Spatial and Temporal Analyses of Healthcare Visits Patterns during the COVID-19 Pandemic

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ABSTRACT

People's mobility have been limited due to the rapid transmission and high mortality rate of COVID-19. In this project, we examine the effects of the COVID-19 pandemic on the mobility of individuals to healthcare facilities. Specifically, we analyze temporal and spatial patterns of visits to health care points of interest (POIs) in the Greater Toronto Area (GTA). We further explore the visit patterns for each Census Block Group (CBG) in this area and use the K-Means algorithm to group CBGs into different clusters based on its visit patterns. Finally, based on the demographic data of all CBGs, we shed some insights on the correlations between demographic characteristics of CBGs and clusters. The experimental results show that the accessibility to healthcare services and facilities have been considerably affected during the pandemic. Moreover, the impacts on each CBG are disparate, which emphasizes the necessity of policy makers to pay more attention to specific socio-demographic groups to ensure equitable access to healthcare.

KEYWORDS

Mobility, COVID-19, healthcare visit patterns, POI analyses, Spatio-temporal analyses, Data visualization

1 INTRODUCTION

The worldwide outbreak of COVID-19 has changed the way people live. To slow the spread of the disease, authorities around the world adopted a range of rules and policies such as stay-at-home orders, business closures, public transport restrictions, and so forth [26]. Nearly all aspects of our life have been affected, of which the movement/mobility of individuals has become one of the most disrupted fields [16]. Meanwhile, in response to the rising number of cases, many health care facilities also tighten their policies, including postponing non-emergency surgeries [1, 6, 15, 18, 27, 29] and imposing visitor restrictions [12, 23, 27]. Combined with the restrictions in transportation systems (such as reduced public transit service, social distancing within transit vehicles, etc.) during the pandemic [17], COVID-19 inevitably makes it more difficult for people to access healthcare services [5].

There have been many studies related to the individual mobility changes due to the COVID-19 [4, 7, 13, 14, 25]. However, they mainly focus on general mobility patterns of people. Our project, in particular, investigates the impact of COVID-19 on individuals' mobility to healthcare facilities. In this project, we want to gain some insights on the trends and patterns exhibited by healthcare/medical visits throughout the period of the pandemic – particularly in Toronto and GTA. Our analyses primarily makes use of the mobility data obtained from SafeGraph [22]. It provides location-based datasets on places, foot insights of individuals and POIs derived from GPS technologies and several mobile applications, while preserving privacy achieved through anonymity and aggregation techniques.

Contributions. Motivated by the real-world SafeGraph data derived from the advances in tracking technologies, we propose to make the following major contributions:

- We assess the impacts of the COVID-19 on the utilization of healthcare services in Toronto and GTA.
- We assess the underlying correlation between healthcare accessibility with socio-demographic characteristics of CBGs.
- We provide some insights on our findings and demonstrate these through clear visualizations and thorough explanations.

2 PRELIMINARIES

2.1 Definitions

In this section, we introduce some definitions and notations; then formally state the problem of interest.

Definition 2.1. (**POI**) Let a point of interest *POI* represent a building frequently visited by individuals, such as groceries, restaurants, schools, etc. Each POI has a particular top-level category (for example, the POI *Shoppers* has 'pharmacy' as its main category).

Definition 2.2. (**Healthcare Facilities**) A *POI* is under the umbrella of 'healthcare facilities' if it belongs to one of these categories: [24]. Some of which include *hopsitals*, *treatment centres*, *pharmacies*, *paramedic services*, *public health units* and so forth.

Definition 2.3. (**CBG**) Let a census block group *CBG* be an area that constitutes of small geographical units on the map with an approximate population of 400-700 [2]. Formally in Canada, these CBGs are known as *Dissmenination Areas (DAs)*; however for the sake of convention and convenience, we will refer to these dissemination areas as *CBGs* throughout this work.

2.2 Problem Statement

Given a year's worth of SafeGraph dataset (May 2020 - May 2021) that contains data on the footprints of individuals at healthcare POIs in Toronto, we intend to:

- Visualize healthcare POIs and the most-visited POIs in Toronto.

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*This is a project report for EECS 6414 Data Analytics and Visualization. All authors contributed equally to this research.

- Identify the correlation between the visits pattern and the COVID-19 daily cases, and the correlation between the visits pattern and different phases of lockdown policies implemented in Toronto.
- Identify the clusters of CBGs with temporal patterns based on the health care visits; visualize the spatial distribution of clusters.
- Examine the association between socio-demographic characteristics and healthcare visits for CBGs.

3 METHODOLOGY

3.1 Datasets

Below are the datasets we used for our project.

(1) **SafeGraph's Weekly Patterns** [21]. This dataset consists of data on visitors and their demographic aggregations on over 600,000 POIs, ~140,000 of which are categorized as health care facilities. Each row consists of a POI with attributes such as the number of hourly/daily visits and the dissemination areas of visitors, which are crucial for our analyses and visualizatons.
(2) **SafeGraph's Core POIs** [19]. This dataset gives a brief overview on the basic characteristics of POIs, including information on its address, postal code, geographical coordinates (longitude and latitude), category name, etc. This dataset can be used as a lookup table to determine which among the POIs from the Weekly Patterns data are of type health facilities.
(3) **SafeGraph's Geometry** [20]. This dataset provides POIs as described by its geographical POI footprint (a Polygon) and spatial characteristics, an important feature in our project.
(4) **Canadian CBGs** [10]. This dataset provides the geometry (geographical coordinates) of the census block groups in Canada. The data is updated as of November 2021 and can be publicly obtained from Statistics Canada [8].
(5) **Canadian Census Profile 2016** [9]. Crawled from Statistics Canada [8], the dataset contains rich information of socio-demographics of individuals residing in Canada (eg. age, race, income, marital status, etc.) as of 2016. It will serve useful when analyzing and making visualizations of the various demographic profiles for each CBG.

Our SafeGraph data ranges for 54 weeks from the beginning of pandemic in May 2020.

3.2 Methods

We analyze the mobility patterns of people who had visited healthcare facilities in 2020 in the city of Toronto through the steps in the Table 1.

Starting from data preparation and preprocessing steps, we first filtered interesting data from SafeGraph datasets: **a)** Merge each dataframe in SafeGraph's Weekly Patterns with SafeGraph's Core POIs and SafeGraph's Geometry dataframes to obtain the *top-category* column aligned with each POI's *place-id*. **b)** From all POIs, keep only those within Greater Toronto Area (i.e., cities of Durham, Halton, Peel, Toronto, and York) having a healthcare related keyword (like Health, Medical, Dental, Hospital, etc.) in their *top-category* value. **c)** Gather POI entries of all 54 weekly pattern dataframes into a single dataframe ordered by *place-id* and *data-range-start* columns (for the ease of aggregation in future). After filtering our POIs of interest, we will find aggregated number of POI visits originated from each existing CBG in the *visitor-home-cbgs* column. Now, we can do the CBG clustering and further experiments and visualizations to gain insights on visit patterns. These experiments on healthcare POIs' visit patterns obtained from the SafeGraph dataset are explained in details in section 4.

Still, in order to validate our clustering method we needed extra features across which to compare clusters. Here comes our next contribution that we crawled Canadian Census Profile data containing demographic features such as age, population, income and employment rate for each CBG. So we stored a huge dataset containing demographic attributes for each CBG for which we had already gathered visits data. Then we extracted demographic attributes of interest for all CBGs and combined them into a single dataframe. Having demographic attributes, we can analyze and correlate each demographic attribute on average for CBGs of the same cluster, as elaborated in section 4.4.

4 EXPERIMENTS

4.1 Heatmaps

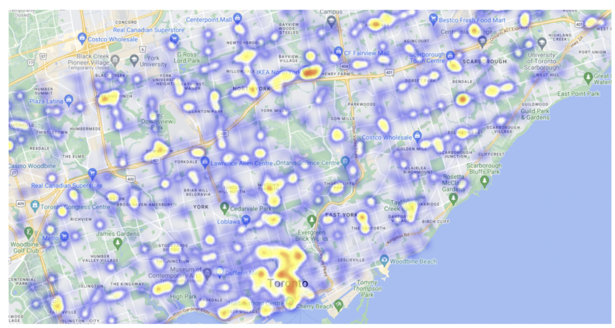

Figure 1: Healthcare POI visits in Toronto

Static Heatmaps. We plot a heatmap (lower intensity in blue indicates lower visits and higher intensity in red indicates higher visits) that shows the number of healthcare POI visits in Toronto, as shown in Figure 1. We went the extra mile and also constructed a similar heatmap for the entire Greater Toronto Area (GTA) and not just for Toronto, as seen in Figure 2. It is interesting to see that majority of the healthcare visits are concentrated in Toronto and its downtown core, as exemplified by the more yellow/red colors on the map.

Animated Heatmaps. While our static heatmap comprises of 54 weeks' worth of aggregated data, our animated heatmap on the Toronto area has been plotted for each week of those 54 weeks. We then compiled those 54 frames to build a gif file that acts as an *animated* heatmap, which displays how healthcare visit patterns can change over the period of those 54 weeks on a weekly basis. As it is infeasible to display this on paper, we have shown this in our class presentation and can be further viewed here.

Method	Description
1. Preprocessing (eg. Pandas, etc.)	First, we need to filter SafeGraph data to directly work on the specific area (Toronto) and specific POIs (healthcare facilities) of interest.
2. Visualization (eg. Matplotlib, etc.)	Then we create an animated heatmap visualization of different POIs' daily visits overtime to get some insights on visit trends. This helps to make sure we have enough data and realistic trends to rely on.
	Moreover, we compare and correlate the overall trend of daily visits across all POIs and COVID-19 daily cases trend in Toronto over time, knowing that Toronto COVID-19 daily cases data is publicly available.
3. Clustering (K-Means)	Given that SafeGraph data provides home CBG data of some (not all) people visiting a certain POI in an anonymized way, we are able to cluster different CBGs based on how frequently people residing in those areas visit a healthcare POI in Toronto.
4. Data Crawling (eg. Scrapy)	We need to crawl Census Profile data (of Statistics Canada) for different CBGs in Toronto to obtain people's aggregated demographic attributes for each CBG.
5. Evaluation	Then we evaluate the quality of obtained clusters of CBGs based on the crawled demographic data and derive useful facts that could differentiate healthcare visit patterns of people in different CBG clusters. For instance, we can measure how demographic attributes, such as income, age, etc., can affect people's visit patterns to healthcare facilities in different areas (CBGs) of Toronto.

Table 1: Sequential steps for this project

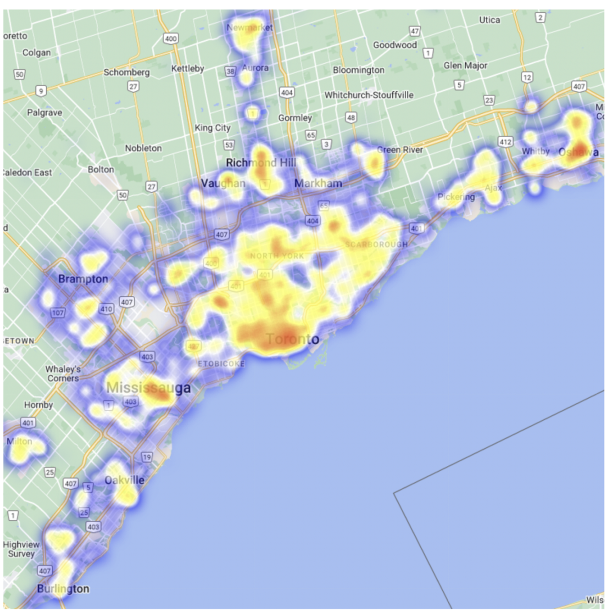

Figure 2: Healthcare POI visits in the Greater Toronto Area (GTA)

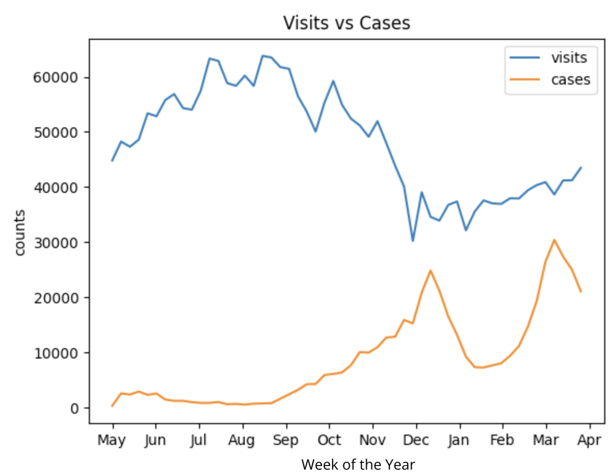

Figure 3: Line plot demonstrating the relationship between Healthcare POI visits vs Daily Cases Number

4.2 Healthcare Visits Patterns

Healthcare Visits Patterns vs Daily Cases Number. Figure 3 shows the healthcare visits pattern versus the daily number of COVID-19 cases. An interesting trend that shows here is that from May to December of 2020, the more daily cases are there, the less POI visits there are. A probable explanation would likely be due to people avoiding to go out of their homes and just staying at home, due to the early stages of the pandemic. The global pandemic was still fairly relatively new at that time and the novelty of its nature has probably caused people to fear that coming out of their homes can significantly increase the risk of catching the virus. Past December 2020 however, it seems that the number of visits are no longer that affected or relevant to the cases number likely due to people starting to adjust and become more adaptive of the pandemic situation. Also, another likely reason is that December 2020 – particularly later in the month, is a holiday season where people come together with family and friends. Many might have felt more 'relaxed' and 'at ease' with the pandemic that the virus was deemed to be not a reason for people not to gather and celebrate.

Healthcare Visits Patterns vs Lockdown Policies. We also tried to examine if there would be a correlation between healthcare visits and lockdown policies throughout the period. However, we had difficulty in the data collection. The data of lockdown policies (guidelines) from the Government of Ontario were not always consistent in all sub-regions. For example, a number of restrictions in York Region were lifted on February 22, 2021 while cities such as Toronto and Peel Region remained the same. As such, the result would be inaccurate if we treated Toronto (or GTA) as a whole instead of analyzing them separately.

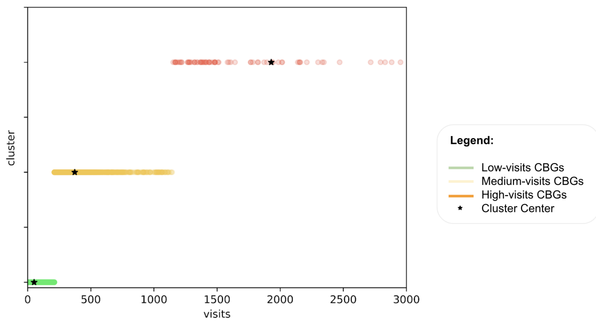

Figure 4: 1D plots showing the healthcare POI visits for CBG in each cluster, as well as their average visit number or the cluster centre (black star)

4.3 Clustering Census Block Groups

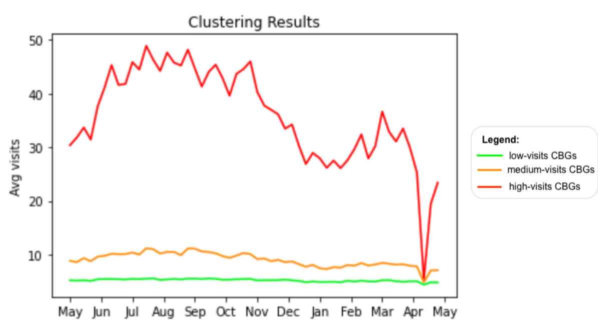

Figure 5: Average visits amongst all CBGs in each cluster on a weekly basis from May 2020 to May 2021.

Clustering Plots. After we cluster the CBGs in Toronto based on its number of visit to healthcare POIs, we obtain three clusters, i.e. low-level visits CBGs, medium-level visits CBGs and high-level visits CBGs. This is displayed in Figure 4 with the green dots to represent the low-visits CBGs, yellow dots representing the medium-visits CBGs and red dots representing the high-visits CBGs. Additionally, we highlight the average number of visits for each cluster (i.e. the cluster centre) using black stars. Furthermore, we also plot average visits of all CBGs in each cluster on a weekly basis in Figure 5. Three clusters of CBGs show an obvious division throughout the year. In particular, the the visit trend of low and medium clusters stays relatively stable over the observation period, which demonstrates COVID-19 had little impact on the people from low and medium CBGs. However, the average visit trend of high-level CBGs has a similar pattern to the overall healthcare POI visits (the blue line) in Figure 3, which shows that the pandemic mostly affects those who visit healthcare POIs often.

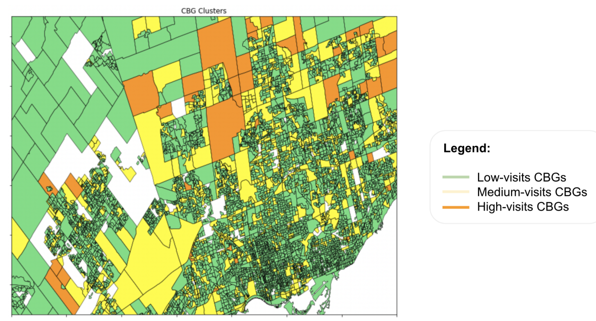

Figure 6: This exhibits the spatial visualization of the census block groups (CBGs) in Toronto based on the clusters formed.

Spatial Visualizations. Figure 6 displays a spatial visualization of CBGs in Toronto by clusters (green regions are the low-visit CBGs, yellow areas are the medium-visit and the red parts are the high-levelled). By healthcare visits, we demonstrate this through a color map visualization as seen in Figure 7.

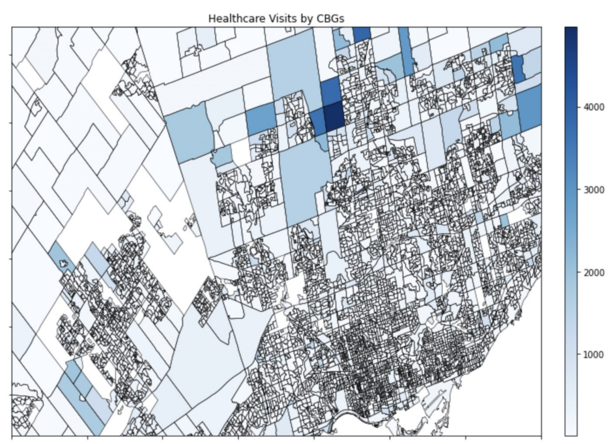

Figure 7: This exhibits a color map depicting the spatial visualization of the CBGs in Toronto based on the healthcare visits. Here, darker blue (higher intensity) indicates CBGs with more visits.

4.4 Demographic Discussion

Demographic Features and CBGs. Now that we have CBG clusters of corresponding healthcare POI visits, we can analyze how well those clusters can explain their average demographic attributes and highlight potential differences.

In this regard, Table 2 illustrates the effect of each demographic attribute on visit patterns represented by low, medium, and high-visit clusters, on average. We go over each feature and explain the association between them separately:

Feature	Mean for cluster0 (low visits)	Mean for cluster1 (med visits)	Mean for cluster2 (high visits)
num_visits	52.25	372.18	1928.52
pop_density	4,747.58	8481.27	7,679.82
pop_avg_age	41.60	38.90	35.00
pop_age_over_65_rate	17.11	13.59	9.26
income_avg	70,960.33	68,659.64	65,353.18
employment_rate	60.20	60.65	62.99
edu_no_degree_rate	14.52	13.15	12.27
orig_north_american_rate	22.73	12.39	8.06
orig_european_rate	61.94	42.33	28.52
orig_african_rate	2.97	5.35	6.88
orig_asian_rate	23.06	43.99	58.75

Table 2: CBG clusters explained by aggregate demographic attributes

- **Num-visits** feature shows the average number of visits to healthcare POIs for each CBG cluster. Actually, CBGs are clustered based on this feature and this is our major feature to analyze.
- **Pop-density**, defined by ratio of population over area, does not seem to have a correlation with number of visits. This implies that it is not necessarily the case that large population density of a cluster leads to more visits of healthcare POIs.
- **Pop-avg-age** indicates that on average, younger people tend to visit healthcare facilities more often, probably because of their higher mobility capability.
- According to **pop-age-over-65**, older people tend to visit healthcare facilities less often, probably because they are more careful due to the fact that they are more vulnerable to COVID-19. This is also consistent to the result from population average age.
- The aggregate numbers for average income, **income-avg**, shows that for people who have more visits, there is a slightly higher probability that their income is relatively lower. As this seems the opposite to our intuition, we need to look closer into the dataset and discretize the income range into different buckets to compare percentage of people in each salary bucket for each cluster. We observe that for people earning more than 30k per year, it is more likely that they have less visits. While for people with under 30k income per year, they tend to have medium visits. As a guess, this might be because Canadians have access to public health insurance, which covers basic health costs. Therefore, income does not make too much difference. Furthermore, wealthier people might have family doctors and they already have a routine health assessment.
- **Employment-rate** has an increasing pattern, i.e., a positive correlation, suggesting that people visiting healthcare POIs more often have slightly higher probability that they are employed. This is intuition-consistent as employers in Canada must pay a certain amount of the health plan cost, the employed individuals are more likely to use healthcare insurance.
- According to **no-degree-rate** feature, in the low-visit cluster, there are more people having no degree, compare to other clusters. In other words, people who have lower visits are more likely uneducated (i.e., tend to have no degree).
- Each of the last four features in **orig-north-american-rate, orig-european-rate, orig-african-rate, orig-asian-rate** show percentage of people belonging to each race for each cluster. We can see that people with North American and European origins tend to have less visits compared to Asian and African groups that tend to visit healthcare POIs relatively more often.

5 RELATED WORK

The relationship between mobility and the spread of an infectious disease has been well documented. Below, we briefly review work that are related to human mobility and epidemics.

Individual mobility changes due to the epidemics. Tea Gamtkitsulashvili and Alexander Plekhanov [7] examine the relationship between quarterly estimates of economic activity and people's mobility during the COVID-19 crisis in 53 economies and they found that the pandemic imposed restrictions on people's movements across majority of economies. Lucchini et al. [13] utilize the GPS-based mobility data to study how individuals adapted their daily movements and person-to-person contact patterns over time during the COVID-19 pandemic. They show that the individual patterns of visits are influenced by the strength of the NPIs policies. In their study, Caselli et al. [3] show that the overall mobility declined during the COVID-19 pandemic because of government lockdowns and voluntary social distancing in selected countries.

The effect of human mobility on the spread of infectious diseases. Yabe et al. [28] analyzed mobility data from mobile phone users in Tokyo and found a correlation between human mobility patterns (i.e. social contact rates) and transmissibility of COVID-19. [11] studied 163 cities around the world and identified a positive correlation between COVID-19 infection risk and human mobility, where the risk of infection is higher in places where the population density is relatively high. Chang et al. [4] find that during the COVID-19 disadvantaged groups have not been able to reduce their mobility as sharply, and that the points of interest that they visit are more crowded and are therefore associated with higher risk.

6 CONCLUSIONS

6.1 Conclusion

Our project analyzes healthcare visit patterns of individuals in Toronto and GTA from May 2020 to May 2021. We found three distinct CBG clusters of temporal patterns of visits to healthcare POI during the pandemic. We investigate the temporal patterns of visits to healthcare POIs and their associations with socio-demographic and spatial characteristics at the CBG level. The findings may be useful for policymakers seeking to improve health care delivery and access.

CBGs with higher percentages of elderly people, unemployed and low-educated individuals had lower use of health care during the pandemic. Authorities and health policymakers need to develop appropriate strategies to address persistent inequalities in health care use by these social groups.

6.2 Future Work

Working with mobility data, specifically on visitations pattern, provides many potentials. For example, given that we have weekly visits numbers to healthcare POIs, we can use this information to build a time-series regression model to predict the number of healthcare visits for a given CBG on weekly basis. Moreover, we can also cluster CBGs based on more demographic features of each CBG. Last but not least, our work at the moment focuses on Toronto and GTA; however, we can scale our work out to larger areas. For instance, the method can be applied to provinces or country-wide level.

GITHUB REPOSITORY

We make source code publicly available here to encourage reproducibility of results.

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