Understanding the dynamic of cities through people's mobility

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Mobility is one of the most important phenomenon in human life, being linked with our existence since the beginning of time. In this work, we use data collected from location-based social networks, specifically Foursquare, in order to unveil the dynamics of cities through people's mobility. The analysis is made by the Complex Network perspective. We build two types of networks: the contact data for people's encounters in a city, and the commute data, for people's trajectories. We investigated data from New York and Tokyo to understand how the cultural distance impact people's behavior and, consequently, the dynamics of cities.

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1 INTRODUCTION

The existence of human beings has always been linked with their ability to move. While earlier human movement were driven by natural environment factors, such as food scarcity and climate change, in modern society, socio-economic factors, such as wage imbalance and globalization, play an increasing role [1]. Understanding this mobility is vital to understand human behavior, individually and as a society, which can be used to increase the knowledge in several fields, such as geography (about the relationships between global change and local development) [7], medicine (worldwide spread of pandemics) [4], engineering (traffic behavior) [12], and many others.

Therefore, it is clear that mobility has a profound impact in human lives and that it is very important to understand such demeanor. Specifically, the human society is organized as cities, complex systems that evolve and adapt their environment along with their population. Many phenomena occur in these systems, for instance, the connections in this social network affect how people learn, form opinions, gather news, and even how diseases are spread. To fully understand these dynamics, the Complex Network field provide an extensive set of tools to analyze, model, and comprehend such dynamics that are inherently present in these networks [5, 8].

Recently, with the growth of Location-based Social Networks (LBSN), it is cheaper than ever to collect participatory information from people, that proactively contribute to the sensing, providing the needed information [11]. Hence, this large amount of human-generated data enable the analysis of urban systems from different perspectives, including the use of Complex Network tools [5, 8].

In this scenario, the main goal of this work is to investigate the dynamics of cities using data collected from LBSNs. Specifically, we use data obtained from Foursquare[1], a very popular location sharing system, in which users can register where they are (this act is called check-in), giving their impressions of the place. We apply

[1]https://pt.foursquare.com

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Complex Network quantifiers in order to investigate how people's mobility can explain the dynamics we can found in a city. We build two kind of networks, the commute and contact network, to examine the contribution of each type of network in our main goal.

This work is organized as follows: Section 2 discusses the related work; Section 3 presents the dataset used and how we build such data into the networks studied, as well as the Complex Network metrics we extracted in our investigation; Section 4 discusses the obtained results; and, finally, Section 5 concludes this work and presents the future work.

2 RELATED WORK

Understand the dynamics of cities is an important subject in our lives in order to improve our quality of life in urban scenarios. Hence, it has been studied in different fields from different perspectives. For instance, physics, economics [2], and politics [6].

Further, with the rise of LBSNs, several studies are focused on understand cities based on data shared by people in such networks. Silva et al. [11] explored Foursquare data to construct images that summarizes the city dynamics based on transition graphs, which map the movement of individuals in participatory sensor networks.

Gallotti et al. [5] characterized the longitudinal human flows through multidimensional network models corresponding to different types of activities across time. They discovered that large cities tend to be more segregated and less integrated, and that human flows at different hours of the day or between different types of activities enable the identification of different behaviors, creating "cities within the city".

Yang et al. [13] extracted key cultural features from daily activity, mobility, and linguistic perspectives, proposing a cultural clustering method to discover cultural clusters. The authors show that their approach is capable of capture cultural features and generate representative cultural maps that correspond well with traditional cultural maps based on survey data.

Chen et al [3] seek to understand people's periodic behaviors and regularities, by developing a large-scale systematic analysis to examine the relationship between revisitation/re-check-in. Hence, they find similarities and differences between urban revisitation and re-check-in, which can improve modeling of human mobility and better understanding of human behavior.

These and much more works can show the importance of the subject we intend to investigate. Therefore, we explore Foursquare data using complex network tools in order to understand human mobility and behavior in urban scenarios.

3 METHODOLOGY

To achieve our goal of understanding the dynamic of cities through people's mobility, we construct temporal networks based on check-ins, from which we extract metrics that can explain some phenomena in mobility. These steps are shown in the remainder of this section: first, we introduce the dataset we used to obtain the check-in data; after, we present the modeling we used to build the complex networks; finally, we describe the network metrics we employ in our analysis.

3.1 Dataset

Foursquare is a world-famous location-based social network created in 2009 and where the user can tell where they are (through check-ins) and find friends who are near. In April 2012, it registered more than 20 million users [11].

The data used in this study were collected by Yang et al. [13]. Foursquare check-ins are not publicly available, but the user can share their status with other social networks, such as Twitter[2]. Hence, the data were collected by

[2]twitter.com

crawling Fourquare-tagged tweets, from April 2012 to September 2013 (about 18 months). It resulted in 33,278,683 check-ins by 266,909 users on 3,680,126 venues. Such check-ins were distributed in 415 cities in 77 countries, each city containing at least 10,000 check-ins. More details about the data is available in [13].

Among these cities, we choose New York and Tokyo, since they are the cities with more check-ins (180,558 and 226,148, respectively). Moreover, their geographic and cultural distance can help us to investigate how different behavior of people impact in the dynamics of cities.

3.2 Network construction

We build two types of networks, one modeling the encounters people have in a city (contact network) and another modeling the trajectories in a city (commute network). They are described in the following.

3.2.1 Contact Network. This network aims to model the encounters people have in a city, hence it can be also called Encounter Network. Every time two users made a check-in in the same place, within the same time interval, we consider it as a relationship between them (we can roughly say that they are in the same place at the same time). Note that we build a temporal network, that can represent days or months of mobility in a city. It is possible to build networks with another time intervals, such as hours or weekdays/weekends, that can certainly provide a different mobility characterization, but it is not explored in this work.

Figure 1 exemplifies the network for people encounters. The network is an undirected graph $G_1(V, E)$, where the nodes V are the users and the edges E are the relationship between them (when they "meet" in a place). The weight w of the edges (v_1, v_2) represent how many times the users v_1 and v_2 met each other in the city (it can be in different places).

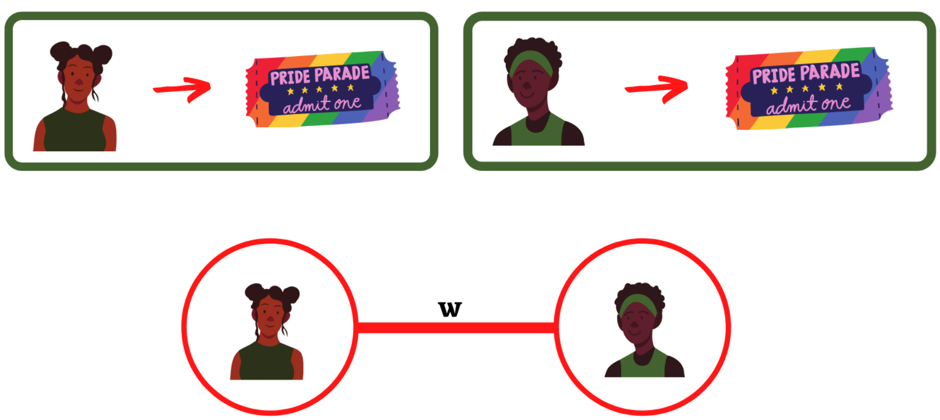

Fig. 1. Example of Contact Network modeling.

When constructing this network we did not consider self-loop, since, semantically speaking, people meeting themselves does not make sense.

3.2.2 Commute Network. A commute network models the trajectories of people in a city. Hence, if people went from place A to place B, within a time interval, an edge is create between these places, indicating a connection between them in people's routine. Similar to the previous network, different time intervals can be explored, but we decide to investigate in this study days and months in a city.

The Figure 2 shows an example of commute network modeling. More formally, the network is a graph $G_2(V, E)$, in which the nodes V represent the places in a city and the edges E indicate that users went from a place to another. The weight in edges (u_1, u_2) computes how many users did this same trajectory from place u_1 to place u_2.

Also, we did not consider self-loop, since they indicate that people made check-in in the same place repeatedly – it may be possible in Foursquare, but does not make sense for this work.

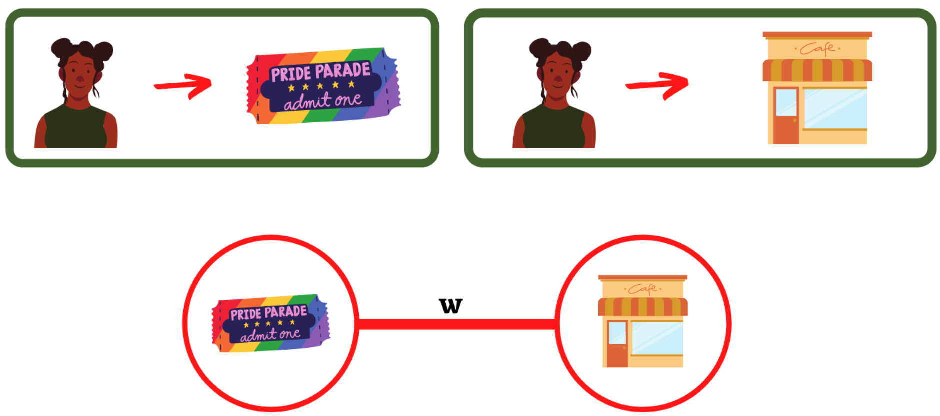

Fig. 2. Example of Commute Network modeling.

3.3 Network metrics

To characterize the networks, i.e., to understand how mobility happens in each network, we extract the following metrics. For each metric, we try to describe their importance in the context of mobility in a city.

- **Nodes and edges**: In the contact network, the number of nodes and edges represent the total of users and how many places they "went together", respectively. On the other hand, in the commute network, the nodes represent the total of visited places in a city and edges describe when people went from one place to another.
- **Subgraphs and connected components**: Connected components is a set of nodes that is linked to each other by paths. Naturally, in both kind of networks, some nodes are not linked to each other: it can be users that do not contact others or places that are visited alone (they are not in a trajectory). Hence, to extract some metrics, such as betweenness, we need to consider a subgraph of G_1 and G_2, due to some particularities of such metrics. A subgraph is a graph in which its nodes and edges are a subset of the main graph. The subgraphs used here are the biggest connected component.
- **Assortativity**: It measures the tendency of nodes to be connected to other nodes that are like (or unlike) them in some way, as defined in [9]. Hence, when assortativity is equal 0, the relationships are between random nodes, when it is more than 0, the nodes present some similarity, and when it is less than 0, the nodes are different.
- **Density**: The density, also called connectance, measures the fraction of edges present in a network, compared to the maximum possible number of edges. That is, we want to calculate how many edges a node has, compared to how many possible edges it could have. If density is high (a complete graph), the network

is dense; otherwise, it is sparse [8]. Therefore, in contact network, a dense network means that a person reach all people in network; sparse networks, analogous, means that a person reach few people (or less people than everybody). For commute network, if it is dense, it says that from a place is possible to reach all places, while in sparse commute networks, from a place we cannot reach all other places in a city.

- **Eccentricity and diameter**: Eccentricity quantifies the maximum distance geodesic from node v to all other nodes in the network. Accordingly, diameter is the maximum eccentricity in the network. In other words, eccentricity can be interpreted as the easiness of a node to be reached by all other nodes in the network. Therefore, for contact network, eccentricity describes the interaction between people – for low eccentricity values (and diameter, consequently), from one person we can meet many other people; otherwise, for high values, there are few contacts between people. For commute network, low eccentricity values show that, from place A, people go to many other places, whereas, for high eccentricity values, people go to few places after (or before) place A. Note that these metrics are calculated to the sugbraph of the biggest component, since, for a non-connected graph, eccentricity and diameter are infinity.
- **Clustering coefficient**: The clustering coefficient estimates the intensity in which nodes tend to cluster together. It can also indicate the tendency of a node to form triangles, hence, showing that the network has the property of triadic closure [10]. It says that, when a node A is connected to B, and B is connected to C, there is a tendency to form a connection between A and C. Hence, for contact network, when a person A meets a person B, and B meets a person C, there is a tendency of people A and C to meet as well (since they frequent the same places). In commute networks, clustering coefficient means that people visit clusters of places (for instance, only places in their neighborhood).
- **Closeness**: It computes the distance from a node v to all other nodes in the network. Since our network is not connected, the closeness centrality calculates instead the distance from a node v to all other nodes in the connected component containing node v. In other words, it measures how "close" a node is to other nodes (hence, a high closeness value represent a low average distance from a node to others). Central nodes (which can be people in contact networks and places in commute networks) are important as they can reach the whole network more quickly than non-central nodes [8].
- **Betweenness**: This metric measures the number of shortest paths that pass through one node, i.e., how much a node falls between others. Hence, nodes with high betweenness values are important to communication and information diffusion [8]. As eccentricity, it is calculated to the subgraph of the biggest connected component, in order to avoid infinity values.
- **Eigenvector**: The eigenvector centrality determines the importance of a node by the importance of its friends. Expressly, if one node has many important friends, it should be important as well. Hence, a high eigenvector value says that a node has many neighbors or has important neighbors [8].

4 RESULTS

In this section we examine how the complex network tools (the metrics described in section 3) can unveil the dynamics of cities.

4.1 Nodes and edges

First, we model monthly commute and contact networks. In Figure 3 we see the nodes and edges found. The top subfigures are the contact networks for New York and Tokyo and the bottom subfigures are the commute networks for New York and Tokyo as well. For contact networks, we can see that both cities have a similar number of users, although Tokyo presents consistently more edges, meaning that Tokyo has much more encounters between citizens than New York. However, in commute networks, we note that New York has more places (i.e., nodes) than Tokyo. In fact, the commute network for Tokyo is "less expressive" than New York, with less edges as well. It means that the people in New York make check-in in more places – they are more open to share their information. On the other hand, Tokyo presents more encounters since they make check-in in less places.

Moreover, we can see that the contact networks present an evident seasonality. For instance, in June in 2012 and 2013, we observe that there is a decay in the total of encounters. In this month, spring ends and summer starts in north hemisphere (in some places it is holidays), what can affect the routine of people in both cities. Furthermore, in September there is a decay in both cities that in a brief investigation we cannot explain. More studies must be conducted to shed light in such phenomena. In New York, the commute network is very similar to the contact network, clearly showing the seasonality. Tokyo, however, due their smaller amount of places, have commute networks that are harder to see the impact of the different months.

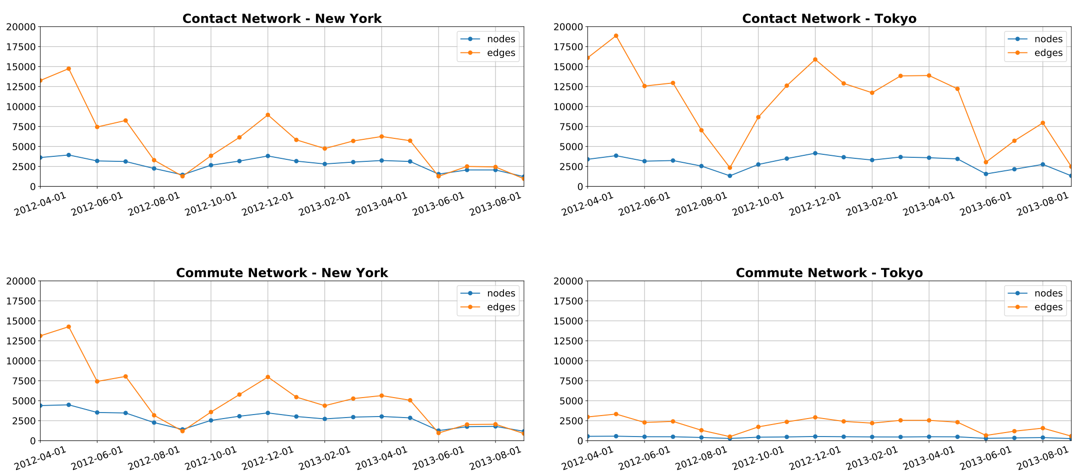

Fig. 3. Nodes and edges for **monthly contact network** for New York (top left) and Tokyo (top right), as well as nodes and edges for **monthly commute network** for New York (bottom left) and Tokyo (bottom right)

As a comparison, let's analyze the daily commute and contact networks. We chose March 2012, since this month shows a high peak in the monthly networks. The Figure 4 we see the the nodes and edges presented every day in March 2012. Similarly to the previous result, the top figures are the contact networks for New York and Tokyo, respectively; and the bottom figures are the commute networks. Day by day, we note that New York citizens are "lone wolves", they do not have many encounters and the places in New York have fewer connections. On the other hand, for Tokyo, we can clearly see several peaks in the contact network: such peaks are friday, saturday, or monday. These peaks can be seen, more timidly, in the commute network as well. Hence, people have more encounters in the weekends. Furthermore, we can see that March 11th to 13th (friday to monday) are the only sequential days that present high number of encounters – March 13th is International Mother's Day, showing that people may be enjoying such days to celebrate it. The top-5 places that people did check-in in Tokyo are train stations, whereas in New York are pubs, airports, baseball stadium, and train station. This finding highlights the difference between the check-in behavior and, consequently, the dynamics in both cities.

Therefore, we see that both intervals, monthly and daily, when building the networks, can help us to understand some phenomena that can happen in cities, based on human mobility. To deeply understand the reason behind such behavior, more studies in this direction must be made.

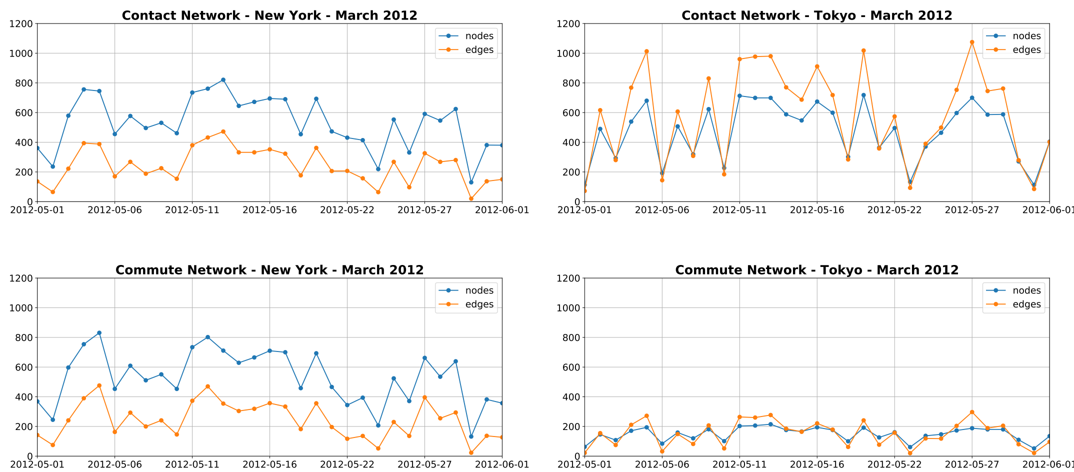

Fig. 4. Nodes and edges for **daily contact network** for New York (top left) and Tokyo (top right), as well as nodes and edges for **daily commute network** for New York (bottom left) and Tokyo (bottom right)

4.2 Density and connected components

In sequence, we study the subgraphs, connected components and density for each month in 2012 for both cities. Table 1 shows the metrics for the contact networks and Table 2 presents the same metrics for the commute networks. Besides the nodes in the biggest component, we also provide the percentage of such component in the network. Furthermore, we have how many subgraphs there is in each network and the network density.

Regarding the density, we see that we have very sparse networks, both in contact and commute networks – the commute networks for Tokyo is less sparse than the others, but it sparse nonetheless. This is a similar result to the friendship network, discussed by Newman [8], where the author stated that "*it seems unlikely that the number of a person's friends will double solely because the population of the world doubles. How many friends a person has is more a function of how much time they have to devote to the maintenance of friendships than it is a function of how many people are being born. Friendship networks therefore are usually regarded as sparse*". We can see a similar effect in both studied networks: only because someone (or someplace) entered the network, does not mean that the number of contacts between people (or places) will increase.

Furthermore, we can see that the number of subgraphs in the two kinds of networks in both cities are very similar. It would be interesting to dive in such results to see if there is a correlation between these results (if the places and people in a subgraph are the same). We can hypothesize that the small subgraphs are formed by people that check-in sporadically, but this analysis is not made in this work, remaining as a future work.

Finally, we can see that the biggest component in most of the networks contains more than 80% of the nodes in the network. A great exception to this is September, in both commute networks and in the contact network for New York, with less than 70%. Certainly, in September 2012 something occurred that makes more people "walking alone" and different places than other people. Unfortunately, we do not have data from September 2013, in order to investigate if this is a pattern or some problem in the data collection.

Table 1. Density, number of subgraphs and nodes in the biggest component for **monthly contact networks** for New York and Tokyo in 2012

Contact Networks - 2012									
City	**Month**	**Density**	**Subgraphs**	**Nodes in the biggest component**	**City**	**Month**	**Density**	**Subgraphs**	**Nodes in the biggest component**
	04	0.002027	77	3539 (97, 84%)		**04**	0.002794	56	3335 (98, 23%)
	05	0.001906	67	3866 (98, 27%)		**05**	0.002546	62	3783 (98, 25%)
	06	0.001461	144	3031 (94, 95%)		**06**	0.002516	78	3069 (97, 08%)
	07	0.001695	159	2957 (94, 74%)		**07**	0.002467	61	3166 (97, 68%)
New York	**08**	0.001304	281	1929 (85, 88%)	**Tokyo**	**08**	0.002163	78	2452 (96, 15%)
	09	0.001202	444	909 (62, 51%)		**09**	0.002660	88	1229 (92, 54%)
	10	0.001088	308	2296 (86, 38%)		**10**	0.002292	75	2661 (96, 72%)
	11	0.001220	207	2950 (92, 94%)		**11**	0.002075	55	3421 (98, 10%)
	12	0.001234	191	3604 (94, 46%)		**12**	0.001840	54	4084 (98, 26%)

Table 2. Density, number of subgraphs and nodes in the biggest component for **monthly commute networks** for New York and Tokyo in 2012

Commute Networks - 2012									
City	**Month**	**Density**	**Subgraphs**	**Nodes in the biggest component**	**City**	**Month**	**Density**	**Subgraphs**	**Nodes in the biggest component**
	04	0.001360	78	4306 (98, 04%)		**04**	0.020042	56	489 (89, 72%)
	05	0.001417	67	4408 (98, 21%)		**05**	0.021130	62	498 (88, 61%)
	06	0.001190	144	3384 (94, 81%)		**06**	0.018664	78	412 (83, 23%)
	07	0.001339	159	3291 (94, 92%)		**07**	0.020067	61	426 (86, 76%)
New York	**08**	0.001240	281	1892 (83, 60%)	**Tokyo**	**08**	0.016436	78	312 (78, 19%)
	09	0.001195	444	775 (54, 80%)		**09**	0.012929	88	192 (68, 57%)
	10	0.001113	308	2136 (84, 16%)		**10**	0.018149	75	356 (81, 46%)
	11	0.001233	207	2816 (91, 99%)		**11**	0.021440	55	413 (88, 05%)
	12	0.001321	192	3246 (93, 43%)		**12**	0.021377	64	459 (87, 76%)

4.3 Assortativity, Clustering Coefficient, and Eccentricity

In Figure 5 we see the assortativity metric for contact and commute network for both cities. The contact networks for Tokyo and New York present similar results, that is a little greater than zero, but they are still smaller. It means that the nodes present some similarity, differently from the commute network, in which the values are smaller than zero (except in September in New York), meaning that the connection are between the different places.

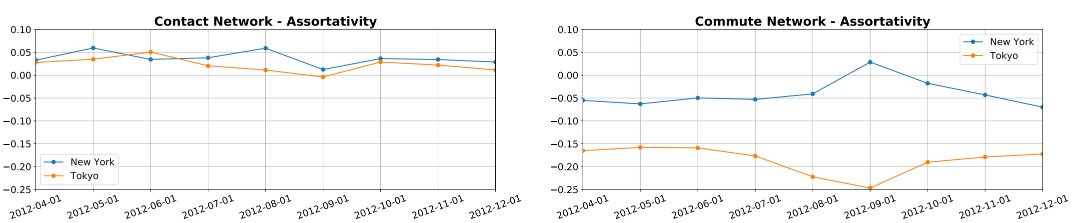

Fig. 5. Assortativity for **contact network** (left) and **commute network** (right)

We observe the clustering coefficient for contact and commute network for New York and Tokyo in Figure 6. The mean values for clustering are very low, meaning that there is a low tendency to form triangles between people and that people visit more than their neighborhood, for instance. In other words, the chance of a place (or person) be connected to other in the network is low.

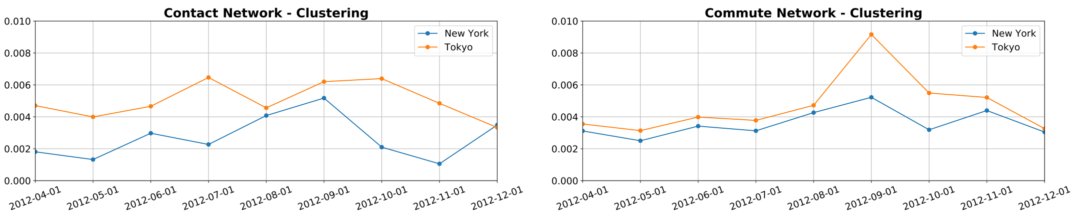

Fig. 6. Clustering coefficient for **contact network** (left) and **commute network** (right)

Figure 7 exhibits the diameter for New York and Tokyo in contact and commute networks, respectively. Regarding the contact network, in New York, we see a high diameter, of 40, that stands out from the other values. The user responsible for this diameter only meets another person in a Dog Park, going to different places from other people in data. In commute network this difference does not occur, since the Dog Park is a subgraph that is not within the biggest component (there is not trajectory from people to this park). Remember that the diameter here is calculated to the biggest component, otherwise, the diameter would be infinity.

In general, New York present more difference in its network, whereas Tokyo is more steady in its diameters along the months.

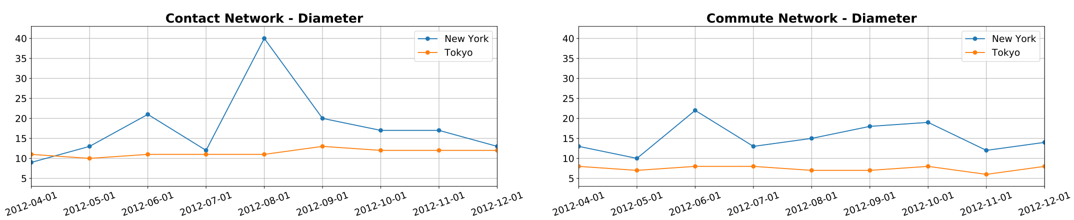

Fig. 7. Diameter for **contact network** (left) and **commute network** (right)

In Table 3 we see the places that present the diameters in monthly commute networks. Such analysis for contact networks is harder to understand, so we do not cover it in this study. Most of the places with highest diameter are places related to food in both cities. It makes sense, since food depends heavily on user's taste, hence, they may choose different places to eat. The other places we see are also dependent on taste, such as stores, record shop, and convention center. Differently from train stations, for instance, where people from all tribes go.

4.4 Closeness, Betweenness, Eigenvector, Eccentricity, and weight distribution

Now we want to understand the relationship between the nodes in both type of networks. In Figure 8 we see the weight distribution for contact and commute network for New York and Tokyo. We show only the distribution for May 2012, due to space constraints. We note that the weight tends to follow a Power Law, since most nodes present low weight and some nodes present high weight. It means that the encounters, regarding the contact network, does not occur often between people in the city. We can also note that there is a considerable amount

Table 3. Places with biggest diameter in commute network

New York									
Month (2012)	**Apr**	**May**	**Jun**	**Jul**	**Aug**	**Sep**	**Oct**	**Nov**	**Dec**
Place	Japanese Restaurant	Women's Store	Record Shop	Coffee Shop	Bar	Coffee Shop	Bakery	Hot Dog Joint	Diner
Diameter	13	10	22	13	15	18	19	12	14
Tokyo									
Month (2012)	**Apr**	**May**	**Jun**	**Jul**	**Aug**	**Sep**	**Oct**	**Nov**	**Dec**
Place	Clothing Store	Bookstore	Convention Center	Italian Restaurant	Indian Restaurant	Food & Drink Shop	French Restaurant	Diner	Japanese Restaurant
Diameter	8	7	8	8	7	7	8	6	8

of people who do not encounter nobody (present 0 weight). Furthermore, two encounters presents the biggest frequency. For commute network, similar phenomenon is observed. However, the biggest weight is higher than the contact network.

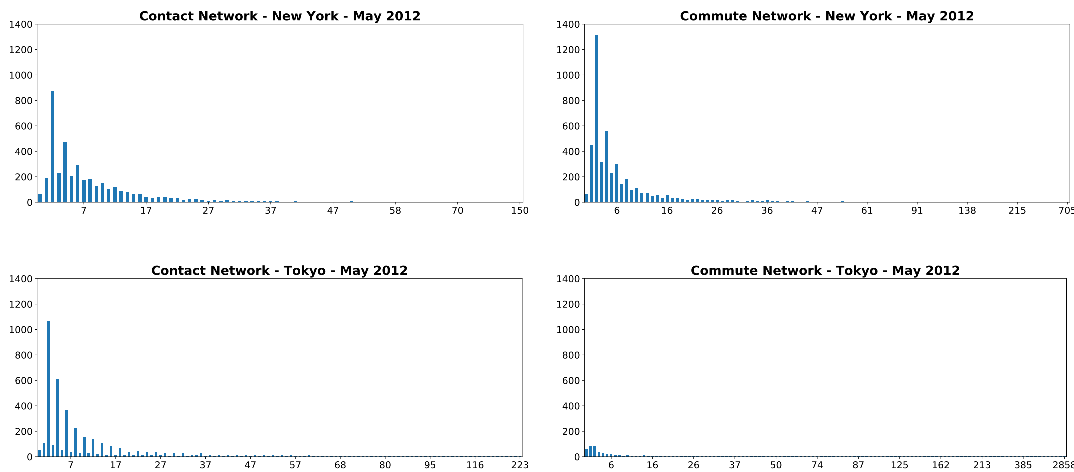

Fig. 8. Weight distribution for **contact network** (top left) and **commute network** (top right) for New York and Tokyo (bottom left, contact network and bottom right, commute network) in May 2012

In Table 4 we see the top-5 places visited in both cities, based on their weight. In Tokyo we see that train stations are the most visited places. They also present the highest betweenness, closeness, and eigenvector among the nodes in the network. Hence, they are very central in the network, and, generally, they are connected in trajectories (indicating that people use a train station to reach another train station, as a transfer). We can conclude that train stations are very important to mobility in Tokyo.

On the other hand, New York present not only train stations, but also airports and a plaza. The train stations and airports are important to mobility as well, since they have the highest betweenness in the network, meaning that they are "in the middle" of many trajectories made in the city. Similarly, train stations are important in New York as well, but airports are as much important as them, since New York is a very visited place, for both business and leisure.

Out of curiosity, the plaza that appears in New York is the Times square, a very famous place that tourists and citizens like to visit, with a largest concentration of entertainment industry (such as Broadway shows) and large stores of famous international brands. Hence, as this result stated, people is likely to visit such place.

Table 4. Centrality measures for commute network in New York and Tokyo, May 2012

New York (May 2012)				
	Weight	Betweenness	Closeness	Eigenvector
Train station	705	0.144	0.357	0.477
Airport	589	0.111	0.364	0.385
Train station	556	0.121	0.360	0.213
Airport	489	0.134	0.371	0.286
Plaza	443	0.068	0.347	0.218
Tokyo (May 2012)				
	Weight	Betweenness	Closeness	Eigenvector
Train station	2858	0.131	0.358	0.490
Train station	2814	0.177	0.367	0.504
Train station	1572	0.159	0.362	0.331
Train station	1537	0.081	0.374	0.340
Train station	1299	0.109	0.355	0.278

5 CONCLUSION

Mobility is very important to human existence, hence, understand such phenomena is paramount to interpret human behavior, individually and as a society. The present work investigated if the dynamics in a city could be understood through people's mobility. To this, we use data collected from a very famous location-based social network (LBSN) called Foursquare, in which people can share their location with friends. We use Complex Network tools to analyze such data.

We build two types of networks: the contact data, that describe the encounters people have in a city; and the commute data, that represent the trajectories that people does between the places in a city. We investigate New York and Tokyo, in order to understand how the cultural distance between these cities impact people's behavior and, consequently, the dynamics of cities.

In our investigation, we observed that people in New York are more open to share their information, whereas people in Tokyo city mainly use the social network in "transitional places", such as train stations. We also detected that people does not form many clusters in both cities, meeting others "by chance". The data present a power law behavior, with most nodes having low weight and few nodes with high weight.

Other discovery is related to the diameter. Food places have the biggest diameter in commute network, since such places are dependent on user's taste, hence, people do not visit the same places to eat. On the other hand, places with the smaller diameter are "transitional places", where people from all tribes go.

Examining such finding and the centralities, we can conclude that train stations are very important to Tokyo's mobility. They are important to New York, as well, but in this city airports are as much important as train stations, since it is a very visited city, for both leisure and business. Interestingly, the Times square, a very famous touristic point, also appears as an important node in New York network.

For future works, we intend to evaluate other time intervals, such as years or time of the day, in order to examine if they can provide more information about the dynamics in cities. We also intend to assess the user's persistence among the networks. Furthermore, we want to evaluate Foursquare data for 2020, in order to study how the COVID-19 pandemics impacted the mobility.

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