grids and save the boundary of the rest grids.

5.2. What Are the Temporal Regularities of Crime in a City? To characterize crime dynamics, we standardize the daily crime data for each grid and group them into different time series. Then, we use K-means to find the closest cluster for each grid. We find that many regions share a similar pattern. Finally, we use the most trends in the different time series to present the temporal crime pattern of the city.

For example, Figure 2 describes the weekly trends of burglary in Chicago in 2018. According to the bar chart, we can see that the first-line chart is the most trends. It means that ten grids have similar trends, which it shows to us. This trend shows that burglary in Chicago is always maximum on Monday, decreases during the whole week, and gets the minimum on Sunday.

5.3. How Are These Temporal Regularities Distributed in a City? We create the grids for each city, so each grid would have a trend. After K-means, some grids share a similar trend, so they are separated into the same cluster. Figure 3 shows the monthly curves of burglary in Chicago in the same year. We can find that the monthly trends of burglary in Chicago have five clusters. They present the temporal patterns of different regions.

According to the bar chart, we can see the most trends in cluster three. Eight grids share similar trends in cluster three. The line chart of cluster three shows that burglary in Chicago is always maximum in October and minimum in April. We can find that the curve has dramatically changed in some periods. It visibly increases from April to May and from June to October. It also significantly decreases from May to June and from October to December.

5.4. How Different Are the Temporal Regularities across Different Types of Crimes? For another type of crime, Figure 4 describes the weekly trends of theft in Chicago in 2018. According to the bar chart, we can find the most trends in cluster zero, and it owns twelve grids. Figure 5 also describes the monthly trends of theft in Chicago in 2018. According to the bar chart, we can see the most trends in cluster four, and it owns six grids.

However, they are different from the trends of burglary. Weekly theft in Chicago is always maximum on Friday and minimum on Sunday, slowly increases from Monday to Friday and immediately decreases from Friday to Sunday. In the monthly trend, theft is always maximum in August and minimum in March. The curve has also dramatically changed in some periods. It increases from March to August and decreases from January to March and from August to November.

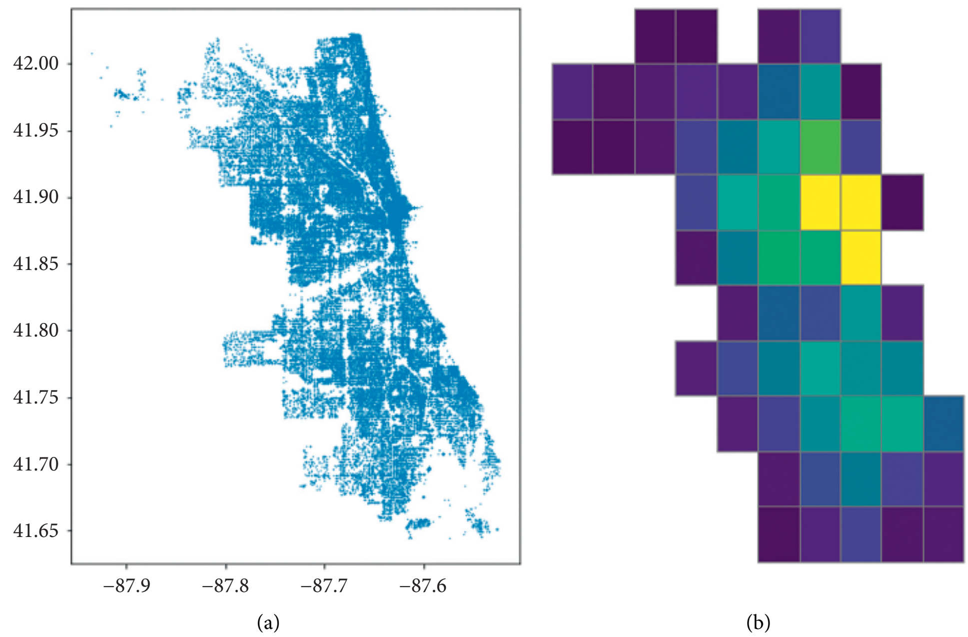

FIGURE 1: Chicago 2018 crime distribution. (a) The map of Chicago city in 2018, and each blue point means a crime. (b) The location of all grids that have crime.

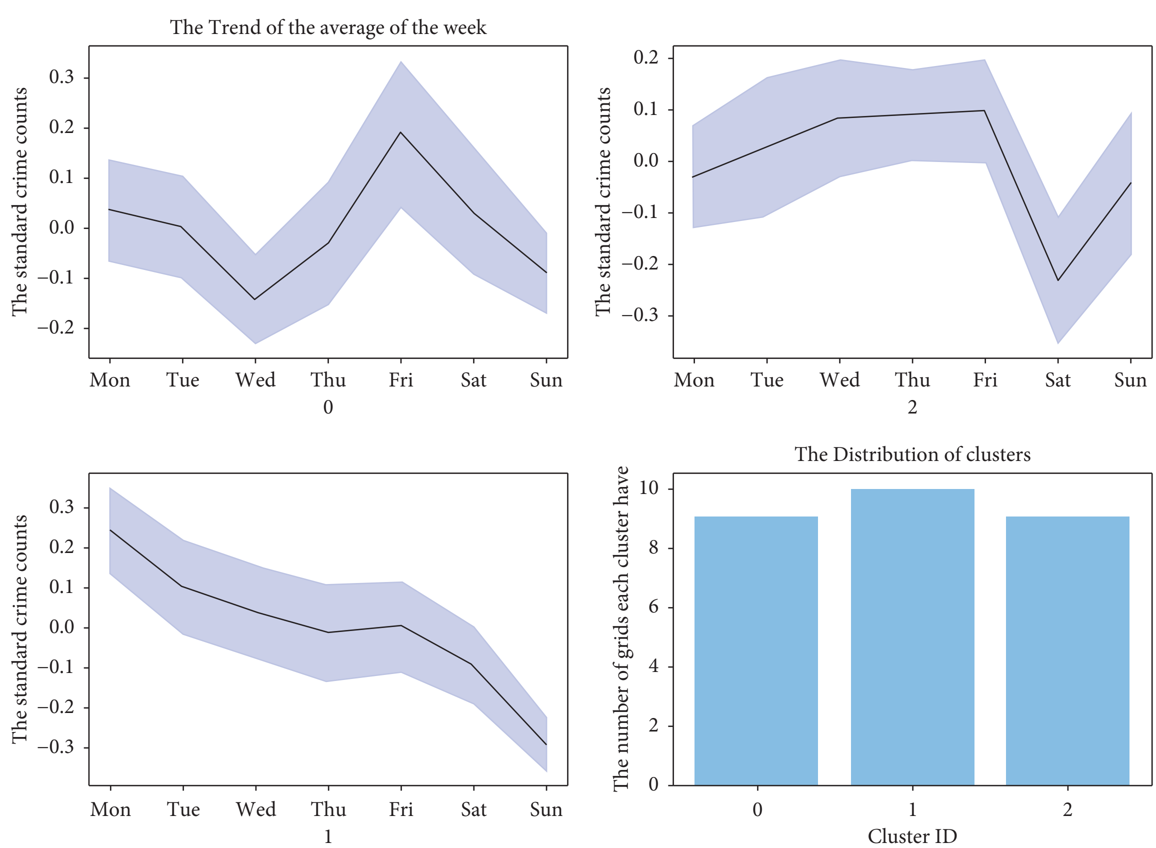

FIGURE 2: Chicago 2018 burglary weekly trends and distributions of the clusters. The line charts are the weekly trends of burglary in Chicago in 2018. The bar chart is the distribution of the clusters.

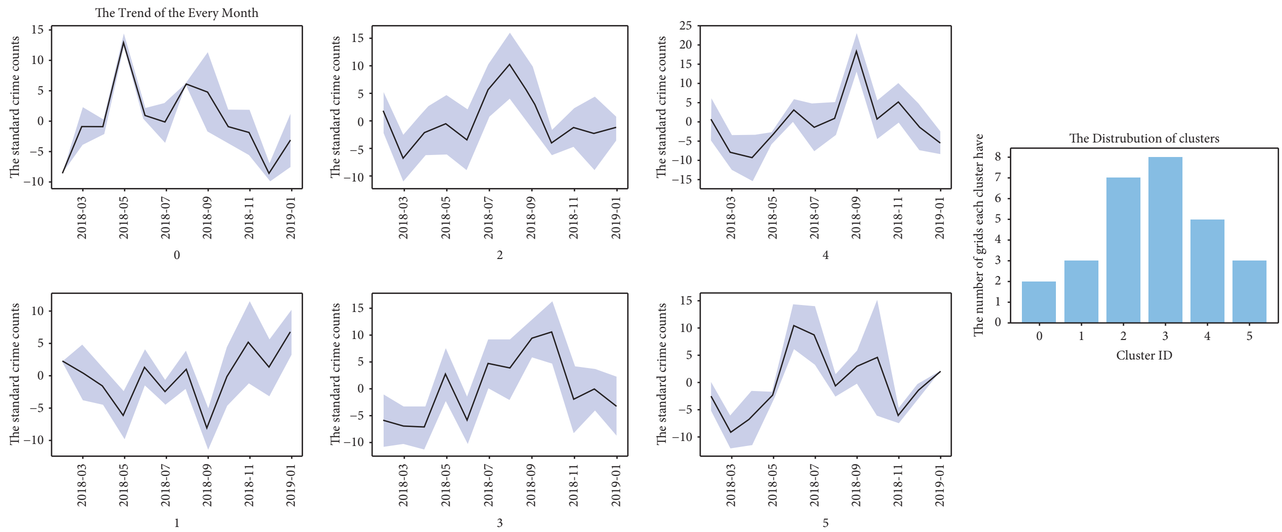

Figure 3: Chicago 2018 burglary monthly trends and distribution of the clusters. The line charts are the monthly trends of burglary in Chicago in 2018. The bar chart is the distribution of the clusters.

5.5. How Different Are the Temporal Regularities across Cities? Figure 6 presents the trends across cities in the different time series. In the weekly curves, burglary in five cities decreases from Monday to Sunday. Some of them have up and down on Friday, like San Francisco and New York. These two cities share a similar pattern from Wednesday to Saturday. It is also similar to weekly theft in San Francisco and New York. It has a great increase from Tuesday to Friday and a drop from Friday to Sunday.

However, Philadelphia has a different pattern that it decreases from Wednesday to Saturday. In the monthly trends, burglary and theft have obviously up and down. Monthly theft in New York has minimum and maximum across cities, partly in January and August. Others are similar. Monthly burglary in Chicago has also minimum and maximum across cities, partly in April and October.

6. Discussion

In this study, we only pay attention to the location and time of which crime happened to avoid infringing on the victim's privacy. In some similar research, cities with high crime rates are called hot cities [21]. Because these studies focus on hot cities, the results are not a common phenomenon, but some regularities may only exist in some hot cities.

Therefore, compared with similar studies in the past, in our project, we further decompose cities and shift the research focus to the crime-prone areas in each city. In this way, we can avoid the difference in the number of crimes across cities to get a universal regularity of urban crime.

Moreover, some similar studies use professional methods to study urban crime, for example, one based on population distribution [10] and one based on transportation system distribution [19]. The data of these methods are changing every year, and the channels for obtaining these data are not stable.

Meanwhile, we still fail to fully understand the dynamics of temporal patterns of crimes in cities. What are the temporal patterns at the microlevel spatial scale? How general? This is important because it can help to understand the underlying mechanisms of crimes [5].

In this study, we can divide the city into square areas, and each one needs to have the same size. Due to many characteristics in the same region, we want to find the main patterns of the crime curve in each area by analyzing the curves. We study the curve in weekly units to find whether its changing characteristics have some time regularity.

From the results, we can find that the two types of crimes have different patterns in the different time series. But they have some special patterns like it would be maximum and minimum on some weekdays. Also in monthly patterns, we can find that the curves change a lot but that are sometimes maximum at the middle of the year. Interestingly, both the monthly trends of Chicago burglary and theft are maximum in September and minimum in March. However, it is not shown in other cities. Finally, we use Table 2 to describe the temporal patterns for five cities.

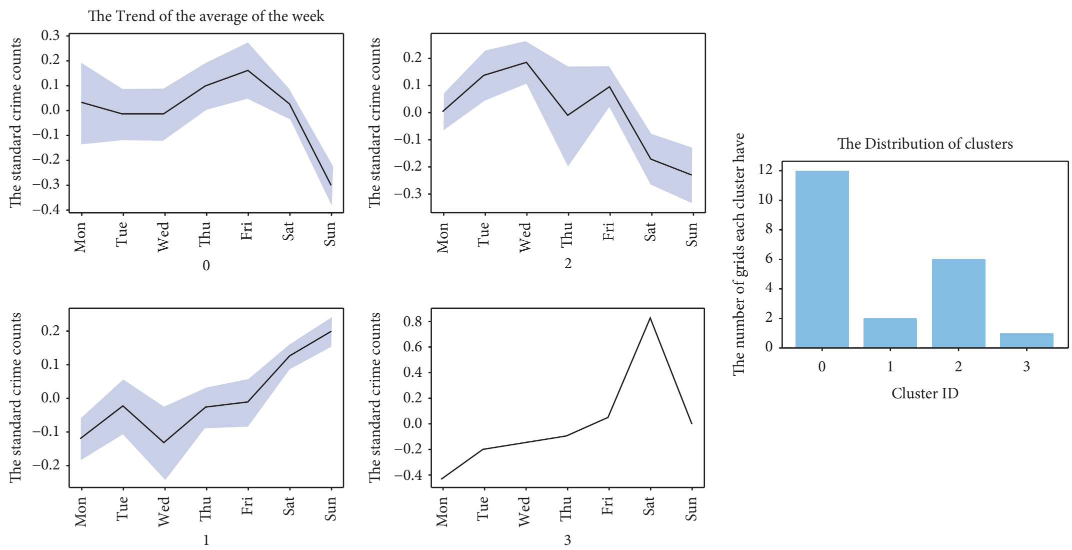

Figure 4: Chicago 2018 theft weekly trends and distribution of the clusters. The line charts are the monthly trends of theft in Chicago in 2018. The bar chart is the distribution of the clusters.

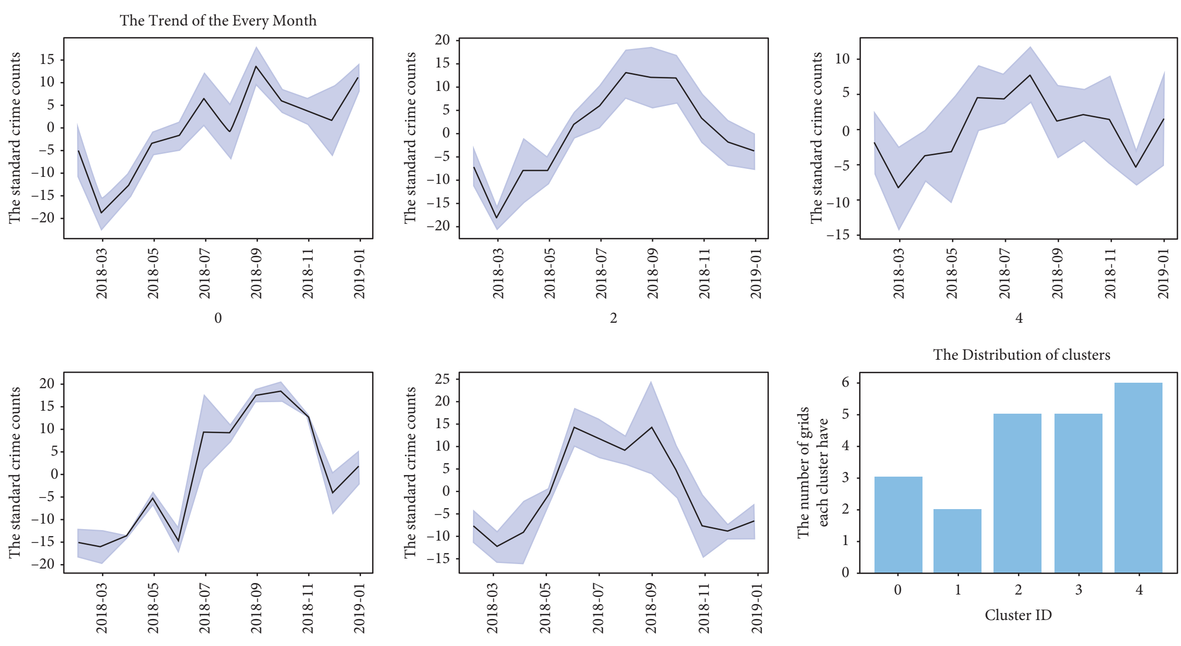

Figure 5: Chicago 2018 theft monthly trends and distribution of the clusters. The line charts are the monthly trends of theft in Chicago in 2018. The bar chart is the distribution of the clusters.

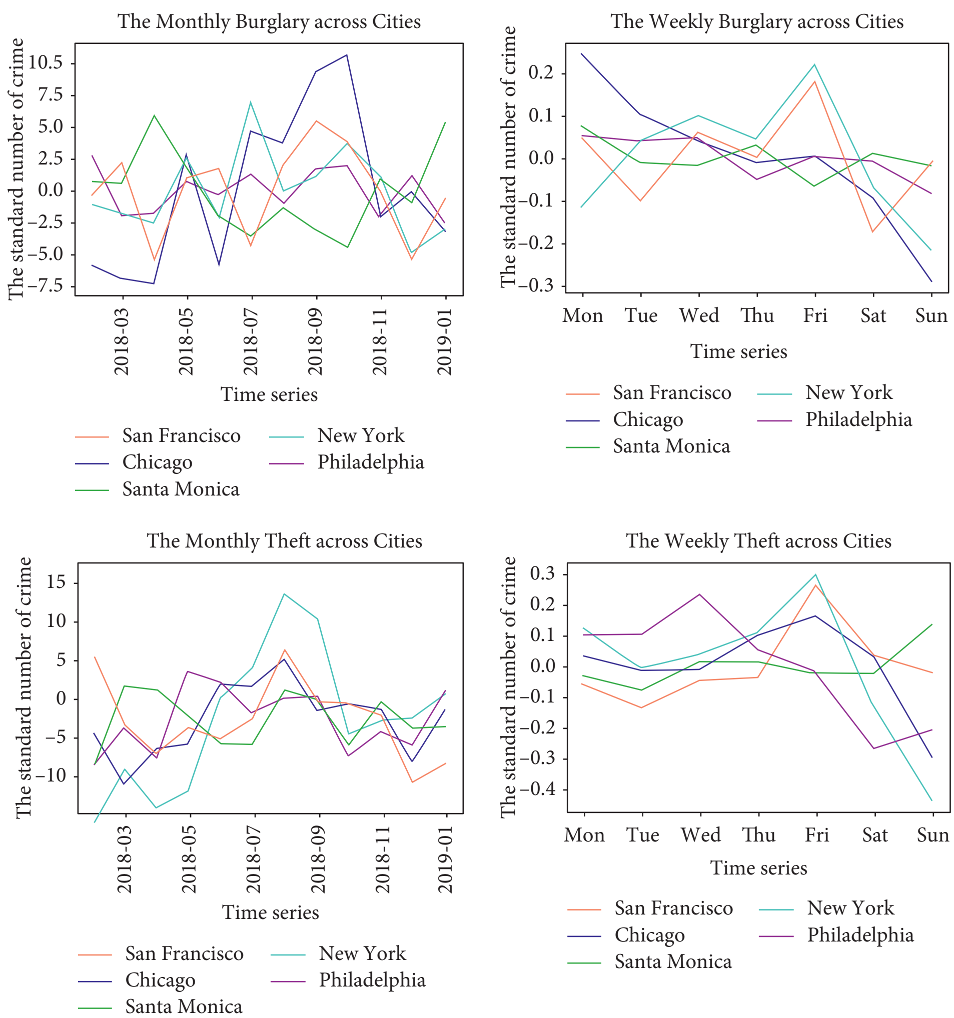

Figure 6: Burglary and theft weekly and monthly trends across cities. The line charts are the monthly trends of theft in Chicago in 2018. The bar chart is the distribution of the clusters.

Table 2: Temporal patterns in five cities in 2018.

Type	City	Maximum	Minimum
Weekly theft	Chicago	Friday	Sunday
	San Francisco	Friday	Sunday
	Santa Monica	Sunday	Tuesday
	Philadelphia	Wednesday	Saturday
	New York	Friday	Sunday
Weekly burglary	Chicago	Monday	Sunday
	San Francisco	Tuesday	Friday
	Santa Monica	Monday	Friday
	Philadelphia	Monday	Sunday
	New York	Friday	Sunday
Monthly theft	Chicago	July	February
	San Francisco	January	December
	Santa Monica	February	January
	Philadelphia	April	January
	New York	July	January
Monthly burglary	Chicago	September	March
	San Francisco	August	March
	Santa Monica	September	March
	Philadelphia	January	December
	New York	November	June

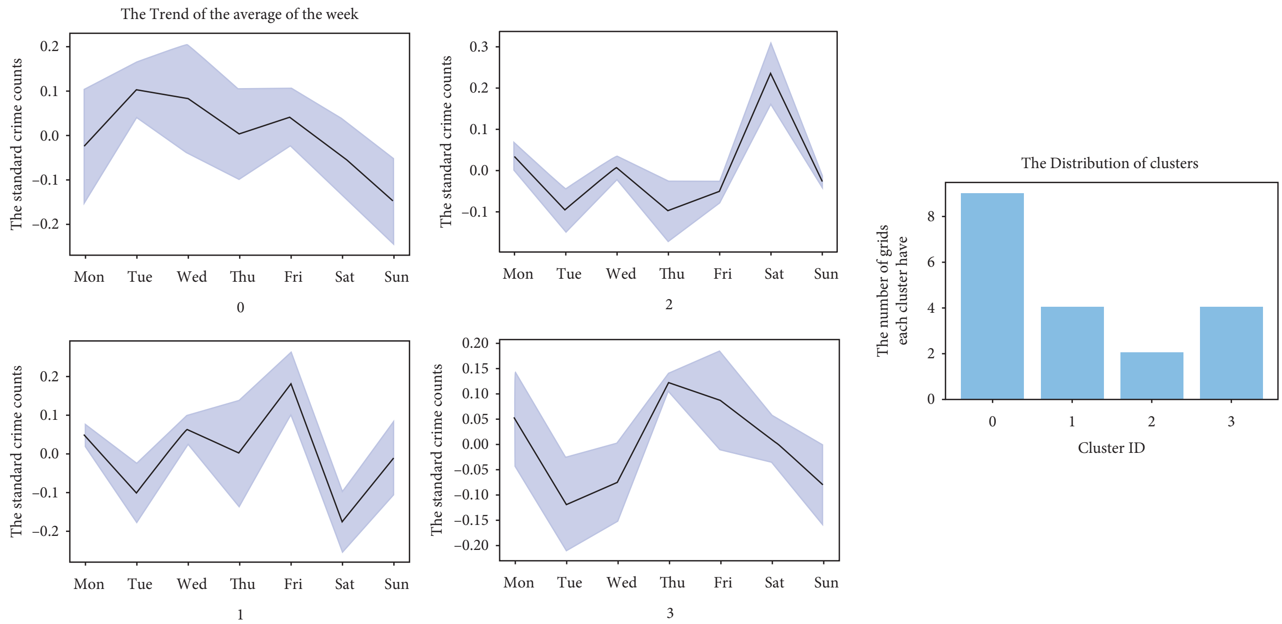

Figure 7: The burglary in San Francisco trends in the average week in 2018 and the distribution of clusters. The line charts are the weekly trends of burglary in San Francisco in 2018. The bar chart is the distribution of the clusters.

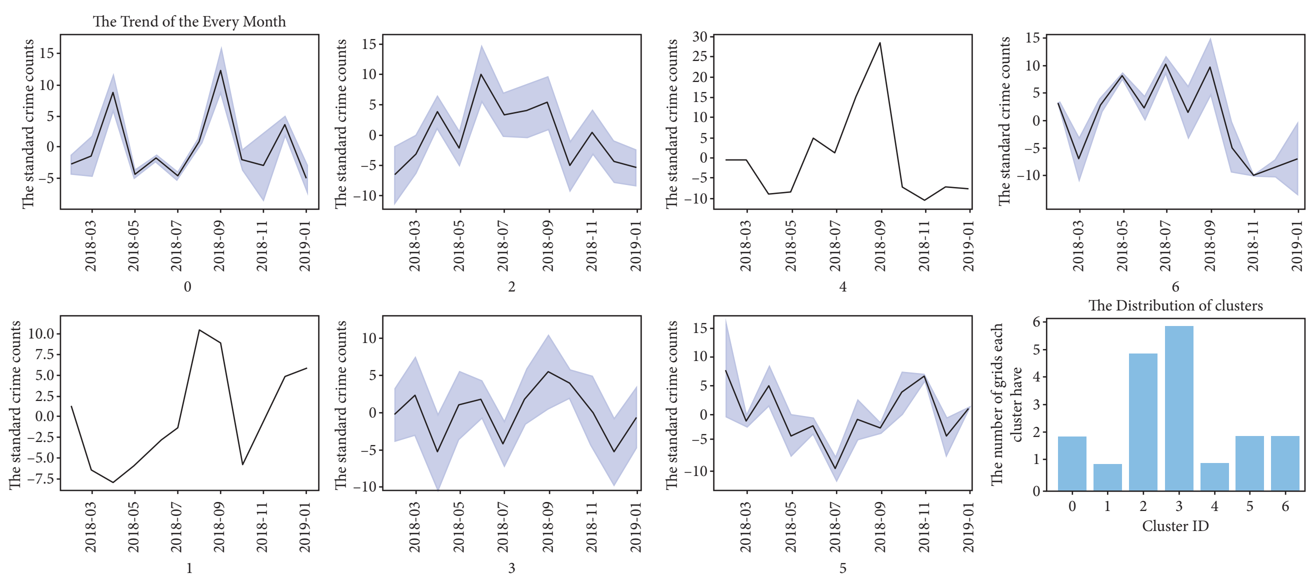

Figure 8: The burglary in San Francisco trends in each month in 2018 and the distribution of clusters. The line charts are the monthly trends of burglary in San Francisco in 2018. The bar chart is the distribution of the clusters.

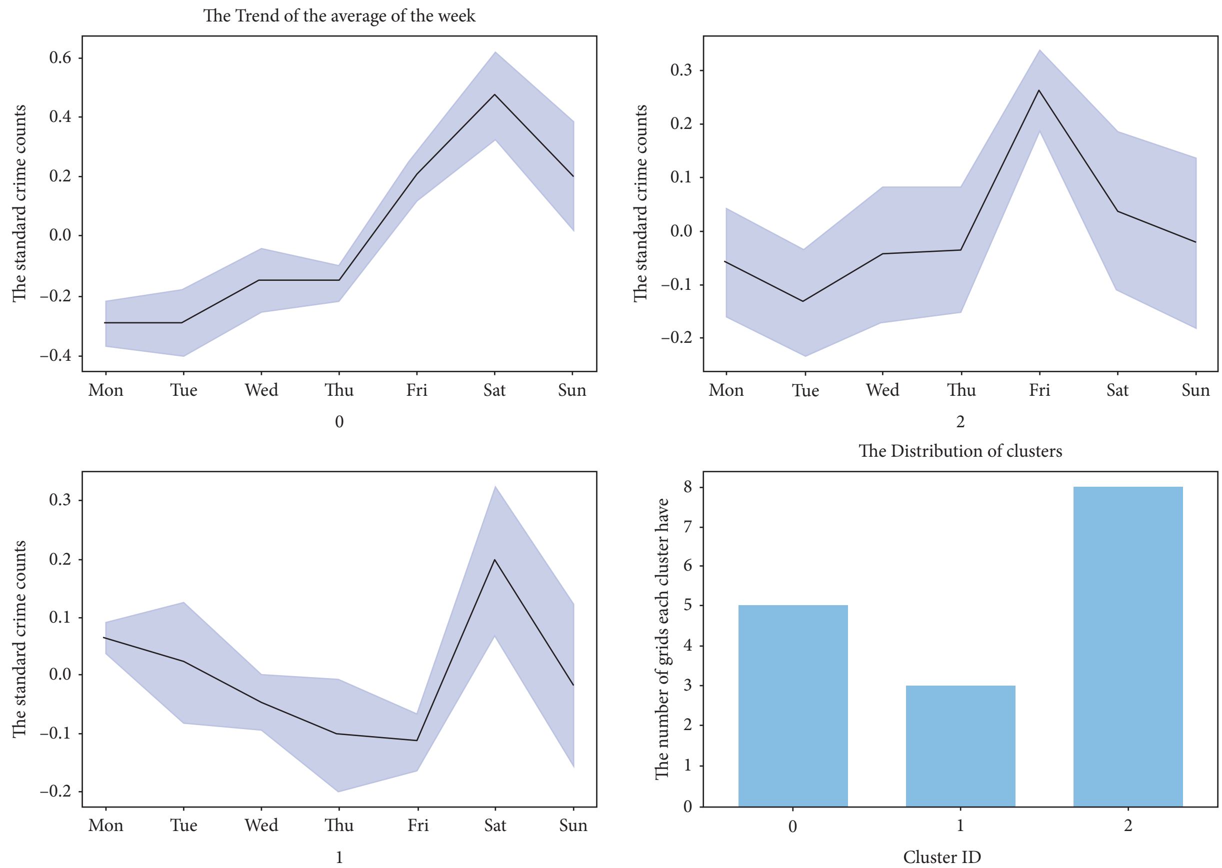

Figure 9: The theft in San Francisco trends in the average weeks in 2018 and the distribution of clusters. The line charts are the weekly trends of theft in San Francisco in 2018. The bar chart is the distribution of the clusters.

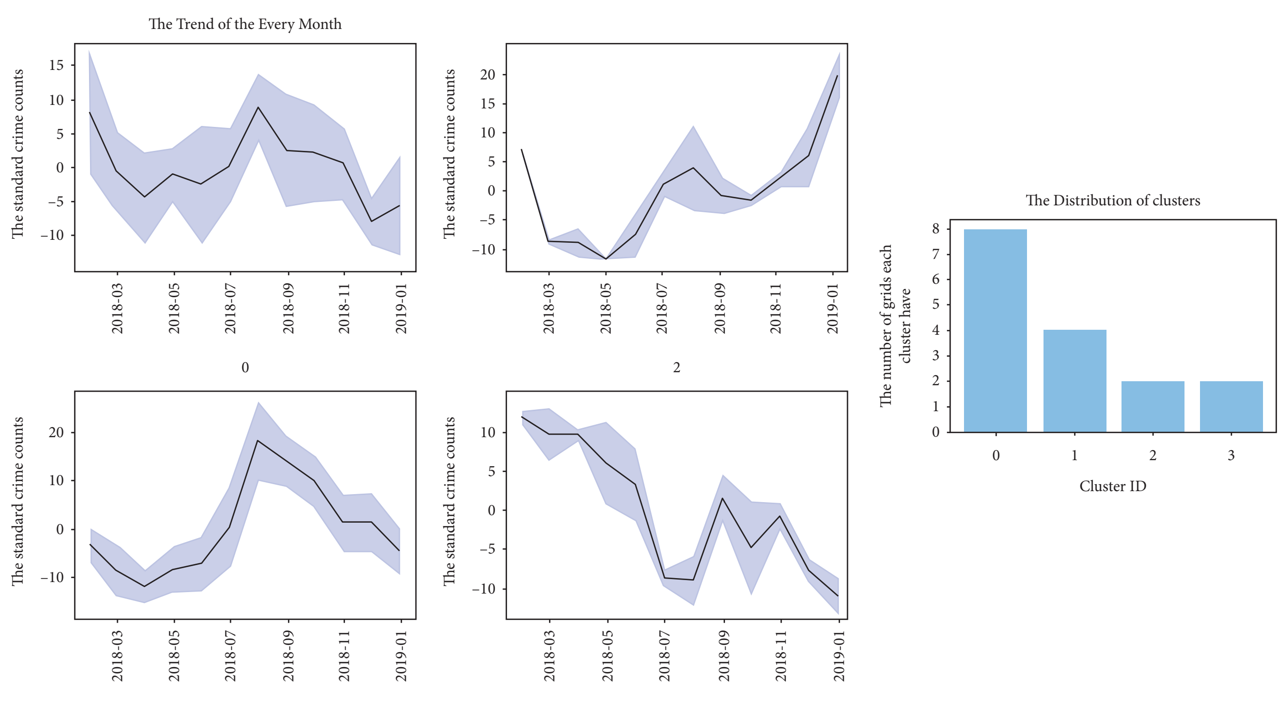

Figure 10: The theft in San Francisco trends in each month in 2018 and the distribution of clusters. The line charts are the monthly trends of theft in San Francisco in 2018. The bar chart is the distribution of the clusters.

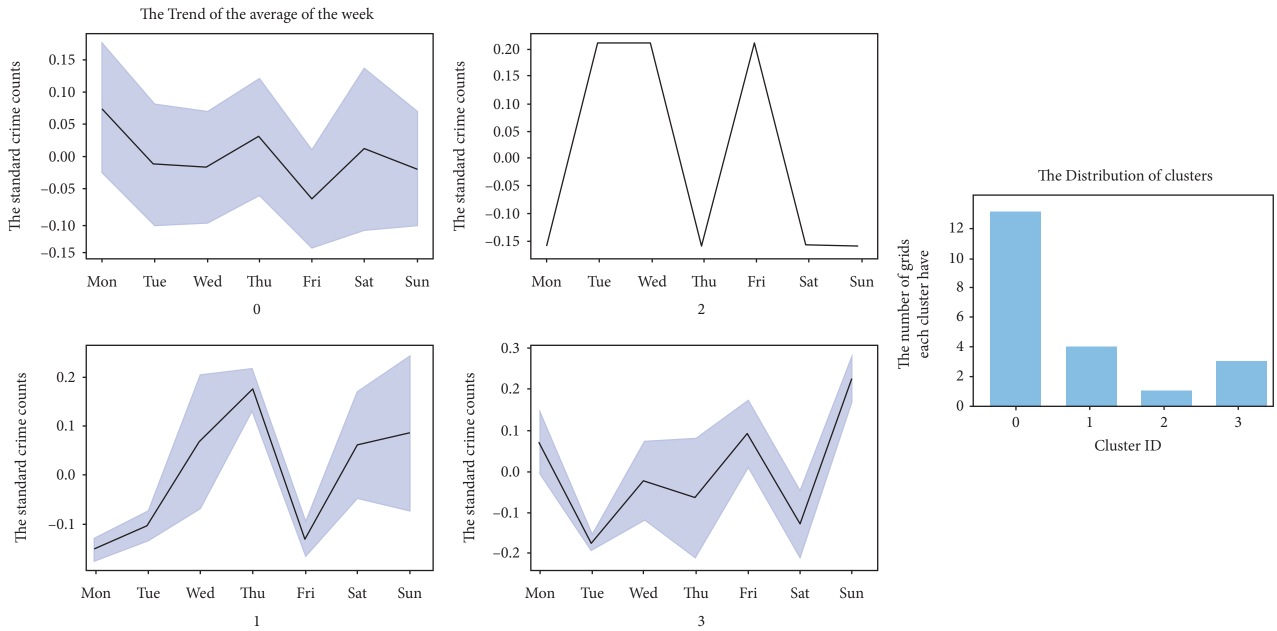

FIGURE 11: The burglary in Santa Monica trends in the average weeks in 2018 and the distribution of clusters. The line charts are the weekly trends of burglary in Santa Monica in 2018. The bar chart is the distribution of the clusters.

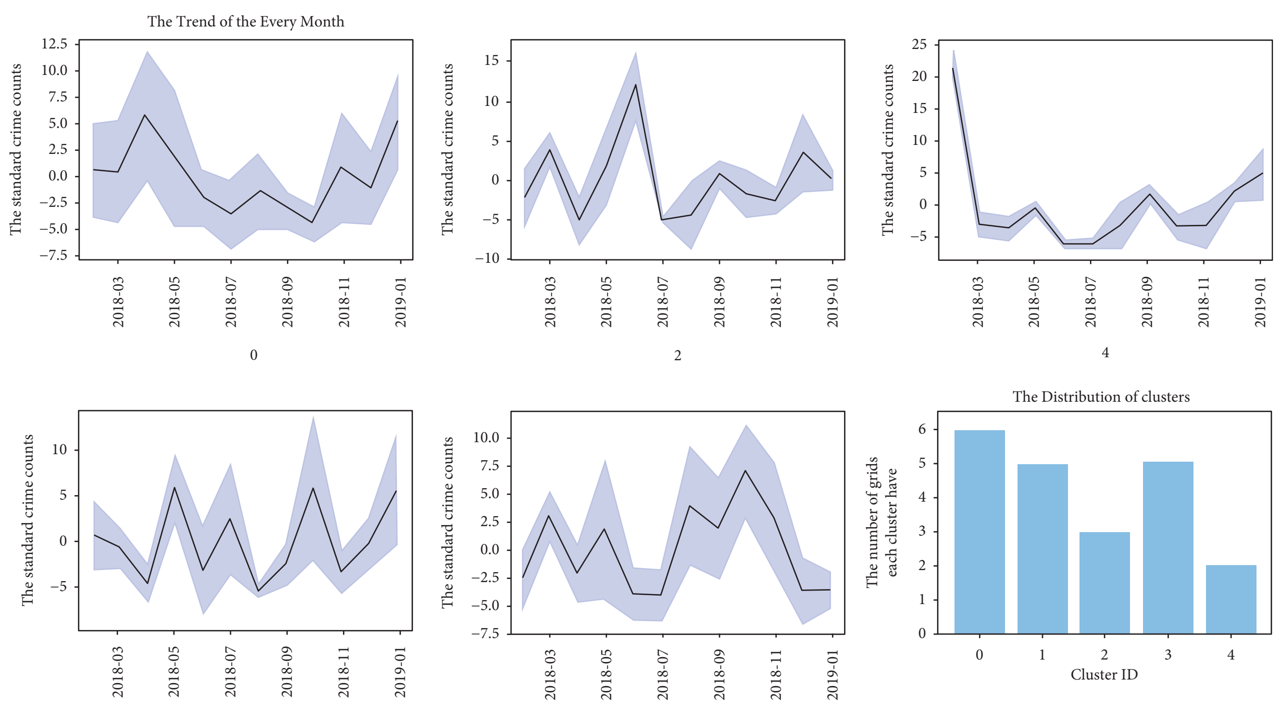

FIGURE 12: The burglary in Santa Monica trends in each month in 2018 and the distribution of clusters. The line charts are the monthly trends of burglary in Santa Monica in 2018. The bar chart is the distribution of the clusters.

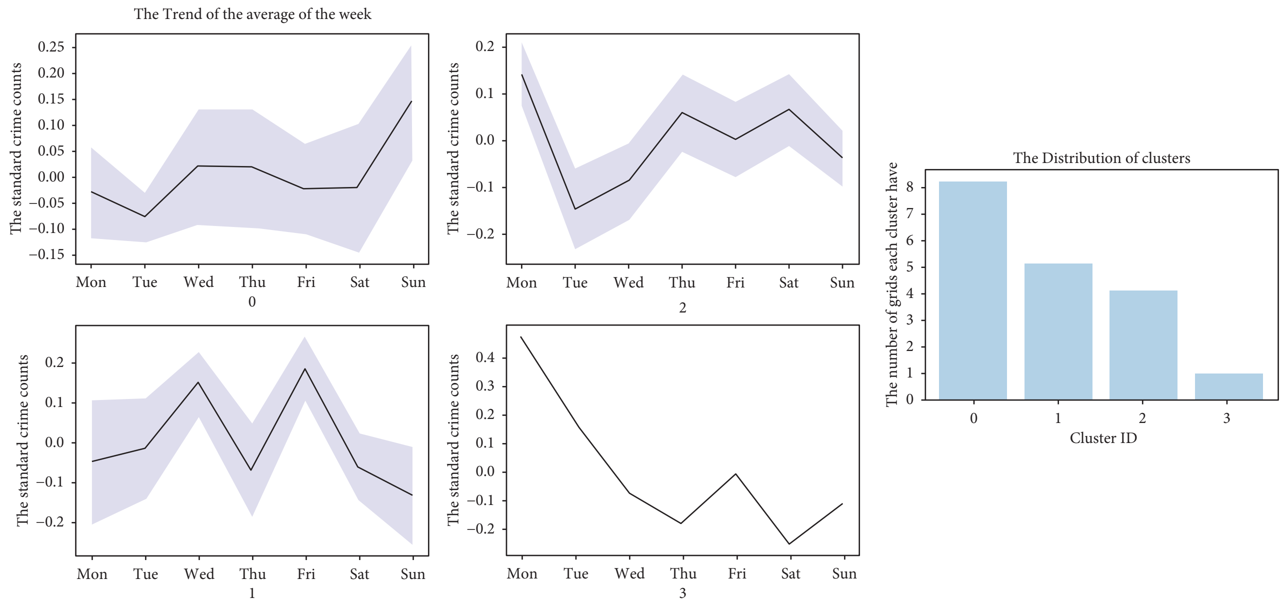

Figure 13: The theft in Santa Monica trends in the average weeks in 2018 and the distribution of clusters. The line charts are the weekly trends of theft in Santa Monica in 2018. The bar chart is the distribution of the clusters.

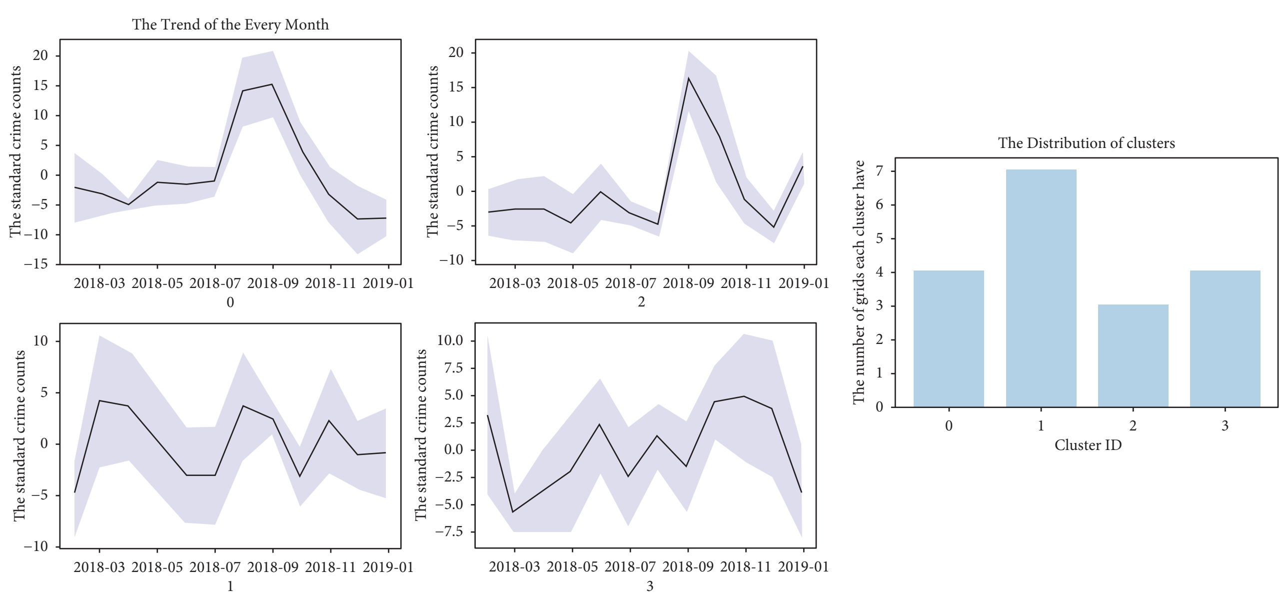

Figure 14: The theft in Santa Monica trends in each month in 2018 and the distribution of clusters. The line charts are the monthly trends of theft in Santa Monica in 2018. The bar chart is the distribution of the clusters.

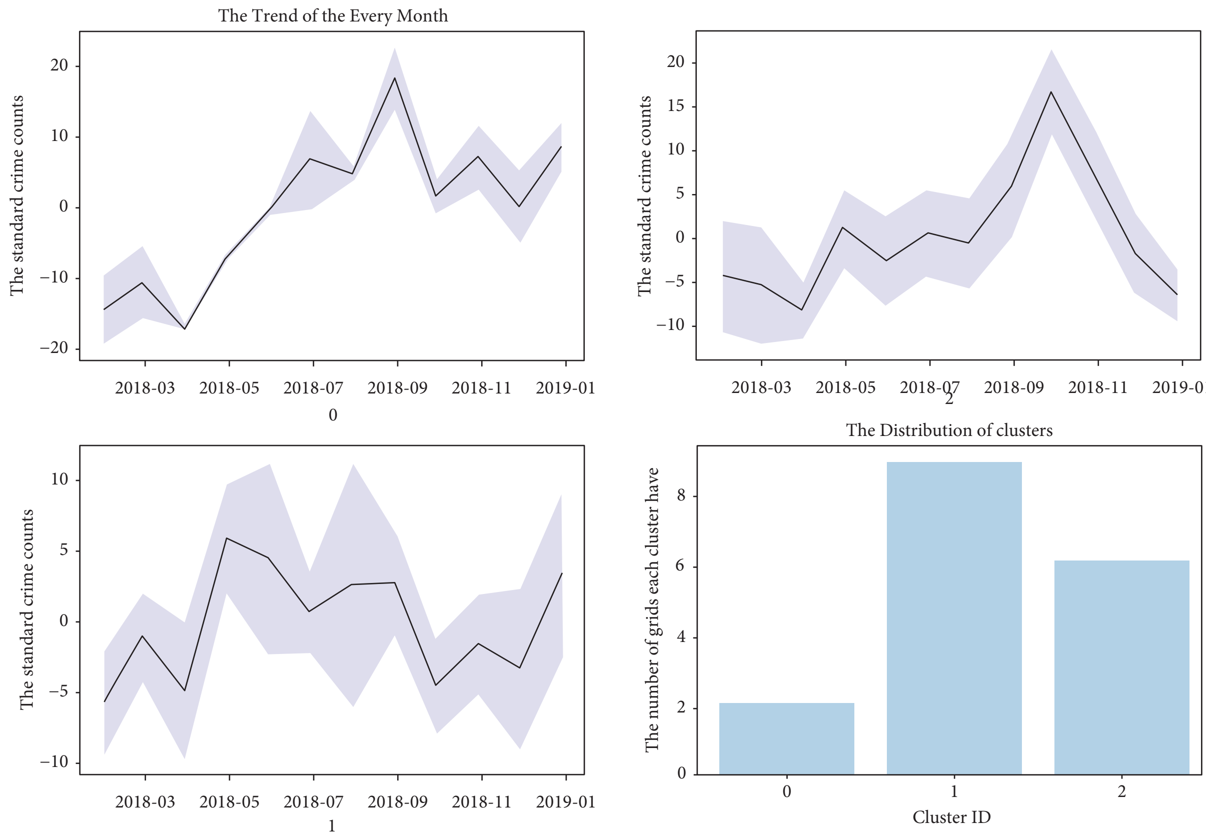

FIGURE 15: The theft in Philadelphia trends in each month in 2018 and the distribution of clusters. The line charts are the monthly trends of theft in Philadelphia in 2018. The bar chart is the distribution of the clusters.

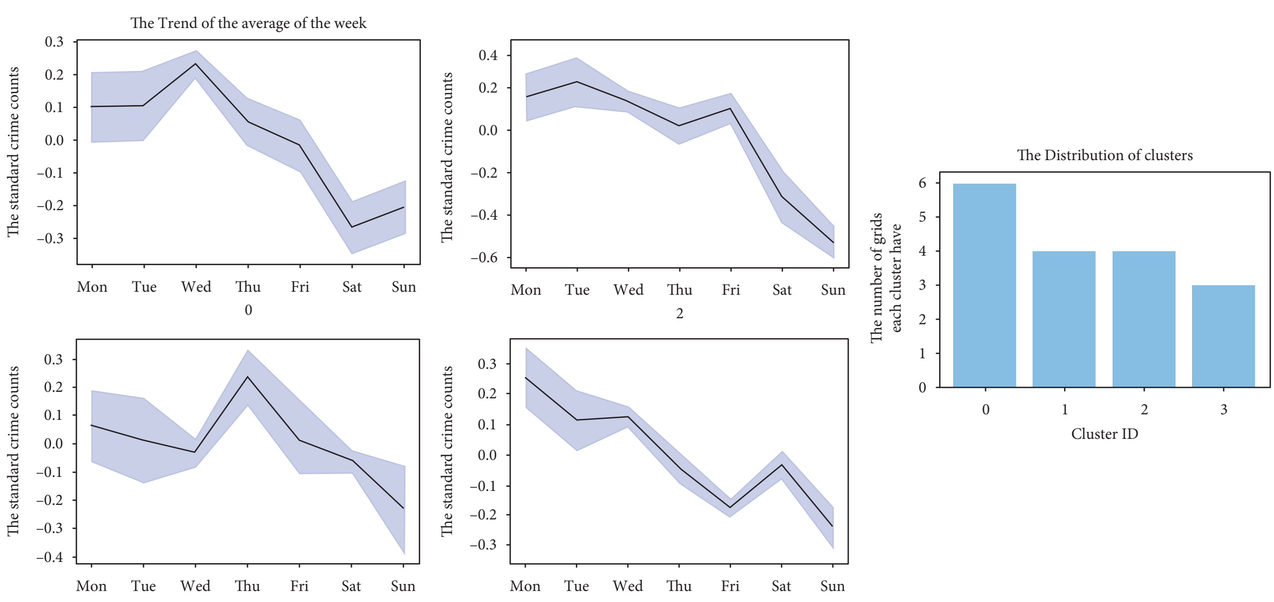

FIGURE 16: The theft in Philadelphia trends in the average week in 2018 and the distribution of clusters. The line charts are the weekly trends of theft in Philadelphia in 2018. The bar chart is the distribution of the clusters.

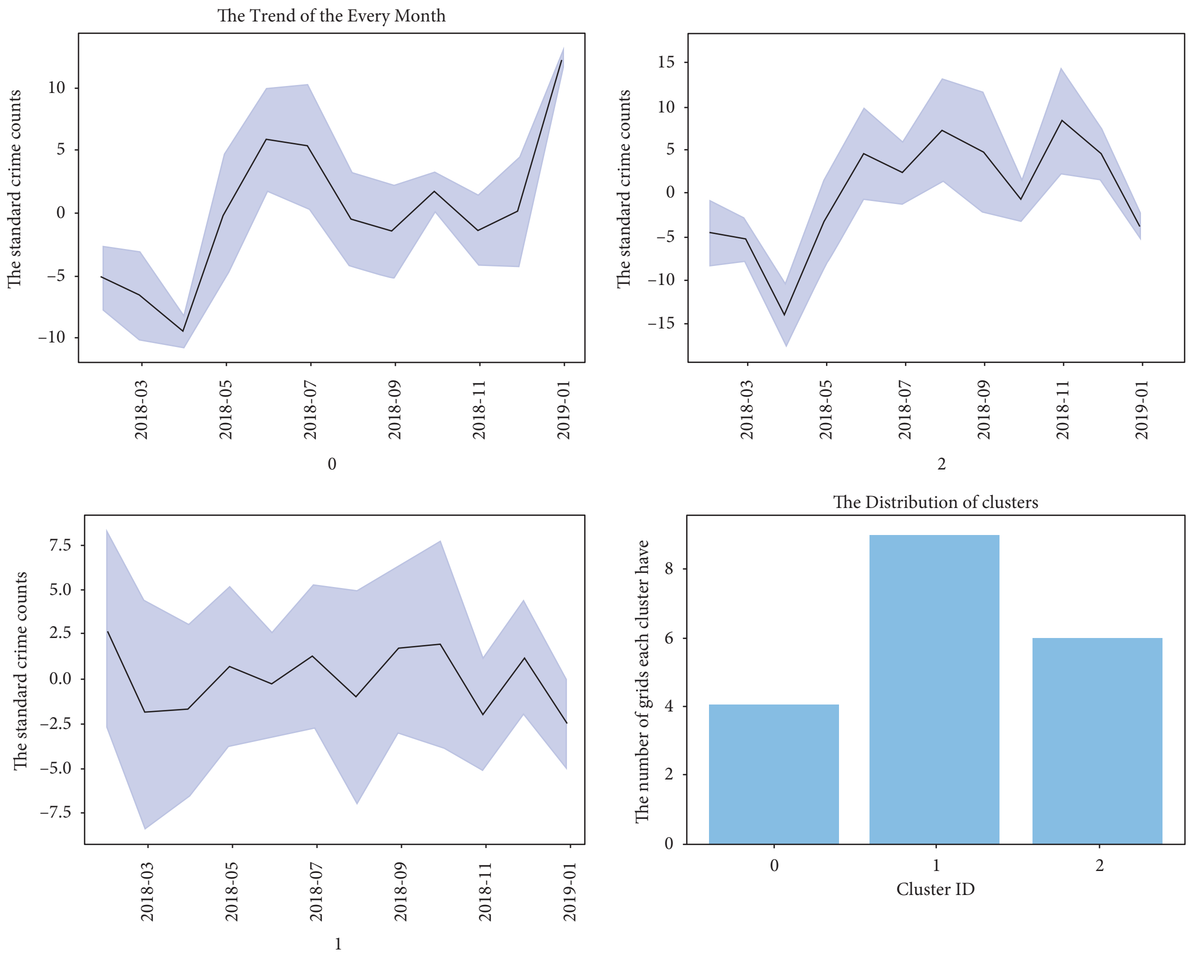

FIGURE 17: The burglary in Philadelphia trends in each month in 2018 and the distribution of clusters. The line charts are the monthly trends of burglary in Philadelphia in 2018. The bar chart is the distribution of the clusters.

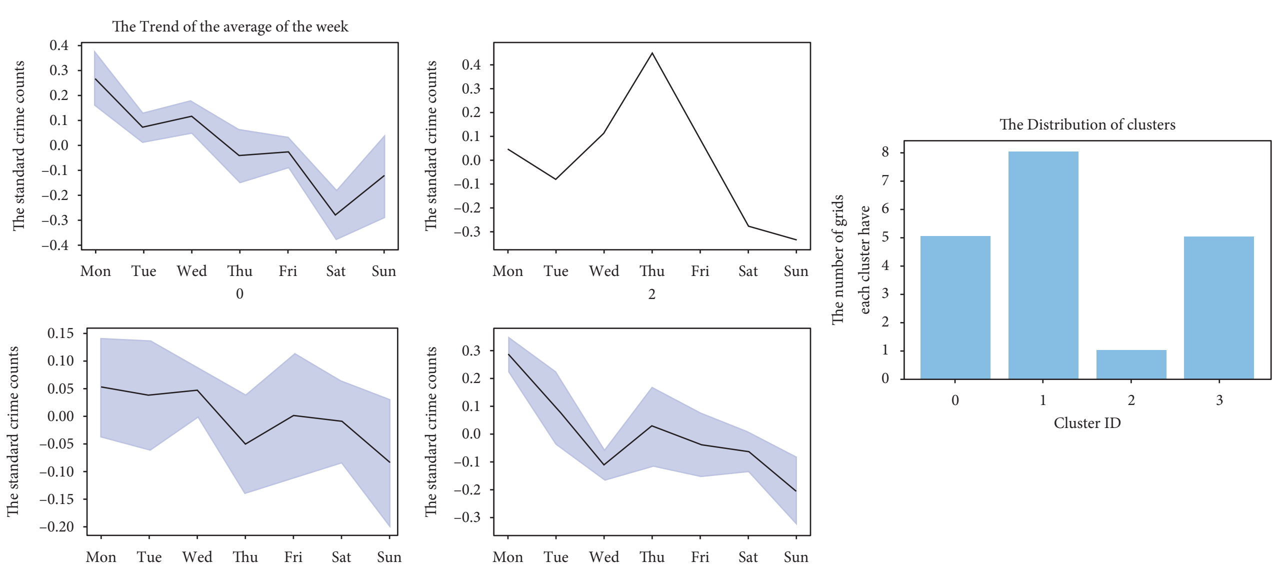

FIGURE 18: The burglary in Philadelphia trends in the average week in 2018 and the distribution of clusters. The line charts are the weekly trends of burglary in Philadelphia in 2018. The bar chart is the distribution of the clusters.

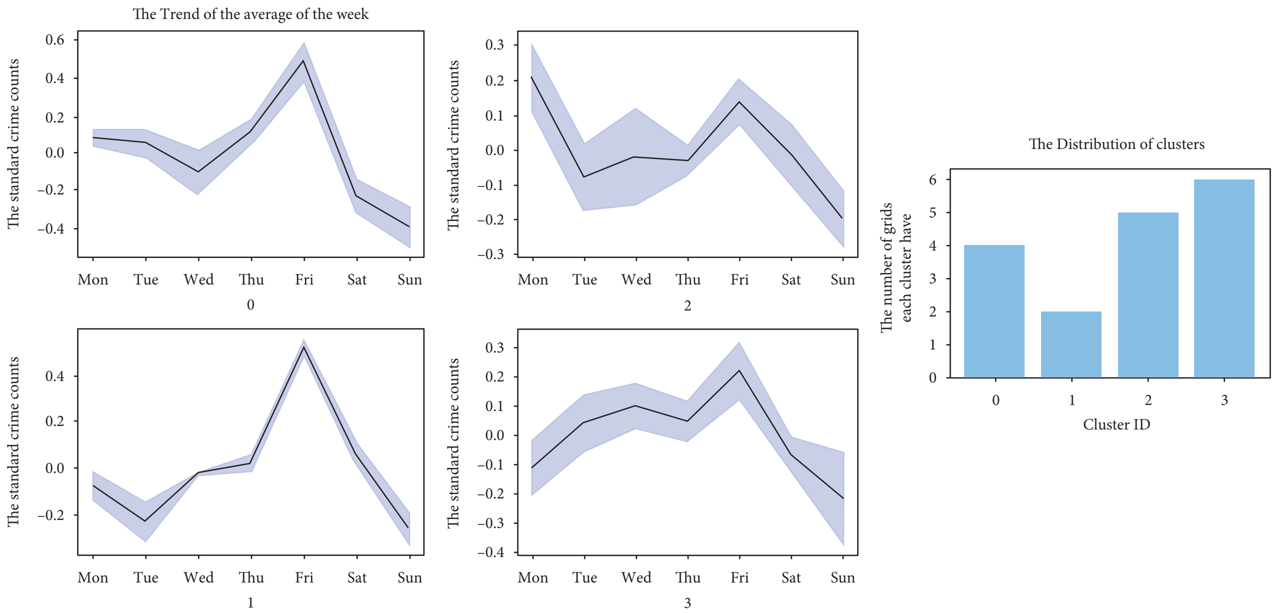

FIGURE 19: The burglary in New York trends in the average week in 2018 and the distribution of clusters. The line charts are the weekly trends of burglary in New York in 2018. The bar chart is the distribution of the clusters.

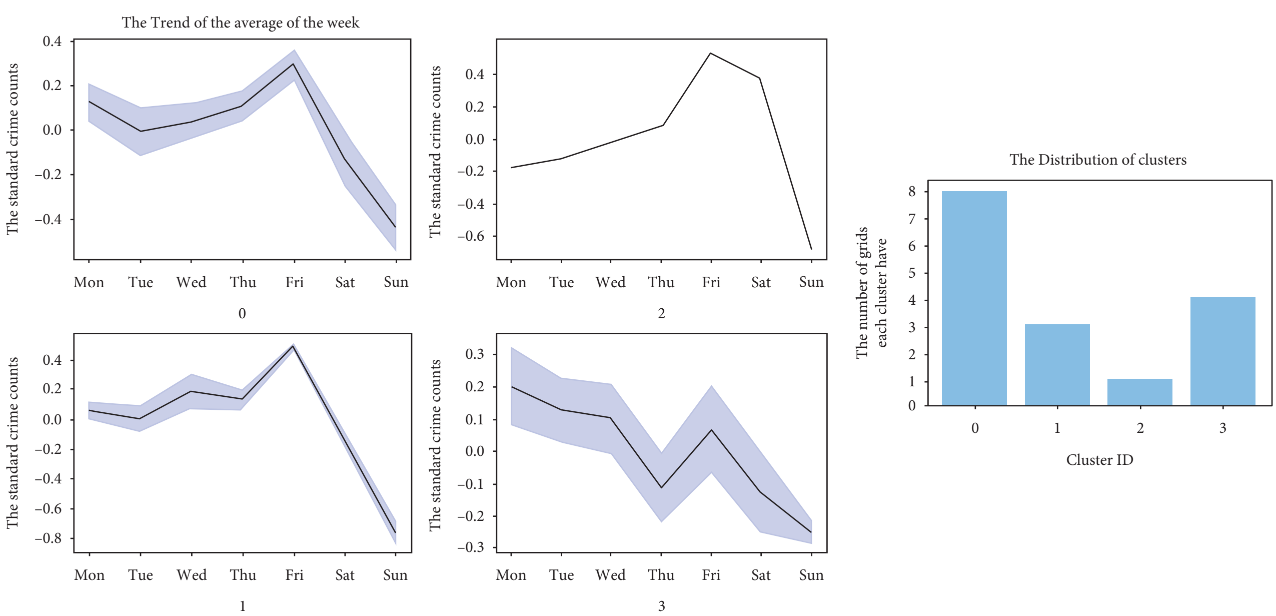

FIGURE 20: The theft in New York trends in the average week in 2018 and the distribution of clusters. The line charts are the weekly trends of theft in New York in 2018. The bar chart is the distribution of the clusters.

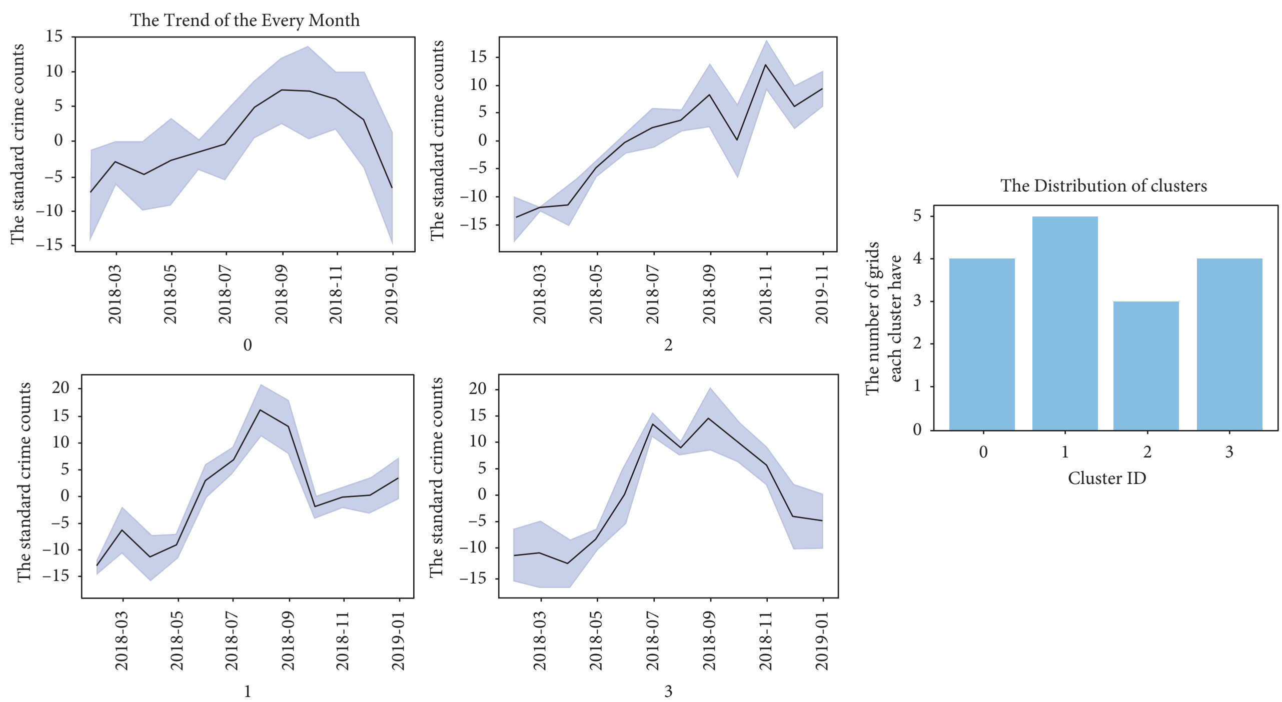

Figure 21: The theft in New York trends in each month in 2018 and the distribution of clusters. The line charts are the monthly trends of theft in New York in 2018. The bar chart is the distribution of the clusters.

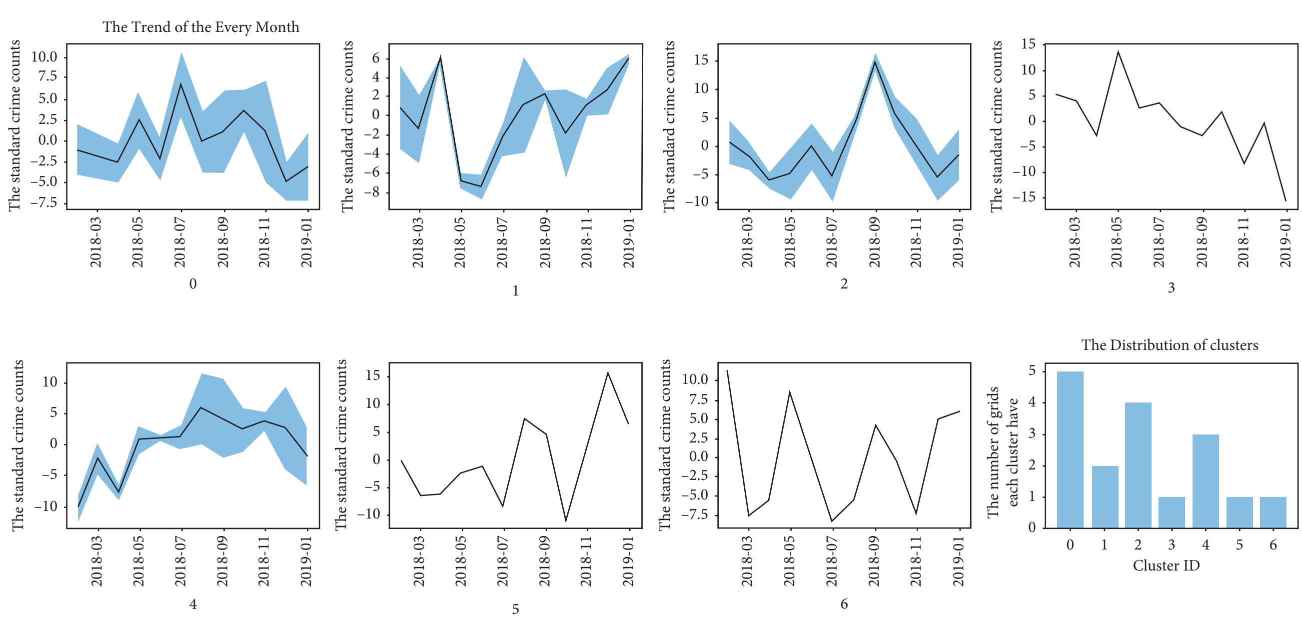

Figure 22: The burglary in New York trends in each month in 2018 and the distribution of clusters. The line charts are the monthly trends of burglary in New York in 2018. The bar chart is the distribution of the clusters.

Table 3: Two types in each considered dataset.

City	Data resource (link)
Chicago	https://data.cityofchicago.org/Public-Safety/Crimes-2001-to-Present/ijzp-q8t2
New York	https://data.cityofnewyork.us/Public-Safety/NYPD-Complaint-Data-Historic/qgea-i56i
Philadelphia	https://www.opendataphilly.org/dataset/crime-incidents
San Francisco	https://data.sfgov.org/Public-Safety/Map-Crime-Incidents-from-1-Jan-2003/gxxq-x39z
Santa Monica	https://data.smgov.net/Public-Safety/Police-Incidents/kn6p-4y74

7. Conclusions

By reading the relevant literature, it is not difficult to find that criminal activities have potential time and space regularities [16]. We hope to study crimes in different cities in a general way to find clearer regularities of them.

Therefore, we no longer pay attention to the previous methods of dividing cities into regions. The previous research methods that used population and public transportation systems are not wise. In terms of time, one year is too long as a unit of time. We need to subdivide units of time such as weekdays.

In this study, we do not need to pay attention to the specific scale of the crime and the loss of victims. If we focus on the value of the crime and set a threshold to separate the level of crime, perhaps we will lose some important data and change the result due to the informal standard.

According to our plan of the experiment, we can acquire the distribution of the crime in the city by locating each crime data as shown in Figure 1. We also divide the grids for clusters that have similar trends after creating grids for the city. From each bar chart, we can find the number of grids of each cluster and the cluster that has the most grids in the city.

We regard the cluster that has the most grids as the main pattern of the city. It can also help us understand the temporal pattern of crime across cities. Moreover, we can also use the same way to find the temporal regularities of two types of crimes in different time series.

By changing the type of crime, we can directly see the weekly and monthly trends of theft and burglary. We understand they are different and how the difference would be by comparing these trends. Once we create a library based on one city, we use the data from other cities to test whether it is stable and reliable. The results of other cities can also show us the differences in temporal regularities across cities.

From the charts of Chicago, we can find some temporal patterns in this city. Compared to the two types of crime weekly trends, burglary in Chicago is always maximum on Monday, decreases during the whole week, and gets the minimum on Sunday. But theft in Chicago in 2018 is always maximum on Friday and minimum on Sunday. It increases from Monday to Friday and decreases from Friday to Sunday. For their monthly trends, burglary in Chicago always is maximum in September and minimum in March.

We can find that the curve has dramatically changed in some periods. It greatly increases from March to April and from May to June. It also greatly decreases from April to May and from September to October. From the monthly curves of theft in Chicago, the maximum and minimum are partly in July and February.

It drops from January to February, from July to August, and from October to November. It immediately increases from February to July and from November to December. Interestingly, the minimum of the weekly trends of burglary and theft is on Sunday.

However, when we get all the final trend of each city, we found there is a delay of each time series of the monthly trends. When we sum them up, we acquire 12 columns, but it is from February in the current year to January in the next year.

It is because the function automatically adds the data in the same month but names them by the name of the next month. Thus, the data staying in the March of 2018 should be the total of February. This means the horizontal coordinates in the trend charts are all incorrect. But we use the correct ones in Table 2.

According to Table 2, we can find some temporal patterns.

7.1. *Weekly Theft.*

Chicago, San Francisco, and New York have the same maximum and minimum. They are all getting top on Friday and turning to the peak on Sunday. Philadelphia and Santa Monica are different in this case. In Philadelphia, the maximum happens on Wednesday and the minimum happens on Saturday. In Santa Monica, the maximum is on Sunday, and the minimum is on Tuesday.

7.2. *Weekly Burglary.*

The minimum of San Francisco and Santa Monica is on Friday. It is the same occasion for Philadelphia and New York. They have the minimum on Sunday. Philadelphia and Santa Monica have the maximum on Monday. But other cities are different. In Chicago, maximum happens on Monday and minimum happens on Sunday. In New York, the maximum is on Friday.

7.3. *Monthly Theft.*

The minimum in the three cities Philadelphia, New York, and Santa Monica is all in January. It is the same occasion for Philadelphia and New York. The trends of crime on both of them reach the minimum on Sunday. But patterns in other cities are different. For example, Philadelphia and Santa Monica have the maximum on Monday. In Chicago, the maximum happens on Monday, and the minimum happens on Sunday. In New York, the maximum is on Friday.

7.4. *Monthly Burglary.*

Chicago and San Francisco are getting the minimum in March and turning to the maximum in September. The date of the minimum of Santa Monica is the same as theirs, but the maximum is in August. However, Philadelphia and New York are different. In Philadelphia, the maximum is in January, and the minimum is in December. In New York, the maximum is in November, and the minimum is in June.

In the future, we want to pay attention to analyze the data in different years of each city to see whether the temporal patterns are stable. Moreover, we can also change the numbers of the grids in each city to see whether the patterns will change. However, this study is based on two types of crimes but the classification of them in different cities is not the same. I think it will affect the results in some way. If the cities of the same country have the same standard classification, it will be better for our experiment.

Appendix

Figure 7 describes the weekly burglary trends of San Francisco.

Figure 8 describes the monthly burglary trends of San Francisco.

Figure 9 describes the weekly theft trends of San Francisco.

Figure 10 describes the monthly theft trends of San Francisco.

Figure 11 describes the weekly burglary trends of Santa Monica.

Figure 12 describes the monthly burglary trends of Santa Monica.

Figure 13 describes the weekly theft trends of Santa Monica.

Figure 14 describes the monthly theft trends of Santa Monica.

Figure 15 describes the monthly theft trends of Philadelphia.

Figure 16 describes the weekly theft trends of Philadelphia.

Figure 17 describes the monthly burglary trends of Philadelphia.

Figure 18 describes the weekly burglary trends of Philadelphia.

Figure 19 describes the weekly burglary trends of New York.

Figure 20 describes the weekly theft trends of New York.

Figure 21 describes the monthly theft trends of New York.

Figure 22 describes the monthly burglary trends of New York.

Table 3 describes the data resource of each city.

Data Availability

The data used to support the findings of this study can be accessed in the following links: Chicago: https://data.cityofchicago.org/Public-Safety/Crimes-2001-to-Present/ijzp-q8t2, New York: https://data.cityofnewyork.us/Public-Safety/NYPD-Complaint-Data-Historic/qgea-i56i, Philadelphia: https://www.opendataphilly.org/dataset/crime-incidents, San Francisco: https://data.sfgov.org/Public-Safety/Police-Department-Incident-Reports-2018-to-Present/wg3w-h783, and Santa Monica: https://data.smgov.net/Public-Safety/Police-Incidents/kn6p-4y74.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

References

[1] J. Warr, *Humean Causation and Crime Theory*, Springer International Publishing, Berlin, Germany, 2016.

[2] L. W. Sherman, "Attacking crime: police and crime control," *Crime and Justice*, vol. 15, pp. 159–230, 1992.

[3] A. Braga, A. Papachristos, and D. Hureau, "Hot spots policing effects on crime," *Campbell Systematic Reviews*, vol. 8, no. 1, pp. 1–96, 2012.

[4] L. W. Sherman and J. E. Eck, "Policing for crime prevention," in *Evidence-Based Crime Prevention*, pp. 309–343, Routledge, London, UK, 2003.

[5] P. Ball, *Broken Windows: The Spread and Control of Crime*, Springer, Berlin, Germany, 2012.

[6] L. E. Cohen and M. Felson, "Social change and crime rate trends: a routine activity approach," *American Sociological Review*, vol. 44, no. 4, pp. 588–608, 1979.

[7] A. Gomez-Lievano, O. Patterson-Lomba, and R. Hausmann, "Explaining the prevalence, scaling and variance of urban phenomena," *Nature Human Behaviour*, vol. 1, no. 1, pp. 1–6, 2016.

[8] A. N. Tennenbaum and E. L. Fink, "Temporal regularities in homicide: cycles, seasons, and autoregression," *Journal of Quantitative Criminology*, vol. 10, no. 4, pp. 317–342, 1994.

[9] G. Farrell, "Crime concentration theory," *Crime Prevention and Community Safety*, vol. 17, no. 4, pp. 233–248, 2015.

[10] M. Oliveira, E. Ribeiro, C. Bastos-Filho, and R. Menezes, "Spatio-temporal variations in the urban rhythm: the travelling waves of crime," *EPJ Data Science*, vol. 7, no. 1, p. 29, 2018.

[11] S. Ruiter, "Crime location choice," *The Oxford Handbook of Offender Decision Making*, pp. 398–420, Oxford University Press, Oxford, UK, 2017.

[12] K. S. Jeong, T. H. Moon, J. H. Jeong, and S. Y. Heo, "Analysis of spatio-temporal pattern of urban crime and its influencing factors," *Journal of the Korean Association of Geographic Information Studies*, vol. 12, no. 1, 2009.

[13] M. Oliveira and R. Menezes, "Spatial concentration and temporal regularities in crime," 2019, https://arxiv.org/abs/1901.03589.

[14] A. A. Braga, "The effects of hot spots policing on crime," *The ANNALS of the American Academy of Political and Social Science*, vol. 578, no. 1, pp. 104–125, 2001.

[15] M. Oliveira, C. Bastos-Filho, and R. Menezes, "The scaling of crime concentration in cities," *PLoS One*, vol. 12, Article ID e0183110, 2017.

[16] S. E. van Sleeuwen, S. Ruiter, and W. Steenbeek, "Right place, right time? making crime pattern theory time-specific," *Crime Science*, vol. 10, no. 1, pp. 1–10, 2021.

[17] T. H. Grubesic and E. A. Mack, "Spatio-temporal interaction of urban crime," *Journal of Quantitative Criminology*, vol. 24, no. 3, pp. 285–306, 2008.

[18] X. Ye, X. Xu, J. Lee, X. Zhu, and L. Wu, "Space-time interaction of residential burglaries in Wuhan, China," *Applied Geography*, vol. 60, pp. 210–216, 2015.

[19] R. Prieto Curiel, J. E. Patino, J. C. Duque, and N. O'Clery, "The heartbeat of the city," *PLoS One*, vol. 16, no. 2, Article ID e0246714, 2021.

[20] N. Shover, "Burglary," *Crime and Justice*, vol. 14, pp. 73–113, 1991.

[21] A. A. Braga, "Hot spots policing and crime prevention: a systematic review of randomized controlled trials," *Journal of Experimental Criminology*, vol. 1, no. 3, pp. 317–342, 2005.