Human mobility in Auckland, New Zealand during COVID-19 lockdowns.

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Abstract

Every day an abundance of movement data is generated by individuals using GPS-enabled devices such as smartphones. Datasets containing detailed coordinates and timestamps of people's movement are widely available from commercial location analysis companies, providing an alternative to survey-based GPS data, call detail records (CDRs) and travel surveys commonly analysed in mobility studies. The availability of new datasets and data mining methodologies including machine learning techniques create opportunities for new insights. This research (in progress) analyses changes to mobility during the implementation of strict government COVID-19 lockdowns in Auckland, New Zealand during 2020. We process raw mobile phone location services data points purchased from UberMedia[1], transforming millions of locations datapoints into usable collective insights using density-based clustering algorithms, semantic enrichment, and mobility metrics. We investigate changes to the distance travelled and reasons for travel, questioning whether COVID-19 magnified mobility disparities and social inequalities between different neighbourhoods and deprivation groups.

1. Introduction

The emergence of COVID-19 has altered human mobility globally, providing ample opportunity to assess the impact of government restrictions and closure of services. In recent months, a variety of research has been published in epidemiology, computer sciences, environmental sciences and GIScience fields in which the rate of transmission of infection through populations is frequently investigated. Examples including Kraemer *et al.* (2020) who investigated the role of lockdowns on transmission in Wuhan, China. Another frequent topic is the economic and social implications of lockdowns, with Bonaccorsi *et al.* (2020) finding the implications are not equally distributed, with lower economic status groups experiencing increased disruption to movement.

Changes to local and global migration patterns are commonly explored, such as Jia *et al.* (2020) who aggregated mobile phone locations in Wuhan, creating rapid models of population flows during border closures. Huang *et al.* (2021) used social media for estimating daily degrees of mobility change using 580 million user-generated tweets. Studies such as these raise ethical considerations with regards to population representativeness, privacy, consent, and the ability to connect sensitive personal information with movement data. Insights gained from Google Community Mobility Reports[2] are common practice now, with these reports providing rapid insights into changing population movement to destinations including sites of recreation, employment, and education. However, these reports have limited application for understanding local neighbourhood-level movements and provide fewer insights into variations between population groups failing also to show movement between destinations. The use of mobile phone location services data is increasing to address these limitations. Gao *et al.* (2020) for

[1] For details on terms and conditions see UberMedia at https://um.co/

[2] Available at https://www.google.com/covid19/mobility/

example, analysed 45 million unique phone records in the USA. Gao's research identifies the challenges of comparing population groups and countries, as the restrictions and enforcement of lockdowns differ. Gao *et al.'s* (2020) conclusions highlighted the need to further research into changes to mobility at different geographic scales.

This research aims to determine the extent to which population mobility changed during the lockdowns in 2020 and to investigate the spatial/socio-demographic variations in these patterns. We propose the use of big data to analyse changes in movement within Auckland, New Zealand during COVID-19 lockdowns. New Zealand is a unique case study where community transmission of COVID-19 was successfully reduced and eliminated temporarily in 2020 due to lockdowns. In August 2021, New Zealand returned to Alert Level 4 with the emergence of community transmission of the Delta variant, illustrating the importance of continuing to research how COVID-19 is impacting mobility within this case study region. Prior to this resurgence cases predominantly emerged from international travellers in Managed Isolation /Quarantine (MIQ) facilities. Using a large mobile phone location services dataset purchased from UberMedia, we introduce our methodology in progress utilising density-based spatial clustering and semantic identification. We identify trips to points of interest, and changes occurring before and during COVID-19 lockdowns by employing a range of mobility metrices to assess collective compliance to government restrictions.

1.1 Case Study

Auckland is the most populated city in New Zealand, with 1.5 million residents. Auckland is a key transportation hub, containing New Zealand's main international airport. This critical transport linkage is a key site for importation and transmission of COVID-19 into New Zealand, with the first confirmed case arriving on the February 28th, 2020. In response a four-tiered COVID-19 Alert Level System was introduced, with the most restrictive Level 4 lockdown, enforced between March 26th, 2020 until April 27th, 2020 (Table 1) (Unite Against COVID-19 2021). This system included regional and nationwide lockdowns, placing restrictions on 'non-essential' workplaces, gatherings such as weddings, funerals, church services, and schools.

Table 1. Overview of New Zealand Alert Levels. Unite Against COVID-19 (2021)

Level	Risk assessment	Example range of response measures
Level 4- Eliminate	*"Sustained and intensive community transmission. Widespread Outbreaks."*	All gatherings are cancelled. Facilities such as gyms, libraries, food courts, educational facilities and non-essential businesses must close.
Level 3 - Restrict	*"Multiple cases of community transmission. Multiple active clusters in multiple regions".*	Education facilities can reopen with limited capacity. Non-essential businesses may reopen for online orders and click and collect only. Inter-regional travel remains restricted
Level 2 - Reduce	*"Limited community transmission. Clusters in more than 1 region."*	Event and gathering capacity (<100 people), social distancing, masks are compulsory in public spaces. Schools and businesses may reopen with compulsory contract tracing posters/records
Level 1 - Prepare	*"COVID-19 is uncontrolled overseas. Sporadic imported cases. Isolated local transmission."*	No restrictions on personal movement or gathering. Compulsory face coverings on public transport. At all levels travellers into New Zealand must undertake 14 days isolation in a managed isolation facility.

2. Methods

In this section we discuss our mobile phone location dataset, and supplementary polygons of interest data used for labelling of stops, and our proposed methodology as evident in Figure 1.

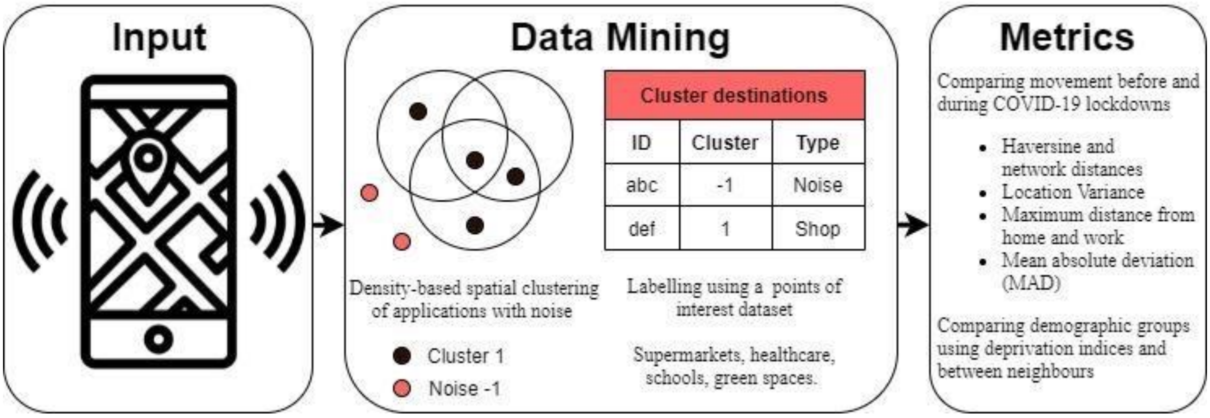

Figure 1. Proposed data inputs, and methods.

2.1 Data

The dataset consists of around 65 billion data points covering movement of at least 1.5 million individuals between January 2019 until December 2020. For this research a sample of 5 weeks (including a baseline, 1 week before, and during Level 4, and 3 lockdowns) have been chosen and cleaned. We identified inclusion criteria, including a minimum number of data points per week (70), and datapoints must be located within the Auckland Territorial Authority boundary. In total 20,272 unique phones are included, with over 92 million rows of coordinates (latitude and longitude) and date/time throughout the sampling period as displayed in Table 2.

Table 2. Raw data example for a single phone user.

Hashed ID	Latitude	Longitude	Date: time
abc	-36.85324788	174.76818406	2020-03-01 00:09:01
abc	-36.85324788	174.76818407	2020-03-01 00:09:10

According to UberMedia, ninety percent of the location data is collected through advertisements via Bidstream, along with social media, sporting, and radio applications utilising software development kits. The data is episodic with some applications tracking locations only when active/opened, creating gaps, while other applications constantly collect locations in the background. The data is pre-processed by UberMedia including obfuscating and jittering the coordinates to protect privacy.

2.2 Data Mining:

2.2.1 Density-based spatial clustering of applications with noise (DBSCAN)

A range of clustering algorithms are currently available, such as K-means, OPTICS, and many modifications of DBSCAN including spatial-temporal (T-DBSCAN and ST-DBSCAN), hierarchical (HDBSCAN) and parallel processing using random partitioning variations (RP-DBSCAN). Following a comparison of methods and a review of relevant literature we initially used the unmodified DBSCAN for our preliminary analyses. Firstly, DBSCAN iterates through the coordinates of each individual hashed ID during the selected week, assigning a cluster number or noise label to each point it iterates through. Then the centroid is calculated on each cluster, with this point progressing through to semantic labelling. In this stage, common night locations are identified by observing points between 11pm and 5am, as a proxy for potential home locations. While misclassification of some individuals' home locations such as night-shift workers, and homeless populations whose patterns do not conform to our assumptions, may occur, our approach is consistent with methods applied elsewhere (Such as Yin & Leurent 2021). To preserve anonymity whilst visualising movement between neighbourhoods, the common night-time locations are then assigned to a neighbourhood level geographic unit called Data Zones containing between 500 and 999 individuals. By utilising Data Zones, variation between different demographic and socio-economic areas can be completed, using the associated 2018 Index of Multiple Deprivation dataset, which contains seven key domains of deprivation including accessibility to services, housing, crime, and education (Exeter *et al.*, 2017).

2.2.2 Semantic Enrichment: Labelling.

We have identified features such as supermarkets, hospitals, parks, recreation, commercial, industrial, and residential unitary land use planning zones using a range of open-source local authority datasets and Open Street Map queries. The centroids as displayed in Table 3 are spatially joined with the polygons of interest dataset.

Table 3. Processed data example for a single hashed identifier.

Hashed ID	Centroid Coordinates	Cluster	Noise	Distance to night location (m)	Polygon of Interest	Neighbourhood unit
abc	-36.85, 174.93	-1	Y	--	--	--
abc	-36.85, 174.83	0	N	0	Night-time location	DZ1001
abc	-36.85, 174.93	1	N	300	Supermarket	DZ1002
abc	-36.85, 174.00	2	N	5600	School	DZ1003

2.3 Data Analysis: Mobility metrics

A range of mobility metrics will be implemented to quantify variations in collective movement prior to and during lockdowns. A conclusive framework has yet to be established, however Kishore *et al.* (2021) and Oliver *et al.* (2020) provide examples of potential methods, including maximum distance from home, using both haversine and network-based distance, location variance, entropy, and number of significant locations. Additionally, movement flows between geographic regions, and land use type boundaries, such as residential to commercial and industrial, to represent travel to places of employment and services will be completed. Utilising metrics, and creating visualisation using collective flows, protects anonymity, showing general trends between neighbourhoods in line with ethics approval and considerations.

3. Conclusion

The abundance of ever-increasingly accurate and intrusive big data like mobile phone location services data provides many ethical challenges for presenting movement trajectories while protecting privacy, but also the opportunity to extract collective insights. Our research will use visualisations to display changes to movement on a local and regional scale. We expect to see that changes to mobility are not equitable between neighbourhoods and demographic groups in Auckland, with influencing factors such as the spatial distribution of points of interest defined as essential services during lockdowns (e.g. health providers, covid testing centres, petrol stations, supermarkets) impacting movement flows. Additionally, the spatial dispersal and concentration of essential workers who must travel to engage in employment, will impact neighbourhood mobility. This research will increase understanding of Aucklanders' different experiences and responses to movement restrictions and remains relevant in the constantly evolving COVID-19 pandemic.

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