Universidad de los Andes

Departamento de Ingeniería Industrial

Proyecto de Grado 2

Temporal social networks within *Recreovía* users: measuring cohesion emerging from a physical activity program in Bogota, Colombia.

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1. Abstract

Physical inactivity is the major risk factor for non-communicable diseases, which in low and middle-income countries account for 48% of globally deaths. The *Recreovía* has been assessed as one of the most influential mass recreational programs aimed to promote physical activity without racial or socio-economical distinctions in Latin America. In the present study, we used static and temporal network analyses to study the characteristics of social networks created around the *Recreovía* program of Bogotá, in order to evaluate if the interaction between participants is creating cohesion and social capital. First, we built a network of the *Recreovía* Facebook user to determine the main stakeholders and communities that form the network. Second, we aggregated the Facebook friendship networks of three *Recreovía* stations to study the temporal network cohesion. We implemented the Time Windows in Networks (TWIN) algorithm to detect relevant events in the network growth and we adapted a scaling model of cities growth to measure cohesion over time. The results suggest that the program main influencers are the physical activity instructors. Moreover, the aggregated network presents meaningful growth changes in cohesion over periods of 20 months, suggesting that the program creates social ties in a super linear way. Even if the network is growing, it is necessary to create sustainable growth strategies. We recommend using physical activity instructors as influential seed-nodes to renew the program's innovative cycles and estimate goals of growth and cohesion.

2. Introduction

The *Recreovía* program of Bogotá started in 1995 with the goal of creating additional spaces for recreation and sport to the *Ciclovía* program of Bogotá, Colombia. [1] The *Ciclovía* is a free, multicultural and community-based program in which streets are temporarily closed to motorized transport, only allowing the entry of individuals for recreation and physical activity purposes. [2] The *Recreovía* aims to promote physical activity, health habits and social equity, through musicalized and directed group classes. [3] Moreover, the classes are free to the public with neither distinction of race, gender nor socioeconomic condition and they are carried out in public spaces such as parks, malls or open streets throughout the city. [3]

Thanks to the facilities that the program offers to citizens, there have been studies that show how the participation in the *Ciclovía* and *Recreovía* programs have social and environmental benefits for the community. In the case of *Ciclovía*, due to use of non-motorized transport on the city streets (Figure 1), such as bicycles, skates or pedestrians, there has been a decrease in pollution caused by motor vehicles during working days. [4] In the case of *Recreovía*, the participation in this program benefits the quality of lives of attendees through the increase in hours and levels of physical activity and its impact on the prevention of non-transmissible diseases [5]. Moreover, the participation promotes an increase in social capital in the community, thanks to citizen mobilization and the inclusion of attendees. [4] [6]

Figure 1 Map of Recreovía program stations and city streets of Ciclovía program in Bogotá, Colombia.

Through studies conducted on the cost-effectiveness of the program, it was noticed that the *Recreovía* has an approximate cost of $0.8 USD to the government, per user per class of 45 minutes and offers great benefits to public health. For example, women who are regular attendees are 2.4 times more active than those who are not attendees; for 2 out of 5 attendees, the *Recreovía* is the only space to practice physical activity. [7] Furthermore, studies have been conducted on the *Ciclovía* program as a social network, which is composed of interconnected organizations that use collaboration and cooperation to promote physical activity. [2] However, there are no studies about the performance of *Recreovía* as a social network; as a consequence, the citizen integration in this program has not been evaluated.

Therefore, it has created the necessity to investigate the ability of the program to generate social capital through the cohesion of its attendees.

Taking into account the above, in this study we seek to understand dynamics around the *Recreovía* social network, in order to evaluate cohesion among its participants and to promote growth of networks created. Hence, we characterized the social network created around the Facebook profiles of the *Recreovía* program, owing to studies that show how people have similar social behavior in online spaces and in real-life. [8] On top of that, the influence of technology tools on physical activity promotion has been demonstrated, where the reception of text messages with information about sports and healthy habits promoted the increase in frequency of physical activity. [6] Thus, first we used the social network of the Facebook profile of the complete *Recreovía* program to study its characteristics and to identify its stakeholders and its community structure. Second, we aggregated the social networks of the Facebook profile of three *Recreovía* stations to study the growth of the aggregated network in regards to number of friends and connections between them, through temporal windows that allowed us to detect relevant events. Finally, we studied the topology of the network in relation to their degree distribution.

3. Methodology

3.1 Data collection

For data collection, we used four different *Recreovía* program accounts that were provided to us by the District Institute of Recreation and Sports (IDRD of its Spanish acronym), which is the organization in charge of designing and implementing the *Recreovía* in Bogotá. The Facebook accounts provided were the main *Recreovía* program account and three accounts belonging to three specific *Recreovía* stations in the city.

Firstly, we used the first account to gather the main *Recreovía* Facebook account friendship network in 2013, by using the Facebook application Netvizz. [9] The network was undirected and composed of 3597 nodes which represented Facebook friends of the *Recreovía* account, and 51361 edges that represented a mutual friendship between the nodes.

Secondly, we used the three specific accounts to gather a Temporal Facebook friendship network in 2016 for the *Recreovía* stations*: Recreovía Valles de Cafam*, *Recreovía Santa Isabel* and *Recreovía Meissen*, by using Lost Circles [10] In these networks, the nodes represented Facebook friends of the specific *Recreovía* station and the edges represented a mutual friendship between the nodes. We also collected the public and available work information for each node from its Facebook profile; we categorized these works in relation to the *Recreovía* program (Table 1), and the starting date of each friendship as an attribute for the edges. We collected data over 98 months, from June 2008 until August 2016. We aggregated the three networks into a single one obtaining a single network for the temporal analysis with 272 nodes and 5130 edges. In all of the networks, the *Recreovía* Facebook accounts were removed to avoid having super connected nodes.

Finally, we conducted a survey of real life attendees of two *Recreovía* stations: *Valles de Cafam* and *Santa Isabel* to validate the analysis made with the Facebook social networks. In the survey we asked questions related to groups and cohesion created in off-line spaces, and the use of Facebook as a tool of information inside the *Recreovía* program and those groups. We didn’t conduct surveys in *Recreovía Meissen* because the station was closed.

3.2 Detection of network communities and principal stakeholders

We performed procedures to characterize the *Recreovía* network, identify communities and their roles inside the network, and detect the principal stakeholders to use them as seed nodes to spread information of Physical Activity and Healthy habits. We gave the results of these procedures to the IDRD to promote the program.

For the Main *Recreovía* Facebook Profile (MRFP) network the principal communities were detected using the Louvain’s algorithm of maximum modularity, [11] where the greatest values of modularity have to be present when similar nodes are in the same community and smallest values of modularity between communities. [12] Initially, we had a community per node and we were grouping communities based on whether they had a positive influence on the total value of modularity of the network. Then, with IDRD agents it was determined who made up every community. Finally, we identified the most influential people inside the MRFP network, taking into account a measure of centrality. Hence, we measured the degree centrality and we filtered the network to find those nodes with more than 300 friends.

3.3 Analysis of temporal network

For the Aggregated *Recreovía* Facebook Profile (ARFP) network we conducted a temporal study of growth in amount of friends and social cohesion of the *Recreovía* in Facebook as an indicator of program success.

3.3.1 Selection of time windows

First, we determined how to divide the network observation time to analyze appropriately the network evolution and find meaningful changes in the network growth. For that purpose, we implemented the TWIN algorithm [13] to identify the time windows with the meaningful resolution level. That algorithm allowed us to detect critical changes in the network structure. We compensated the noise caused by oversampling, due to watching the network one month at a time, and the loss of information, due to watching the network only one time at the end of the timeline of 98 months

We started the algorithm by creating a compressed network with the most connected nodes of the ARFP network and we took individuals with more than 100 connections. In each iteration we divided the timeline in T windows of size w and we created a graph time series with the entire network $G_w = [G_1, G_2, \ldots, G_T]$, where we calculated a time series of one statistic $F_w = [f(G_1), f(G_2), \ldots, f(G_T)]$. Due to the network characteristics, we used the average length of the shortest path between each pair of nodes. Subsequently, we determined the variance of the statistical time series $V(F_w)$ and it was compared with the compress ratio $R(F_w)$

$$R(F_w) = \frac{u}{c}$$

Here u is the length of the vector F_w for the entire network and c in the length of the vector F_w to the compress network. Finally, we selected the windows of size w that minimized the gap between the variance as noise measured in F_w and the compress ratio as a hidden information measured in F_w; it was represented as $argmin_w|V(F_w) - R(F_w)|$.

3.3.2 Evolution of the network growth

After finding the appropriate window size we evaluated the network growth in terms of the number of nodes and edges, per window and over a timeline of 98 months. Then, we determined if the dynamic of the network growth was related with the generation of social capital among the *Recreovía* Facebook friends. To carry this out, we adapted to our context the scaling model of cities growth of Bettencourt & Geoffrey B. West [14], where we used the next equation to measure social activity and its growth related with the population size over time. In our context, Y represented the number of friendships as a measure of social capital and $N(t)$ represented the number of friends at the time t.

$$Y(t) = Y_0 N(t)^{\beta}$$

Here we had to estimate β to characterize the network growth. In the case of $\beta < 1$ we would consider a sublinear model with a growth of number of friends greater than the growth of connections between them; in the case of $\beta = 1$ we would consider a linear model with growth of friends and connections at the same rate, and in the case of $\beta > 1$ we would consider a super linear model with growth of friends smaller than growth of connections.

3.4 Topology of the Network

Finally, with the temporal study we calculated the degree distribution of the ARFP network. That is the probability $p(k)$ that each Facebook friend has k different friends, and we approximated different distributions to know what was the kind of network and the theoretical behavior that it should follow.

4. Results

4.1 Detection of network communities and principal stakeholders

As a result of the maximum modularity algorithm in the MRFP network, we detected 48 communities, with 5 principal communities whose nodes corresponded to 83% of the total population inside the MRFP network. (Figure 2-Left) We identified the kind of stakeholders in each community and we determined that the instructors of physical activity and other members of IDRD was the biggest community with 20.84% of the total nodes. That community was studied as an independent network to understand its characteristics and components. For example, it had a greater density and clustering coefficient, and smaller diameter (Table 1) than the MRFP network because the instructors network was a more connected network. Additionally, we identified the communities inside the independent network with the maximum modularity algorithm [11] and we found that a division related to 3 leading instructors was made (Figure 2-Right).

Figure 2 ***Left:*** *The Main Recreovía Facebook Profile (MRFP) network. Each color represents a community detected with maximum modularity algorithm of Louvain. The green color represents workers of Fitness companies, the light blue color represents attendees to the Recreovía classes, the pink color represents city hall members, the red color represents different institutions, organizations and famous people, the dark blue color represents the instructors of physical activity and other members of the IDRD and the yellow color other communities.* ***Right:*** *The instructors of physical activity and members of IDRD community in the main Recreovía Facebook friendship network. Each color represents a community detected with maximum modularity algorithm of Louvain. The red color represents friends of the instructor WM, the green colors represents friends of the instructor LH and the yellow color represents friends of the instructor WP. That information was determined with IDRD members.*

4.2 Time windows in the temporal network

We implemented the TWIN algorithm to the ARFP network, and we created a compressed network with those nodes whose degree was greater than 100 (Figure 3-Right). In the compressed network the more connected nodes were the physical activity instructors with 48.57% of the nodes. The result of the algorithm showed us that the appropriate windows size was 20 months, with 5 windows to detect the meaningful changes in the network over time (Figure 4). The timeline division with those time windows showed us how the increase over time is faster for the number of connections than for the number of nodes. (Figure 5) For example, between windows 4 and 5 there was an increase of 34 nodes while 954 new friendships in Facebook were created between friends of the *Recreovía* program.

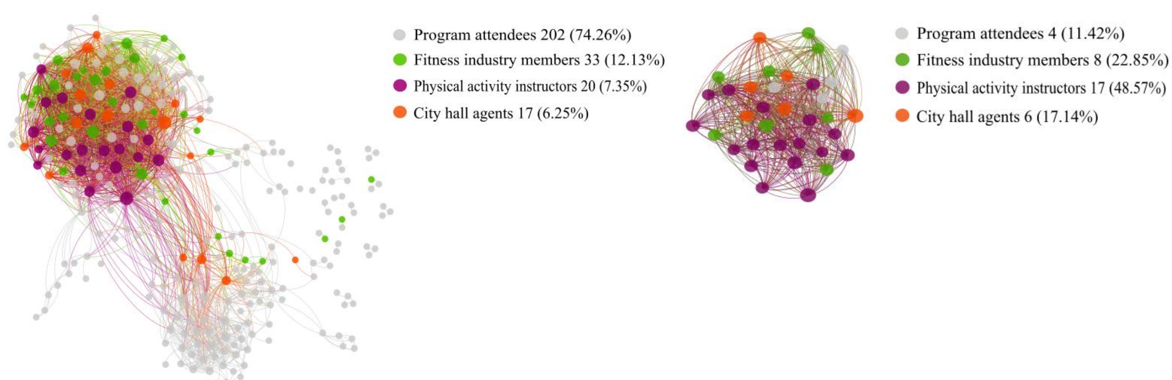

Figure 3 ***Left:*** *The aggregated Facebook profile network of Recreovía Valles de Cafam, Recreovía Santa Isabel and Recreovía Meissen, where the size of nodes represents their degree.* ***Right:*** *The compressed aggregated Recreovía Facebook profile network, it is composed by those nodes with degree greater than 100.*

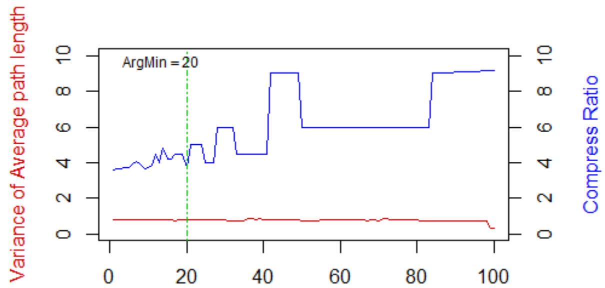

Figure 4 Results of all iterations of the Time Windows in Networks algorithm in the aggregated Facebook social network of three Recreovía program stations in Bogotá, where the minimum argument was found with windows size of 20 months, the green dashed line represents this minimum value.

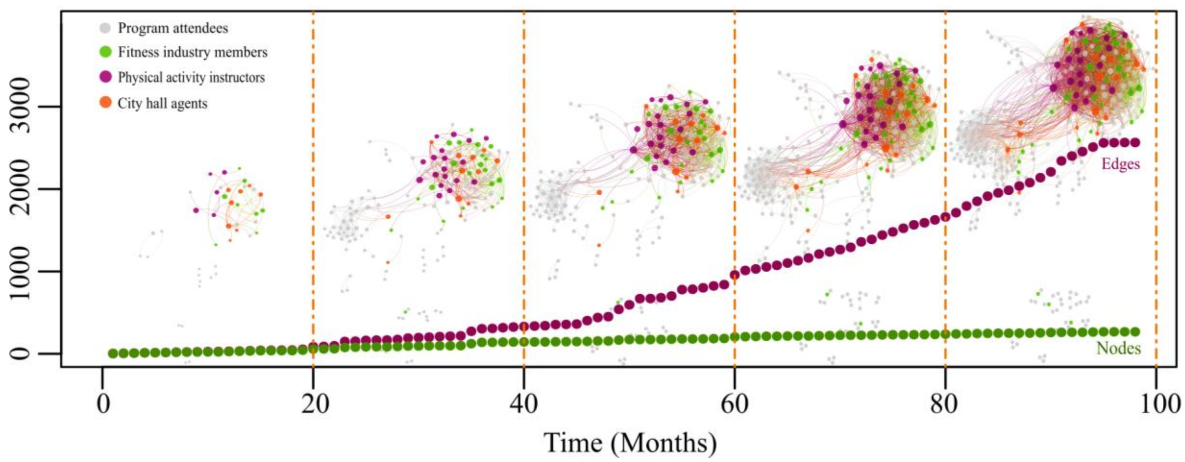

Figure 5 Temporal growth of the aggregated Facebook social network of stakeholders of three Recreovía program stations in Bogota in windows of 20 months. The purple graph represents the number of edges and the green graph represents the number of nodes over time. The orange dashed lines represent the time windows where relevant growing events were detected.

4.3 Evolution of the network growth

We evaluated the growth of the size and cohesion in the network during every time window (Figure 6) and we found two jumps in the growth of number of friends between consecutive months. Also we found a deaccelerated growth for network size in the last three windows ($\hat{\alpha}_3 = 2.7, \hat{\alpha}_4 = 1.5, \hat{\alpha}_5 = 1.7$) in relation with the slope in the second window ($\hat{\alpha}_2 = 4.4$) and we observed a linear slope for the transformed data with the natural logarithm. Similarly, we evaluated the growth of connections, and, in this case, it had an accelerated behavior in all time windows ($\hat{\alpha}_1 = 3.1, \hat{\alpha}_2 = 12.1, \hat{\alpha}_3 = 32.4, \hat{\alpha}_4 = 35.7, \hat{\alpha}_5 = 55.3$). We also observed a super linear slope in the number of connections transformed by the natural logarithm.

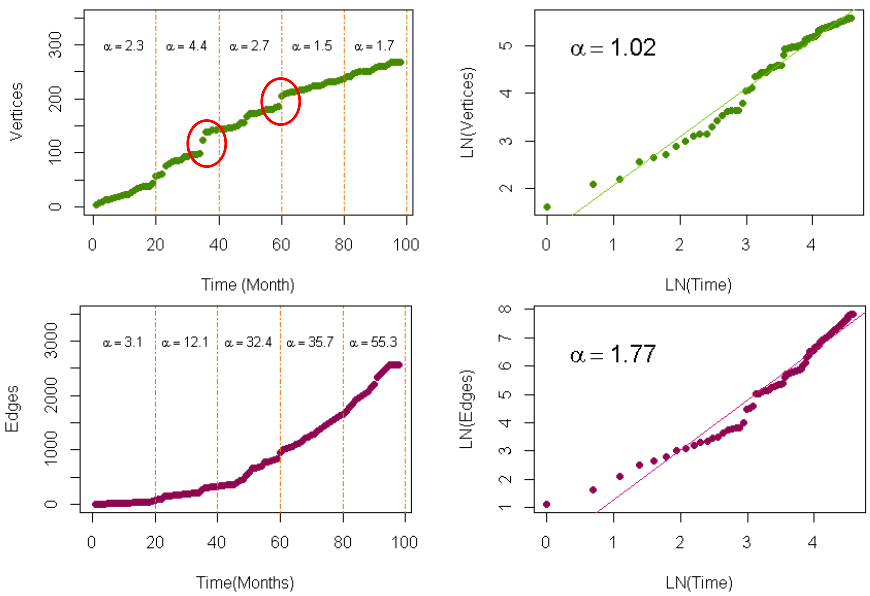

Figure 6 ***Top left:*** *Growth of the number of friends in the aggregated social network of the three Recreovía stations Facebook profiles above the 98 months, he dashed lines represent the time windows and the alpha values the slope in every window.* ***Top right:*** *Growth of the number of friends and time transformed with natural logarithm to correct the scale.* ***Bottom left****: Growth of the number of friendships in the aggregated social network above the 98 months, the dashed lines represent time windows and the alpha values the slop in every window.* ***Bottom right:*** *Growth of the amount of friendships and time transformed with natural algorithm to correct scale.*

With the scaling model of cities growth, we found a super linear model with a growth of friends smaller than the growth of connections in the ARFP network, with $\beta > 1$ and a R^2 near to one (Figure 7). Likewise, we studied each *Recreovía* station separately and we found that the slope of every single station is super liner too; nevertheless, their values are smaller than the slope of the aggregated network. (Figure 8) What is more, we detected some jumps in each growth; only the amount of connections grows as in the fourth window of *Recreovía Meissen* and in the second and fourth windows of *Recreovía Santa Isabel.*

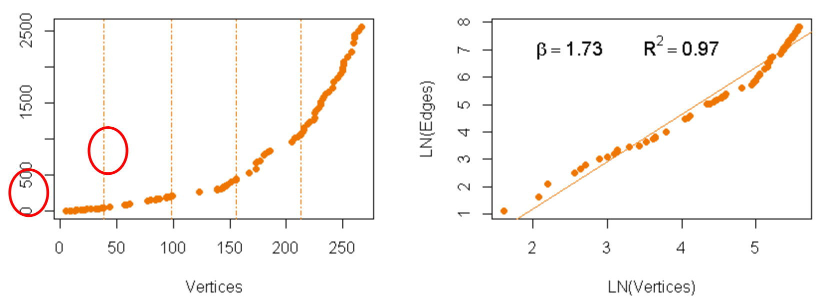

Figure 7 Temporal review of the aggregated social network of three Recreovía stations with the scaling model of cities growth of Bettencourt & Geoffrey B. West. ***Left:*** *Relation between amount of friends and friendships in the Facebook profile of the program, and dashed lines to represent the relations in the time windows found with the TWIN algorithm.* ***Right:*** *Natural logarithm transformation of nodes and edges to correct scale problems.*

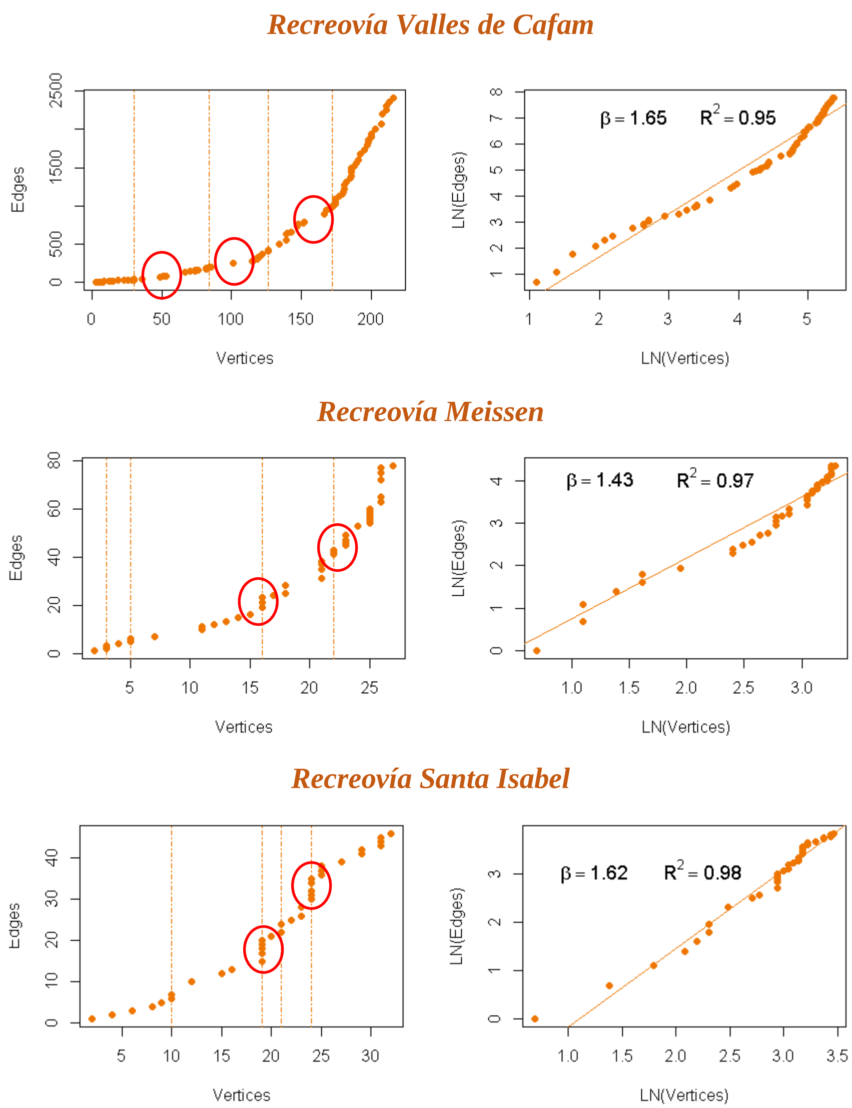

Figure 8 Temporal review of the social network of three Recreovía stations with the scaling model of cities growth of Bettencourt & Geoffrey B. West. ***Left:*** *Relation between amount of friends and friendships in the Facebook profile of each station, and dashed lines to represent the relations in the time windows found with the TWIN algorithm.* ***Right:*** *Natural logarithm transformation of nodes and edges to correct scale problems.*

4.4 Topology of the network

We studied the topology of the ARFP network and we found that its degree follows a Power-Law distribution: $P(k) = C \cdot k^{-\lambda}$, [12] with a p-value of 0.99 in the Kolmogorov & Smirnov test to adjust distributions. (Figure 9)

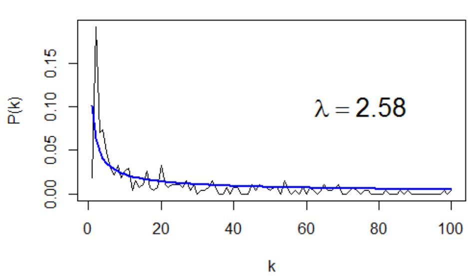

Figure 9 Power-Law degree distribution of the ARFP network where it follows a preferential attachment behavior where few nodes had the majority of connections and many nodes had connection amounts near to zero.

5. Discussion

The *Recreovía* is a cost-effective program that benefits the quality of lives of attendees, thanks to the increase in levels and hours of physical activity. [3] [7] Therefore, it is necessary to know how the program creates social ties and information systems as a social network [15] to promote physical activity and healthy habits. Taking into account the increase in physical activity due to technological tools which spread information, [6] the online social networks could help us to characterize physical activity programs in a cost-effective way. This study is the first to evaluate the social network created around the *Recreovía* Facebook profile as a static and temporal network. The analysis showed how the *Recreovía* Facebook profile has created a growing social network among attendees of the program, members of IDRD and fitness institutions.

In spite of the low densities as evidence of scattered networks [12], the MRFP network and the ARFP network have clustering coefficient and diameter values (Table 2) of Small World, where these networks have cohesion properties that allow an accelerated spreading process of information and social activity between their nodes. [16] The community detection algorithm implemented to the MRFP network and the compress network in the TWIN algorithm implemented to the ARFP network showed how the members of the IDRD are the most connected components in these networks. Moreover, their values of density, clustering coefficient and diameter (Table 2) are better to follow Small World properties, making faster the spread of information. Also, this community has clusters in relation to three super connected instructors that should be used as seed nodes to start spreading processes of information about healthy habits in both networks.

In the temporal study of the ARFP network, we noticed how the number of friends had a slower and more decelerated growth than the number of connections, inside the time windows and over the timeline. With the scaling model, we detected that for every new friend there was 1.73 new connections in the network. (Figure 7-Right) Thus, the ARFP network has an innovative behavior with the creation of social capital inside the online environment of the program. [14] With the study of every single station, we noticed that *Recreovía Valles de Cafam* had the biggest amount of nodes in the online community, where there are jumps in the number of nodes related to activities encouraging the online participation in off-line attendees. Also, in *Recreovía Meissen* and *Recreovía Santa Isabel* the jumps where in relation to number of nodes and connections.

The last results were corroborated with the surveys made to those points, where *Valles de Cafam* had an average of 100 attendees and *Santa Isabel* an average of 30. Moreover, the surveys gave us information about how the age range of attendees influenced the use of technological tools in every station. For example, in *Recreovia Santa Isabel* there were more pensioner attendees (>57 year), people resistance to use Facebook as technological communication tool; while in *Recreovía Valles de Cafam* there were more employees ([18,57] years), people open to use Facebook to know information about the program.

With the degree distribution, we found that the ARFP network had a behavior of preferential attachment [17] where there are few super connected nodes: those found in the TWIN algorithm with the compressed ARFP network (Figure 5-Right); and there are many nodes with connections near to zero: the attendees. It caused a Scale Free network, where the average degree didn't tell us anything about the network thanks to the variability of the distribution, and the value of the power-law coefficient λ between 2 and 3 made an Ultra Small World Network. [18] In consequence, the super connected nodes should shrink the distance between nodes doing faster the information flow in the network. However, the compress AFRP network is highly dense (Table 2 and Figure 5) and those super connected nodes weren't connected with the isolated attendees. As a result, we detected a cohesive community composed by fitness industry members, physical activity instructors and city hall agents with many paths of information flow; while there were many isolated attendees with few or any paths in the network.

Finally, we recommended to the *Recreovía* directors the promotion of online social networks in its attendees, due to their low cost and efficiency as an information tool. Moreover, they should use the instructors of physical activity as promotors and made activities to create interaction among popular friends in Facebook and the isolates ones. For future work, we opened the possibility of create growing models to estimate goals of population and cohesion in online and offline networks of the program, and create experiments related to spread information inside communities of attendees.

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Table 1 Kind of nodes in the Aggregated Recreovía Facebook Profile network

Work	Description
Program attendees	Facebook profiles without a job description related with the *Recreovía* program
Fitness industry members	Facebook profiles without a job description related to the *Recreovía* program but related to Fitness and Health care centers
Physical activity instructors	Facebook profiles with a job description of physical activity instructor of the *Recreovía* program
City hall agents	Facebook profiles with a job description related to the city hall or administrative staff of *IDRD* and *Recreovía* program

Table 2 Characteristics of the principal networks

Network name	Nodes	Edges	Density	Clustering coefficient	Diameter
The main *Recreovía* Facebook Profile	3184	51361	0.008	0.407	10
The instructors of physical activity and members of IDRD community in the main *Recreovía* Facebook Profile	750	9864	0.035	0.53	7
The Aggregated *Recreovía* Facebook Profile	272	5130	0.139	0.212	7
The Compressed Aggregated *Recreovía* Facebook Profile	34	954	0.941	0.464	2