Traffic Flow Analysis Using Uber Movement Data

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***Abstract*— Different techniques to analyze traffic flow of different cities is proposed in this paper, with the motivation to solve traffic issues particularly traffic congestion and bottlenecks by identifying peak rush hours and other mobility patterns. The analysis uses Uber Movement data consisting of Uber trips held in various cities and is based on the comparisons of spatial and temporal graphs. These graphs visualize geographical structure of the city incorporated with various traffic movement patterns based on mean travel times between the trips. Centrality measures such as Degree, Closeness, Betweenness and PageRank were used to identify peak rush hours and the effect of bottlenecks, while Greedy Modularity algorithm was used as a community detection technique to observe how communities change throughout the day with respect to traffic flow. This approach is selected because it gives us a clear view of analyzing the impact of traffic flow at various locations. This analysis would help transportation sectors especially cargo and courier companies to deliver goods smoothly without any issues, while government departments can also use this analysis to plan solutions for the improvement of roads and infrastructure in different localities. For future, this analysis could lead to more impactful outcomes when new data is added, so that more solutions can be proposed for traffic related problems.**

I. Introduction

Traffic congestion has long been a critical issue in different parts of the world. The ever-increasing population and infrastructure have created a challenge for the people to commute freely yet facing traffic congestion problems at various ends. For this reason, the analysis of traffic flow patterns has been a subject of discussion in recent years [1].

The need to solve traffic congestion problems as well as identifying peak rush hours is very important, as it causes several difficulties to consumers as well as businesses, which demand a clear traffic flow for smooth end-to-end deliveries. Peak traffic times are different for different cities, depending upon the work hours and business schedules. Hence, heavy traffic is usual in these times which have become a source of problem for everyone.

To solve this problem, we studied and applied several network measures to analyze traffic flow patterns of different cities across the world. Through these measures, we were able to identify traffic congested areas, peak rush hours, and how traffic bottlenecks affect the flow across various cities. This analysis could help different businesses especially transportation sector, while government departments can also provide solutions for urban planning by taking key steps for the improvement of roads & infrastructure.

The literature review involved analysis of traffic flow patterns through comparison of spatial and temporal graphs of different cities. For instance, it used Uber movement data to compare the patterns of different cities such as Manila, Johannesburg, Washington, and Paris. It used centrality measures such as degree, betweenness, closeness, and page rank algorithms to identify different mobility patterns as per analysis. It also used Girvan-Newman Algorithm as a community detection technique to analyze traffic patterns across various times in a day [1].

In this analysis, we used Uber movement dataset of different cities, which include Auckland, Mumbai, Toronto and Washington. The temporal and spatial graphs of these cities were created and analyzed using the same centrality measures, and traffic flow patterns were identified to extract various insights. Also, Greedy modularity algorithm is used in this analysis as a community detection technique.

Furthermore, it'll be seen in detail that how our traffic flow analysis is related with the previous work and research papers on the same topic. The measures, models, and algorithms to identify traffic congested areas, peak rush hours and traffic bottlenecks are discussed, and results are presented in the form of visualizations, through spatial and temporal graph comparisons. We have also discussed how can we improve the analysis by adding pros and cons of the same.

II. Related Work

A. Data Collection

The dataset used for traffic flow analysis is "Uber Movement" which is readily available to access on Uber's website. The dataset includes more than two billion Uber trips across 07 different cities of the world. For the analysis, the dataset also includes arithmetic mean, geometric mean, and standard deviations for aggregated travel times for each specified date range between every traffic analysis zone pair in each city [1]. In the case of spatial graphs, the graph is undirected, and weights are computed as the pairwise distance between geographic centroids of each node, computed using Haversine distance. While for temporal graphs, the graph is directed, and weights are the mean travel times between the source and destination as available in the dataset [1].

The data for trips used here is taken on a granular level, i.e., in the terms of hourly aggregates. Also, in total, 24 temporal graphs are generated, each with its own set of weights [1].

The other dataset was the New York City taxi dataset which consists of data from more than 4.5 million Uber rides in the city along with the time, latitude, and longitude of the journey [2].

Data was gathered from various sources, such as mobile phone call records and sensors installed on the cabs. Dataset of more than 14 million cab journeys approximately 14,776,615 taxi rides that were gathered in New York City over the course of one month was used for their analysis [3].

B. Methodology

Centrality measures such as degree, closeness, and betweenness are calculated for weighted directed graphs. For that, node degrees and shortest paths between each node are calculated for the weighted case. Additionally, for node importance, the PageRank algorithm is used, which is defined in terms of the out-degree of its nodes and is also calculated for the weighted case [1].

The calculated measures from the temporal graphs in terms of traffic flow are interpreted, so that insights can be extracted across different hours of the day and can be compared with the same measures of spatial graphs. Traffic bottlenecks and rush hours are identified using betweenness centrality and PageRank Algorithms. Using Girvan Newman's Algorithm, community detection is applied to detect communities in both temporal and spatial graphs [1].

For the spatial approach, the visualizations that were mentioned include a choroleth map, a difference choroleth map, and traffic flow fields. Choroleth maps are used to distinguish between the regions that are faster to reach and those that take more time by using a color gradient. The colors represent the mean travel time and are made from a given source point. Different choroleth map helps us to understand the change in travel times from the same source to all other areas during a certain period for example a day, week, or year. With their help, we can observe that the average travel time from any place to a popular tourist destination always increased on weekends [2].

Visualizations through temporal information include the polar coordinates and the calendar view. Through polar coordinates, we were able to represent information in the form of a circle where the radius of the circle represents the average travel times between two places. Hence, we were able to identify the hours at which it takes the maximum time to travel between two places. The calendar view is used to identify the times of heavy traffic [2].

A dynamic network technique has been used to analyze travel patterns in the city. They created 744 sub-networks by aggregating the rides dataset into hourly snapshots. Many ride networks each provide data for fixed-length periods with similar distances between their beginning places. Such an approach is useful for tracking changes in various properties [3].

Here, nodes represent the number of unique pick-up and drop-off locations of rides made during this time window. Number of edges represent the number of unique pick-ups to drop-off pairs of rides made during this time window. Average Betweenness centrality yields an estimation of the network's efficiency, concerning the number of nodes whose adequate availability is required to preserve the network's ability to maintain efficient flow without increasing the length or duration of trips between arbitrary points. Average Closeness centrality yields an estimation of the compactness of the network, that is – how short it is to travel between an arbitrary pair of network nodes [3].

C. Results and Findings

There are 24 temporal graphs constructed, with each measure calculated for each city and each hour of the day, using distances as edge weights. Whereas for spatial networks, each measure is calculated for each city, undirected [1].

1. In-and-out degrees: Found that traffic congestion in rush hours keeps on increasing in the morning time in Johannesburg [1].

2. Betweenness centrality: For temporal graphs, betweenness is found only in a few sub-regions of Manila in the morning. For spatial graphs, betweenness reduces as it is a function of the distance between one region and the center of the network [1].

3. Closeness centrality: Both temporal and spatial networks show almost similar results for closeness centrality in Washington city. A difference highlighted was some lighter nodes in the temporal graph are darker in spatial graphs, which shows a less developed area of Washington [1].

4. PageRank: The PageRank score of Paris city at 09:00 am (morning time) is analyzed. The graph with darker tone areas has a higher PageRank score, while with lighter tone areas has lower scores. In the temporal graph, in the core center of the city, the score is higher, while around the concentric rings, the importance is decreased, and hence score is lower. In spatial graphs, the nodes which are far away from their neighbors have higher PageRank scores, while the rest of the nodes have uniform patterns across nodes, which is of lesser interest [1].

Using Girvan Newman Algorithm, community detection for Johannesburg city is done for both temporal and spatial graphs. For temporal graphs, upon analysis of four different times of the day, it is observed that traffic flow keeps on increasing towards the city center during morning rush hour. Also, upon continuous analysis, it is observed that the traffic flow starts to reduce as soon as it approaches nighttime. Similarly, distance-based communities are detected for spatial graphs [1].

It was discovered that the dynamic network approach produces lower valued results than the previous calculation using the overall aggregation (10% decrease), caused by the fact that each node pair's possibility of being connected is decreased [3].

The findings of their analysis show that ride-sharing usage is very volatile over time, indicating that any strategy or plan that ignores this feature and opts for a static approach would unquestionably be either extremely wasteful or supply insufficient resources. They demonstrate that it is possible to model the potential use of ride-sharing based on the topological aspects of the rides network using their suggested technique [3].

D. Pros & Cons

In this study, it is shown how network measures can help in analyzing traffic flow problems in different cities of the world. The problems of traffic congestion, traffic bottlenecks, and rush hours were identified and highlighted by analyzing different mobility patterns across various cities. This is done by observing and comparing the change in measures in both temporal and spatial networks [1].

This study identified and performed analysis on mobility patterns for weekdays, and not for weekends. However, the same traffic data can be analyzed for weekends, so that people's travel patterns on weekdays and weekends can be compared, and the change in measures can be observed. Also, we can add more data from previous years as well as the rest of the years to obtain in-depth mobility patterns across the cities [1].

One strength of this study is its methodology, which starts with a background examination of the traffic planning techniques used in the urban design process and then moves on to talk about data-driven mobility modeling, to estimate human movement. Such modeling is essential because it enables a more thorough, fact-based understanding of "how people travel." That has given researchers a broad perspective on traffic congestion, urban transportation, and its underlying dynamics [3].

Since their suggested approach is agnostic to the actual route taken by the drivers. It would be interesting to study how the introduction of ride-sharing affects additional parameters like deviations (that for a merged journey may become cost-effective), usage of toll routes, etc. In addition, crucial elements like incentives and fees elements can be better represented as "remedies" to analyze travel patterns changes but they were absent from the network dataset [3].

III. Ground Work

This section explains certain important graph concepts to the weighted case that will be helpful in our study, as well as a description of the travel time data we used and the temporal and spatial graphs we created from it.

A. The Data Set

Beginning July 2017, Uber introduced its Uber Movement service. It offers access to an overview of travelling time between various areas of the chosen city and contains billions of trip data [3].

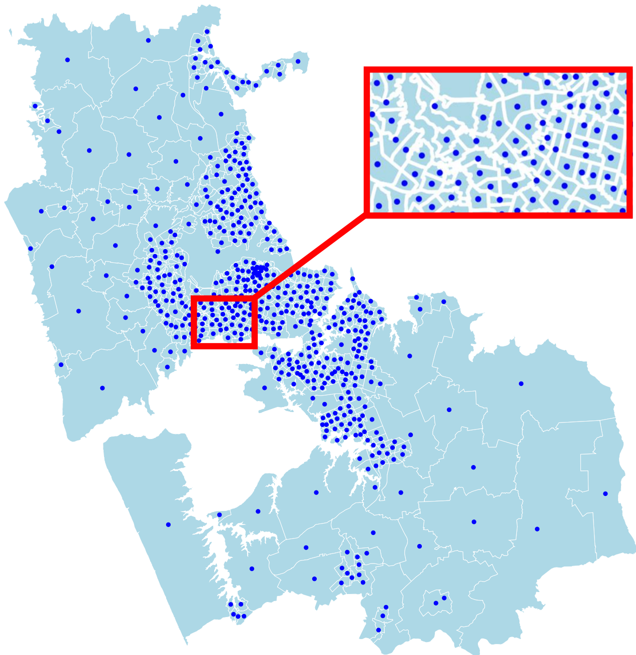
The researchers are welcome to use Uber Movement, which is available for direct download in .csv and in .JSON format from its website. In this work, we mainly focus on the trip times data for the cities of Auckland, Toronto, Mumbai, Washington D.C., Johannesburg.

For each zone pair in each of these cities, it offers the geometric mean, arithmetic mean, and standard deviations for aggregated trip times over a selected month, weekday, and hour of the day (HOD). In terms of the statistic used, our focus for this work is the arithmetic mean [7].

B. Data Processing

The limitation with uber movement data is that it is not possible to directly create a graph so to detect traffic congestion within a city. Therefore, we must create a graph that represents the fundamental city structure upon which trips depend [3].

To depict the connection of the areas on which Uber collects data, we constructed a City structure graph. The data comes includes a GeoJSON file that describes the polygons that define a city's zones. Each zone is defined by set of polygons and each polygon is represented by a list of points in the lat-long coordinate system. The entire data is available as part of the Uber movement GeoJSON format. We then compute the centroids of these zone [2].



Once we have a graph that depicts the layout of the city, we specify two sets of weights, leading to two distinct readings of the graph.

a) Spatial graph: Consider the graph as being undirected, with the weights representing the separations between the distance between the areas. Each area geographic centroid was calculated, and using the Euclidean distance, we then calculated the pairwise distances between centroids. $G_S = (V_S,E_S,w_S)$ where (V_S,E_S) is the graph, and w_S is a weight i.e., distance between regions [5].

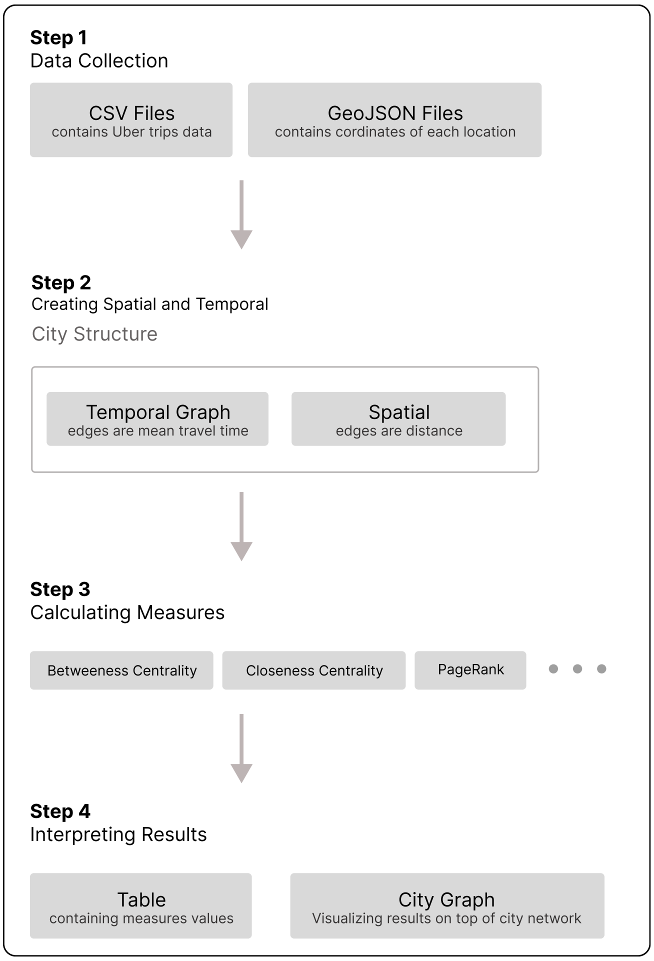
b) Temporal graph: Consider the graph as being directed, with the weights representing the travel time. Reason it's a directed graph is because because the average travel time from area A to area B may differ from the time of travel from area B to A. Moreover, Weightes can be treated as any of the four total trip length metrics offered by Uber, but for the sake of time, we have only treated arithmetic mean as the weights for the temporal graph. $G_t = (V_t, E_t, w_t)$ where (V_t, E_t) is the graph, and w_t is a weight i.e., arithmetic mean of travel times between regions [5].

C. *Project lifecycle*

As previously mentioned, we will be working with two weighted graphs: an undirected geographical graph and a temporal graph (directed). We must adapt the centrality metrics we learnt in class to weighted directed graphs in order to find the structurally significant nodes in our graph after gathering the dataset and making graphs from it.

We need to extend these definitions to the weighted case in order to use metrics like closeness and betweenness in our research because they are specified in terms of node degrees and shortest pathways. We will evaluate the Page Rank in addition to these metrics to assess the significance of our nodes. Important insights are also being identified using a number of additional metrics.

The process diagram that follows details each of the significant actions we took to complete each task.



IV. EXPERMENTAL RESULTS

A. *Dataset*

There were different datasets that were used from the uber movement repository. While selecting the datasets we had a few things in mind. a)

Population size. The greater the population the greater the number of uber trips to region. b) Developed and developing region. We selected different data sets from the developed regions such as Auckland and Washington, and developing region such as Mumbai. This was done to compare the traffic patterns between developing and developed regions.

IDENTIFYING STRESS REGIONS

We made use of indegree centrality to identify the high traffic or stress regions across an area. In degree centrality will tell us about the number of uber trips that ended in that region.

The distinction between areas is done through a color gradient. The darker regions represent high stress zones, and the lighter regions represent low stress zones.[1]

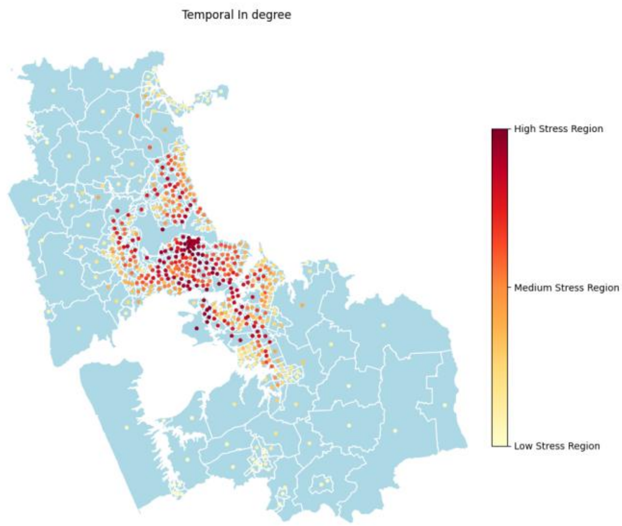


Figure 1

Area ID	In Degree Centrality
260	0.901141
136	0.899240
264	0.887833
308	0.868821
298	0.861217
...	...

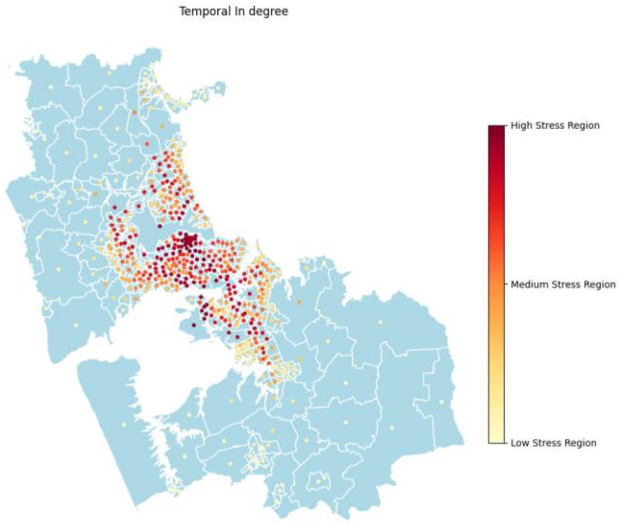


Figure 2

Area ID	Out Degree Centrality
260	0.931559
264	0.910646
136	0.904943
308	0.889734
298	0.865019

Both the indegree and outdegree centrality measures give us almost the same results since every trip that ends at a location will also start from that position.

IDENTIFYING BOTTLENECKS

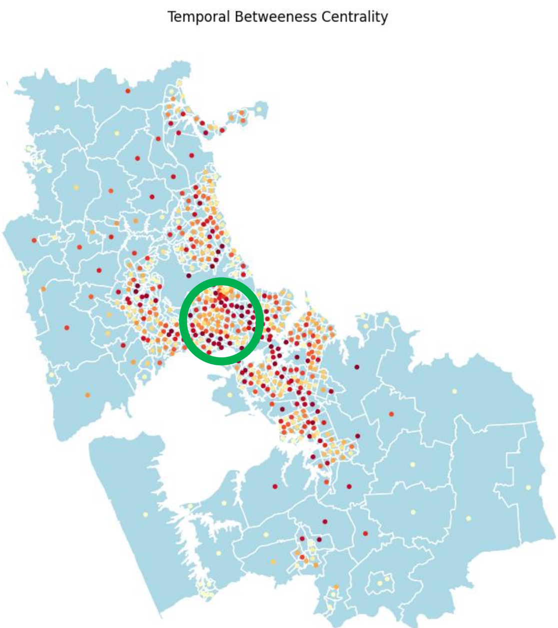
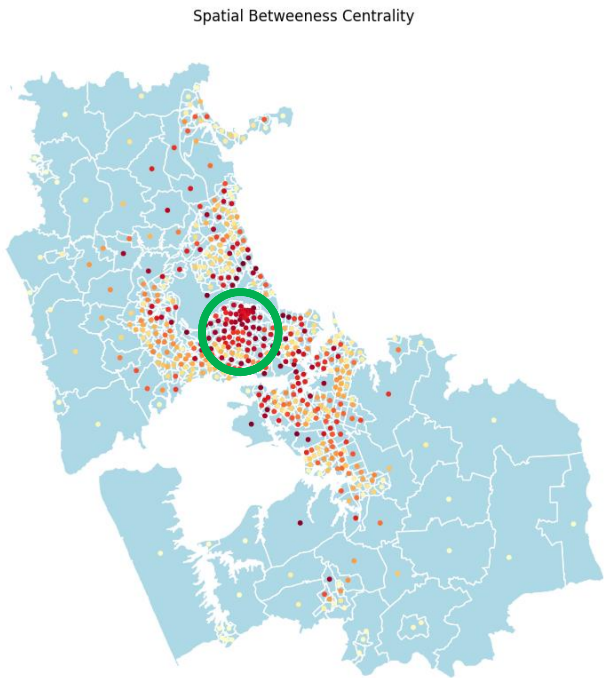


Figure 4

Bottlenecks are those where the traffic abruptly comes to a stop or where the density of traffic becomes very high suddenly. There can be a few reasons for that.

1) The cars are being parked on the road and they occupy the last two lanes of the road. This will convert a four lane road to a two lane raod and bottlenecks will be created.

2) A three lane road convert to a two lane road due to a road which was under construction.



In our analysis we have made use of the betweeness centrality to identify bottlenacks. The temporal and spatial graphs are made using the betweenes centralit.

The portion of the graphs where it shows a dense region in the spatial graph and a non dense in the temporal graph is the region where a bottleneck exists.

Betweenness centrality is calculated based on the shortest distance between the nodes. For the spatial graph it tells us about the dense traffic regions.

Or the regions where a particular node was crossed the most. For the temporal graphs the weights are kept as the average time between two destinations.

Therefore, the shortest path will be calculated based on time rather than the distance which was the case in the spatial graph.

Hence there will be different dense region in the temporal since the region which is dense in the spatial graph will be lighter in the temporal graph. [1]

IDENTIFYING CITY CENTERS

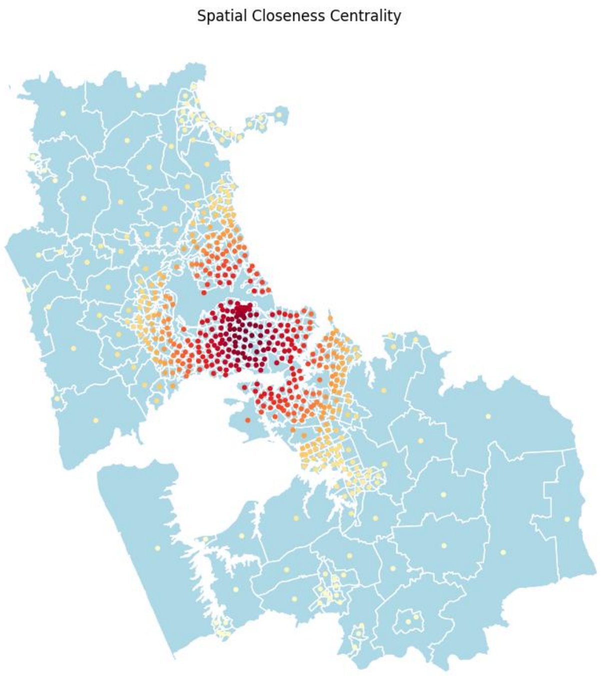


Figure 5

We made use of closeness centrality to identiify city centers. City centers are those regions which are more developed as compared to the other parts of the city.

Closeness centrality gives us those nodes that are clossest to all other nodes in the graph. Since the spatial graaph is based on distance, the nodes whoch represent the centroid of the graph will have a high closeness centrality.

This visualozation doesn't give us any useful insights because it only gives us the centroid.

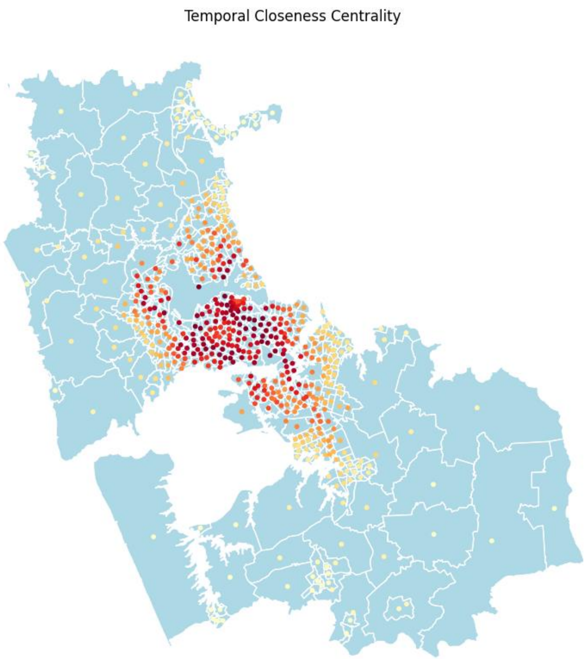


Figure 6

For the temporal graph, centrality is calculated using at average time.

This will highlight regions that are easiest to reach since they will be the one which are closest to all other nodes based on time.

Hence the city centers will have a high closeness centrality and they are represented by the darker regions in the temporal graph. [1]

Area ID	Betweenness Centrality
34	0.383076
356	0.10994
365	0.081157
289	0.065615
297	0.047999
...	...

Table of Figure 5

Area ID	Closeness Centrality
34	0.001104
360	0.001091
271	0.001070
356	0.001066
348	0.001064
...	...

Table of Figure 6

IDENTIFYING HOTSPOTS

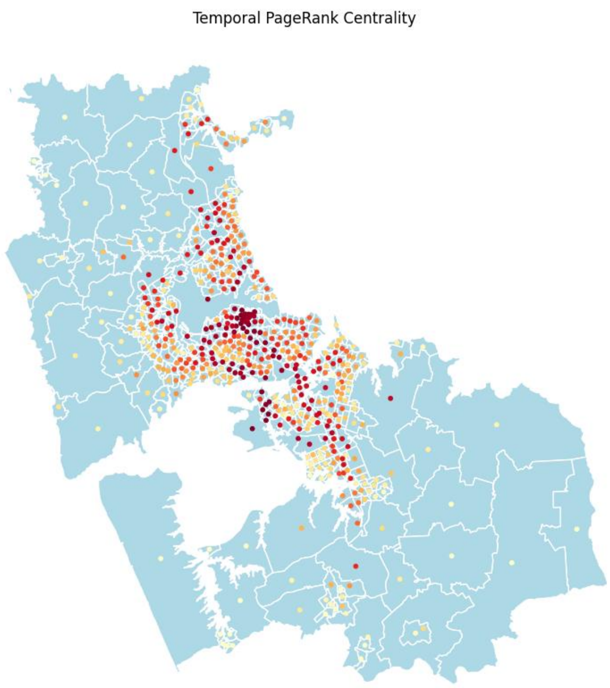


Figure 7

Hotspots are identified using the eigen vector centrality. Hotspots are those regions whose adjoining regions are high stress zones.

For city councils to quickly identify traffic congestion hotspots in a certain urban region and implement appropriate measures there, this type of representation may be useful.

For example, in Karachi there is millennium mall whose neighboring regions are high stress zones.

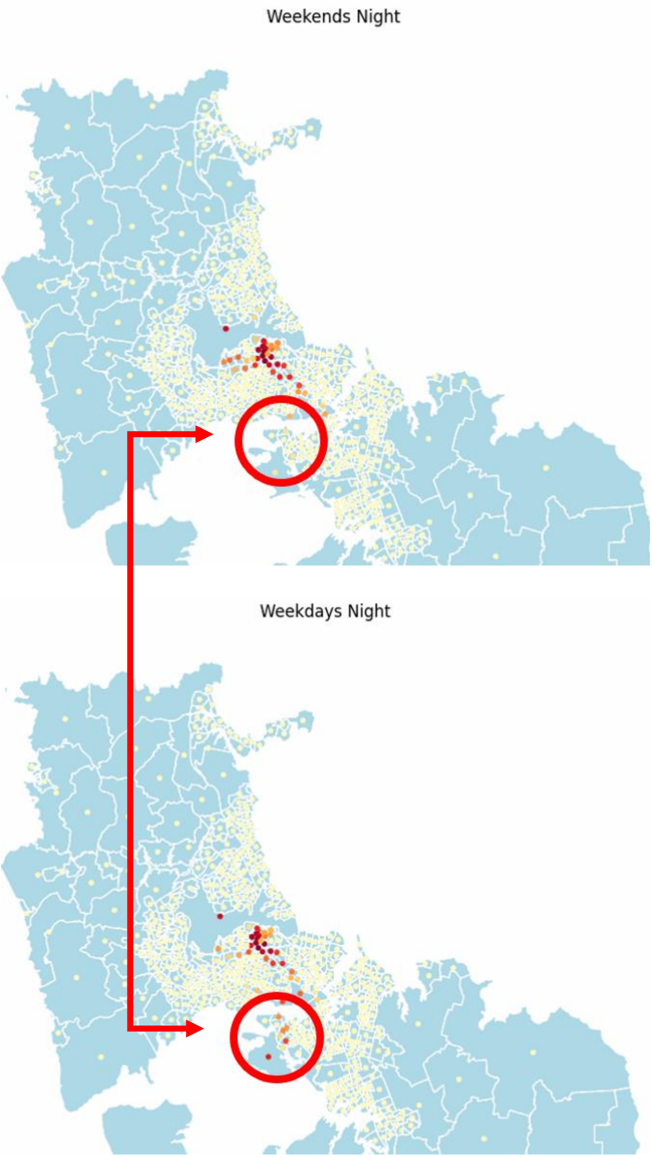
These trouble areas, which typically correlate to crossroads, pose a threat to network effectiveness as well as the safety of vehicles and pedestrians.

This means that millennium mall will be a hotspot. Eigen vector centrality gives more weightage to those nodes who are connected to the important nodes. Therefore, the darker regions can be considered as hotspots. [1]

IMPACT OF HOLIDAYS

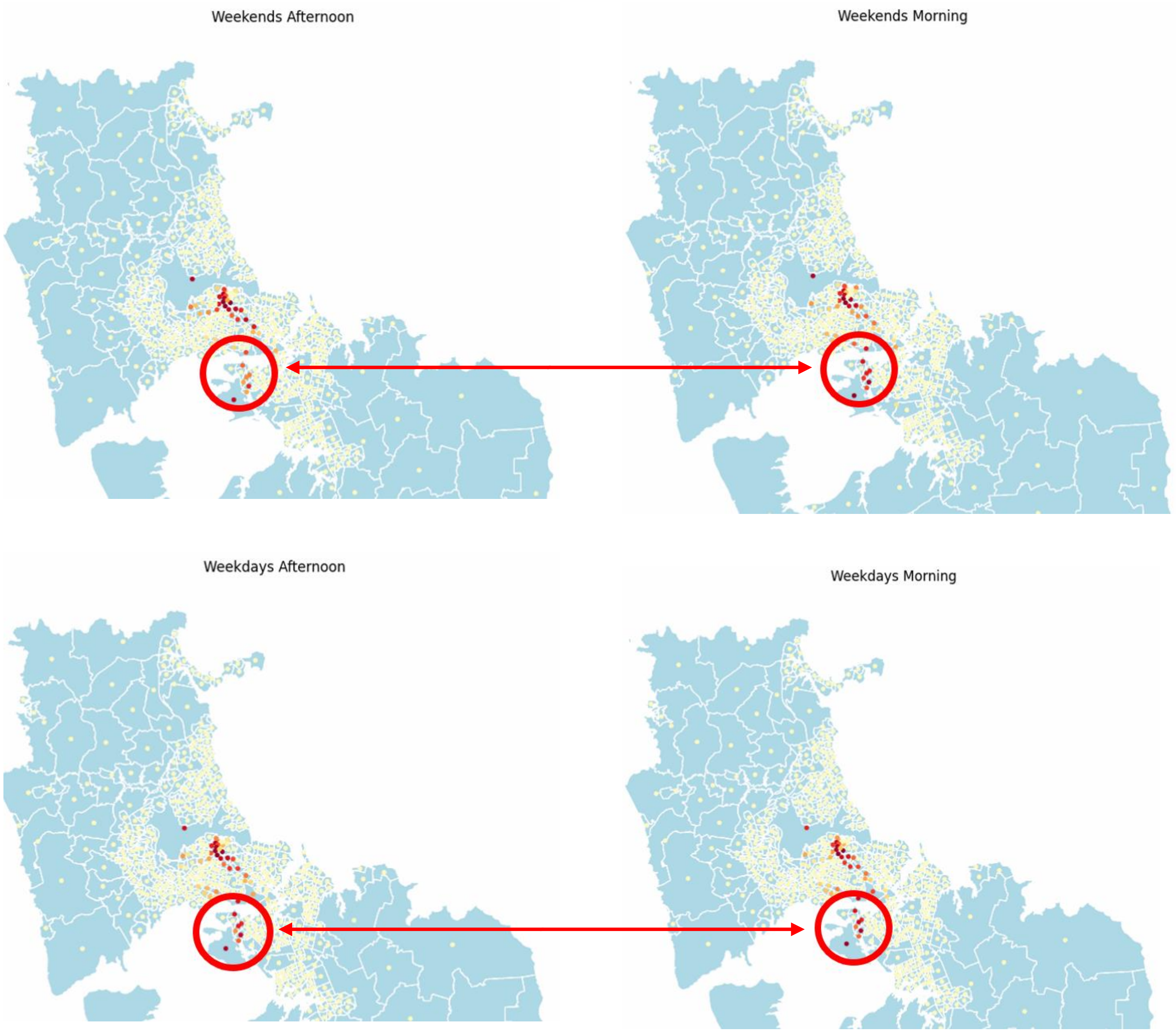
We can expect different traffic patterns for weekdays and weekends. For weekdays the commute is usually from the place of residence to the workplace. While on weekends people usually prefer to visit parks, lakes and places for liesure activities.

To identify this distinction we made use on indegree centrality measure and made temporal graphs for different time periods during the day. In the figures below you can see different comparisions.

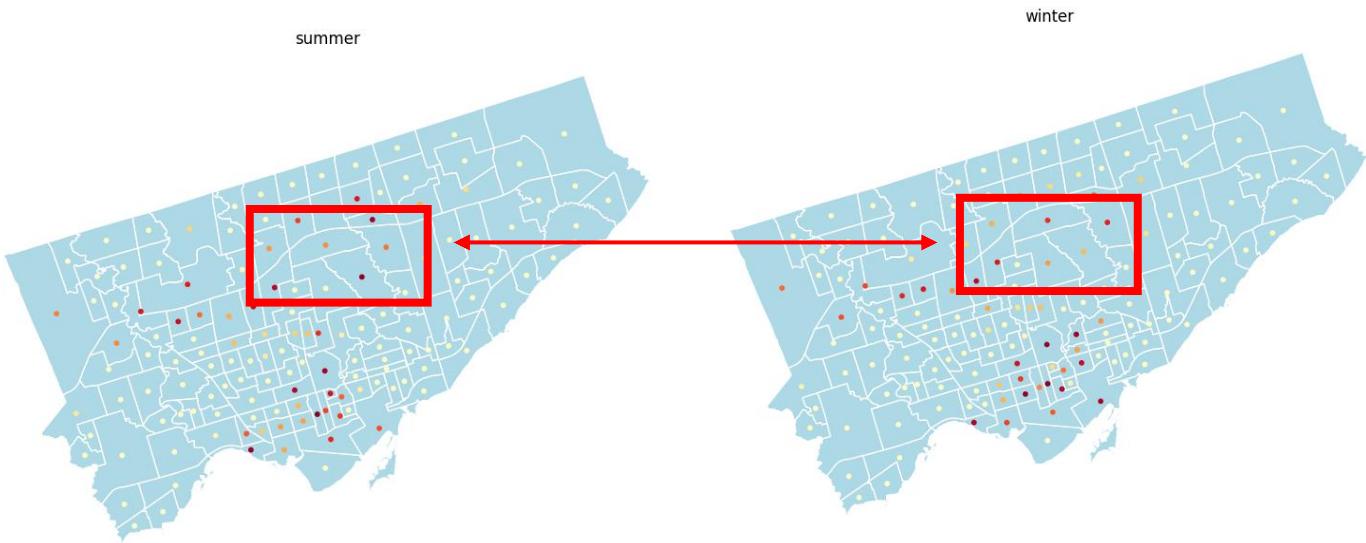


For the highlighted region weekdays have lighter nodes as compared to the weekends. This can be because of the pubs and bars which the people tend to visit more during the weekends.

It can also be because of the existence of parks in this region which people which will have a higher number of visitors on weekends. [2]



IMPACT OF SEASONS

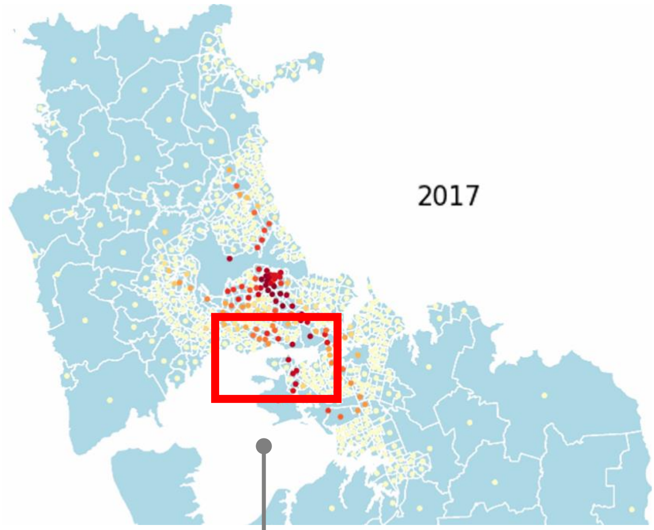


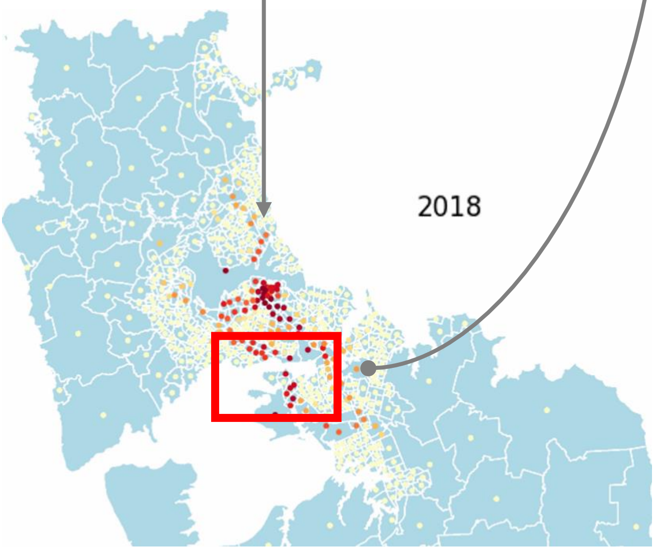
These two graphs were made using the uber movement dataset for Toronto, Canada. We made use of the in-degree centrality measure.

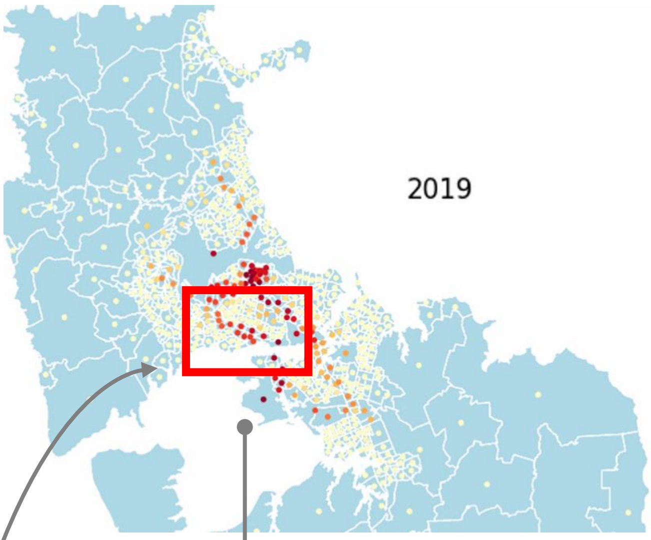
If you closely look at the highlighted regions for both graphs, you will observe that there are some nodes which were dark in the summers and light in the winters.

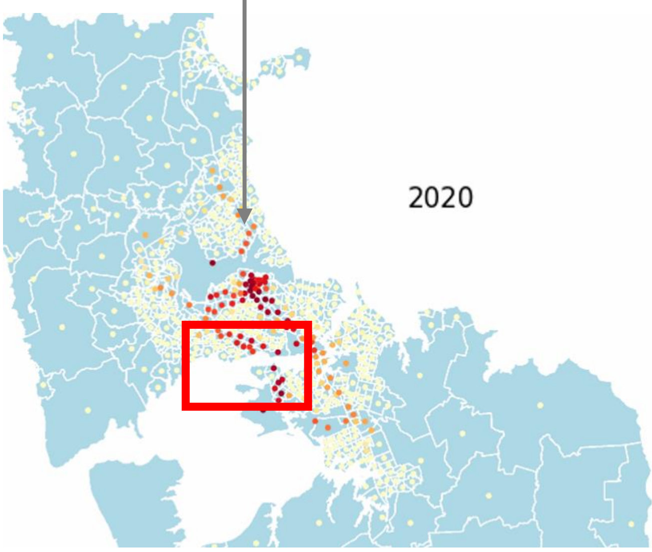
This is because in this region there exists a waterfall which gets frozen during the winters. Therefore, fewer number of people visit that place. This analysis was also verified by Google maps. [2]

YEARLY TRAFFIC PATTERNS









These graphs were made using the indegree centrality. If we go from 2017 to 2018, we can see big difference in the highlighted area.

The reason for this change can be linked with the development of a school, office, malls, or any other place with a high footfall.

That is why the density of traffic goes from low to high. After 2018 there a lot of difference that is observed which means that the traffic patterns were almost similar during these years. [2]

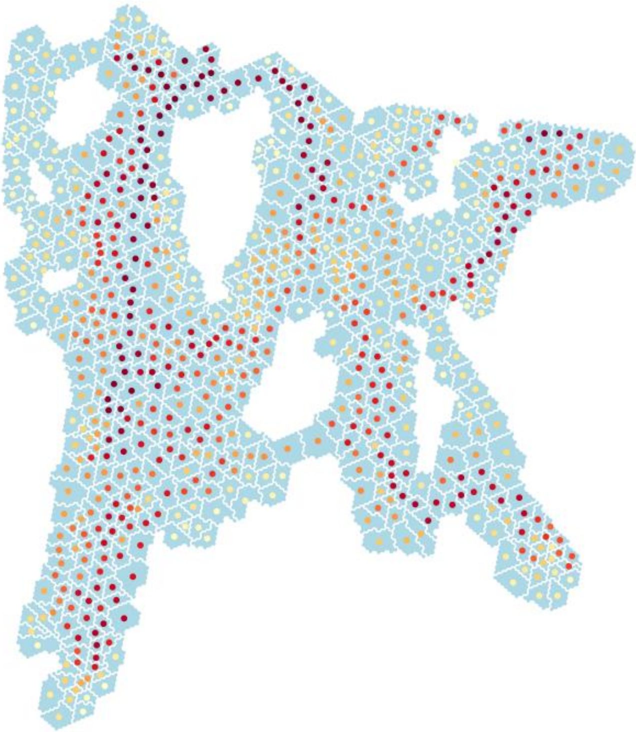
DEVELOPED VS DEVELOPING COUNTRIES

The basic difference between developed and developing regions is that the developed regions have a better infrastructure and road network as compared to the developing regions.

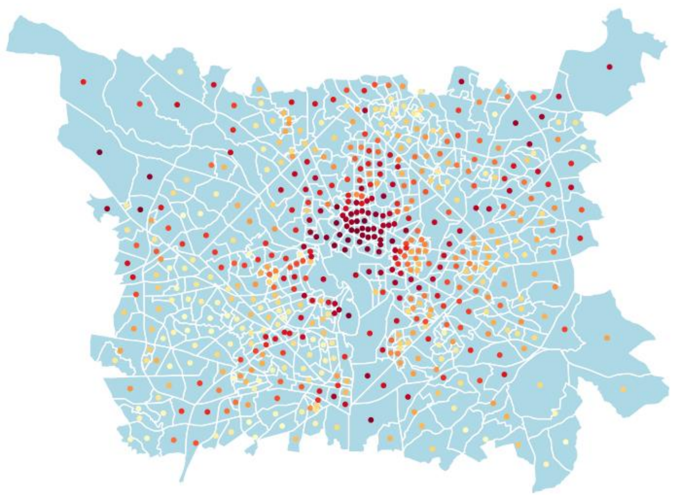
Therefore, if we make a temporal graph for these regions, we should observe a clear difference.

To differentiate between these regions, we identified hotspots for both. The developing region which is Mumbai has hotspots spread around the whole map, while the developed region which is Washington only hotspots in the center.

MUMBAI



WASHINGTON



EVOLUTION OF TRAFFIC

Finding communities within our network is one of our aims to understand the composition of our traffic flow data.
This would make it possible to identify certain areas inside or between our cities that behave in concert at particular hours of the day or certain days of the year.

We will use a greedy modularity maximization to do this, starting with each node in its own community and continually joining the pair of communities that lead to the biggest modularity until no more gain in modularity is conceivable (a maximum).

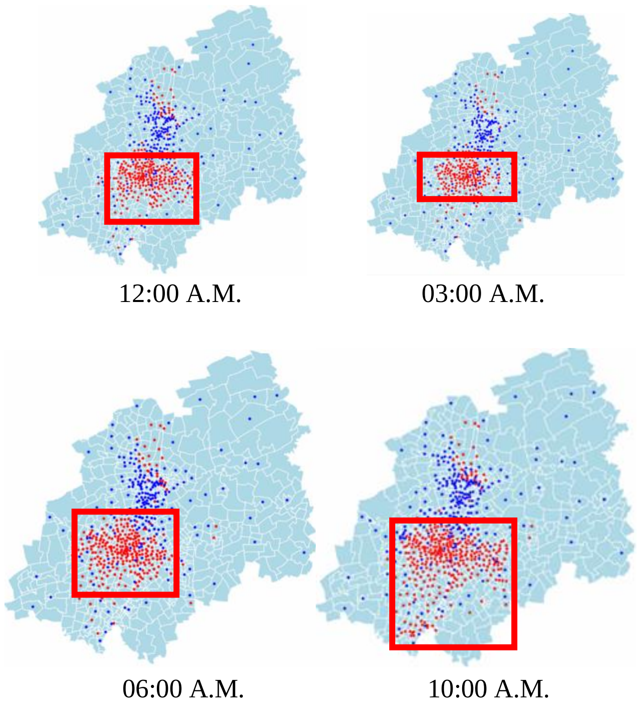


Figure 10: Johannesburg Communities

Figure 10 shows the detected communities at four different times of day: 12:00 a.m., 3:00 a.m., 6:00 a.m. and 10:00 a.m. We identify two communities in the temporal graph: the blue and the red regions. During morning rush hour, it is easy to watch how the red community expands as traffic begins to go in that direction. We would have observed a contracting behavior as the time wore on if we had conducted our investigation later in the day.

CONCLUSION

In the above analysis we have discussed about the stress regions using the indegree centrality. We also identified bottlenecks and the city centers. There was also a comparison that was made between the traffic patterns of weekdays and weekends, and summer and winter seasons. All of these visualizations and analysis will be useful for the government organization since they will be able to work on the urban planning of the city. These results are also useful for the logistic companies since they will be able to figure out the best route to deliver their items.

REFERENCES

[1] Mackenzie Pearson, Javier Sagastuy and Sofia Samaniego. Traffic Flow Analysis Using Uber Movement Data: 2017, http://snap.stanford.edu/class/cs224w-2017/projects/cs224w-11-final.pdf

[2] Vihang Godbole and Shane Pearlman. Analysis of Uber travel times across major cities in the world, https://users.soe.ucsc.edu/~pang/261/w19/projects/vgodbole/Final/CMPS261_final_report.pdf

[3] Tal Altshuler, Rachel Katoshevski and Yoram Shiftan. Ride Sharing and Dynamic Networks Analysis: 2017, https://arxiv.org/pdf/1706.00581.pdf

[4] Arun V Sathanur, Vinay Amatya, Arif Khan, Robert Rallo, and Kelsey Maass. Graph Analytics and Optimization Methods for Insights from the Uber Movement Data, https://arifulkhan.github.io/publication/15/15.pdf

[5] Xi Liu, Li Gong, Yongxi Gong, and Yu Liu. Revealing travel patterns and city structure with taxi trip data, https://sci-hub.se/10.1016/j.jtrangeo.2015.01.016

[6] Yeran Sun, Yinming Ren, Xuan Sun. Uber Movement Data: A Proxy for Average One-way Commuting Times by Car https://www.researchgate.net/publication/340146586_Uber_Movement_Data_A_Proxy_for_Average_One-way_Commuting_Times_by_Car

[7] Travel Time Analysis with Uber Movement (QGIS3) https://www.qgistutorials.com/en/docs/3/travel_time_analysis.html

[8] Uber Movement: Travel Times Calculation Methodology https://movement.uber.com/_static/c9bce307d99643c3.pdf