

Temporal Evolution of Scientific Communities

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ABSTRACT

Categories and Subject Descriptors

H.4 [Social Network]: Temporal Analysis; J.4. [Computer Applications]: Social and behavioral sciences Miscellaneous

General Terms

Human Factors, Measurement.

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communities, scientific communities, core community, evolution

1. INTRODUCTION

Since its beginning, society has been organizing itself into communities, which are groups of people with common interests. Particularly, the proliferation of new communication technologies based on the Internet has facilitated the rapid formation and growth of online communities. Communities exhibit a wide range of characteristics and serve a variety of purposes, from small groups engaged in tightly niche topics such as a very specific scientific community, to millions of users linked by an interest such as a community related to a sport team or fans of a celebrity.

Often, individuals who are socially connected in a community tend to share interests and similarities. Although, there are many factors that might determine a community formation and its growth, there are two main driven forces used to explain similarity in a community formation: influence and homophily. On one hand, influence posits that individuals change to become more similar to their friends in the community. On the other hand, homophily postulates that individuals create social connections within a community precisely because they are already similar. Recent efforts have provided quantitative evidences of both forces [1,3–5] and existing theories [19,24], models [9,10], and approaches [21,25] rely on identifying a group of influential

individuals with the power to affect not only the underlying network structure of a community, but also to interfere on the spread and flow of information within a community.

In this paper, we take a different perspective and study a complementary problem. Here, we focus on studying the roles that scientific community leaders play and how they can impact intrinsic evolving properties of research communities. When prolific research leaders decide to join or leave communities, they take with them resources, experience, students and they possibly influence other authors to do the same, which makes scientific communities very suitable for this kind of study. We used data from DBLP to identify scientific communities, represented by the main ACM SIGs conferences. Then, we propose a strategy to infer the community core, the leaders of a given scientific community in a given period of time. Finally, we investigate how aspects of the core impact on the community structure.

The study of the community core of scientific communities is of interest from two different perspectives. The first is sociological, stemming from the necessity to understand how segments of society evolve as well as to answer longstanding questions related to the interaction among different types of participants. On the other hand, from a technological perspective, understanding these aspects is critical not only for link prediction as well as the designing better recommendation systems, but it is also a necessary step for viral marketing strategies and social campaigns. Such a study, however, has been difficult as essential components like human connections and a proper definition of leadership is hard to be reproduced at a large scale within the confines of a research laboratory.

Our results show that (TO DO).

The rest of this paper is organized as follows. Next section surveys related efforts. Then, Section 3 describes our strategy and dataset used to construct the connections around scientific communities and analyzes the main evolving properties of this communities. Section 4 describes our strategy to compute the community core and Section 5 investigate the main properties of these sets of authors within their communities. Finally, Section 6 concludes the paper and provides directions for future work.

2. RELATED WORK

There has been a number of recent efforts that attempt to analyze and model and community structure and network evolution. Viswanath *et al.* [23] study the evolution of activity between users in Facebook and found that that links in the activity network tend to come and go rapidly over

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time, and the strength of ties exhibits a general decreasing trend of activity as the social network link ages.

Kumar *et al.* [11] [3]

[18]

[13]

[12]

[26]

Scientific communities. [15]

[8]

Games [6]

When it comes to identifying the community core, there are many approaches that extract the core based on structural properties of the graph. Particular,

[20]

[22] Here we take a different approach by measuring the

Is shown in another study [11] the components evolutions of two social networks of a big company. These study analysis the components of three ways. The analysis is done about nodes that have degree one, intermediate components (components that are not the gigant component and has more than one degree) and the gigant component. In the intermediate components is showed the concept of star nodes, this nodes are importants to the social networks, because they can make the social network grow. Also proposed is mathematic model that making the predicion of behavior identified in these study. In this study [11] is done a characterize about the nodes type too where they can be passive, linkers and invites.

3. SCIENTIFIC COMMUNITIES

The notion of community can be understood as a dense group of nodes in a network, with more edges inside than edges linking the rest of the network. There are multiple definitions and strategies of identifying communities and they vary according to the context. In our context, a scientific community is defined in terms of a large and well established scientific conference able to aggregate authors working in similar research topics along a considerable number of years. Next, we describe how we have built a large set of scientific communities.

In order to build a set of scientific communities to study, we have gathered data from DBLP¹ [14], a digital library containing more than 2.1 million publications from 1.2 million authors that provides bibliographic information on major Computer Science conference proceedings and journals. DBLP offers its entire database in XML format, which facilitates gathering and reconstructing entire scientific communities.

Each publication is accompanied by its title, list of authors, year of publication, and publication venue, i.e., the conference or journal. For the purposes of our work, we consider a scientific community as a graph in which nodes represent researchers and edges links coauthors of papers from the same community. In order to define such communities, we focus on the publications from the flagship conferences of major ACM SIGs (Special Interest Groups). Thus, we define a scientific community by linking people that have

coauthored a paper in a certain conference, making the flagship conferences of the ACM SIGs to act as communities where coauthorships are formed. We have removed young conferences without enough data for a temporal analysis as well as conferences whose entire history is not registered on DBLP, to allow us carrying out temporal analyses. In total, 24 scientific communities were considered. Table 1 lists these communities, including the respective ACM SIG, the conference acronym, the period considered (some conferences had the period reduced to avoid hiatus in the data), the h-index² and the total number of authors, publications and editions as well as ratios extracted from these last three figures.

4. DEFINING COMMUNITY CORE

Previous attempts for identifying the community core of a scientific community are based on algorithmic approaches that aim at identifying dense clusters of nodes in the network [22]. However, as we plan to investigate the role of a core in the network structure, any approach that makes use of the network structure to identify such nodes could lead us to a biased set of authors. Instead, we focus on developing a metric that quantifies the involvement of a researcher in a scientific community during a certain period of time. Intuitively, this metric should be able to capture i) the prolificness of an author in different communities and ii) the frequency of involvement of the author with the community in a certain period of time.

First, in order to capture the prolificness of an author, we use a common metric namely h-index [7]. This metric consists of an index that attempts to measure both the productivity and impact of the published work of a researcher. It is based on the set of the researcher's most cited papers and the number of citations that they have received. More specifically, a researcher a has h-index h_a if h of her N papers have at least h citations each, and the other $(N - h)$ papers have no more than h citations each. Thus, if an author have 10 papers with at least 10 citations, she has h-index 10.

Second, as an attempt to capture the importance of an author to a specific community in a certain period of time, we multiple the h-index by the number of publications this author has in a certain community during a time window. We name this measure as *Core Score*. More formally, the Core Score of an author a in a community c during a period of time t , $CoreScore_{a,c,t}$, is given by its $h-index_a$ multiplied by the number of publications a has in c during t .

$$CoreScore_{a,c,t} = h-index_a * number\ of\ publications_{a,c,t} \quad (1)$$

We note that the first part of the equation captures the importance of an author to the scientific community in different areas and periods and the second part weight this importance based on the activity of the author in a certain community and time. By computing the core score for the members of a community we define the community core in a certain period of time as the top researchers of that community in terms of their core scores in the given period. Next, we detail how we inferred the h-index of authors in Section 4.1. Then, Section 4.2 discusses how we define two

¹<http://dblp.uni-trier.de/>

²Obtained from the SHINE (Simple H-INDEX Estimator) projet: <http://shine.icomp.ufam.br>

Table 1: The data of DBLP of flagship conferences of ACM SIGs

SIG	Conference	Period	H-Index	Authors	Publications	Editions	Aut/Edi	Pub/Edi	Aut/Pub
SIGACT	STOC	1969-2012	94	2159	2685	44	49.07	61.02	0.80
SIGAPP	SAC	1993-2011	59	9146	4500	19	481.37	236.84	2.03
SIGARCH	ISCA	1976-2011	102	2461	1352	36	68.36	37.56	1.82
SIGBED	HSCC	1998-2012	-	846	617	15	56.40	41.13	1.37
SIGCHI	CHI	1994-2012	144	5095	2819	19	268.16	148.37	1.81
SIGCOMM	SIGCOMM	1988-2011	140	1593	796	24	66.38	33.17	2.00
SIGCSE	SIGCSE	1986-2012	51	3923	2801	27	145.30	103.74	1.40
SIGDA	DAC	1964-2011	98	8876	5693	48	184.92	118.60	1.56
SIGDOC	SIGDOC	1989-2010	23	1071	810	22	48.68	36.82	1.32
SIGGRAPH	SIGGRAPH	1985-2003	119	1920	1108	19	101.05	58.32	1.73
SIGIR	SIGIR	1978-2011	116	3624	2687	34	106.59	79.03	1.35
SIGKDD	KDD	1995-2011	124	3078	1699	17	181.06	99.94	1.81
SIGMETRICS	SIGMETRICS	1981-2011	71	2083	1174	31	67.19	37.87	1.77
SIGMICRO	MICRO	1987-2011	81	1557	855	25	62.28	34.20	1.82
SIGMM	Multimedia	1993-2011	80	5400	2928	19	284.21	154.11	1.84
SIGMOBILE	MobiCom	1995-2011	106	1151	480	17	67.71	28.24	2.40
SIGMOD	SIGMOD	1975-2012	147	4202	2669	38	110.58	70.24	1.57
SIGOPS	PODC	1982-2011	59	1685	1403	30	56.17	46.77	1.20
SIGPLAN	POPL	1975-2012	85	1527	1217	38	40.18	32.03	1.25
SIGSAC	CCS	1996-2011	97	1354	676	16	84.63	42.25	2.00
SIGSAM	ISSAC	1988-2011	-	1100	1177	24	45.83	49.04	0.93
SIGSOFT	ICSE	1987-2011	111	3502	2248	25	140.08	89.92	1.56
SIGUCCS	SIGUCCS	1989-2011	-	1771	1593	23	77.00	69.26	1.11
SIGWEB	CIKM	1992-2011	82	4978	2623	20	248.90	131.15	1.90

important thresholds: the size of the community core and the time window used in our analyses.

4.1 Inferring Authors H-index

There are multiple tools that measure the h-index of research authors, out of which Google Citations³ is the most prominent one. However, to have a profile in this system, a researcher needs to sign up and explicitly create her research profile. In a preliminary data collection of part of the profiles of the DBLP authors we found that less than 30% of the authors of these communities had a profile in the Google citations. Thus, this strategy would reduce our dataset and potentially introduce bias for network analysis.

To divert from this limitation, we used data from SHINE, the Simple HIndex Estimation project⁴, to infer community authors' h-index. SHINE is a search system that allows users to check the h-index of thousands of computer science conferences. They crawled google scholar, searching for the title of papers published in a number of conferences, which allowed them to effectively estimate the h-index of these target conferences based on the citations computed by google scholar. Although SHINE does not allow one to search for an author instead of a conference, the shine builders kindly allowed us to access their database to infer the h-index of authors based on the conferences they crawled.

There is one important limitation with this strategy. As SHINE does not track all the existent computer science conferences, authors' h-index might be underestimated when computed with this data. To investigate this issue, we compared the h-index of a set of authors with account on Google citations with their estimated h-index based on the SHINE dataset. We randomly selected 10 researchers for each conference from Table 1 and we extracted their h-index from their Google scholar profiles. In comparison with the H-

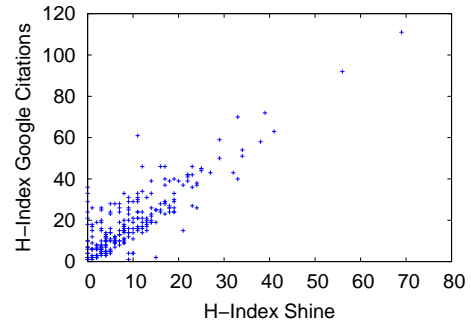


Figure 1: Correlation between the inferred H-Index and Google Scholar Citations

index we estimated from SHINE, the Google scholar values are, in average, 50% higher. Figure 1 shows the scatter plot for the two h-index measures. We can note that although SHINE h-index is smaller, the two measures are highly correlated. The pearson correlation coefficient is 0.85, which indicates that authors might have proportional h-index estimations in the two systems.

4.2 Setting the thresholds

There are two important thresholds in our approach we need to define to determine the core of a scientific community. The first is related to the time window in which the core community is computed. In other words, should we compute the community core at each year, at each two years, or for a larger time window? The second threshold is related to the size of the community core. As we define the core of a community as the top researchers in terms of their core score during a certain time window, it is important to define the threshold for choosing the top ones.

Our strategy to define these thresholds consists of vary-

³<http://scholar.google.com/citations>

⁴<http://shine.icomp.ufam.edu.br/>

ing each of them and quantifying how they impact on the changes on the members of the community core. To measure these changes, we compute a metric namely resemblance, as used in [23], which measures the fraction of members in the core at time t_0 and remain in the core at the time t_1 . For each conference, we vary the window size from 1 to 5 years and the size of community core from 10% to 60% of the entire community.

Intuitively, high resemblance variations indicate bad threshold choices, and thus, we should seek for values in which threshold changes causes slightly changes on resemblance. Figure 2 shows the resemblance values as a function of the window size, providing different curves for the community core size. We choose the SIGMOD and CHI for this analysis. The rest of the communities are omitted due to lack of space, but the same observations hold for them. By visual inspection we would set the core size as 10% due to the proximity of the curves and the window size as 2 or 3, as most of the communities showed a more stable resemblance after these values. To help us decide we compute the angular coefficient for the 10% core size curves of each community and obtained the average angular coefficient for them. Based on this value, we choose the window size for our experiments as 3.

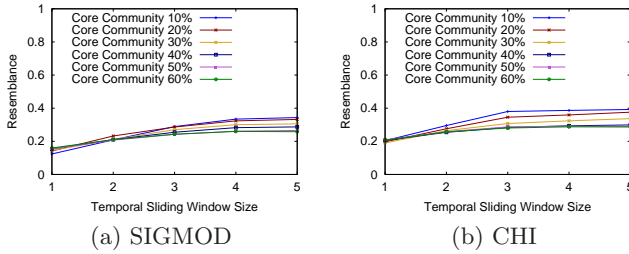


Figure 2: Average of the values of resemblance

4.3 Validation

Based on the measure of core score, we expect that the members of the community core would be members of standing that actively contribute with publications to a certain community. The validation of these matters is, by nature, subjective. Next, we provide evidences that our approach correctly captures these expected properties.

First, we analyze the core score of two WWW 2013 keynote speakers: Jon Kleinberg and Luis von Ahn. Figure 3 shows the ranking position in terms of percentage (i.e. position 5% of that community) of these two authors in the communities they have published. The red line divides the members of the community core from the other members. We can note that Jon Kleinberg was a member of the community core of STOC for years, a theoretical conference. Indeed, he was part of the STOC core for **twelve** years, publishing seven STOC papers in a single period of three years. With Kleinberg’s involvements on KDD, he became less active in STOC and left the core that community for some time. During this period he published several KDD papers, whereas his publications in STOC were drastically reduced. When it comes to Luis von Ahn, we can note that he is more active in the CHI community, a community in which he published

6 papers along his academic life. He reached the core of the CHI community along three consecutive time windows, publishing four CHI papers in a single period.

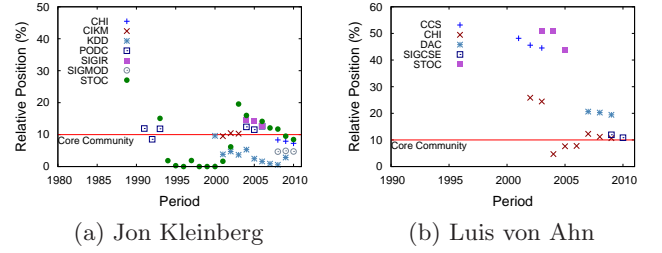


Figure 3: Core score of two WWW 2013 keynote speakers

Next, we compute a ranking of researchers that appear most often in the community core of each scientific community. We choose the CIKM, KDD, SIGIR, and SIGMOD to show the top 20 researchers in Table 2 as they are Web related conferences. We can note that several big names appear in this ranking, including past keynote speakers of these events as well as awarded authors by their life time contributions in that community. Indeed, by analyzing the awarded researchers from SIGMOD and SIGIR we found that a large fraction of them appeared in the community core at least one time in the conference history. More specifically, these fractions are 60% of the awarded SIGIR⁵ members and 80% for SIGMOD⁶. These observations provides evidences that our approach correctly captures the notion of a scientific community core.

5. PROPERTIES OF THE COMMUNITIES CORE

Next, we present a series of analyses about the scientific communities core. First, we analyze the network properties of scientific communities evolution in Section 5.1. Then, Section 5.2 contrasts the properties of the communities core over time against the properies of the remaining communities authors. Then, in Section ?? we compute the average core score of a community to investigate variations properties of the members of the core of each community. Finally, Section 5.3 correlates these variations with the network properties of the communities.

5.1 Communities Evolution

As an attempt to understand the main structural properties of the scientific communities, next we examine the evolution of the structure of their networks on the light of complex network analysis. To do so, we calculated various network metrics for each of the scientific communities. We present four popular metrics here: assortativity, average clustering coefficient, average path length, and the size of the largest connected component. Figure ?? shows how each of these four metrics vary over time for a set of six scientific communities selected among those that span over the longest period in our dataset. Our analysis are performed

⁵<http://www.sigir.org/awards/awards.html>

⁶<http://www.sigmod.org/sigmod-awards>

Table 2: Researchers who appear most often in the Core Community over the years.

	CIKM	KDD	SIGIR	SIGMOD
1 st	Philip S. Yu	Heikki Mannila	W. Bruce Croft*	David J. DeWitt*
2 nd	Jiawei Han	Jiawei Han	Clement T. Yu	Michael Stonebraker*
3 rd	Ling Liu	Eamonn J. Keogh	Susan T. Dumais*	H. V. Jagadish
4 th	Clement T. Yu	Martin Ester	James Allan	Rakesh Agrawal*
5 th	Christos Faloutsos	Bing Liu	Justin Zobel	Christos Faloutsos
6 th	James Allan	Padhraic Smyth	Alistair Moffat	Raghu Ramakrishnan
7 th	Elke A. Rundensteiner	Charu C. Aggarwal	Norbert Fuhr*	Jiawei Han
8 th	Ke Wang	Philip S. Yu	James P. Callan	Gerhard Weikum
9 th	Amr El Abbadi	Ke Wang	Yiming Yang	Philip A. Bernstein*
10 th	W. Bruce Croft	Hans-Peter Kriegel	Edward A. Fox	Jeffrey F. Naughton
11 th	Ming-Syan Chen	Rakesh Agrawal	Gerard Salton*	Hector Garcia-Molina*
12 th	Divyakant Agrawal	Jian Pei	Ricardo A. Baeza-Yates	Michael J. Carey*
13 th	C. Lee Giles	Wynne Hsu	Jian-Yun Nie	Joseph M. Hellerstein
14 th	Weiyi Meng	Qiang Yang	Mark Sanderson	Philip S. Yu
15 th	Berthier A. Ribeiro-Neto	Christos Faloutsos	Charles L. A. Clarke	Divesh Srivastava
16 th	M. Tamer Özsu	Huan Liu	Chris Buckley	Michael J. Franklin
17 th	ChengXiang Zhai	Mohammed Javeed Zaki	ChengXiang Zhai	Jennifer Widom*
18 th	Javed A. Aslam	Pedro Domingos	Alan F. Smeaton	Hans-Peter Kriegel
19 th	Hans-Peter Kriegel	Jon M. Kleinberg	Zheng Chen	Hamid Pirahesh
20 th	Bing Liu	Vipin Kumar	Ophir Frieder	Surajit Chaudhuri*

* Researchers awarded by a lifetime of innovation and leadership inside that community.

under two perspectives. The first consists on analyzing the network evolution year by year of accumulating nodes and edges to a single final snapshot of the graph. This perspective allow us to observe the final network structure of a community as a function of time. The second perspective consists of analyzing snapshots constructed based on nodes and edges created on an predefined time window (three years, as discussed in Section 4.2). This analysis allow us to investigate network variations with potential to impact the final network structure. Our analysis results are similar for the other communities, but we omit them due to lack of space.

We can note from Figure 4 that the largest connected component tend to largely increase as a function of time. This suggests that at early stages, scientific communities are formed by several small and segregated research groups. With time, some reserachers (e.g., students) leave an institute and begin collaborations with other research groups. Additionally, as the community evolves, heads of research groups tend to colabrate with other peers of the same community. Thus, with time, authors from different groups tend to collaborate and increase the size of the largest connected component. As a consequence, the average shortest path, computed only on the largest connected component, tends to increase, becoming stable around typical small-world values (i.e., from 4 to 10 hops) [2, 16]. We can also note that the average clustering coefficient tends to values between 0.1 and 0.2, thus suggesting that the coauthors of an author have 10% to 20% of chance to be connected among themselves. These values tend to slightly diminishe over time, as small components tend to connect to form larger components reducing the average clustering coefficient value. When it comes to assortativity, we see that this measure tends to 0, but it is still positive. This means that there is a slight tendency in these communities of nodes to connect with others with similar degree. A positive value for assortativity is a typical characteristic of sociological networks [17].

In general, we can note that scientific communities have similar evolving characteristics and these properties are dy-

namic as they change over time. More important, our observations suggest that a small set of authors are responsible for the social clue that create the paths among smaller and more connected research groups. Next, we seek to further investigate this group of authors. To that end, in the next section we propose an approach to identify the authors' core of scientific communities.

All in all, we can note that scientific communities have similar evolving characteristics and these properties are dynamic as they change over time. More important, our observations suggest that a small set authors are responsible for the social clue that create the paths among smaller and more connected research groups. Next, we seek to further investigate this group of authors. To that end, in the next section we propose an approach to identify the author's core of scientific communities.

5.2 Core vs. Other Members

So, to what extend the properties of the core community differ from the rest of the community? Next, we compute node network properties for members and non-members of the core community. We consider the time window analysis to understand the variations that these two classes might have in the global measure. Figure 5 shows the average degree and the average clustering coefficient computed by the members and non-members of the SIGMOD core community. Additionally, we also measure the fraction of community core members as well as non-members that are in the largest connected component. We can make key observations from theses analysis. **First, we can note that the average degree of the members of the core considerably higher in comparison with non-members, as they tend to stablish more and more connections as a function of time. However, the clustering coefficient of the members of the core tend to be slightly smaller in comparison with non-members meaning that they might act like hubs, by connecting different groups with small intersection. Indeed, by analyzing the fraction of members of the core community that are part**

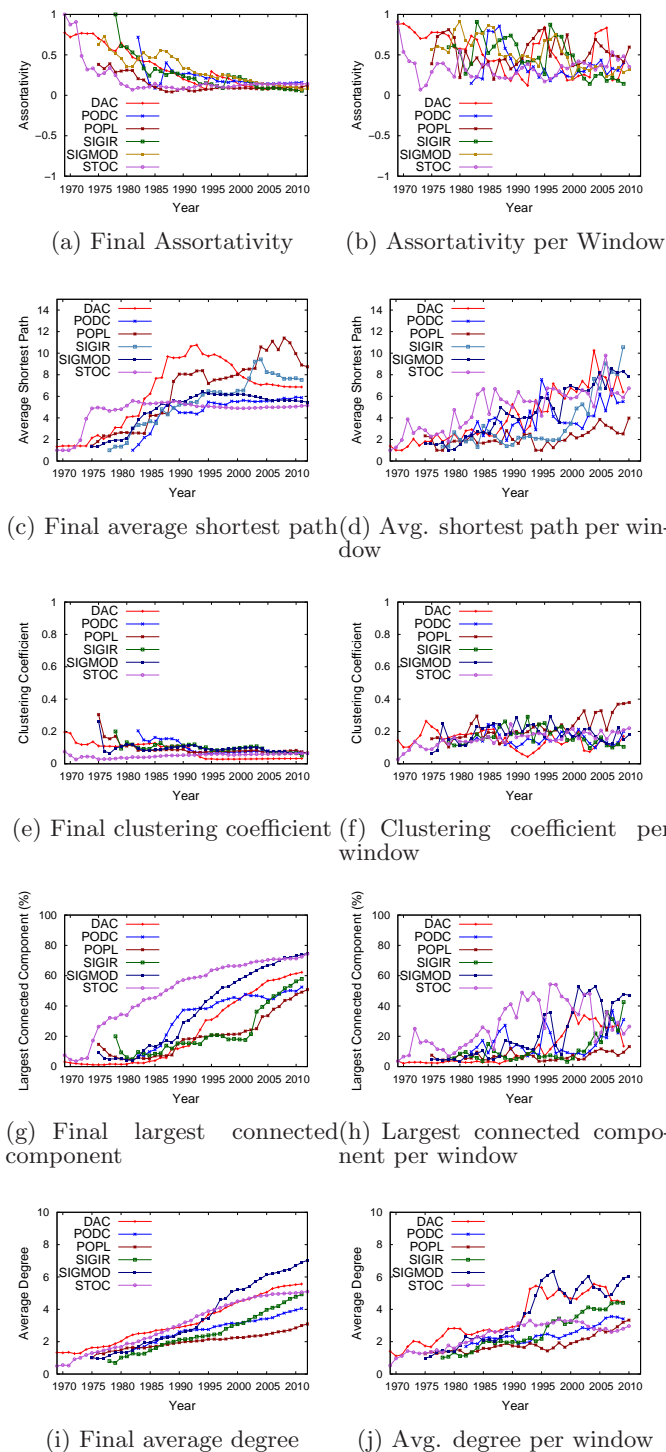


Figure 4: Network evolution metrics for scientific communities

of the largest connected component, we can note that it is much larger than the fraction of non-members, suggesting that they might be connecting smaller components. Next, we investigate how aspects of the members of a core community can impact in the overall structure of the community.

5.3 Core communities and Network Structure

reproduzir trabalho do rich club [27]

We now examine to what extent the community core fluctuations affect the network structure.

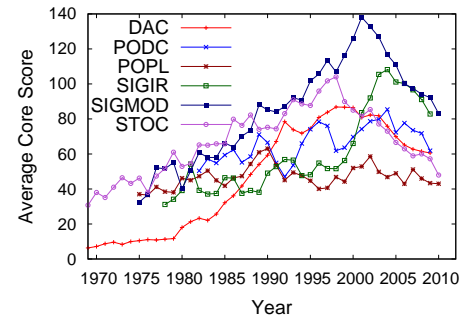


Figure 6: Average Core Score

6. CONCLUSIONS

7. FUTURE WORK

-Ajustes na formula de Core Score:

-Computar h-index a todo momento, considerando o tempo t em analise

-Mudar a formula para considerar publicacoes feitas no passado, no entanto, colocar uma penalidade. (vida trabalho do peterson)

-Realizar estudo semelhante em outra rede, tipo twitter, o h-index poderia ser alterado para um calculo de influencia

8. REFERENCES

- [1] A. Anagnostopoulos, R. Kumar, and M. Mahdian. Influence and correlation in social networks. In *Proc. of KDD*, 2008.
- [2] L. Backstrom, P. Boldi, M. Rosa, J. Ugander, and S. Vigna. Four degrees of separation. In *Proc. of ACM Web Science*, 2012.
- [3] L. Backstrom, D. Huttenlocher, J. Kleinberg, and X. Lan. Group formation in large social networks: membership, growth, and evolution. In *Proc. of KDD*, 2006.
- [4] M. Cha, H. Haddadi, F. Benevenuto, and K. P. Gummadi. Measuring User Influence in Twitter: The Million Follower Fallacy. In *Proc. of ICWSM*, 2010.
- [5] D. Crandall, D. Cosley, D. Huttenlocher, J. Kleinberg, and S. Suri. Feedback effects between similarity and social influence in online communities. In *Proc. of KDD*, 2008.
- [6] N. Ducheneaut, N. Yee, E. Nickell, and R. J. Moore. The life and death of online gaming communities: a look at guilds in world of warcraft. In *Proc. of CHI*, 2007.
- [7] J. E. Hirsch. An index to quantify an individual's scientific research output. *Proc. of PNAS*, 102(46):16569–16572, 2005.

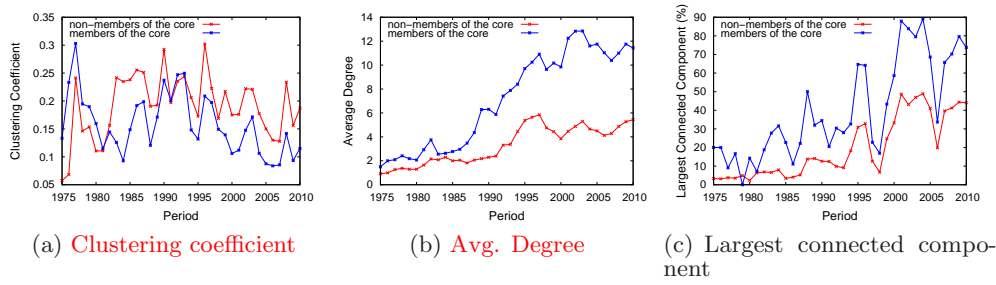


Figure 5: SIGMOD network properties for members and non-members of the core

Table 3: Corelation between average core score of the core community and the metrics of complex networks

Conference	Diameter	Avg. Short P.	Clus. Coef.	Assort.	Larg. WCC	Avg. Deg.	Num. Nodes
CCS	0.34	0.2	0.23	-0.2	0.45	0.14	-0.13
CHI	0.75	0.79	-0.62	-0.74	0.76	0.77	0.58
CIKM	0.56	0.56	-0.52	-0.67	0.39	0.87	0.64
DAC	0.8	0.85	-0.49	-0.63	0.76	0.92	0.84
HSCC	0.17	0.45	-0.62	-0.71	0.87	0.55	-0.55
ICSE	0.81	0.83	-0.52	-0.84	0.68	0.8	0.78
ISCA	0.63	0.55	0.54	-0.32	0.63	0.81	0.41
ISSAC	0.05	0.01	-0.25	-0.43	-0.07	0.21	0.78
KDD	0.1	0.17	-0.33	-0.67	0.2	0.14	0.2
MICRO	0.35	0.35	0.28	-0.36	0.52	0.51	0.36
MOBICOM	-0.04	0.11	0.13	-0.65	0.23	-0.09	0.02
Multimedia	0.67	0.68	-0.91	-0.95	0.67	0.69	0.75
PODC	0.4	0.42	-0.23	-0.2	0.13	0.68	0.57
POPL	0.21	0.2	0.23	-0.43	0.25	0.19	0.05
SAC	0.48	0.59	0.16	-0.39	-0.55	0.16	0.23
SIGCOMM	0.18	0.19	0.05	-0.81	0.49	0.41	-0.03
SIGCSE	0.88	0.84	-0.22	-0.5	0.93	0.87	0.8
SIGDOC	0.73	0.78	-0.36	-0.89	0.66	0.76	0.05
SIGGRAPH	0.79	0.85	-0.45	-0.75	0.94	0.88	0.55
SIGIR	0.83	0.85	-0.42	-0.77	0.7	0.89	0.88
SIGMETRICS	0.31	0.24	0.3	-0.44	0.37	0.64	0.43
SIGMOD	0.78	0.81	0.27	-0.61	0.77	0.87	0.68
SIGUCCS	0.38	-0.22	0.53	-0.13	0.51	0.7	0.57
STOC	0.61	0.63	0.54	-0.37	0.82	0.88	0.68
Average	0.49	0.49	-0.11	-0.56	0.5	0.59	0.42

- [8] J. Huang, Z. Zhuang, J. Li, and C. L. Giles. Collaboration over time: characterizing and modeling network evolution. In *Proc. of WSDM*, 2008.
- [9] D. Kempe, J. Kleinberg, and Éva Tardos. Influential nodes in a diffusion model for social networks. In *Proc. of ICALP*, 2005.
- [10] D. Kempe, J. Kleinberg, and E. Tardos. Maximizing the spread of influence through a social network. In *Proc. of KDD*, 2003.
- [11] R. Kumar, J. Novak, and A. Tomkins. Structure and evolution of online social networks. In *Proc. of KDD*, 2006.
- [12] J. Leskovec, L. Backstrom, R. Kumar, and A. Tomkins. Microscopic evolution of social networks. In *Proc. of KDD*, 2008.
- [13] J. Leskovec, J. Kleinberg, and C. Faloutsos. Graphs over time: densification laws, shrinking diameters and possible explanations. In *Proc. of KDD*, 2005.
- [14] M. Ley. Dblp: some lessons learned. *VLDB*, 2(2):1493–1500, 2009.
- [15] G. R. Lopes, M. M. Moro, and J. P. M. de Oliveira. Temporal influence in collaborators recommendation in social networks. In *Proc. of IADIS*, 2011.
- [16] A. Mislove, M. Marcon, K. P. Gummadi, P. Druschel, and B. Bhattacharjee. Measurement and Analysis of Online Social Networks. In *Proc. of IMC*, 2007.
- [17] M. Newman and J. Park. Why social networks are different from other types of networks. *Phys. Rev. E*, 68, 2003.
- [18] A. Patil, J. Liu, B. Price, H. Sharara, and O. Brdiczka. Modeling destructive group dynamics in on-line gaming communities. In *Proc. of ICWSM*, 2012.
- [19] E. M. Rogers. *Diffusion of Innovations*. 1962.
- [20] M. Sachan, D. Contractor, T. A. Faruque, and L. V. Subramaniam. Using content and interactions for discovering communities in social networks. In *Proc. of WWW*, 2012.
- [21] D. Saez-Trumper, G. Comarela, V. Almeida, R. Baeza-Yates, and F. Benevenuto. Finding trendsetters in information networks. In *Proc. of KDD*, 2012.
- [22] M. Seifi and J.-L. Guillaume. Community cores in

- evolving networks. In *Proc. of WWW*, 2012.
- [23] B. Viswanath, A. Mislove, M. Cha, and K. P. Gummadi. On the evolution of user interaction in facebook. In *Proc. of WOSN*, 2009.
- [24] D. Watts and P. Dodds. Influentials, networks, and public opinion formation. *Journal of Consumer Research*, 34(4):441–458, 2007.
- [25] J. Weng, E.-P. Lim, J. Jiang, and Q. He. Twitterrank: finding topic-sensitive influential twitterers. In *Proc. of WSDM*, 2010.
- [26] B. Wu, F. Zhao, S. Yang, L. Suo, and H. Tian. Characterizing the evolution of collaboration network. In *Proc. of SWSM*, 2009.
- [27] X.-K. Xu, J. Zhang, and M. Small. Rich-club connectivity dominates assortativity and transitivity of complex networks. *Phys. Rev. E*, 82:046117, 2010.