# London Crime Patterns During Coronavirus Lockdowns

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**Abstract**—While Covid-19 lockdown measures imposed wide range of economic and social effects on society, crimes have shown unprecendented patterns in urban cities. Understanding how crime patterns evolved during stay-at-home measures might provide crucial insights into anticipating future crime trends. Even though lockdown measures led to sudden change in daily lives and better handling of pandemic, it is still unclear how they effected crime trends. This study provides exploratory spatial and temporal analysis of Lodon crimes before and after the nationwide lockdowns, which combines several visualization tools and cluster analysis. The study was carried out on dataset obtained from Metropolitan Police Service and City of London Police, in conjuction with Google mobility data and Covid-19 restriction timelines. This study attempts to find crime patterns in Greater London Region during stay-at-home measures, through space and time. Additionally, partition-based and hierarchical clustering methods were evaluated on their ability to facilitate the interpretation of crime patterns previously discovered through visual analytics.

## 1 Problem Statement

Last year was a year unlike any other. Like the rest of the world, England was in the grips of the pandemic and faced unprecedented restrictions resulting in three different nationwide lockdowns. Consequently, there were fewer businesses open and less people on the streets to steal from, the restrictions of social mixing presented less opportunities for potential sex offenders, while also reducing the number of violent crimes and other criminalities generally occurring at crowded places. Recent studies have also shown that the stay-at-home policies were associated with a considerable drop in urban crime, but with substantial variations across cities and types of crime [1].

However, understanding how the crime trends were affected by restriction measures is challenging. It is an uncharted territory and drawing definitive conclusions from the latest crime data might prove to be difficult at first sight.

The unique nature of Metropolitan Police Service and City of London Police dataset used in this study, allows the patterns to be explored at temporal granularity and at multiple spatial resolutions. We will conduct temporal analyses to assess the impact of Covid-19 restrictions on 14 types of police-recorded crimes in City of London and Greater London Area.

Research questions developed to investigate in this study are:

1. How do individual crime-types changes along timeline (periodicity, time cycles)?
2. How can the variations in crime with the respect to time be explained?
3. How do the spatial patterns of crime types displace before, during and after national lockdowns?

## 2 State of the Art

Clustering is common method in identifying crime patterns, where crimes are partitioned into different groups based on similarities in distance. K-Mean is common in traditional clustering algorithms used in literature [2][3][4]. Hazarika et al [3] performed k-means clustering on subset of crime dataset in Delhi to investigate missing children and their possible links to kidnapping. The authors plotted the Geo-location of each locality and used this data for Geo-spatial clustering in k-means using different distance metrics. The performance of each of the distance matrix is later compared and the results are used to evaluate the best metric for location-based clustering. Alkhaibari and Chung [4] present a similar study on NYC Graffiti crime dataset. Authors compare different clustering algorithms (K-Means, Agglomerative clustering), based on the visual evaluation of average silhouette scores and optimal number of clusters.

The data in our research represents the unique opportunity to identify patterns of different crime times at different temporal and spatial resolutions. We will be using similar techniques mentioned in above papers for our partition and hierarchical cluster analysis. However, for our temporal analysis we are facing a common problem of data not providing enough fine temporal granularity. In situations where an event occurs at a known location but at an unknown time, Aoristic analysis can provide a temporal weight and give an indication of the probability that the event occurred within a defined period [5]. Examples from previous work in this area have come from the field of crime analysis [6], where the authors have developed their own conceptual framework for analysing temporal dimensions of number of crime categories with unknown time of occurrences.

Another widely used method for representing spatial distributions of crimes is Grid Thematic Mapping [7]. Grid Thematic Mapping of hotspots is used as a basic form of crime prediction, relying on retrospective data to identify the areas of high concentrations of crime and where policing and other crime reduction resources should be deployed [8].

This research delivers partition based (K-Mean) clustering for temporal and hierarchical (agglomerative) clustering for spatial pattern identifications of London crimes. Although this study does not consider other attributes (i.e., census data, borough profiles), additional datasets were evaluated in conjunction with the crime data in order to explain both spatial and temporal patterns observed.

This study will adapt similar analytical frameworks and clustering techniques mentioned in above research papers, to better understand spatial and temporal variations of crime in London before Covid-19 pandemic, and during lockdown measures. Additionally, Grid Thematic Mapping Technique is employed to determine crime hot spots in finer geo-location resolution and find spatial relationship of Covid-19 pandemic with crime patterns. Aoristic analysis is utilized to better observe periodicity. Generally, however, visual approaches and human reasoning will be adapted to identify different crime patterns.

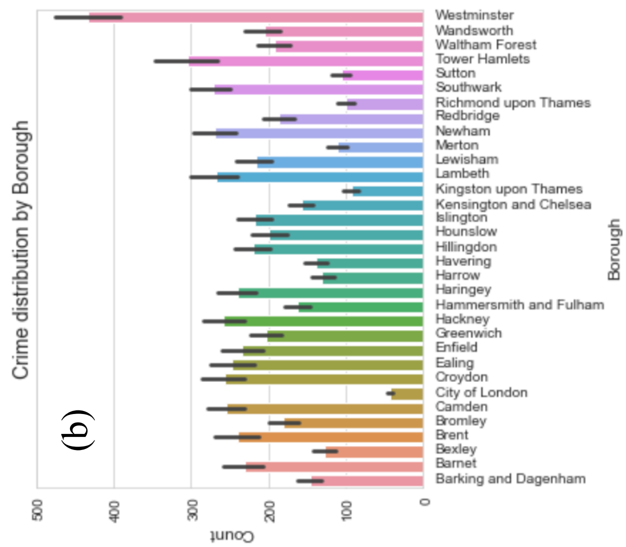
## 3 Properties of the Data

Dataset acquired from UK police database [9] include crime numbers from two police forces (London City Police, Metropolitan Police Service). After the removal of missing values in X and Y coordinates and keeping only 33 London boroughs, there were a total of 3,259,045 crime entries recorded by police between January 2019 and November 2021. Brief time granularity is provided in years and months for crime occurrences, which provides enough room for periodicity analysis, crime timespan and trend over pre and during Covid-19.

Longitude (-0.5076220 ~ 0.3071510), latitude (51.29442-51.68717) coordinates of exact crime locations are given. Data is classified into 33 Boroughs and 4831 Lower Layer Super Output Areas (LSOA). The data is also classified by 14 crime types: ‘Anti-social behaviour', 'Burglary', 'Criminal damage and arson’, 'Other theft', 'Public order', 'Vehicle crime', 'Violence and sexual offences', 'Other crime', 'Robbery', 'Drugs', 'Possession of weapons', 'Shoplifting', 'Bicycle theft', 'Theft from the person'. No numeric attributes are given; therefore the study uses multiple data transformation and aggregation techniques to acquire meaningful information.

Mobility trends during Covid-19 pandemic were evaluated in conjunction with police crime data to explain the temporal variations in crime patterns. Mobility data were acquired from Google Mobility Report [10] which estimates changes in how many people are staying at home and going to places of work compared to pre-pandemic baseline. The mobility data is categorised in terms of 33 London boroughs and changes in movement in 'Retail and Recreation', 'Grocery and Pharmacy', 'Parks', 'Transit Stations', 'Workplaces', 'Residential'. The values for movement categories were interpolated to replace any missing values, as well as seven day rolling average was applied to avoid data distortion produced by weekends and bank holidays. Finally, the data was resampled in months to compare with crime data which is also given in months.

Additional data being evaluated by the study are, Covid-19 Restrictions Timeseries [11], and Stop-and-Search police data [9], to further explain the variations in crime patterns.



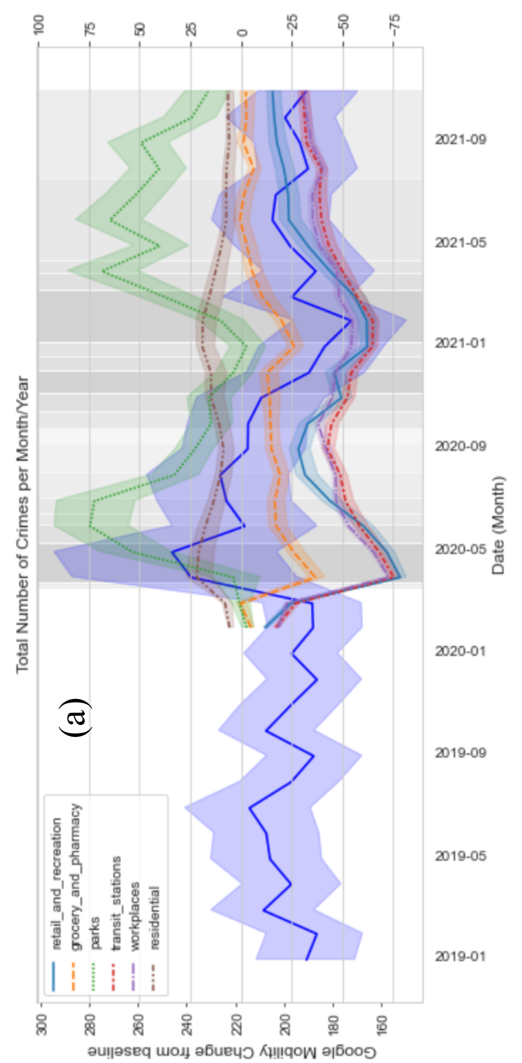




Figure 1. (a) Total number of crimes and Google mobility trends expressed in month/year overlain on top of Covid-19 Restriction timeseries data; (b) Crime distribution by 33 London

## 4 ANALYSIS

### 4.1 Approach

This study adapts visual analytics approach using human reasoning on recognizing spatial and temporal crime patterns in Greater London Region between January 2019 and November 2020.

The first step in the study was to simplify the crime dataset to facilitate abstraction of relevant information from the complex data items by use of visual computation techniques such as spatialization and aggregation. Crime patterns is recognized based on aggregation of crime numbers at different timelines and boroughs, as well as crime categories. Aggregation method is decided based on variance over time. Data attributes not sensitive to crime trends were excluded as a result of visual mapping.

Mobility data were interpolated to compensate for missing values, and seven day rolling average and resampling was applied to remove further noise. The data was later partitioned and visualized with respect to individual boroughs and mobility activity categories to identify relationship between citizens' movement and crime types.

Visual analytics tools such as Aoristic analysis and Grid Thematic mapping were utilized to smooth any irregularities in our data and provide an alternative conceptualisation of space and time that is both comprehensible and meaningful.

Human validation was engaged in identifying computational method parameters during partition based and hierarchical clustering. Visualization tools were used to assess the internal variation withing clusters and understand how clusters differ from each other. Both temporal and spatial analysis employ human reasoning for parameter tuning, through appropriate visualizations.

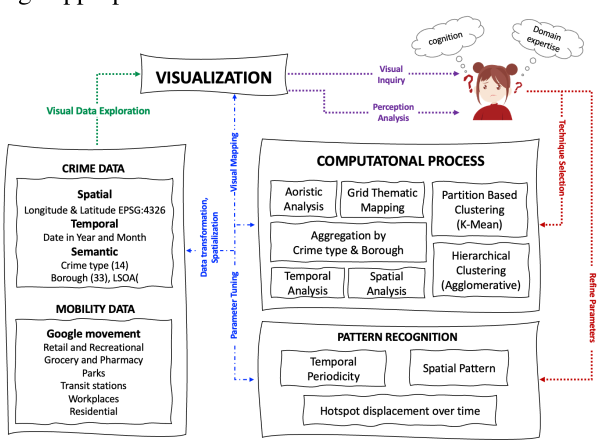



Diagram 1. Workflow diagram for the study.

#### 4.1.1. *Temporal Analysis*

This study identifies temporal patterns before, during and after the Covid-19 lockdown measures in Greater London region. Different visual analytics approaches were employed in identifying temporal patterns with respect to spatial and semantic properties of the data:

1. Use different plots to observe overall trend by use of colour palette and temporal resolutions throughout the analysis.
2. Adjust appropriate aggregation methods to see if significant variances are present with respect to Covid-19 restriction timelines.
3. Explain temporal patterns in data attributes by analysing additional data (google mobility) in conjunction with crime data.
4. Employ temporal query by use of Aoristic analysis to compensate for temporal imprecisions in our data and smooth irregularities in temporal variables relating to spatial objects.
5. Utilize partition-based clustering (K-Means) to visualize periodicity and the cyclic behaviour of time in our data and find correlation between Covid-19 nationwide lockdowns and crime.

#### 4.1.2. *Spatial Analysis*

The study will attempt to find hotspots for different crime types, to identify spatial displacements of hotspots over pre-pandemic and during Covid restriction timelines. Different visualization methods are to be compared to identify best mapping technique by latitude and longitude in order to investigate detailed locations of crime.

1. Grid Thematic Mapping to identify high level geographical density of individual crime types (pre-, during-, post-Covid measures)
2. Agglomerative Clustering based on bottom-up hierarchy approach to find patterns in space and time and the frequencies of combinations of attribute values. Partitioning by crime-type category will be performed and visualized to understand spatial variance between categories.

### 4.2 Process

#### 4.2.1. *Temporal Analysis*

At first look (figure 1), one might deduce that London crime has increased with the introduction of Covid-19 lockdown measures (apart from City of London), which negatively correlates with the residential movement, which makes no sense. However, at closer inspection (figure 2) we can see that individual crime types behave differently at different restriction time intervals (dark grey – lockdowns, lighter grey – easing of lockdown measures). Changes in citizen's movements and activities has made a huge impact on the volume and types of crime being committed. Especially residential and workplace (work-from-home) closely align with most of the crime patterns. We can see that certain crime types has indeed been at their lowest during stay-at-home measures, proving our initial hypothesis to be true. Crimes such as burglary, shoplifting, robbery, and theft all experienced remarkably sudden declines during April (1st lockdown), January (3rd lockdown) in comparison to previous year. The comparison of crime with mobility data also shows that more stringent restrictions over movement in public space were predictive of larger declines in crime.

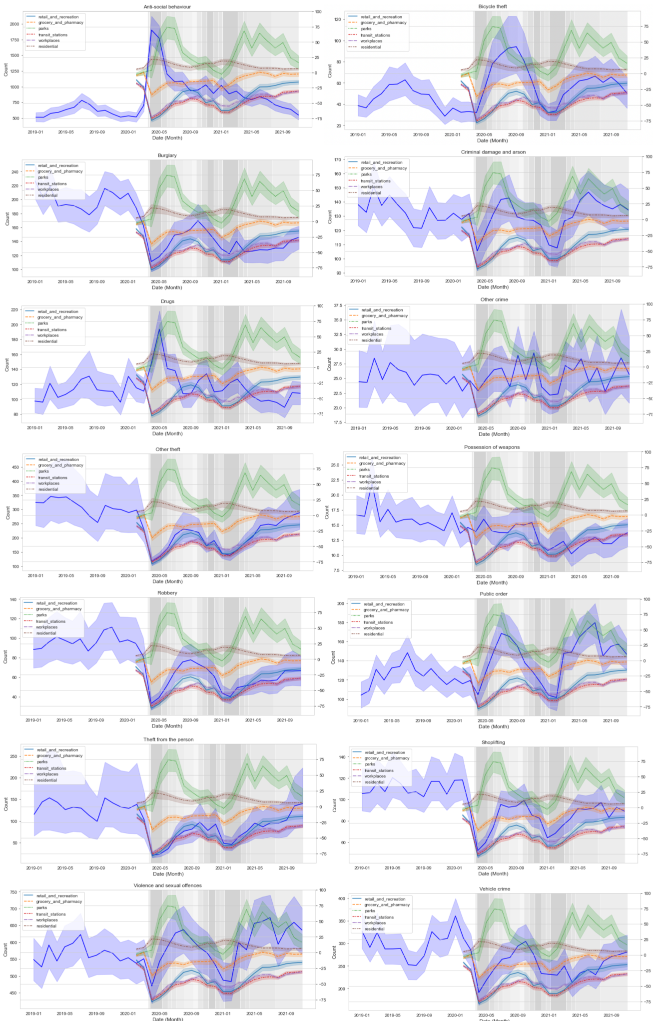



Figure 2. Timeseries plots of London crime data per individual crime type, w.r.t. Google mobility data and Covid-19 restriction timelines.

However, police recoded anti-social behaviour and drug offenses on month-to-month bases shows one of the starkest trends. Between March and May, the number of anti-social crime cases has skyrocketed by almost 300%. An increase at this time of year is expected, but a rise of this magnitude is unprecedented. It could be explained by the genuine shift of traditional antisocial behaviours during lockdowns (i.e., nuisance noise from neighbours might have gone up due to more people staying indoors, contributing to the number of anti-social crimes recorded). However, when looking at stop and search police data (figure 3), we can see that stops and searches by police officers in London has gone up by 40% during first lockdown. It looks like the drop in crime at the height of the pandemic provided more opportunities for officers to go on the frontlines and target drug and gang related crimes, which also resulted in catching people that were breaching lockdown guidelines, contributing towards anti-social crime numbers. Hence, stop and search police data can fully explain the increase in these two crime types.

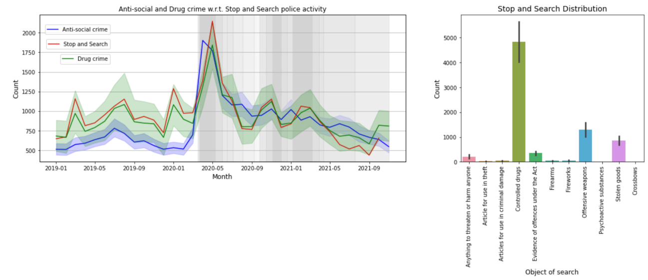



Figure 3. Evaluation of patterns in drug and antisocial behaviour related crimes w.r.t. stop and search police data.

#### *4.2.2. Aoristic Analysis*

Since the police recorded crime data is recorded as end-of-month total offence counts, Aoristic analysis can provide an alternative conceptualization of time that is more comprehensible in terms of the crime behaviour over time span. As seen in figure 4, robbery, other theft, burglary, theft from the person, shoplifting, and vehicle crime, all follow a similar trend between March 2020 and March 2021, After March 2021 lockdown measures have eased and lives have more or less returned to normal, and the crimes started to exhibit similar periodicity seen in 2019. From figure 5 we can also see that, Covid-19 restrictions had no discernible impact on criminal damage and arson, violence and sexual offenses, public order, possession of weapons or the other miscellaneous crimes.

An additional insight can be visible in bicycle theft which generally tend to increase during springtime. However, between May 2020 and December 2020, the bicycle theft has gone up substantially, which could be attributed to people not using their bikes to commute and leaving them unattended for longer periods of time.

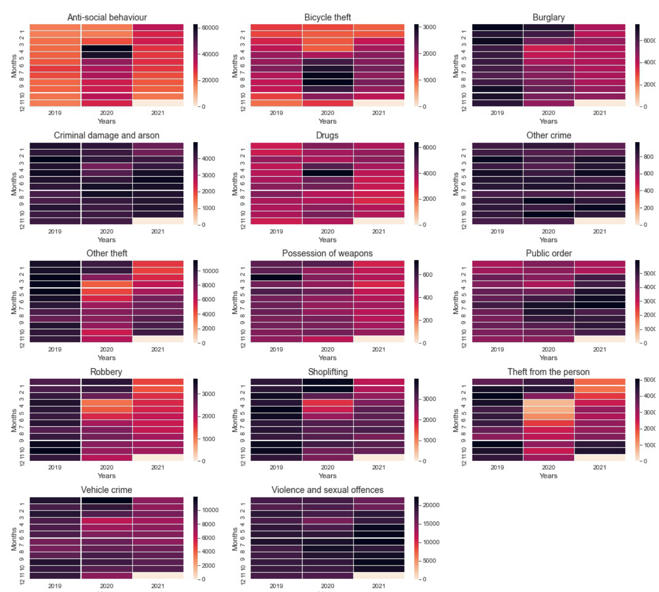



Figure 4. Aoristic Analysis on temporal pattern of crime types in Greater London Region.

### 4.2.3. *Partition-based clustering*

Partition based clustering was carried on the crime time series to account for the cyclic organisation of the time in our data. The objective of the clustering was to divide the crime incidents into time clusters such that the items within the subsets are more similar than between the subsets.

K-Means algorithm was applied ($k$=4) to aggregated data consisting of monthly counts (35 months) of crimes per-borough-per-crime-type (14 crime types x 33 boroughs = 462 features). The spatialisation (projection) is applied to the cluster centroids in order to generate colours for each cluster. To visualise the temporal distribution of the cluster membership a 2D plot was constructed where one dimension corresponds to year cycle, and the other dimension the monthly sequence of the years. Each monthly interval is represented by a colour in the cluster this interval belongs to.

As seen in figure 6, up until March 2020, all the months are organized under one cluster (purple). May, April months of 2020, and January, February months of 2021 are clustered together coinciding with 1st and 3rd lockdowns (yellow). Since 2nd lockdown only span only a short period of time, it is not detected in our crime data, due to the nature of the granularity of our time series. Crimes between 1st and 3rd lockdown is also being grouped together (light blue) as an intermittent period of the pandemic. Starting February 2021 however, all crimes are grouped into final cluster representing different pattern.

We will be using the results from partition based clustering to find how felony crimes displaced over time in our grid thematic analysis. We will differentiate our crime patterns, as pre-covid (January 2019 – March 2020), during-covid (April 2020 – February 2021), post-covid (March 2021 – November 2021)

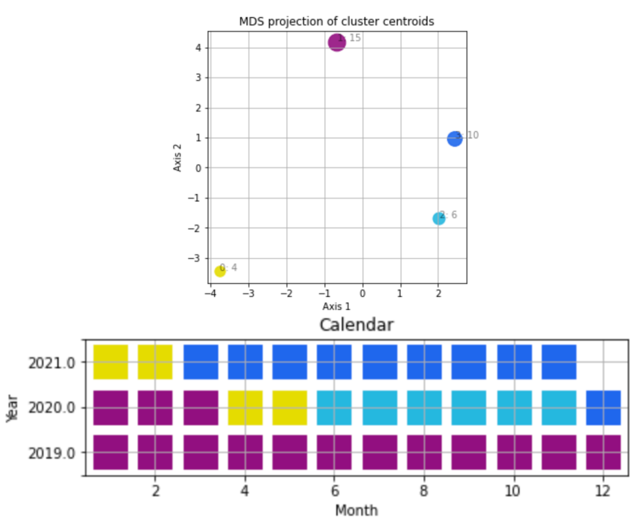



Figure 5. MDS projection of partition-based cluster centroids and the results of the cluster in 2D calendar plot.

### 4.2.4. *Grid Thematic Mapping*

To observe how crime activities associated with space have displaced over the time, grid mapping is performed (figure 7). During pre-covid times no spatial pattern is found apart from small concentration in City of Westminster. However, it is observed that during Covid-19 lockdown measures the crime hot spots moved away from London City and towards greater London area, mostly concentrated north of the river.


Figure 6. Grid Thematic mapping pre-, during-, and post-covid.

As the lockdown measures eased, starting from March 2021, the crime hotspots started to resemble the same trends as before lockdown.

Looking at the grid mapping by crime type, crime activities are mostly associated with anti-social behaviour, burglary, criminal damage and arson, public order, vehicle crime and violence and sexual offenses. Even though most crimes have indeed decreased during this period, the predictability of crime locations have become more varying vs. pre-pandemic. This is mostly attributed to the fact that most offenders are confined closer to their homes due to movement being restricted to only necessary travel and exercise.

### 4.2.5. *Agglomerative Clustering*

We are using Agglomerative (bottom-up) approach hierarchy to recursively unite similar items or groups during covid (April 2020 – February 2021) crimes. The reason agglomerative clustering was chosen in this study is to have capabilities to add connectivity constraint so that only adjacent clusters can be merged.

The purpose of our clustering is to identify how different clusters manifest themselves spatially, the original theory being that the borough next to another borough is likely to be related to each other in terms of the dominant crime types. However, we must impose spatial constraints on our clusters, thus making sure we get clusters that make sense both geographically and in terms of their data profiles. We want to see spill over between boroughs that are next to each other, hence use contiguity spatial matrix. Essentially this examines spatial units who share a common border and vertices. Since this study is concerned with neighbourhoods that crime may spill over, contiguity will be defined by Queens (Moore's neighbourhood) algorithm. We can visualise how this weights matrix looks on a map (figure 7).

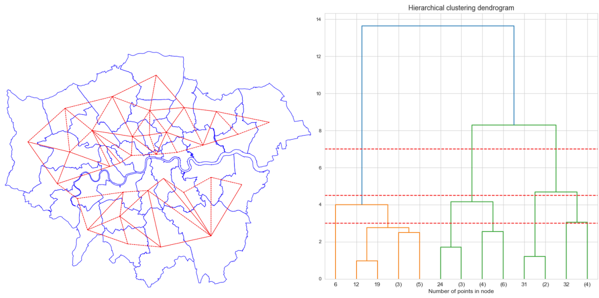



Figure 7. spatial weights matrix defined by Queen's contiguity showing connections that occur between boroughs of London (left). Hierarchical clustering dendrogram (right).

The next question is to what extent are the variables that we used to cluster are spatially autocorrelated. We can test how much crime percentages are geographically close by using Moran's I value, which measure the global degree of spatial autocorrelation. Essentially, this measures how much crime percentages are related across areas that are geographically close. From Moran's I values, we identified that bicycle theft, theft from person, vehicle crime, possession of weapons and robbery have significant degree of spatial autocorrelation.
Looking at the hierarchical clustering dendrogram we run our cluster algorithm iteratively, each with different parameters, and compared the results in order to find suitable range of settings and gain knowledge in the process. As a result, we identified 6 distinct geographical clusters as seen in figure 8.

As seen in the bar plots cluster 3 is only limited to City of London, where due to covid measures, the overall movement came to a hull, with offices practically vacant, business and hospitality closed, and streets empty. Neighboring boroughs around City of London is grouped as one. Cluster 0 is represented by the rest of the boroughs north of the river. South of the Thames, our model identified 3 clusters (SW London, South London, and SE London), all of which show decrease in crime numbers on all crime types compared to pre- and post-covid timelines identified earlier.

### 4.3 Results

This study reveals clear temporal and spatial patterns of crimes during Covid-19 pandemic. By analysing our police recoded crime data in conjunction with google mobility data, we were able to explain the increase in anti-social behaviour and drug related crimes as part of the side effects of 40% increase in stop and search by police. We were also able to show that Changes in citizen's movements and activities has made a huge impact on the volume and types of crime being committed. The study was also able to determine that more stringent restrictions over movement in public space were indeed predictive of larger declines in crimes. Aoristic analysis further showed that Covid-19 restrictions had discernible impact on criminal activity with clear periodicity.

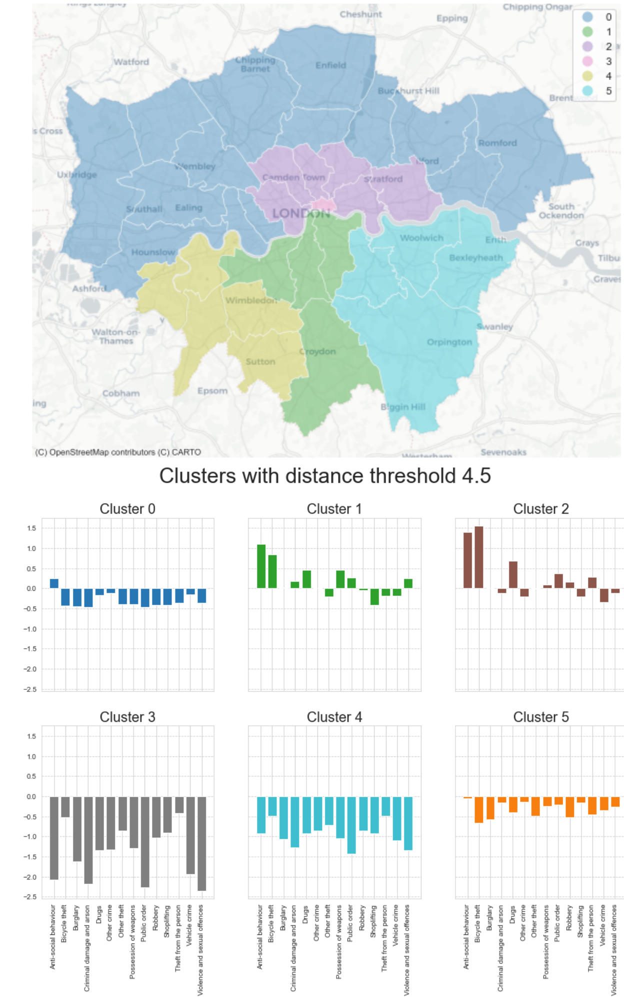



Figure 8. Agglomerative cluster results on a 2D map, and bar plot showing the distribution of crime types for each cluster.

Using partition-based clustering the study was able to account for the cyclic organisation of the time in our data which clearly aligned with Covid-19 timelines. Using the partitions as a guide, the study was also able to generate Grid Thematic Mapping, where we were able to show how crimes associated with space have displaced during Covid-19.

Last but not least the study generated spatial clusters using contiguity matrix to account for crime spill over between neighbouring boroughs. Moran's I value was evaluated which measured the global degree of spatial autocorrelation of each individual crime types. Resulting spatial clusters, manifested themselves spatially in clear boundaries.

## 5 Critical Reflection

This study offers a preliminary analysis on spatial-temporal pattern of felony crime in Greater London regions by examining all police recorded crimes in the past 3 years with visual analytic approach. We were able to prove our hypothesis that with most people constrained to their homes, shopping limited to essentials, and movements restricted to necessary travel and exercise, the opportunities available to offenders to commit most crimes were severely curtailed. However, considering other attributes (i.e., census data, borough profiles) may further provide additional insights into the temporal and spatial crime patterns during and post covid. The study was only carried out on crime data recorded between January 2019-November 2021. Future revisiting of this study, with additional data is recommended, to understand how the patterns change in post-pandemic environment.

One of the drawbacks of the dataset, was it being recorded on a monthly basis. Having a more granular time data, would provide additional resolution in our analysis. Possible proposal is to contact London police for censured data acquisition. Part of the analysis not presented in the report, is the density heat map analysis which produced no discernible spatial patterns, since it is best at identifying street-level hotspots. Grid Thematic Mapping proved to be useful to analyse hotspots with fixed grid size, yet reduction of cell size impacted the visualization patterns. Other mapping approaches such as kernel density per grid cell may improve hotspot mapping for future studies.

Additionally, due to the temporal and spatial nature of the data density-based clustering could be a good approach, however it requires high computational power for this large dataset. Separation of crime types can identify more accurate spatial-temporal patterns and reduce the current computational burden.

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## References

The list below provides examples of formatting references.


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