Do broken windows encourage criminality

Final Technical Report

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[Abstract]

Since the broken window theory was introduced in 1982, it has influenced many cities' policing strategies. However, in recent years, there have been more and more criticisms that believe that the decline of the crime rate is affected by many factors, which can not prove that broken window policing is effective. And so far, no literature can verify the authenticity of this theory through data. To answer this question, our study mainly uses 311 requests data and NYPD complaint data of New York City from 2015 to 2019 to research the correlation relationship between disorder behavior and crime on both time aspect and spatial aspect. This study found there is a certain correlation between disorder and crime, but it still cannot prove that the broken window theory and broken window enforcement are true and effective. According to the results, we put forward suggestions to improve the efficiency of the police.

Key words: Broken window theory, Disorder, Crime, Police, Policy

Introduction

The broken windows theory is a kind of criminology theory, which thinks that such behaviors as breaking windows, even littering, will have a negative impact on the whole community environment, and even cause crime (Wilson & Kelling, 1982). The theory has had a significant impact on police policy in the United States. Since the 1990s, the New York Police Department (NYPD) has widely implemented broken window policing by stop, question, and frisk. Then NYPD Commissioner Bratton introduced his Broken Windows-based Quality of Life Initiative between 1994 and 1996. It encourages the police to issue quality-of-life summonses or arrest individuals involved in misdemeanors, low-level crimes, and violations such as broken windows, drug abuse, or urination in public. During these two years, in New York, the felony rate and homicide rate decreased by nearly 40% and 50%, respectively (Kelling & Sousa, 2001). In the past, the New York City Police Department and the community attributed the decline in crime to broken windows policing, which believes that stopping, questioning, and frisking the perpetrators of minor crimes such as disturbing public order will help to reduce the occurrence of felonies. However, in recent years, many skeptical voices have emerged. Critics argue that broken windows policing may not be directly responsible for the drop-in crime rates. It seems that there is no evidence that disorderly conduct leads to crime (O'Brien, 2019).

Therefore, the goal of this research would be to verify whether the broken windows theory actually causes the crime rate to increase by using New York City crime incident data and disorderly incident data to further discuss whether broken window policing is effective or not. This project aims to improve the New York police policy-making and arrangement by justifying the significant level of the broken windows theory in New York City. By analyzing the regionality differences in New York City, seasonality change, and various kinds of crime and disorder behavior, this research set the purpose which is to dig deeper and find how the theory reflected differently on different regions and changed with time.

Literature review

The broken windows theory was introduced by social scientists James Wilson and George Kelling (1982). It is a criminological theory that states that a broken window or other disorder behaviors in neighborhoods lead to elevated crime by inviting additional criminal activity and discouraging the positive social behavior that prevents crime. Disorder behavior refers to some behaviors that may be listed as minor crimes, such as graffiti, public drinking, jaywalking, urinating in public, or drug use. In the article, James and George (1982) suggest that policing methods that target such minor crimes or disorder behaviors help create an atmosphere of order and lawfulness, thereby preventing more serious crimes.

In past decades, the broken windows theory has been subject to debate both within the social sciences and the public sphere. Some studies seem to have found support for the broken window theory, while others have not, leaving a blurry picture of the popular perspective.

The mayor of New York City, Rudy Giuliani, and his new police commissioner, William Bratton were supporters of this theory. They promoted the application of the broken window theory in policing and began to make efforts to clean up the streets and restore order to the neighborhood. According to The New York Times in 1997, “The crime rate in New York City fell 9.1 percent last year, with murders dropping to their lowest level since 1967.”

However, Harcourt (2005), the Columbia law professor, was skeptical. Harcourt points out that during that period, the crime rate not only fell in New York City but also in many other cities where there was no broken window policing. In addition, he also mentioned that broken window policing has brought about a surge of complaints about improper law enforcement by the police.

In addition, many scholars have discussed the authenticity of broken window theory and the effectiveness of broken window law enforcement. Daniel O'Brien et al. (2019) and his team conducted a meta-analysis of 96 related studies to examine the effects of the disorder. They found no consistent evidence that disorder induces greater aggression or more negative attitudes toward the neighborhood. Their study, in a sense, disproves the broken window theory, which seems to imply that the significant financial resources and effort police departments invest in broken window policing each year is ineffective.

Moreover, Daniel O'Brien, Robert J. Sampson, and Christopher Winship et al. (2015) carry out three echometric analyses based on Boston's constituent relationship management (CRM) system. Their study provides an example of how the large-scale administrative data on the open platform can be used in the research of urban science and provides us with the inspiration to test the broken window theory using 311 request data.

Problem statement

From previous studies, it is known that the broken window theory has been applied to policy arrangements a long time ago. Nevertheless, some analyses are showing that there is no significant amount of evidence to support the broken windows theory. So we are facing the question that does broken window policing really works or is it a waste of manpower and resources？

This research hopes to verify whether the relationship between crime and disorder reflected by broken windows theory is true or not and put forward some suggestions on improving police measures through our research results to improve the police's efficiency and allocate resources better to address specific criminal activities.

Our study aims to investigate the following research hypotheses:

- **Hypothesis1.** According to the broken windows theory, higher levels of the disorder are correlated with higher levels of crime.
- **Hypothesis2.** Higher levels of police activity are correlated with lower levels of disorder and crime.
- **Hypothesis3.** The demographic census data might impact the disorder and crime data. Lower levels of education, income and house price are correlated with higher levels of disorder and crimes

Data and Methodologies

In this study, we mainly use three types of data: major crime, disorder, and police activity, to investigate the broken windows theory. In addition, we will use the income, house price, education level and other livelihood data provided by the census as demographic factors for further research.The sources and specific information of these data are shown in Table 1.

Disorder Classification

Table 2 shows the classification and sources of the disorder data. The first part comes from the 311 Service Requests data-set. We filter the types of requests related to disorder behaviors and classify these requests into seven categories: Uncivil Use of Space, Drug & Alcohol, Trash, Noise, Damage, Graffiti and Others. These data are the central part of the disorder. Another part comes from NYPD complaint data. In addition to major crimes, this data set also records misdemeanors and violations in New York City, which can also be regarded as disorder behaviors.

Crime Classification

The data on major crimes are mainly from NYPD complaint data, as shown in Table 3, from which select eight main types of crimes: murder, rape, robbery, default, burger, grand larceny, grand larceny auto, and dangerous drugs. We further divide these crimes into property crimes and violent crimes according to the related NYPD report.

Exploratory data analysis

In order to explore the correlation between different disorder types and two crime categories, in this section, a basic exploration of data analysis on 311 Service Requests data and NYPD complaint data is conducted.

We firstly extract all disorder records in 311 dataset during 2015 and 2019. After pre-processing, a disorder record based on 311 dataset is obtained with three elements: zip code, disorder type and corresponding time. Furthermore, we process NYPD complaint historic dataset and obtain disorder records with three elements: zip code, disorder type and corresponding time. However, the zip code information is not included in the NYPD complaint dataset. Therefore, based on the New York Shapefile dataset, we map each NYPD complaint record into the geographical dimension and then obtain the zip code information. After disorder records are extracted from 311 dataset and NYPD complaint dataset, we combine two disorder records into one disorder dataset which contains the disorder type, corresponding time and zip code.

The crime dataset is extracted from NYPD complaint data which also contains three elements: crime category, corresponding time and zip code. Similar to the process of extracting disorder dataset, New York shapefile dataset is utilized to obtain the zip code information.

Then, based on the obtained disorder dataset and crime dataset in New York, we conduct sufficient analysis and explore the correlation between different disorder types and different crime categories.

New York Shapefile dataset

The New York shapefile dataset contains population information for each zip code. Firstly, we visualize the spatial shapefile dataset in Fig.1.

Fig.1 shows the spatial distribution of New York, each region is an area surrounded by polygons which is identified by zip code. In addition, the New York shapefile dataset also contains the population of each region. In the latter analysis, shapefile will be utilized to visualize geo-spatial related distribution.

Disorder dataset

We firstly explore the disorder distribution and crime distribution based on disorder dataset and crime dataset, respectively. Python package “geopandas” is utilized to visualize the spatial distribution of disorder types. Based on the zip code and disorder types, we compute the number of disorders in each zip code. Fig.2 shows the geo-spatial distribution of disorder count in New York. In order to show the percentile of disorder count for each zip code, python method “stats.percentileofscore” is employed to compute the percentile of disorder count in zip code. Fig.3 shows the geo-spatial distribution of percentile of disorder count in New York.

Fig.2 shows the geospatial distribution of disorder count in New York, the corresponding color is related to the disorder count in different areas. Fig.3 shows the geospatial distribution of percentile of disorder count in New York, which can identify the geospatial distribution of areas with higher disorder count.

Disorder dataset contains ample temporal information. Therefore, we map disorder records into corresponding time intervals and explore the temporal features of disorder. Fig.4 shows the distribution of disorder count with temporal change.

Fig.4 shows the temporal distribution of disorder count in New York, the figure means that temporality is highly relative with disorder count.

Based on the time information, we split the disorder dataset into weekday dataset and weekend dataset. We also show the percentile of disorder count on weekends and weekdays in Fig.5.

Fig.5 intends to show whether weekends and weekdays have a high influence on disorder count in different areas. However, based on Fig.5, we observe that the weekend and weekday make minor influences on the disorder.

The disorder dataset contains eight disorder types. Therefore, we explore the distribution of different disorder types with temporal information. Fig.6 shows the distribution of different disorder types in temporal dimension.

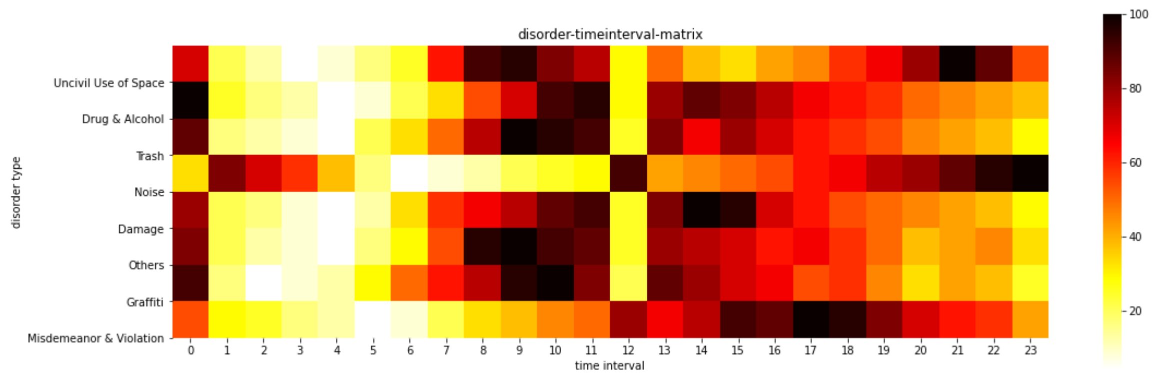

Fig.6 The distribution of different disorder types with the hour change

Fig.4 shows the distribution between temporal factors and overall disorder count, however, Fig.6 shows the temporal distribution with different disorder types. From Fig.6, we find that time has a strong impact on disorder count, and the temporal influence on different disorder types are diverse. This may be because different disorder behaviors will appear in different time periods. For example, people tend to carry out illegal activities such as graffiti, drug abuse and alcohol abuse at midnight to avoid being found.

In addition, we explore the long-term distribution of disorder count in Fig.7.
From Fig.7, we find that the disorder count increases in a long-term observation. In addition, the disorder count in New York changes periodically in the long-term.

Crime dataset

In addition to the disorder dataset, we also explore the basic analysis based on the crime dataset. Fig.8 shows the distribution of crime count and the percentile of crime count in New York.

Similar to the analysis on disorder count, in this section, we show the geospatial distribution of crime count in New York, which can identify the geospatial distribution of areas with higher disorder count. In Fig.8, we can find that crime distribution is related to disorder distribution.

In addition, we map the corresponding time of crime records into different time intervals and then explore the distribution of crime count with the change of time interval. Fig.9 shows the distribution of crime count with the change of time interval.

From Fig.9, we can find that temporal information is highly relative to the crime count in New York. In addition, Fig.9, shows that the crime count in 5pm and 0am are relatively higher than other time intervals.

Similar to the data exploration on disorder dataset, we also analyze the influence on crime on weekends and weekdays. Therefore, Fig. 10 shows the distribution of percentile of crime count on weekends and weekdays.

In Fig.10, we intend to find whether weekends and weekdays are relative to the crime count in New York. However, the results show that day of week has a minor influence on crime count.

The crime dataset contains two crime types: Violent Crime and Property Crime. Therefore, we explore the distribution of different crime types with temporal information. Fig.11 shows the distribution of different crime types in temporal dimension.

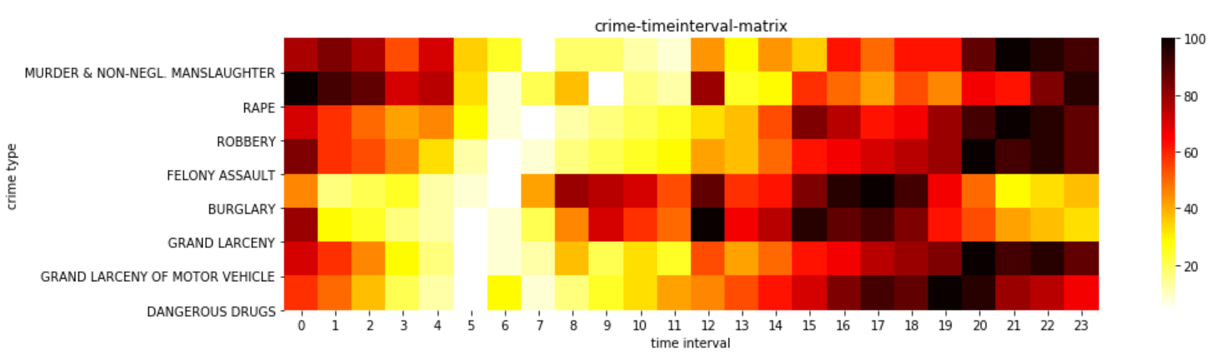

Fig. 11 The distribution of different crime types with the hour change

Similar with the analysis on disorder dataset, we visualize the temporal influence on different crimes in Fig.11, the result shows that temporal factors have a high influence on different crime types, in addition, the temporal influence on different crimes are also diverse. However, we can see that most criminal activities occur in the evening, while there are few criminal activities in the morning.

In addition, we explore the long-term distribution of crime count in Fig.12 where crime dataset are mapped into different months in long-term.

Fig. 12 shows that the crime count decreases in a long-term observation. In addition, Fig.12 shows that the crime count changes periodically in the long-term. Overall, the number of crimes peaked in summer, which may be related to weather.

Density Exploration

We have introduced New York shapefile dataset, disorder dataset and crime dataset. Then, in order to explore the density of each unit in terms of population, Fig.13 first visualizes the population distribution and percentile population distribution in New York, respectively.

As we mentioned before, the New York shapefile dataset contains population information, therefore, In Fig 13, we visualize their population distribution in New York, which will identify the population number in different areas.

Therefore, we compute the disorder density of each unit in terms of population in different zip codes in Equation (1). In addition, Equation (2) computes the crime density of each unit in terms of population in different zip codes.

$$Density_{disorder} = \frac{Count_{disorder}}{Population} \tag{1}$$

$$Density_{crime} = \frac{Count_{crime}}{Population} \tag{2}$$

Based on Equation (1) and (2), we compute the distribution of disorder density and crime density of each unit in terms of population.

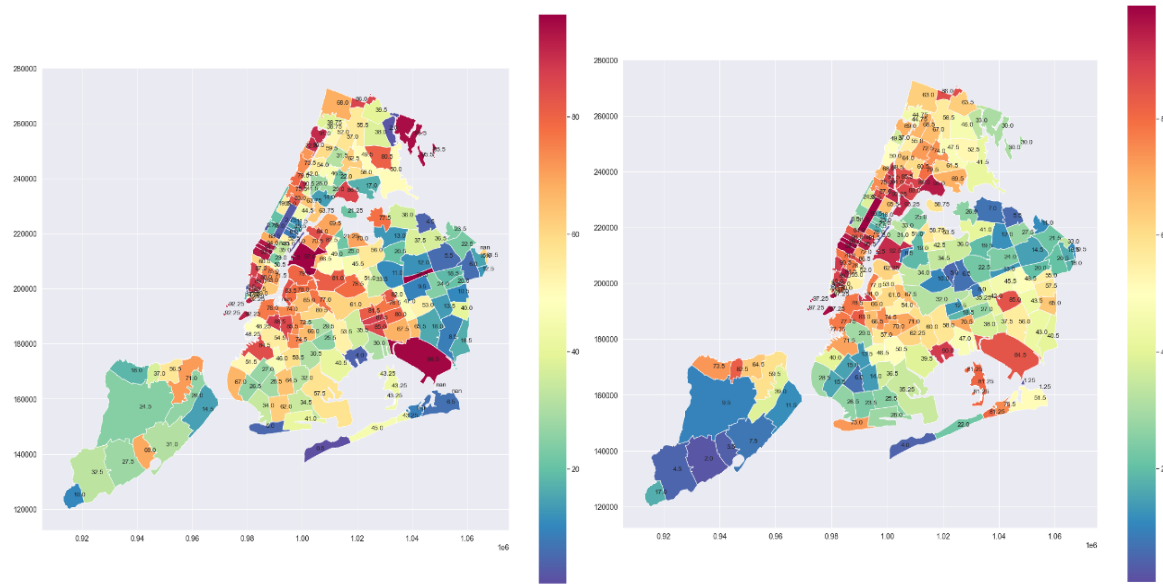

Fig.14 The distribution of disorder density and crime density

The distribution of disorder density and crime density is shown in Fig.14. The left figure in Fig. 14 shows the disorder density in New York, and the right figure in Fig.14 shows the crime density in New York. From Fig.14, we can find that crime distribution is relative to the disorder distribution.

Then, based on the disorder dataset and crime dataset, we utilized the python method “pandas.corr()” to compute the correlation of different disorder types and different crime categories.

The police activity dataset

The police activity dataset comes from NYPD's Stop, Question and Frisk Dataset. There is rich geo-spatial information in the police dataset, then, based on the New York shapefile dataset, we can map each police record into New York City in different zip codes, which will help to analyze the relationship between police dataset and disorder and crime dataset.

Firstly, we map the police activity dataset into the geospatial level, more specifically, the New York shapefile dataset is utilized to map police records into New York City in different zip codes. Then, we obtain the total number of police records in different zip codes for further analysis. Based on the New York shapefile dataset, Fig.22 shows the distribution of police record numbers in New York City.

Then, we combine the police activity dataset with the disorder and crime dataset so that the correlation between police records and disorder/crime information in different zip codes. Similar to the above analysis method, pandas.corr() method is employed to obtain the relationship between police and disorder/crime dataset.

Demographic dataset

Demographic information is an important factor to describe the relationship between disorder and crime. The demographic dataset is sourced from the Census. More specifically, four factors are included in the demographic dataset, that is, age, income, education, house price. In addition, each item has been transformed into a percentile of items, which will help our model aggregate information from different sources. The relationship and correlations between demographic factors and disorder and crime will be shown in the result part.

Result

In this section, we explore the correlation between different disorder types and different crime categories. Disorder dataset and crime dataset are combined into one dataset, then python method “pandas.pivot()” is utilized to transform the dataset into a new dataset, where the disorder types and crime categories are regarded as variables.

Then, the python method “pandas.corr()” is utilized to compute the correlation of different variables. Fig.15 shows the correlation of disorder types and crime categories in two perspectives.

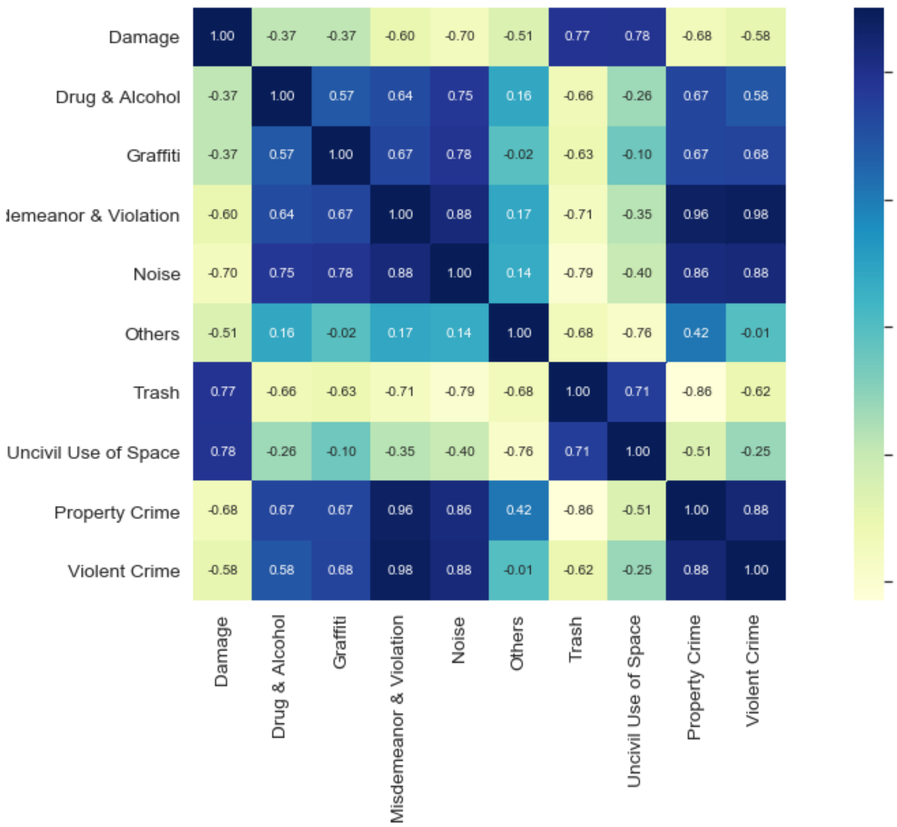

Fig. 15 The correlation of disorder types and crime categories.

Fig.15 shows that property crime and violent crime is more relative with “Misdemeanor & Violation” and “Noise”. In addition, we find that “Uncivil Use of Space” is more relative with “Damage”.

Temporal analysis

Then, we analyze the correlation between disorders and crimes in terms of temporal information. Firstly, we average all zip codes disorder data and crime data, “pandas.corr()” method is utilized to compute correlation between different disorder types and crime categories. Then, heatmap is employed to visualize the correlation between different disorder types and crime categories of average all zip codes in Fig.16.

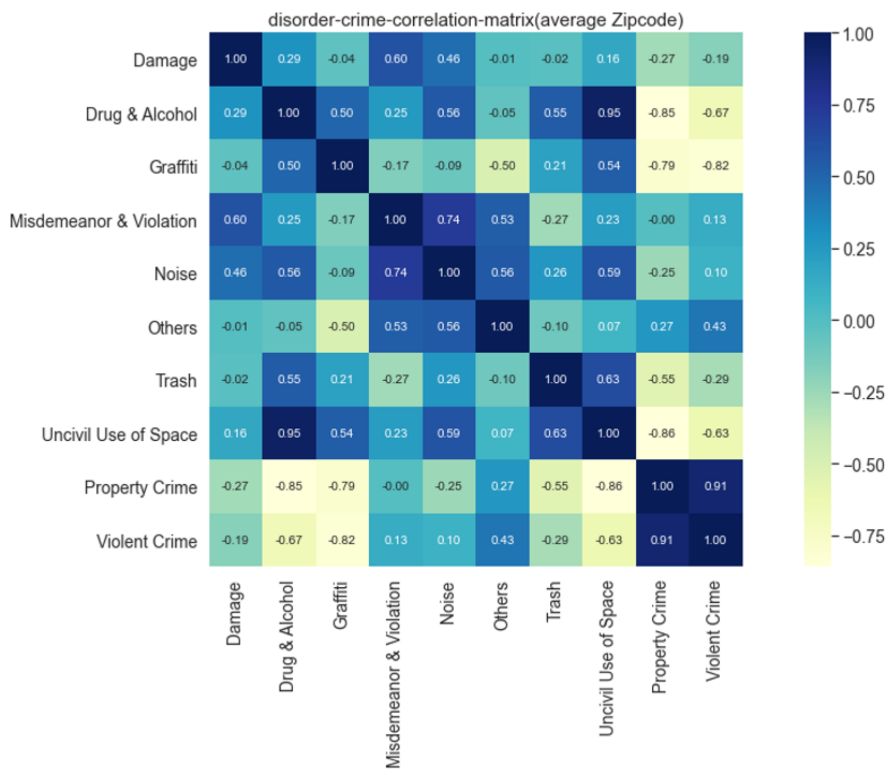

Fig. 16 The correlation between different disorder types and crime categories is the average of all zip codes.

Based on Fig.16, we find that the correlation between "Uncivil Use of Space" and "Drug & Alcohol" is relatively high. In other words, " Drug & Alcohol " will affect "Uncivil Use of Space".

Geo-spatial analysis

In this section, the relationship between different disorders and crime under different zip codes was analyzed. We average the data from January 2015 to December 2019 in each zip code firstly. More specifically, disorder includes Trash and Uncivil Use of Space, crime includes Property Crime and Violent Crime. Then, the spatial distribution of correlation of Trash and Property Crime, Uncivil Use of Space and Property Crime, Trash and Violent Crime, Uncivil Use of Space and Violent Crime are computed. What's more, based on New York shapefile dataset, we visualize four geo-spatial distribution of Trash and Property Crime, Uncivil Use of Space and Property Crime, Trash and Violent Crime, Uncivil Use of Space and Violent Crime in Fig.17, Fig.18, Fig.19 and Fig.20, respectively.

Fig.17, Fig.18, Fig.19 and Fig.20 show the geospatial distribution between different disorders and different crimes. From these figures, we can find that the correlation between different disorder-crime pairs in different regions are diverse. The correlation between Trash and Property Crime is higher within more areas in New York, the correlation betweenTrash and Violent Crime has similar distribution. However, the correlation between Uncivil Use of Space and Property Crime is higher only in a few regions in New York, similar distribution also shows in the correlation between Uncivil Use of Space and Violent Crime.

Human perspective and Environment perspective

Based on the above analysis, eight disorder types can be classified into two classes: human-related and environment-related. Therefore, in this section, we will conduct further analysis based on the human perspective and environmental perspective.

Damage, drug & alcohol, misdemeanor & violation, and graffiti are human-related disorder types, Uncivil Use of Space, others, trash, and noise are environment-related disorder types. Then, the number of two perspectives disorder records is computed, the heatmap is also utilized to show the correlation between two perspective disorders and different crime categories.

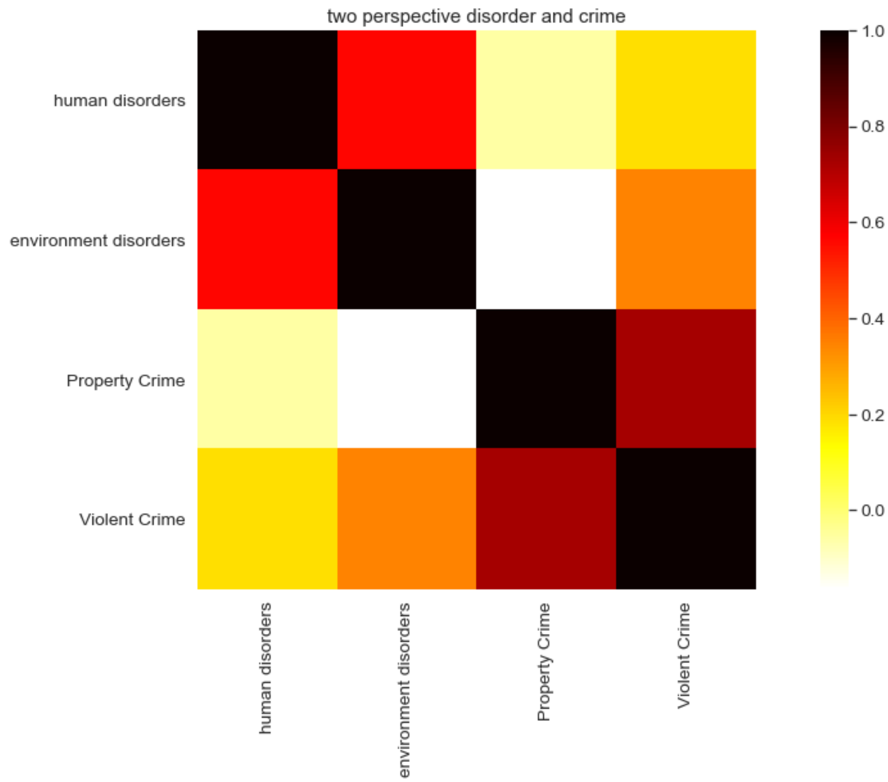

Fig. 21 The correlation between human/environment disorders and crimes

Fig.21 shows the correlation between human/environmental disorders and crimes. Human disorders are more related to property crime, and environmental disorders are more related to violent crime.

In addition, the results show that disorder data is more relative to crime data, which proves that hypothesis 1 is right.

Police activity analysis

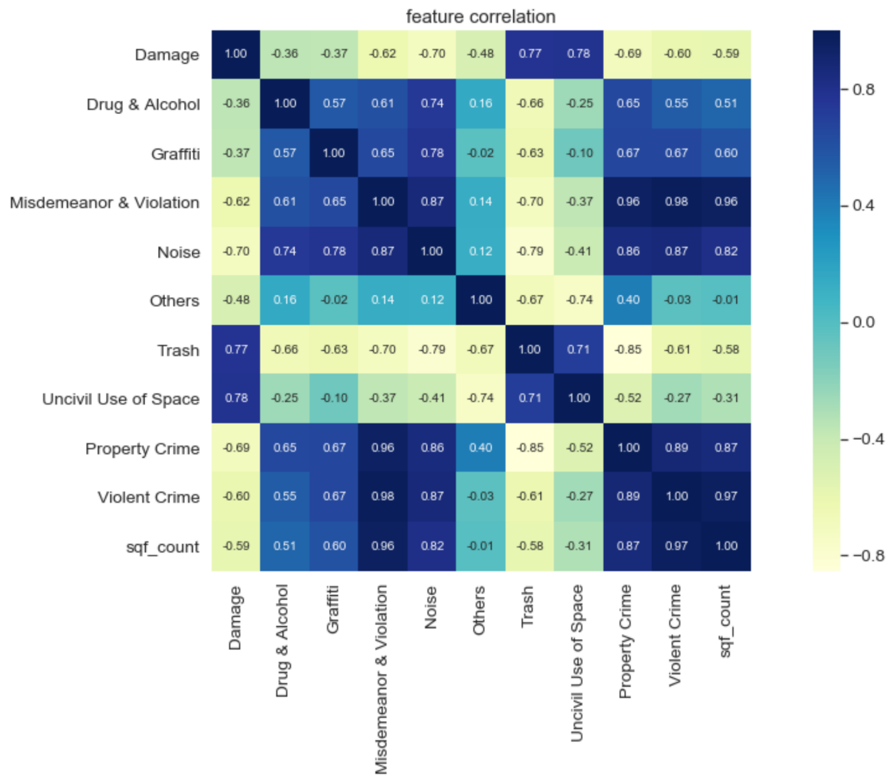

Fig.23 the correlation between police record count and disorder/crime types

Fig.23 shows the correlation between police record count and disorder/crime types, the figure shows that police record count is highly related to different disorder types and crime categories.

We can see that major crimes and misdemeanors have a strong positive correlation with police activities, while disorderly behaviors such as damage and trash have a negative correlation with police activities, which proves that hypothesis 2 is wrong to some extent. This may be because the more police activities, the easier criminal acts are to be found, so there will be more crime data.

Demographic analysis

As above-mentioned, disorder and crime phenomena usually are highly impacted by demographic datasets. Age, income, house price, and education can affect the rate of disorder and crime in a given area. Therefore, in this section, we will analyze the correlation between the demographic dataset and disorder and crime data. Similar to the above analysis method, the heatmap is utilized to show the relationship between different factors.

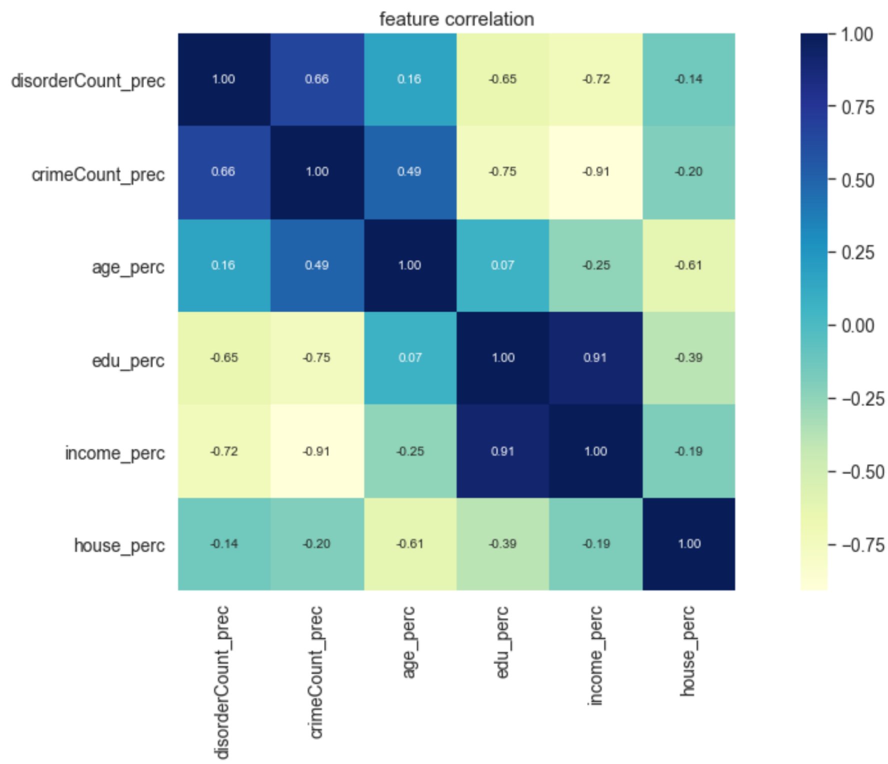

Fig. 24 The correlation between demographic factors and disorder and crime data

Fig.24 shows the correlation between different demographic factors and disorder and crime count, considering the demographic information has been transformed into percentile types, therefore, the disorder count and crime count will also be transformed into percentile types, which will help to compare the correlation between different factors in the same unit.

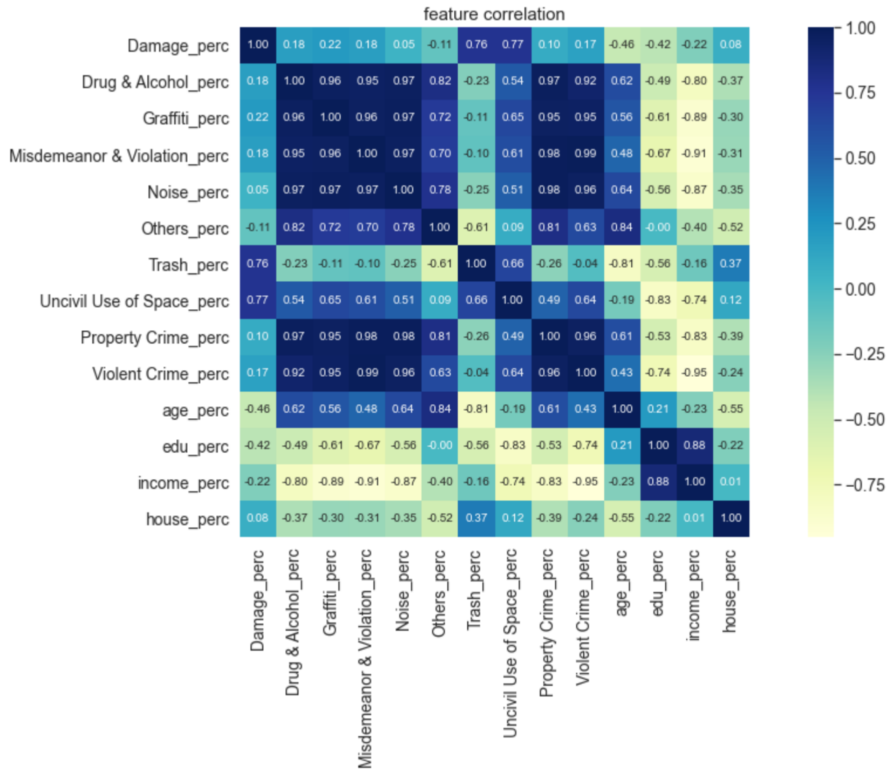

Fig.25 the correlation between demographic factors and disorder/crime types

In addition, for more specific analysis, we compute the correlation between demographic factors and different disorder types, and different crime categories. The correlation result is shown in Fig.25.

From Fig.25, demographic census is relative to disorder and crime data to a certain extent. It is obvious that education and income are the most influential factors to disorder and crime count. The higher the education level and the higher the income, the lower the disorder and crime in the region.

Conclusion

Based on the disorder, crime, police activity and demographic data, we computed the correlation between all factors and found that some kind of crime number showed a positive correlation relationship with some types of disorder. This seems to indicate that the more disorder behaviors, the more crime could occured in the region. However, from the geospatial point of view, we found that the correlation relationship between different disorder-crime pairs in different regions presents a diverse pattern. Nevertheless, major crimes and misdemeanors have a strong positive correlation with police activities, while disorderly behaviors such as damage and trash have a negative correlation with police activities, which cannot prove that the more police activity, the less crime and disorder. The demographic data also showed a strong relationship between disorder and crime. We could see that education level and income are the most influential factors to disorder and crime count. The higher the education level and the higher the income, the lower the disorder and crime in the region. To sum up, there is definitely a relationship between disorder behavior and crime number, but we still cannot say that the broken window theory and broken window law enforcement are true and effective.

Limitation

In addition, our research has some limitations, which may affect the accuracy of the results.

Firstly, our research involves many types of data sets, and some of them do not have the latest data. We can only select all the data from 2015 to 2019, which may lead to some lag in the timeliness of the data. Besides, part of the data types or some months of the dataset might be missed. Even though we can find similar data as a sub to fulfill the missing part, there would be some differences between datasets and we must manage different datasets with different methods. In addition, due to different data sources, it is difficult to establish unified standards for data analysis.

What's more, the NYPD does not disclose the details of quality-of-life summonses and misdemeanor arrests data at present, so we can only use 311 data to represent disordered data for research. Although we try our best to split these complaints into different types of the disorder according to previous research and literature, the reliability of these data is still worthy of further consideration.

This study mainly uses the Python toolkit to analyze the correlations between disorder behavior and crime, even if there is a correlation, we still can not conclude that more disorder behavior causes more crime because the Broken Windows theory concludes a causal relationship between the two. Besides, there is no evidence to show that police activity counts and crime numbers are two independent datasets. Therefore we can not justify the reliability of the section about the correlation between police activity counts and crimes. The crime dataset represents only the reported crimes. Even if its number increases or decreases, it can only represent the increase or decrease of the reported crimes, which does not mean that the total number of crimes has really changed.

Policy suggestion

In order to further study the effectiveness of broken windows enforcement in the future, we put forward following policy suggestion:

- NYPD should make the specific data of quality-of-life summonses and misdemeanor arrests public, including time, place, type and other information.

Only in this way can we test the effectiveness of broken windows enforcement in a more accurate and scientific way.

Further Research

For future research, similar to census data, some kinds of social data, like poverty level, job availability, and employment status should be included in the consideration of the relationship with a crime rate as well. With a view to worldwide cities, the degree of urbanization, even with respect to the population with transportation, such as commuting pattern, population stability and mobility, and planning of city roads could be potential influential factors of crime and play an important role in considering public safety. Besides, we can consider using more powerful tools for in-depth analysis in subsequent research.

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Appendix:

Table1. Data source

Data	Source	Time	Temporal	Spatial
Police Activity	**Stop, Question and Frisk Data** Link: https://www1.nyc.gov/site/nypd/stats/reports-analysis/stopfrisk.page	2003-2020	Accurate to minutes, Daily	Coordinate, Address, Street, Borough, Police Precincts
Crimes	**NYPD Complaint Data** Includes all valid felony, misdemeanor, and violation crimes reported to the New York City Police Department (NYPD) Link: https://data.cityofnewyork.us/Public-Safety/NYPD-Complaint-Data-Historic/qgea-i56i	2006-2020.7	Accurate to minutes, Daily	Coordinate, Borough, Park-name, Patrol Borough, Police Precincts
	NYPD Arrest Data Includes all valid felony, misdemeanor, and violation crimes reported to the New York City Police Department (NYPD) Link: https://data.cityofnewyork.us/Public-Safety/NYPD-Arrests-Data-Historic-/8h9b-rp9u	2006-2020	Accurate to minutes, Daily	Coordinate, Borough, Park-name, Patrol Borough, Police Precincts
Disorder	**311 Service Requests** Link: https://data.cityofnewyork.us/Social-Services/311-Service-Requests-from-2010-to-Present/erm2-nwe9	2010-2021	Accurate to seconds, Daily	Coordinate, Address, Street Community, Borough, Zip-code, BBL

Data Sources

Table 2. Disorder data

Types of disorder	Dataset	
Uncivil Use of Space	311 Service Requests	'Illegal Parking', 'Blocked Driveway', 'Mass Gathering Complaint'
Drug & Achol		'Drug Activity', 'Hazardous Materials',' 'Smoking'
Trash		'Abandoned Vehicle', 'Street Sign - Damaged'
Noise		'Noise - Residential', 'Noise - Street/Sidewalk', 'Noise - Vehicle', 'Noise - Commercial', 'Noise - Park', 'Noise - Helicopter'
Damage		'Street Sign - Damaged', 'Animal-Abuse', 'Maintenance or Facility', ''Sidewalk Condition', 'Root/Sewer/Sidewalk Condition', 'Street Condition', 'Curb Condition'
Others		'Homeless Person Assistance', 'Bus Stop Shelter Placement', 'Non-Emergency Police Matter'
Graffiti		'Graffiti'
Misdemeanor & Violation	NYPD Complaint Data	'Misdemeanor', 'Violation'

Table 3. Crime data

Types of crime	
Major Crime	murder, rape, robbery, assault, burglary, grand larceny, grand larceny auto, dangerous drugs
Violent Crime	murder, rape, robbery, and assault.
Property Crime	burglary, grand larceny, and grand larceny auto.

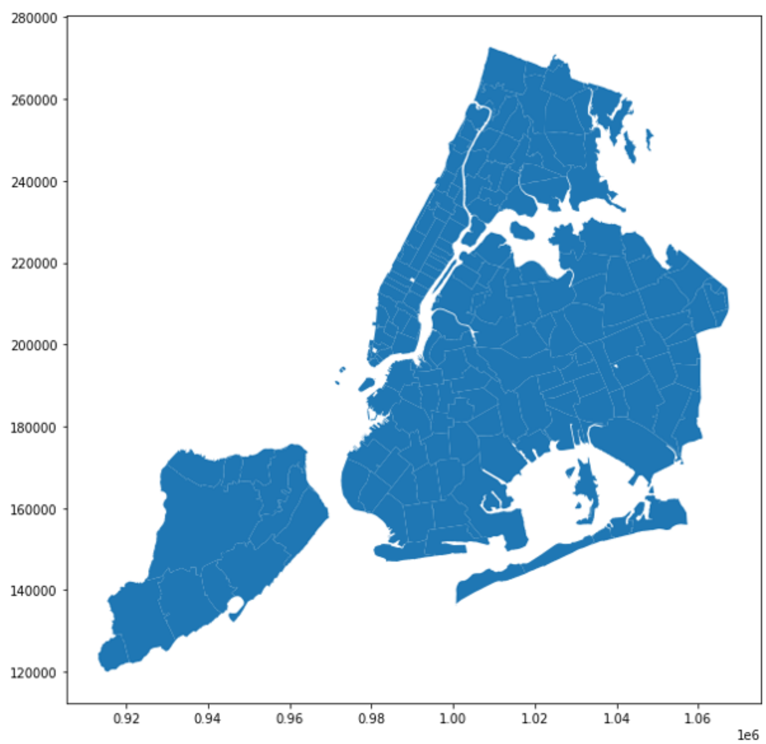

Fig.1 The spatial shapefile dataset of New York

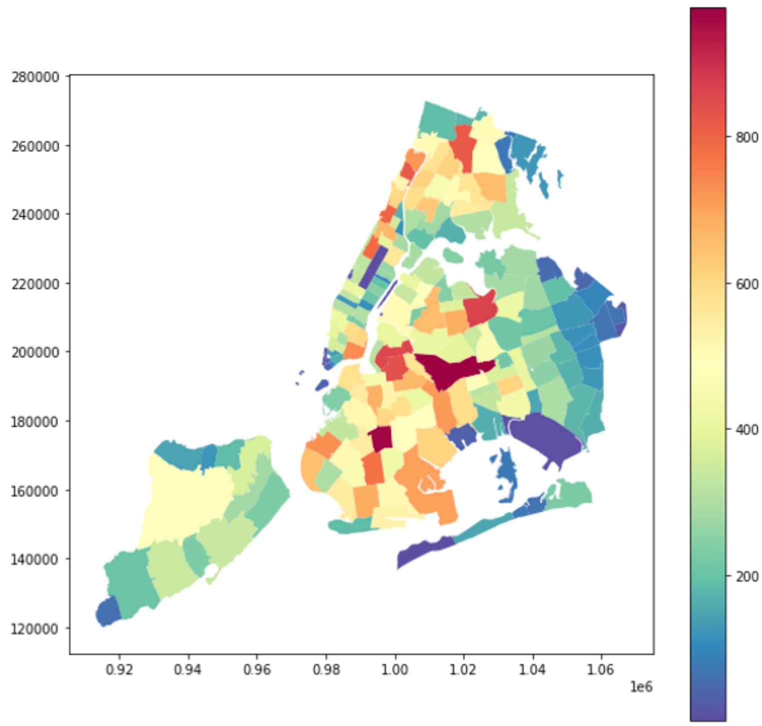

Fig.2 The geo-spatial distribution of disorder count in New York (counts)

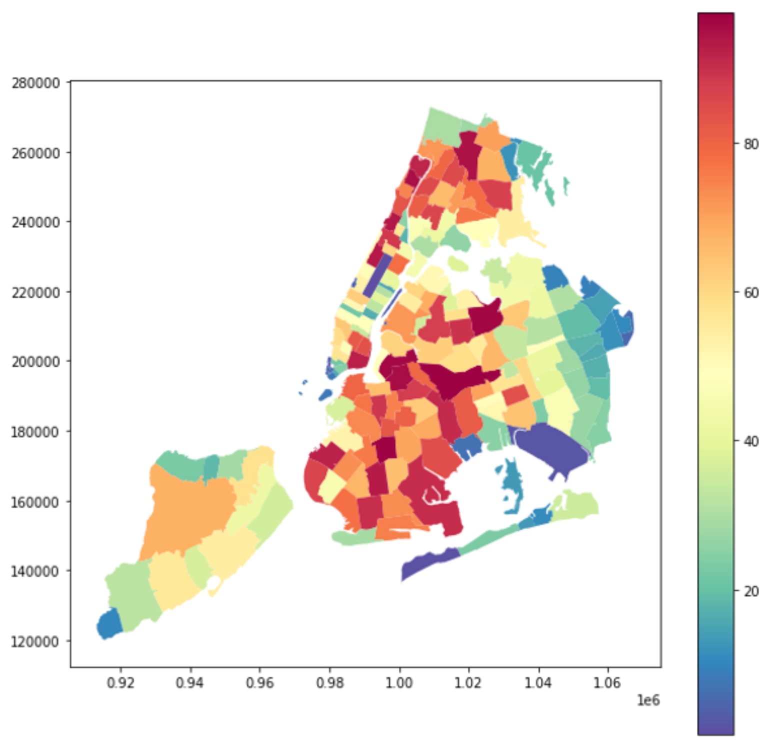

Fig.3 The geo-spatial distribution of disorder count in New York (percentile)

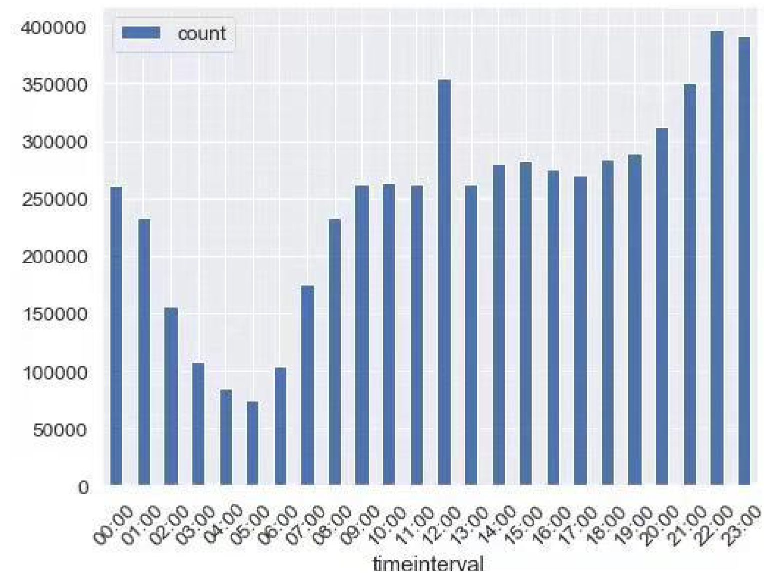

Fig.4 The distribution of disorder count with the hour change

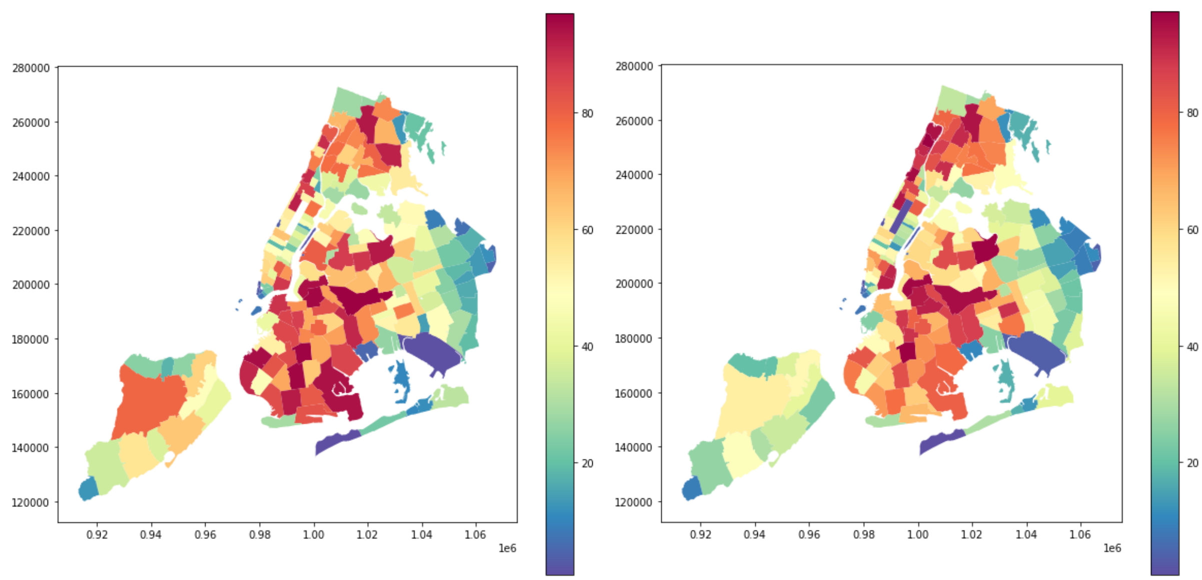

Fig.5 The distribution of percentile of disorder count on weekend(left) and weekday(right)

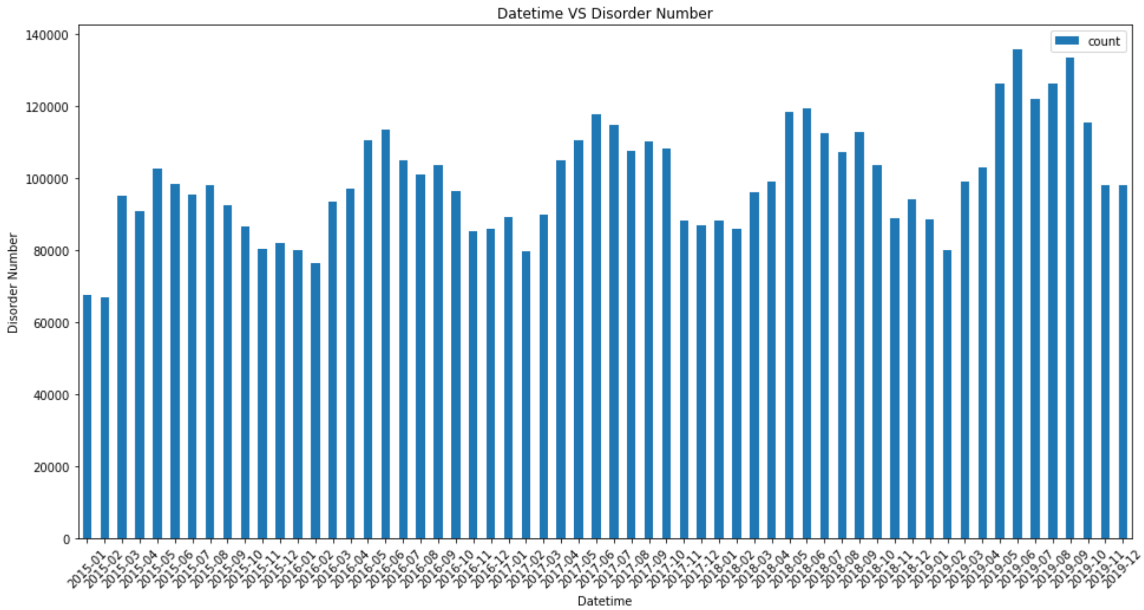

Fig.7 The temporal distribution of disorder counts in long-term.

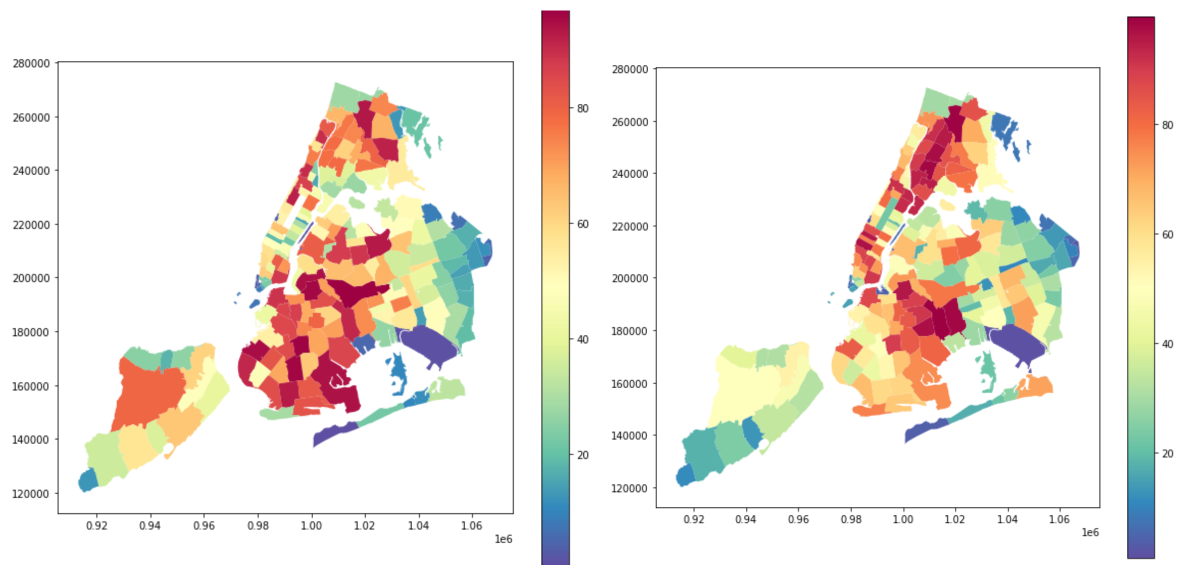

Fig.8 the distribution of crime count (left) and the percentile (right) of crime count in New York.

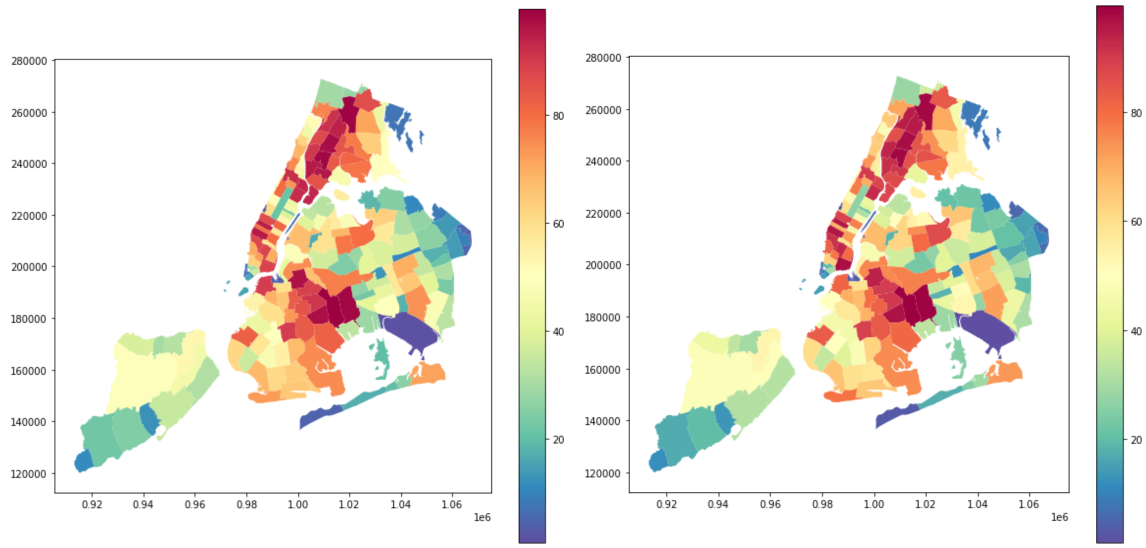

Fig.10 the distribution of percentile of crime count on weekends (left) and weekdays(right).

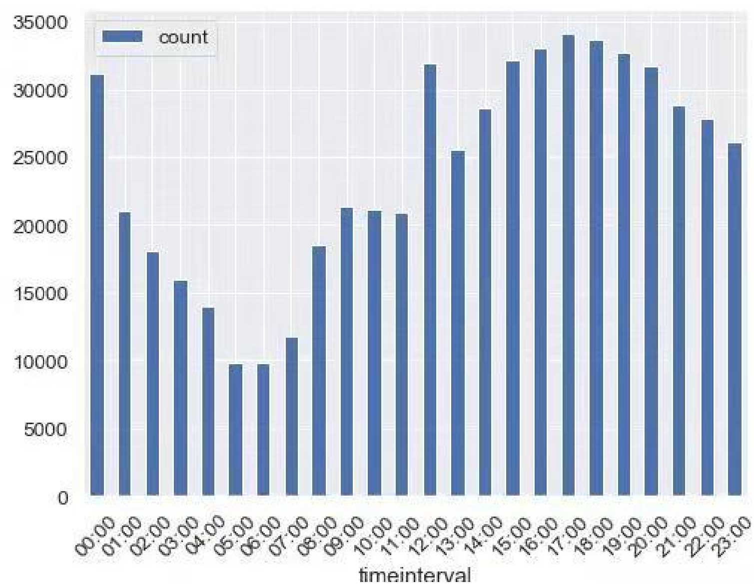

Fig.9 The distribution of crime count with the hour change

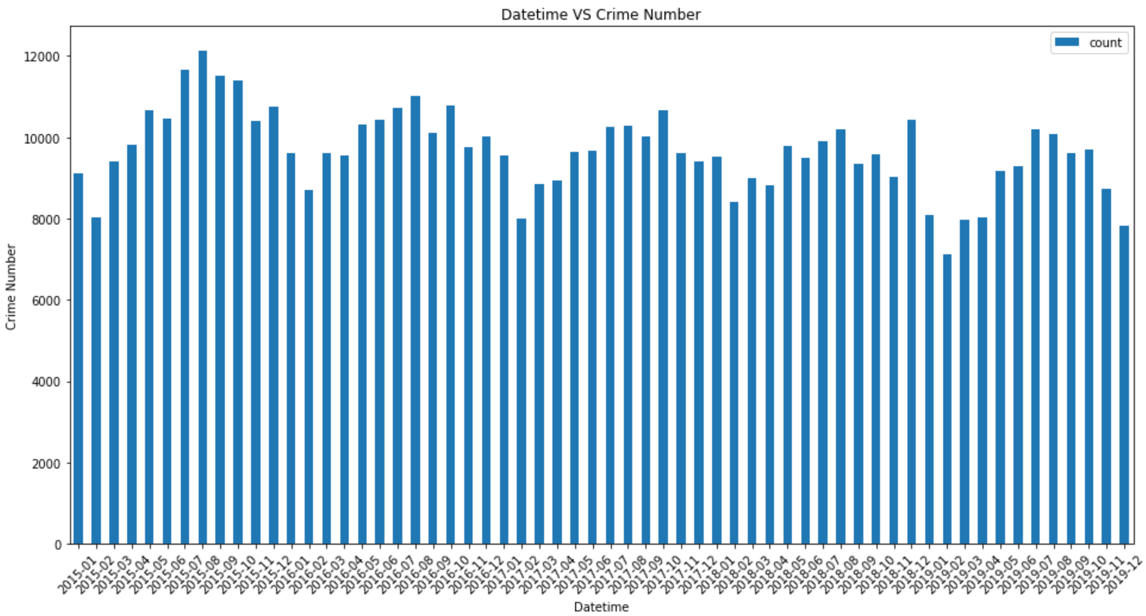

Fig.12 the long-term distribution of crime count

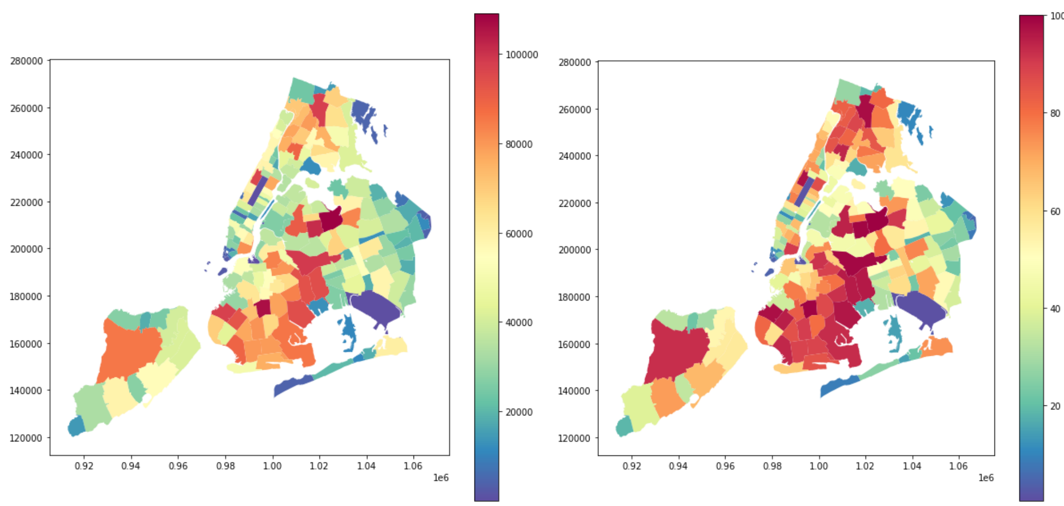

Fig. 13 The distribution of population and percentile population in New York

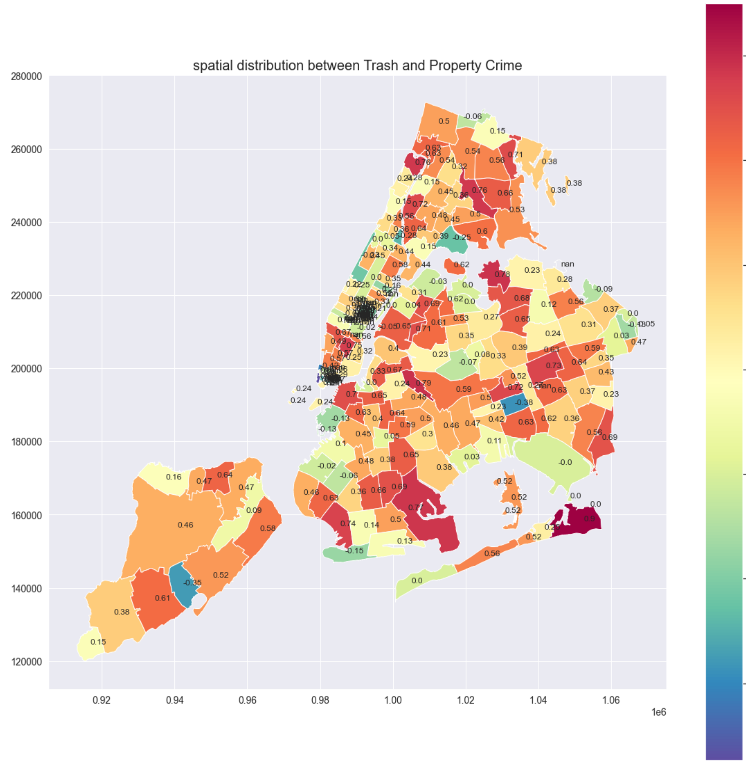

Fig. 17 The spatial distribution of correlation between Trash and Property Crime

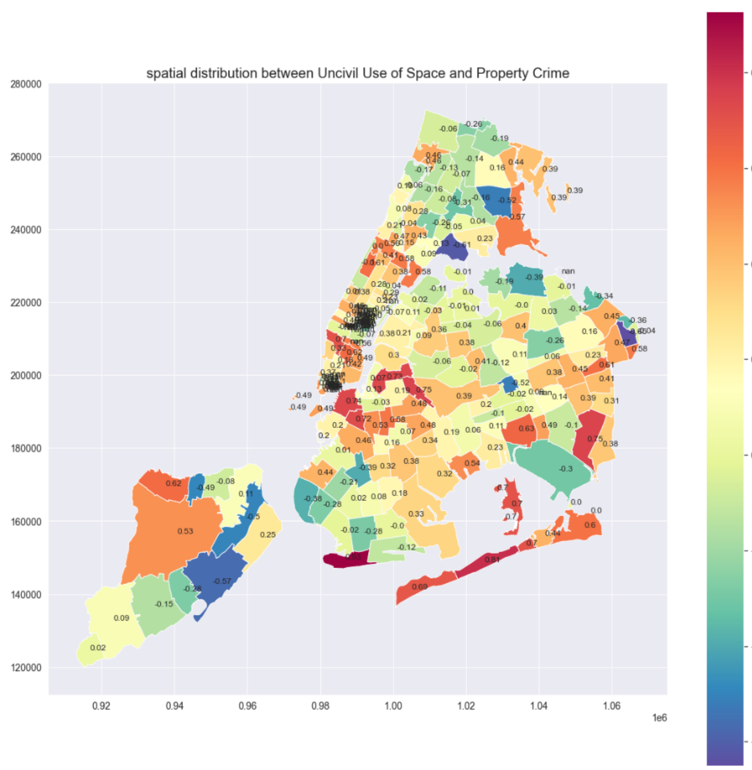

Fig. 18 The spatial distribution of correlation between Uncivil Use of Space and Property Crime

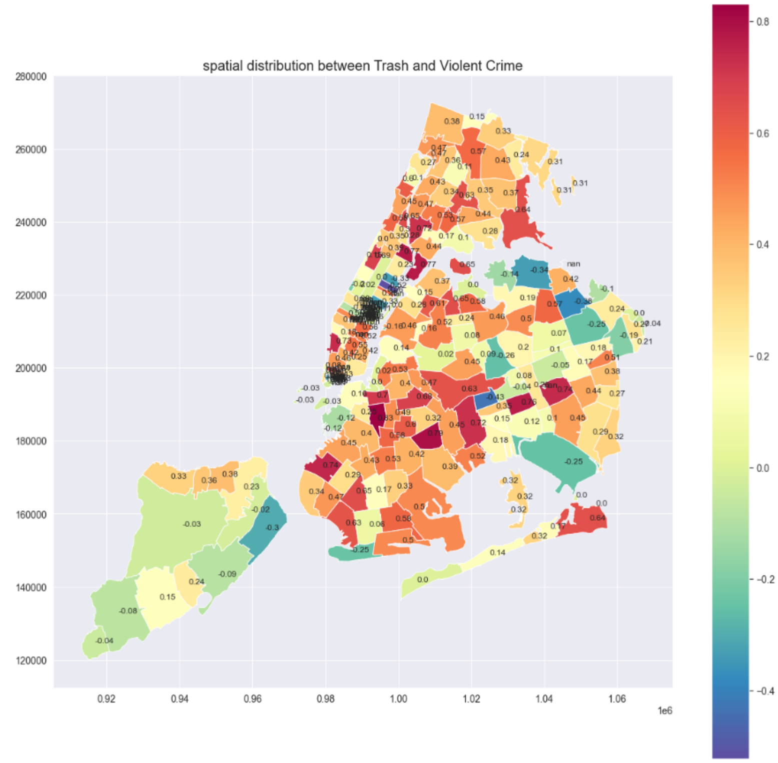

Fig. 19 The spatial distribution of correlation between Trash and Violent Crime

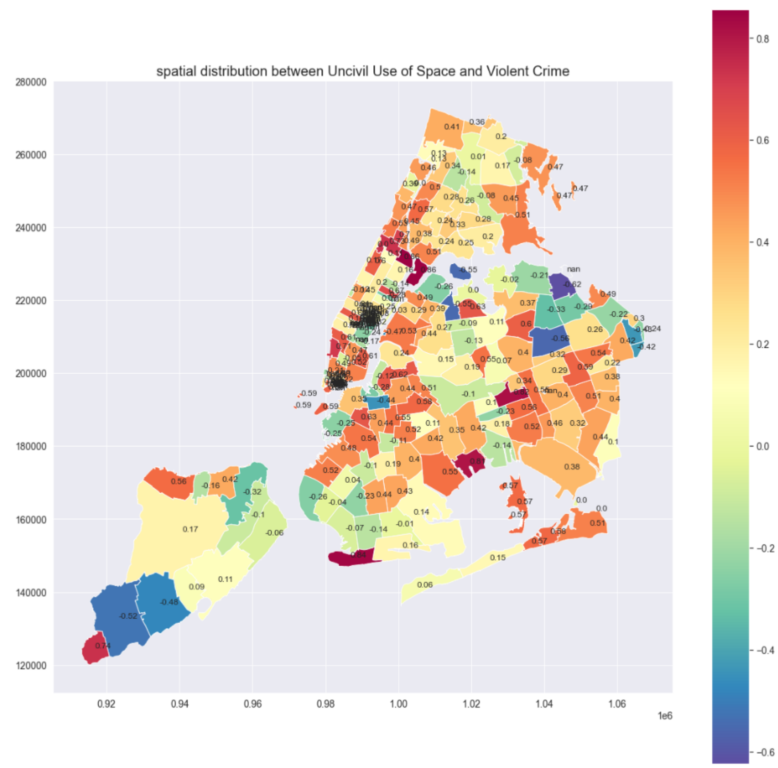

Fig. 20 The spatial distribution of correlation between Uncivil Use of Space and Violent Crime

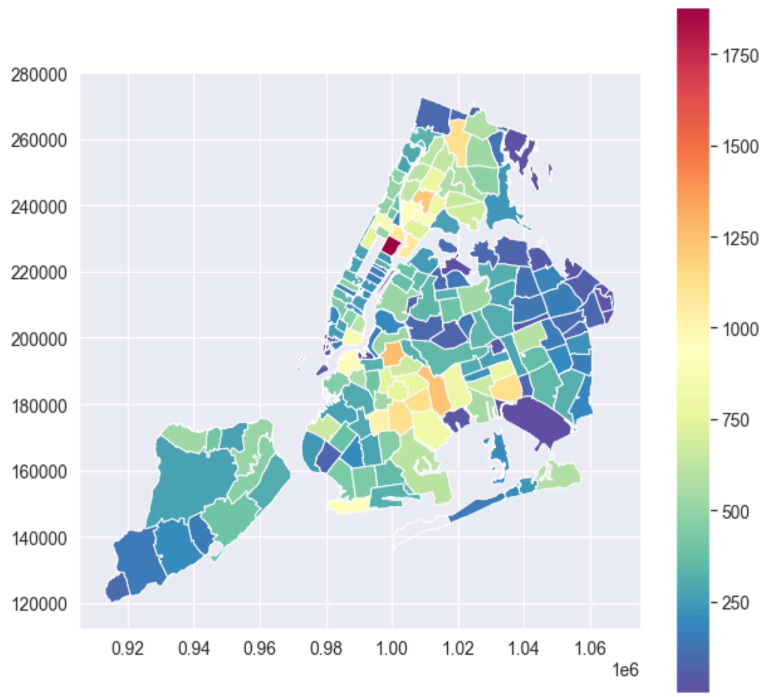

Fig.22 the distribution of police record (stop, question, frisk) number in New York City