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Centrality Metrics and Line-Graph to Measure the Importance of Links in Online Social Networks

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***Abstract*— Importance of nodes and tie strength are necessary elements to characterize and analyze networks, as well as to study the processes that occur in their interior. We believe that it is also necessary to know the importance of links to have a better characterization of the networks in the study of those processes. In response to this situation, we propose a method to measure the importance of the links.The method is based on applying the line-graph mathematical concept to the graph representing the network, thus we create a new graph in which we apply centrality metrics to find the importance of network links.**

***Index Terms*— Importance of Links, Centrality Metrics, Line-Graph. Social Networks Analysis.**

I. Introduction

The online social networks (OSNs) [1] are technologies used by a growing number of users to establish and maintain contact between them, as well as to be rapidly informed of the events that happen around them. Also, these technologies are used to try to influence people in different situations. Thus the OSNs are changing strongly the habits and the life of millions of people. On the other hand, the appearance and rapid growth of the OSNs is an important cause of the increase of traffic in Internet. [2], [3].

It is important to know the structure and characteristics of networks and studying the dynamics that occur in its interior. Thus is possible to make a better design of the business linked to the OSNs, advertising campaigns, web applications, and to predict traffic in Internet generated by the OSNs[4].

Two of the above dynamics that occur in online social networks are the diffusion of informationand the spread of influence. A way to study and simulate these phenomena is by applying Social Network Analysis[5], which in turn uses a part of mathematics called Graph Theory. A social network can be represented mathematically by a graph, which is made up of vertices and edges. In a social network the vertices represent individuals and edges represent the relationship between individuals.

There are many studies about the dynamics of the spread of information [6] and influence[7] in social networks that are on the importance of nodes and strength of ties. There are several centrality metrics for determining the importance of the nodes.Also there are metrics of strength of ties based on the amount of information exchanged between nodes.

We believe that it is also necessary to consider the importance of the links of the network. Thus we can characterize best the networks, which will allow us to study its internal dynamics such as the diffusion of information and spread of influence. Since there are few metrics to measure this feature, we propose a general method to apply to the links the metrics of centrality exist and in this way to measure their importance.

In our method we represent the network with a graph called G. We apply in G the mathematical concept line-graph to create a new graph L(G) whose nodes represent the links of G. Then we use the metrics of centrality in L(G) to calculate the importance of its nodes. These values correspond to the importance of the links of the graph G. Later we will again refer to the graphs G and L (G) in this document.

We have implemented the concept line-graph in a software program, we have tested its performance in a real network of friends on Facebook, we applied five centrality metrics, and we have analyzed their results.

This document has the following content: Section II makes reference to some studies of importance of links; Section IIIdescribes some theoretical concepts and definitions; Section IV explains our method to measure the importance of links; Section V presents experimental results and analysis after applying our method to calculate the importance of the links; Section VI contains conclusions and comments; and Section VII suggests future work.

II. Related Work

There are few defined metrics to measure the importance of links. These metrics have been presented in the following works.

M. Girvanand M. E. J. Newman [8] generalize Linton C. Freeman's betweenness centrality to edges to find which edges in a network are most closer between other pairs of vertices, defining the edge betweenness of an edge as the number of shortest paths between pairs of vertices that run along it.

A. S. Teixeira et al. [9] define the spanning centrality of an edge for undirected and weighted graph as the number of spanning trees in which the edge participates, assigning to the

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edge an importance score.

That is, important edges participate in many spanning trees. This metric is defined as the fraction of minimum spanning trees where a given edge is present.

P. Meo et al. [10] generalize the centrality of node k-path of Donald S. Sade to edges, defined as the number of paths of at most length k that connect with other edges.

Table I: Meaning Of Importance For Nodes And Links

Degree Centrality
Nodes. It measures the number of neighbors that has a given node. A node with high degree is possibly a bridge node, or maybe it can propagate information in fast form. In social networks a person with high degree is possibly influential, or can control the communication between other people. Links: It measures the number of neighboring nodes that has a couple of linked nodes. A link with high degree is possibly a bridge link.
Closeness Centrality
Nodes. It measures the proximity and facility of a node to reach to other nodes. It measures the reciprocal of the shortest average distance from a node to all other nodes. A node with a high closeness can propagate information in fast form. In social networks a person that has a central position in a social environment is an important person. Links. It measures the proximity and facility of a pair of linked nodes to reach other pairs of linked nodes. It measures the reciprocal of the shortest average distance from a link to all others link. It measures the total number of shortest paths that pass through a specific link, acting as a bridge. A link with high closeness can support high traffic of information.
Betweenness Centrality
Nodes. It measures the importance of a node in terms of connecting other nodes. It measures the total number of shortest paths that pass through a specific node, acting as a bridge. A node with high betweenness can propagate information to greater distances. In social networks betweenness measures the control of a person on the communication between other persons. Links. It measures the importance of a link in terms of connecting two pairs of nodes, being the nodes of each pair connected to each other. It measures the total number of shortest paths that pass through a specific link, acting thus as a bridge. A link with high betweenness can support high traffic of information. In a network social, the link betweenness metric measures the importance that has a couple of people in the communication of other couples through that relationship.
Katz, Eigenvector and PageRank Centralities
Nodes. These metrics of centrality are based on the premise that the importance of a node depends on the importance of its neighbors, which in turn depend on the importance of their neighbors, and so on. In social networks a person with a high value in any of these metrics is a very influential person. Links. The importance of a link depends on the importance of its neighboring links, which in turn depends on the importance of their neighbors, and so on. A link is strong if links two clusters; or if its nodes have links to many nodes in common. In social networks the relation between two people with a high value in any of these metrics is a very important relation.

S. M. Faisa et al. [11] define the importance of the links as they maintain the structure of the communities of the network. Key intuition behind the method is: if two vertices of an edge share a lot of common neighbors, it is very likely that the edge belongs to a community structure in the graph.

III. SOME CONCEPTS AND DEFINITIONS

The importance of nodes and links are criteria that helpus to characterize networks. In general, the term "importance" refers to the relative preponderant position that has a node or link within the network, facilitating thus the flow of information [12].

There are multiple metrics of centrality to determine the importance of nodes [5], which in turn are based on the topological structure of the network. Some of these metrics are: degree centrality, closeness centrality, eigenvector, Page Rank, betweenness centrality and k-path centrality.The two last named metrics expanded its definition to apply to links in order to determine its importance.

It is important to point that, although the L(G) graph nodes represent links in the graph G, the meaning of betweenness link metric directly applied to the links of G has a slightly different meaning if this metric is applied to the nodes of L(G). As its is known, edge betweenness centrality applied to G measures the importance of a link in terms of connecting to other nodes.

Table shows the meaning of these centrality metrics applied to nodes, as well as the extension of these concepts applied to links. Recall that these metrics are applied to the graph L(G).

IV. DESCRIPTION OF THE METHOD

Here we describe the process performed to calculate the importance of the links; then we perform an initial intuitive explanation of the mathematical concept line-graph. We present a formal definition of line-graph; and finally we describe the algorithm that finds the adjacency matrix of line-graph A (L (G)).

A. General Processes

In this section we explain the general processes needed to determine the importance of edges.Fig. 1shows a processes diagram and Table 2.

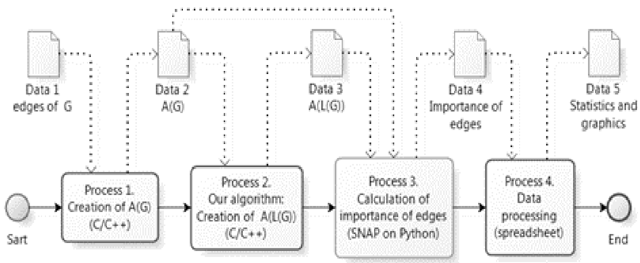

Fig.1: Processes Diagram

Process 1creates A(G) (Data 2) which is the adjacency matrix of the graph G. The input data (Data1) is a text file containing links G.

Process 2 creates A(L(G)) (Data3) which is the adjacency matrix of the graph line-graph L(G). The input data (Data2) is the adjacency matrix A(G) of the graph G.

Process 1 and 2 have been implemented using the programming language C/C++.

Process 3 calculates the importance of the vertices of the graph L(G) equivalent to the importance of the edges of G. These results are stored in a text file (Data4). The input data of this process are the adjacency matrices of G and L(G) (Data2 and Data3). In this process we used the SNAP [13] programming environment developed by Stanford Network Analysis Project. This environment provides tools that implement centrality metrics. The programs were developed using the Python programming language.

Process 4 calculates some statistical tables and graphics (Data 5) that permit characterize the graphs.

B. *Intuitive Explanation of Line-Graph*

Our method is based on the central idea that, if we look at the links of a network as if they were nodes, then we can apply centrality metrics in these "nodes" and thus determine the importance of the links of the network.

In the context of the graph theory, as well as the vertices have neighboring vertices, also the edges have neighboring edges; as well as exists vertices adjacency matrix, also we can constructan adjacency matrix of edges. In this way we can look the edges as if they were vertices.

The idea of looking at the edges as if they were vertexes rests on the mathematical concept called "Line Graph" [14], which mathematical formalization is showed below.

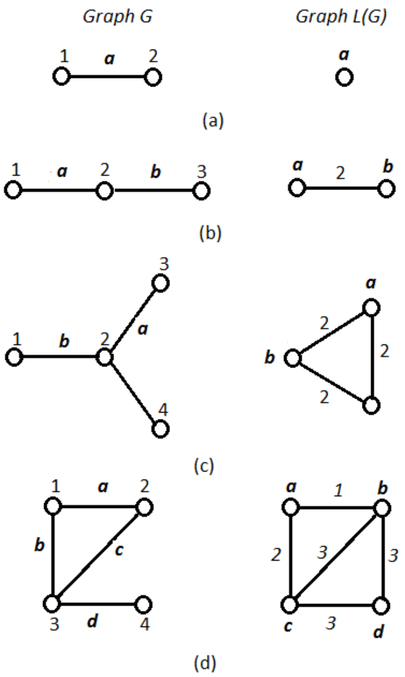

Fig.2: Graphs G and L(G).Vertices in L(G) represent edges in G.

We start by giving an intuitive graphic explanation through four simple examples of graphs G and its respective L (G), which are presents in Fig.2. As we observe in this figure, the transformation process from G to L(G) is reversible.

C. *Mathematical Formalization of Line-Graph*

Given a graph G = (V, E), where V = {v1, . . . , vn} is the set of vertices; the set of edgesE = {e1, . . . , em}; the number of vertices n = |V|; and the number of edges m = |E|.

A(G) = (aij) is the matrix of adjacency of G of order n x n, where aij is the number of edges between vi and vj. B(G) = (bij) is the matrix of incidence of G of order n x m, where bij = 1 if vi and vj are incidents, and bij = 0 in other cases.

Line Graph L(G) is the graph whose vertices represent edges of G. A(L(G)) = (lgij) is the matrix of adjacency of L(G)whose order is m x m.

Then,

$$A(L(G)) = (B^tB) - 2I_m \qquad (1)$$

Where I_m is identity matrix of dimension m.

D. *Description of the Algorithm*

Our algorithm constructs the adjacency matrix A (L (G)) from the adjacency matrix A (G). The algorithm comprises the following three main steps:

a. We create the adjacency matrix A (G) of the graph G which represents a social network.

b. In A(G) we count and identify the number of edges.

c. We create a square matrix with number of rows and columns equal to number of edges of A(G). Each row or column in this new matrix corresponds to an edge of A((G)). In the new matrix we mark with 1 all pairs of adjacent edges.

In this way we obtain the adjacency matrix A(L(G)), on which we apply any measure of centrality of nodes to determine the importance of vertices of graph L(G) that corresponds to the importance of edges of graph G.

As an example, we present in Table 2 the previous three steps applied to the graph of the Fig. 1(c) whose edges are: E={(1,2), (2,3), (2,4)}.

Table II: Steps applied to A(G) to find A(L(G))

Step a	Step b	Step c
$A(G) = \begin{bmatrix} 0 & 1 & 0 & 0 \\ 1 & 0 & 1 & 1 \\ 0 & 1 & 0 & 0 \\ 0 & 1 & 0 & 0 \end{bmatrix}$	$A(G) = \begin{bmatrix} 0 & 1 & 0 & 0 \\ 1 & 0 & 2 & 3 \\ 0 & 2 & 0 & 0 \\ 0 & 3 & 0 & 0 \end{bmatrix}$	$A(L(G)) = \begin{bmatrix} 011 \\ 101 \\ 110 \end{bmatrix}$

Now, we present a textual description, a flow diagram and the pseudocode for each one of the three main steps of our algorithm. All steps were programed using C/C++ programming language.

Step *a*:

This step creates the adjacency matrix of nodes of graph G. To do this, each row of text file that contains the links of the graph G is read and the data captured are stored in the variables node1 and node2 respectively. It assigns “1” to the elements of adjacency matrix G that are in the row and column (node1, node2) and (node2, node1) respectively. It closes the text file. Fig.3 presents the flow diagram of Step *a*.

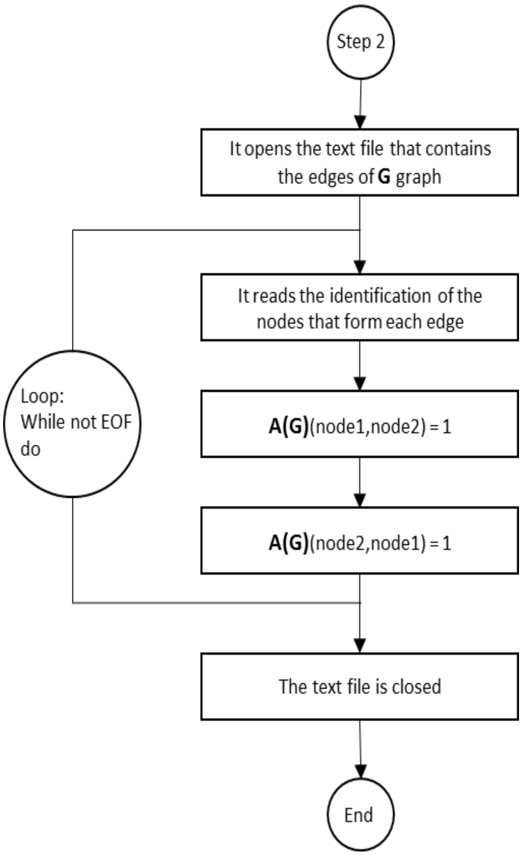

Fig.3: Diagram of flow of Step a.

Pseudocode of Step *a*:

```
file.open(fileNameGraphA,ios::in);
while (!file.eof()) {
        file >> node1 >> node2;
        A(G)[node1][node2] = 1;
        A(G)[node2][node1] = 1; }
file.close();
```

Step b:

We travel A(G) from left to right, starting with the first row to number sequentially from 1 to the upper triangular elements that have the value of 1. Then, for each element a_{ji} of the lower triangular A(G) we assign the value corresponding element a_{ij} of the upper triangular. Each element $a_{ji} > 0$ is the identification of the vertices in the graph L(G). Fig.4 presents the flow diagram of this step.

Pseudocode of Step b:

```
number_edges = 0;
for (i = 1; i < total_nodes; i++) {
      for (j = i+1; j < total_nodes+1; j++) {
          if A(G)(i,j) > 0 {
                A(G)(i,j) = ++number_edges;
                A(G)(j,i) = A(G)(i,j); } } }
```

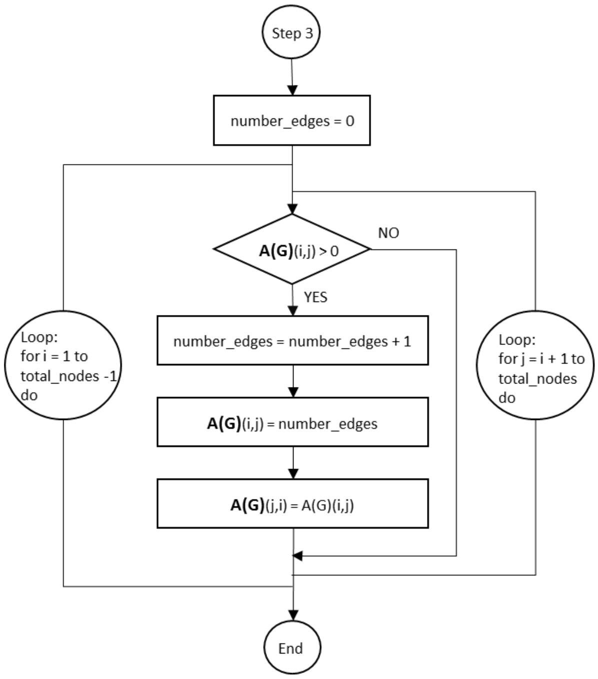

Fig.4: Diagram of flow of Step b.

Step c

With each and every one of the rows of the A(G) we perform all possible combinations between the elements greater than zero. Each combination represents an edge in the graph L(G). In this way, the first and second elements of each combination are the row and column respectively of each of the adjacency matrix of vertices in the graph L(G), which in turn represents the adjacency matrix of edges of the G. Fig.5 presents the flow diagram of Step 4.

Pseudocode of Step c:

```
for (i = 1; i < total_nodes+1; i++) {
       for (j = 1; j < total_nodes; j++) {
        if A(G)(i,j) > 0 {
                row = A(G)(i,j);
                for (k = j+1; k < total_nodes+1; k++) {
                     if A(G)(i,k) > 0 {
                         column = A(G)(i,k);
                         A(L(G))(row,column) = 1;
                        A(L(G))(column,row) = 1; } } } } }
```

V. EXPERIMENTAL RESULTS AND ANALYSIS

The different results of the tests we have done serve to intuit that centrality metrics applied to links can be very useful in the study of processes dissimilar, in certain processes using a particular metric while in other processes using other metrics. Two of these different processes could be the dissemination of information and the spread of influence. This section contains the following aspects: 1) the importance of links after applying the different metrics of centrality. 2) Accuracy of the results from degree centrality and betweenness centrality. 3) Effectiveness of the proposed measure. 4) Computational complexity of software that transforms the graph G on L(G), and of the application of the metrics on L(G).

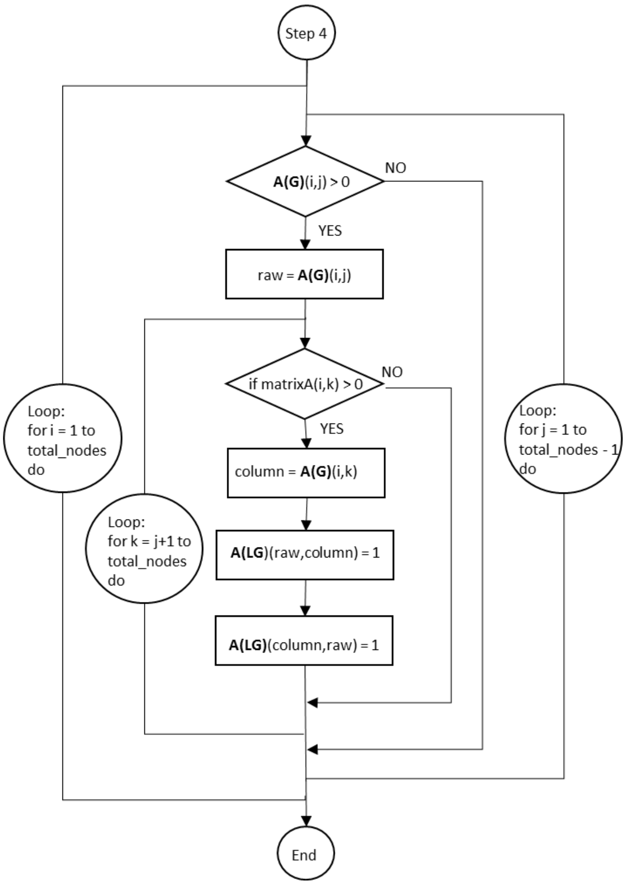

Fig.5: Diagram of flow of Step c.

A. *Result and Analysis of the Measurements*

We have conducted experiments in a dataset of circles of friends of Facebook [14] whose network has 4,039 nodes and 88,234 links. The metrics of centrality that we have applied to the network of friends there are five: degree centrality, closeness centrality, betweenness centrality, eigenvector centrality and PageRank. Thus we will be able to compare different results of importance of links calculated through the various metrics.

The metrics of centrality give results each with different scales, for this reason and in order to compare between these results we have normalized their valuesexpressing them in per unit (p.u.). Next we present some comparative graphics of the importance of links measured with different metric of centrality.

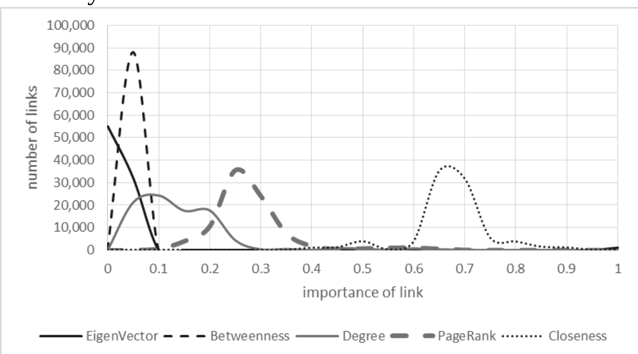

Fig.6: Frequency distribution of importance of links

Fig. 6 shows the distribution of frequencies by grouping data by ranges of importance and indicating the number of observations for each range. Inthis figure we find that the metrics give greater importance to the links are, in the first place, closeness centrality, then PageRank, degree centrality, betweenness centrality, and finally eigenvector centrality.

Fig. 7 shows the cumulative frequency distribution to have a clearer idea about the values of importance of links along the network.

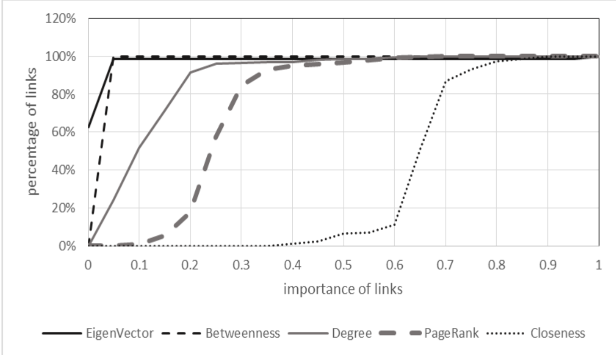

Fig.7: Cumulative frequency distribution

Fig. 7 shows thatthe metrics of centrality betweenness, eigenvector and degree give a maximum value of up to 0.25 expressed in value per unit(p.u.) to 96.2% of the links or more. See Table 3 for more details.

Table III: Percentage of links according to different values of importance

	Importance of link up to: (p.u.)		
Centrality metric	**0.25**	**0.50**	**0.75**
Betweenness	99.9	99.9	99.9
Eigenvector	98.8	98.8	98.8
Degree	96.2	98.6	99.9
PageRank	57.6	96.6	99.9
Closeness	0	6.6	93.0

B. *Accuracyof the Results*

The accuracy of the results obtained both degree centrality and closeness centrality applied to L(G) is exact. This is derived directly from the mathematical definition of line-graph: nodes in the graph L(G) represent the links of the graph G.

With relation to betweenness centrality, we already have indicated in the section 3 that the definition of edge betweenness centrality applied to G not is equal to the definition node betweenness centrality applied to L(G). For this reason, their respective values are very similar but not exactly the same.

Fig. 8 shows that the curves edge betweenness centrality in G and node betweenness centrality in L(G) virtually are overlapping.

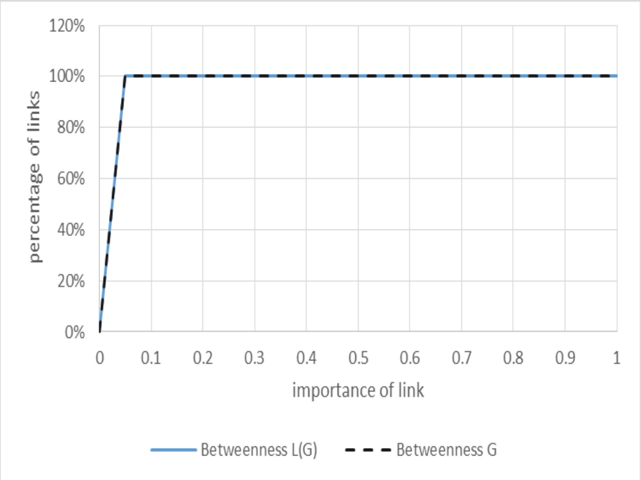

Fig.8: Frequency distribution of importance of links

We cannot verify the accuracy of measurements of the importance of links made with Eigenvector and PageRank because there are no other works that measure the importance of the links using these metrics.

C. Effectiveness of the proposed measure

A way of demonstrate the effectiveness of our measures in the real world is, for example the measure of centrality of edge. This metric can determine the number maximum of messages that a vertex must send to the neighbors of his neighbors and receive the respective acknowledgement.

In regard to the metric of centrality of closeness, a married couple (link) is more important as a couple if it is closer to the other couples married within a network of parents of an educational unit.

Another practical use is, betweenness centrality metric as we have redefined it.Beyond social networks,in a road network, this metric allows to know the importance that has a road that interconnects to other roads in order to allow communication between origins and destinations.

In a road networks of telecommunications, this metric allows to know the importance that has a link that interconnects to other links in order to allow communication between origins and destinations.The same utility we can find in networks of electrical distribution.

D. Computational complexity

Computational complexity of the centrality metrics

Many real-world networks are networks Power-Law, including the topology of the Internet and social networks [15], such as the network of Facebook that we have used in this work. The grade distribution of Power-Law networks follows the behavior $p(k) = \frac{k^{-\gamma}}{\zeta(\gamma)}$,where $\zeta(\gamma)$ is the Zeta Riemann function. γ exponent is between 2 and 3 for social networks [10].

Let G be the graph representing a social network, if n is the number of vertices then the number of edges is:

$$m = \frac{n\zeta(\gamma - 1)}{2\zeta(\gamma)} \qquad (2)$$

L(G) has m vertices and its number of edges is $e = \frac{n\langle k\rangle!}{2(\langle k\rangle-2)!}$(see section 4.4 Step c), where $\langle k\rangle$ is the mean grade of G, with $\langle k\rangle = \frac{\zeta(\gamma-1)}{\zeta(\gamma)}$.

Once determined the number of vertices m and edges e of L(G) we can find the computational complexity of the algorithms that implement the centrality metrics, which are fully defined in different documents [16].

Space of memory required by our algorithm that finds A(L(G))

According to the definition mathematical (1) of line-graph presented in the section 4.3, it is necessary define the following matrices: A(L(G)) with O(m2), B(G) with O(n x m), Bt(G) with O(m x n) and I with O(m2), where n is the number of vertices and m the number of edges. Of course, also is necessary A(G) with O(n2) to calculate B(G). The total of space required is of the order of O(n2 + 2(n x m) + 2m2).If optimizing algorithm that implements the formal definition of line-graph do not need Bt matrix, then the space required is the order O(n2 + n x m + 2m2).

The algorithm that we have designed to find A(L(G)) does not implement the formal definition of line-graph. Our algorithm only needs work with two matrices: adjacency matrix A(G) and line graph matrix A(L(G)), needing a space of the order O(n2 + m2). This represents a saving of space in the order O(n x m + m2) in relation to the optimized algorithm that implements the formal definition of line-graph.

Quantity of time required by our algorithm that finds A(L(G))

The processing time of our algorithm has been determined considering the loops of programming used (see section 4.4).Step b requires a time on the order of $O\left(\frac{n^2+n}{2}\right)$. Step c requires a time on the order of $O\left(\frac{n^2(n-1)^2}{2}\right)$. Therefore, the total time required approximately is $O\left(\frac{(n^2-n)^2}{2}\right)$.

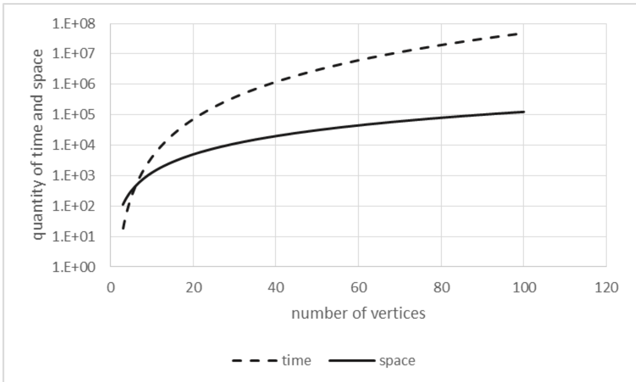

Fig.9: Quantity of time and space required by our algorithm

Fig. 9 presents a comparative picture between the amount of time and the amount of space needed by our program to find the adjacency matrix of line-graph A (L (G)). The number of edges m has been estimated considering the exponent γ = 2.1 (see mathematical expression 2).

VI. CONCLUSIONS AND COMMENTS

We have found few jobs that propose ways to measure the importance of the links. Here is the importance of our work that allows you to apply to the links the metrics of centrality.

The metrics of centrality used to measure the importance of links use different measurement criteria. Some metrics give greater importance to the links that Granovetter [17] called "weak" and less importance to the strong bonds, while other metrics give reversed results. The process of the spread of new information through a network, which depends on the links weak, is different to the process of dissemination of influence that depends on the strong bonds. Here lies the importance of the different metrics of centrality when studying these processes.

Our algorithm that finds (L(G)) can be improved to reduce the execution time at the expense of using more memory space. At the moment this is practical for working with a network of several tens of thousands of nodes and around one hundred fifty thousand links.

Finally, we have defined a new concept of edge betweenness centrality metric, which is somewhat different traditional concept.

VII. FUTURE WORKS

Strength and importance of links are two different concepts, but we have found evidence that for some metrics there is a direct relationship with the strength of the links, while for other metrics would be inverse relationship. We believe important to realize a comparative study of strengths versus importance of links.

We believe that it is important to realize studies of spread of information, rumours and influence in social networks applying the centrality metric ones both to nodes and to links.

REFERENCES

[1] A. R. M. Teutle, Twitter: Network properties analysis, Electronics, Communications and Computer (CONIELECOMP), 2010 20th International Conference on, Cholula, pp. 180-186, 2010.
[2] Song Xin-fang, Survey of model and techniques for online social networks, Computer Science & Education (ICCSE), 2013 8th International Conference on, Colombo, pp. 1495-1498, 2013.
[3] S. Ding, K. Lai and D. Wang, A Study on the Characteristics of the Data Traffic of Online Social Networks, 2011 IEEE International Conference on Communications (ICC), Kyoto, pp. 1-5, 2011.
[4] V. Bolotaeva,T. Cata. Marketing Opportunities with Social Networks. Journal of Internet Social Networking and Virtual Communities. Northern Kentucky University, 2011.
[5] M. E. J. Newman, Networks, An Introduction, Oxford University Press, New York, USA, 2010.
[6] A. Guille, H. Hacid. C. Favre1 D. A. Zighed. Information Diffusion in Online Social Networks: A Survey. SIGMOD. Vol. 42, No. 2, June 2013.
[7] K. AlFalahi, Y. Atif, A. Abraham, Models of Influence in Online Social Networks. INTERNATIONAL JOURNAL OF INTELLIGENT SYSTEMS, VOL. 00, pp. 1–23, 2013.
[8] M. Girvan, M. E. J. Newman, Community structure in social and biological networks, Vol 99, No. 12, pp. 7821-7826 2002.
[9] A. S. Teixeira, P. T. Monteiro, J. A. Carrico, M. Ramirez, and A. P. Francisco. Spanning edge betweenness. In Workshop on Mining and Learning with Graphs, 2013.
[10] P. De Meo, E. Ferrara, G. Fiumara, A. Ricciardello. A Novel Measure of Edge Centrality in Social Networks. Knowledge-Based Systems, Vol 30, pp. 136-150, 2012.
[11] S M Faisal, G. Tziantzioulis, A. M. Gok, N. Hardavellas, S. Ogrenci-Memik and S. Parthasarathy, Edge Importance Identification for Energy Efficient Graph Processing. IEEE Xplore, 2015.
[12] S. P. Borgatti, Centrality and network flow. Volume 27, No. 1, pp. 55–71, January 2005.
[13] Stanford Network Analysis Project, http://snap.stanford.edu.
[14] F. Harary, Graph Theory, Addison-Wesley Publishing Company, 1969.
[15] L. A. Adamic, O. Buyukkokten, and E. Adar. A social network caught in the Web. First Monday, 8(6), 2003.
[16] Centrality – Wikipedia, https://en.wikipedia.org/wiki/Centrality
[17] M. Granovetter. The Strength of Weak Ties. American Journal of Sociology, Vol. 78, No. 6, pp. 1360-1380, May 1973.

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