Chaos, Solitons & Fractals 57 (2013) 9–18

Contents lists available at ScienceDirect

Chaos, Solitons & Fractals

Nonlinear Science, and Nonequilibrium and Complex Phenomena

journal homepage: www.elsevier.com/locate/chaos

Scientific collaboration network of Turkey

Abdullah Çavuşoğlu [a], İlker Türker [b,*]

[a] Department of Computer Engineering, Faculty of Engineering and Natural Sciences, Yıldırım Beyazıt University, Ankara, Turkey
[b] Department of Computer Engineering, Faculty of Engineering, Karabük University, Karabük, Turkey

ARTICLE INFO

Article history:
Received 18 November 2012
Accepted 30 July 2013
Available online 28 August 2013

ABSTRACT

Networking via co-authorship is an important area of research and used in many fields such as ranking of the universities/departments. Studying on the data supplied by the Web of Science, we constructed a structural database that defines the scientific collaboration network of the authors from Turkey, based on the publications between 1980 and 2010. To uncover the evolution and structure of this complex network by scientific means, we executed some empirical measurements. The Turkish scientific collaboration network is in an accelerating phase in growth, highly governed by the national policies aiming to develop a competitive higher education system in Turkey. As our results suggest the authors tend to make more number of collaborations in their studies over the years. The results also showed that, node separation of the network slightly converges about 4, consistent with the small world phenomenon. Together with this key indicator, the high clustering coefficient, (which is about 0.75) reveals that our network is strongly interconnected. Another quantity of major interest about such networks is, "the degree distribution". It has a power-law tail that defines the network as scale-free. Along with the final values, the time evolutions of the above-mentioned parameters are presented in detail with this work. In a good agreement with the recent studies, our network yields some significant differences especially in growing rate, clustering properties and node separation. In contrast with the recent studies, we also showed that preferring to attach popular nodes result with being a more popular node in the future.

1. Introduction

Exploring scientific collaboration in-between the international or nationwide scientists is attracting more and more attention due to the usage of this data in university ratings and the effect of social interactions on the science and so forth. One of the reasons for this increasing attention in recent years is that, scientific collaboration networks are accepted as close prototypes of complex evolving networks. The key feature of these scientific databases was the opportunity they offered: every links between the nodes (authors) were captured in the time domain by the publication date of the relevant paper they co-authored together. So, the dynamic evolution of the network could be tracked explicitly [1].

The networks derived from the scientific collaboration databases are of important value that the structure of these networks and their way of composition and growth are so natural as the growth and interconnectedness of the world wide web [2,3], the fast spreading of epidemics [4–6] or similar networks' dynamics [7]. Since the links between the nodes defining the collaboration network are constructed by the collaborators' self decisions, these networks are between the areas of interest for the concepts of evolution of cooperation [8–10] and coevolution [11,12] as well. For these reasons, the scientific collaboration networks are of interest for understanding the topological and dynamical laws governing complex networks, rather than their bibliometric meanings [1,24].

There are various studies on growing networks, some track distinct scientific sub-disciplines [1,22,23,27,28],

* Corresponding author.
E-mail addresses: abdullah.cavusoglu@ybu.edu.tr (A. Çavuşoğlu), iturker@karabuk.edu.tr (İ. Türker).

0960-0779/$ - see front matter © 2013 Elsevier Ltd. All rights reserved.
http://dx.doi.org/10.1016/j.chaos.2013.07.022

while some track whole national databases [7,26]. The motivation of this study has been to uncover the network dynamics of a whole national scientific collaboration network for a large time span and state out the similarities and differences with the other studies in the literature. This will also enable us to say a few words on the effects of scientific improvements and developments of a nation opposed to scientific collaboration network. We also aimed to uncover the dynamic evolution of our network to lead further predictions about the main parameters.

2. Dataset and preliminaries

Our dataset consists of the manuscripts data supplied by the Web of Science, limited by the publications addressed from Turkey between 1980 and 2010. The html formatted raw data was parsed in order to construct a structural database in MS-SQL format, yielding three tables namely: publication, author and collaboration. The collaboration table, indicating the author partnerships, helped us to construct the co-authorship network up to a desired year. In this network, every author is represented by a node and a link is assigned between these nodes if the authors write a paper together. In the structural database, the construction date of each node and relevant link is signified by the publication date in a year based resolution. So, the evolution of the network in time is tracked well. This provides us a dynamic view to the network, instead of investigating its final static state.

Before constructing the network with the supplied data, the factors affecting the data analysis need to be emphasized here. First, the authors in the database are represented by their surname and initials. In some cases, this may cause two separate authors to be considered as a single node. Also, sometimes an author may not use his/her middle name in some publications, that consequently causes one author to be represented by two different nodes (i.e. instead of a single node). These two cases are showed by Newman [14] to be of the order of a few percents. Also, we would like to paint out another artifact that may cause misinterpretation of our database. If the fact mentioned above causes two authors of different disciplines to be represented by a single node, this will assign a fake link between rather distant disciplines (e.g. engineering and medicine) and this fake link may introduce an effective artifact over the ''average distance'' computations because the interdisciplinary co-authorships are awaited to occur seldom.

In the time span of 30 years, the co-authorship network enabled us to investigate the issues like average distance, degree distribution, publication statistics, network velocity, author statistics, clustering coefficient, number of authors per paper and papers per author statistics and links per node, as subjected to examinations in many studies including Newman [13,22,23], Barabási et al. [1], Perc [7] and others [26,27].

Our Turkish scientific collaboration network starts with 774 authors in the year 1980 and reaches the value of 151,745 authors in the year 2010. In this time interval, the number of publications, starting from 413, reaches the value 237,409. These statistic results are visualized in the following section, where the results of the empirical measurements are also given.

3. Data analysis

Investigating the statistical properties of the database is the first step of the data analysis procedure. Running appropriate database queries, the illustration in Fig. 1 has been obtained. The graph shows the growth of the collaboration network in Turkey over the years. The exponential growth characteristic of the number of authors graph differs from the results reported by Barabási et al. [1] which shows a smooth decay in the linear growth rate, and from Tomassini and Luthi's study [26] that indicates a linear growth for the last 10 years of the time span. The exponential growth characteristics of our network (both the number of authors and publications) are outlined in the inset graphs of the Fig. 1, where log-linear scaled data are well

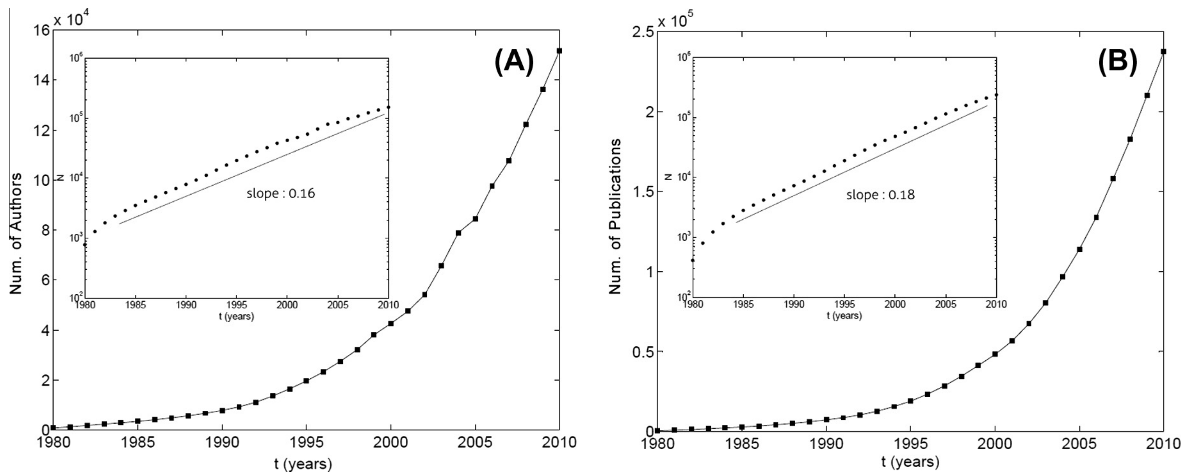

Fig. 1. Statistical properties of the Turkish scientific collaboration network. (A) The cumulative number of nodes (authors) vs. years. The inset graph shows the log-linear plot of the same data with an exponential fit a $*$ exp(bx), where $b = 0.16$. (B) The cumulative number of publications vs. years. The inset graph shows the log-linear plot of the same data with an exponential fit where $b = 0.18$.

fitted by exponential fits having exponents 0.16 and 0.18 respectively.

The involvement rate of the new authors to the Turkish scientific collaboration network is unique in this manner and this is probably as a result of Turkeys economic performance over the last decade, which in turn effects the total amount (i.e. ~1% GDP allocated for the research, a figure doubled within the last decade [29]; and the average income per person reached $10,022 from $3,021 in the same period [30]). In addition, we consider that the steeper increasing rate of the Turkish authors' community is primarily boosted by the increase in the number of universities in Turkey (i.e. the total number of both state and foundation universities has reached 170 from 76 within the last decade), where the number of academicians have increased by 50% in this period [29]. The dependency of the academic grading with the scientific citation indexes in Turkey also promotes the number of publications.

In this sight of view, although the recent framework about scientific collaboration networks is similarly applied to the Turkish scientific collaboration database, the results are distinctive in pointing out the relation between economic and social development of a country with its scientific community.

The notion of accelerating in physical network systems is recently studied. Smith et.al [32] defined the network velocity $v(t)$ as follows:

$$\boldsymbol{v}(\boldsymbol{t}) \equiv \frac{\boldsymbol{dM}(\boldsymbol{t})}{\boldsymbol{dN}(\boldsymbol{t})} = \frac{\boldsymbol{m}(\boldsymbol{t})}{\boldsymbol{n}(\boldsymbol{t})} \approx \frac{\boldsymbol{M}(\boldsymbol{t}) - \boldsymbol{M}(\boldsymbol{t}-\mathbf{1})}{\boldsymbol{dN}(\boldsymbol{t}) - \boldsymbol{N}(\boldsymbol{t}-\mathbf{1})} \quad (1)$$

Here, $\boldsymbol{M}(\boldsymbol{t})$ is referred as the number of total links and $\boldsymbol{N}(\boldsymbol{t})$ is the number of total nodes at time t. The notations $\boldsymbol{m}(\boldsymbol{t})$ and $\boldsymbol{n}(\boldsymbol{t})$ describe the rate of link and node additions respectively. They also describe the acceleration of the network as follows:

$$\boldsymbol{a}(\boldsymbol{t}) = \frac{\boldsymbol{dv}(\boldsymbol{t})}{\boldsymbol{dt}} \quad (2)$$

where the positive values of $\boldsymbol{a}(\boldsymbol{t})$ labels the network as accelerating.

We derived the time evolution of the link-node phase space and network velocity graphs as shown in Fig. 2. Both the number of total nodes and total links appear to increase in time, so one can say from Fig. 2a that no negative network velocity occurs in the network, consistent with the study of Smith et al. [32]. In addition, right side graph in Fig. 2 is attractive in the manner it demonstrates an exponential increasing network velocity, contrary with the mentioned study outlining three different networks showing an initial accelerating trend before non-accelerating behavior is reached. Besides being an accelerating network, the Turkish scientific collaboration network stands out with maintaining this behavior in the whole time span.

In addition to the results mentioned above, we have obtained the time dependence of average degree as shown in Fig. 3. This value can be calculated as the average links (number of collaborators) per nodes up to a desired year. The graph yields a steep increment in time especially for the last 6 years, thus we can say that the network has been much more interconnected in recent years.

Considering the years spanned in the studies, the average degree values resulted by our study reaches uniquely high values (35.03 in 2010) compared to MEDLINE – biomedicine (18.1 in 1999), Los Alamos archive (9.7 in 1999), NCSTRL – the computer science database (3.59 in 1999) [22,23], neuroscience database (~12 in 1998), mathematics database (~4 in 1998) [1], Slovenian database (10.7 in 2010) [7], Swiss database (~4 in 2006) [26], Mathematical Reviews database (2.94 in 1999) [27]. We suppose that this unique behavior is highly related to the special case Turkish scientific community encounters, mentioned above.

To uncover the relations between the papers and authors, we derived the mean value of papers per author and mean value for authors per paper graphs as in Fig. 4a and b respectively. Fig. 4a shows that the productivity of the authors increases in time, starting from the average papers per author value of 0.73 by the year in 1983, and reaching 1.56 in 2010. Also Fig. 4b implies that the collaboration tendency of the authors also increase by years, starting with

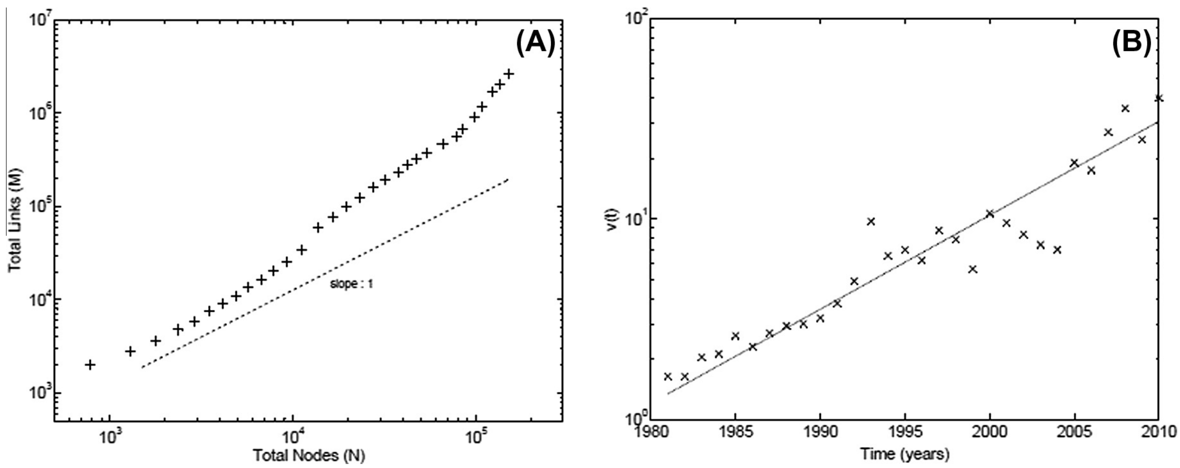

Fig. 2. (A) The evolution through the link-node phase space of total node and link numbers. The slope of the dashed line is 1. (B) The evolution of network velocity. The solid line corresponds to the exponential fit having exponent 0.108.

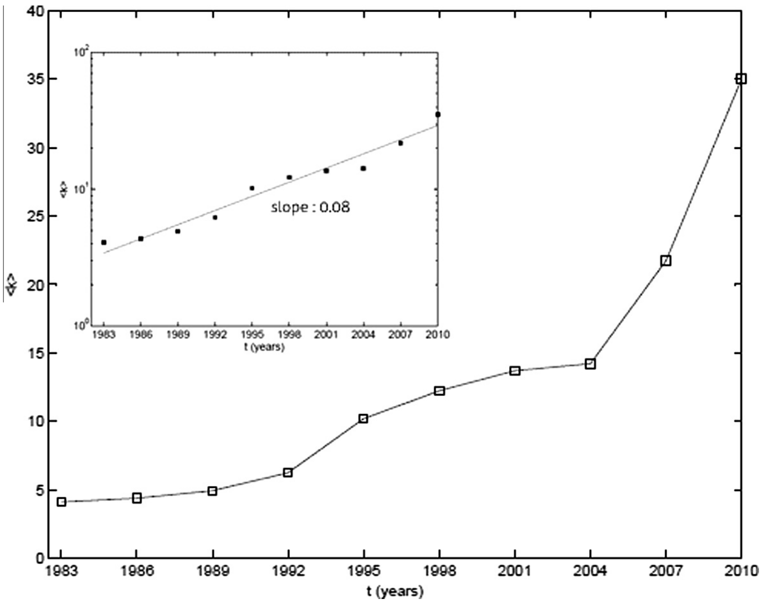

Fig. 3. Average degrees (⟨k⟩) of the nodes up to the given year (cumulative). The inset graph shows the log-linear plot of the same data with an exponential fit a ∗ exp(bx), where b = 0.08.

an average authors per paper value of 2.43 for 1983, and reaching 4.08 in 2010. One can say from the last three graphs that the network gets more inner-connected (Fig. 3), more productive (Fig. 4a) and more collaborative (Fig. 4b) in time. But a fact that helps the raising regimes in these graphs is that, our database spans all of the scientific sub-disciplines including medical sciences and applied physics, including some papers collaborated by hundreds of authors (or research assistants as well). These papers are regarded as super-node papers, taking the responsibility for the scattered points in the right sides of Figs. 5 and 6a.

Compared to the other databases, we can say that the average papers per author values of our database (represented in Fig. 4a) are consistent with mathematics and neuroscience databases of Barabási et al. (∼1 in 1998) and smaller than Grossman's Mathematics Review database (6.87 in 1999) [27], Newman's MEDLINE, Los Alamos archive, SPIRES and NCSTRL databases (6.4, 5.1, 8.96, 2.22 respectively, in 1999) [22,23] and Swiss database (3.16 in 2006) [26].

The authors per paper values that we calculated seem to be greater than all of the outputs mentioned in the studies above except for the MEDLINE and SPIRES databases, where higher numbers of collaborations are evident.

An important quantity for such network topologies is the degree distribution that gives the probability that a randomly selected node has k links [1]. Our network states a $P(k)$ graph having a power-law tail as seen in Fig. 5a and b, indicating that it is scale-free [15,16]. The power-law tail is evident from the uniformly binned data on the left side

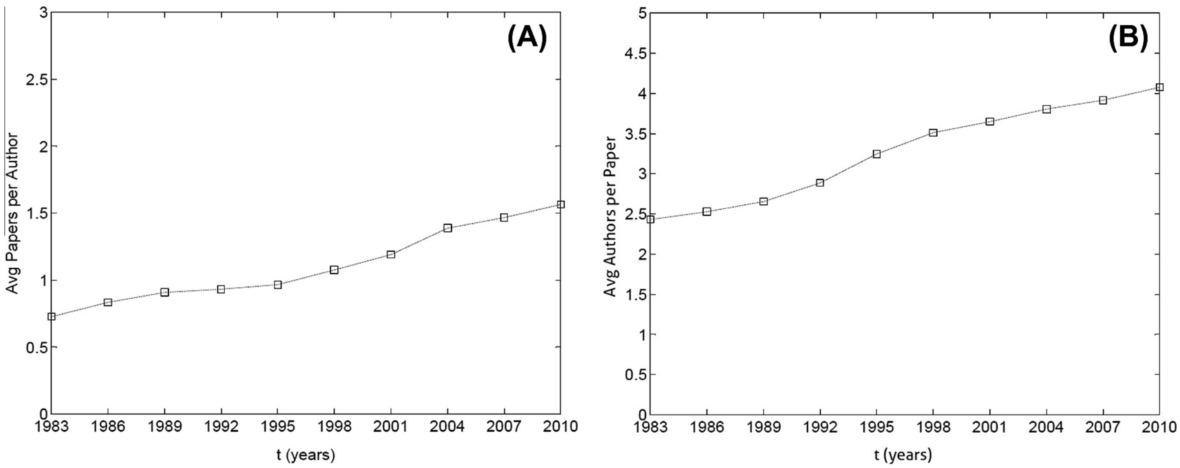

Fig. 4. (A) Average papers per author. (B) Average authors per paper. (Based on the cumulative data up to the corresponding year).

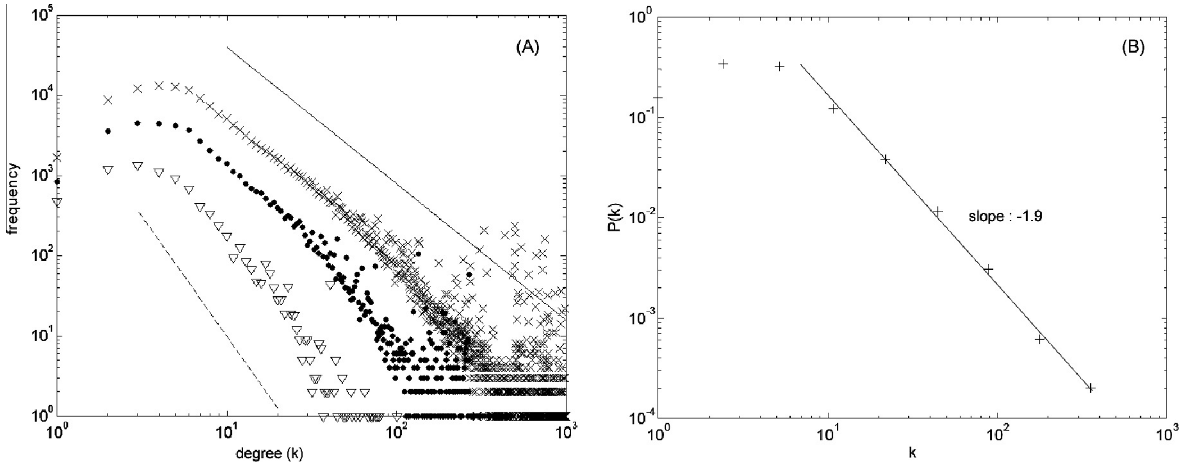

Fig. 5. (A) Frequency values of the degree occurrences in the whole network, showing the cumulative data up to 1990 (▽), 2000 (●) and 2010 (×). The lines correspond to the power-law fits having the exponent 3 (dashed) and 1.7 (solid). (B) Degree distribution graph for the log-binned network data up to 2010, with a power-law fit of exponent 1.9 performed.

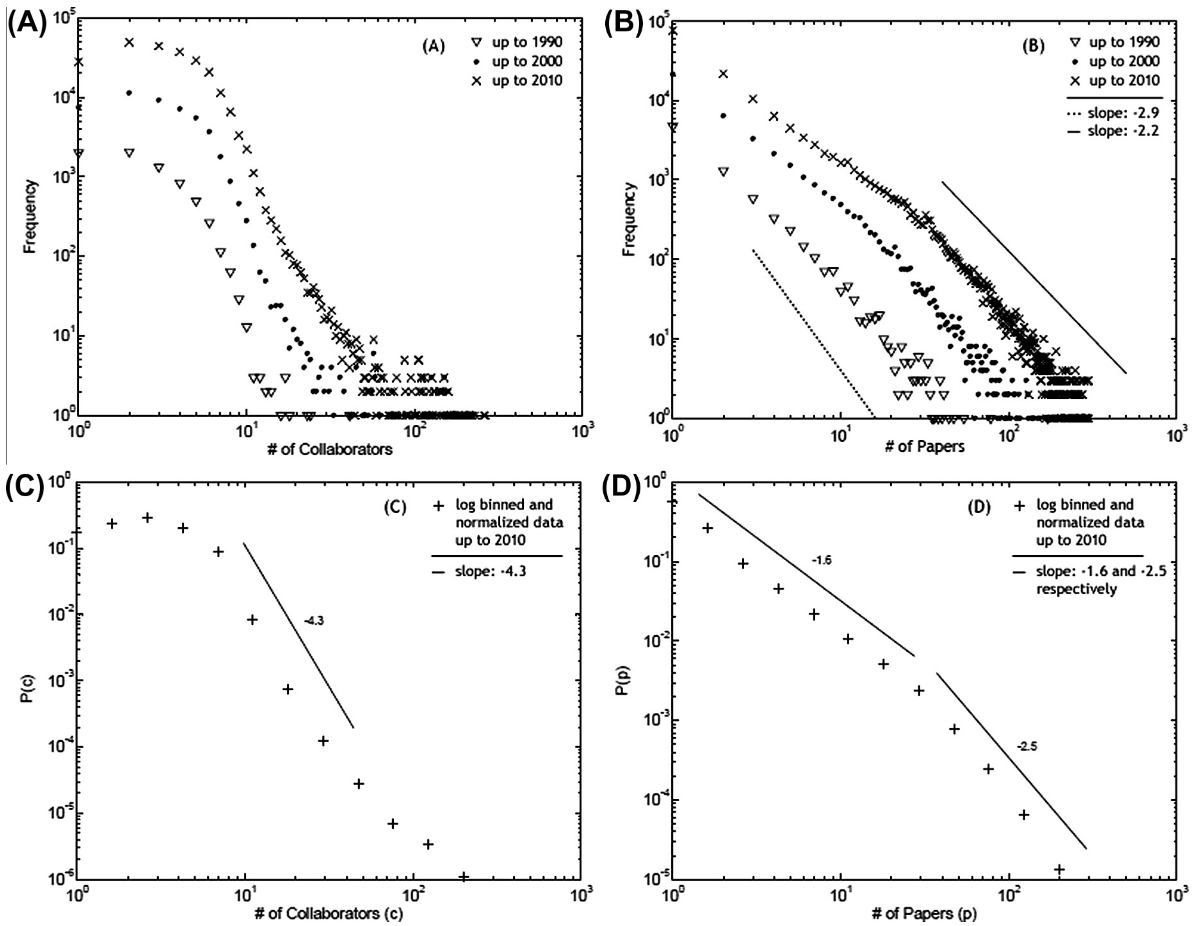

Fig. 6. (A) Histogram of the authors (collaborators) per paper. (B) Histogram of the papers per author. (based on the cumulative data up to 1990 (▽), 2000 (•) and 2010 (x).) (C) Distribution of the log binned data up to 2010 in A, with a power-law fit of exponent 4.3 performed. (D) Distribution of the log binned data up to 2010 in B, with power-law fits of exponent 1.6 and 2.5 performed.

graph, while the scaling regime is better seen on the right side graph that shows the logarithmic binned data up to 2010 (as stated in [34]), with a pure power-law fit of exponent 1.9 performed. The scaling property also indicates the emergence of preferential attachment that the nodes connect with higher probability to those nodes that already have a larger number of links [1,15]. The meaning of the degree distribution to follow a power-law is that, the number of vertices of degree x is proportional to $x^{-\alpha}$, where α (exponent) typically lies in the range $2 < \alpha < 3$ in real world situations [1,22,24,25,34]. The 10 year intervals also indicate that the degree distribution is time dependent in our network, having a decreasing exponent by the years.

Histograms of authors (collaborators) per paper and papers per author are also derived from the database, as shown in the upper plots of Fig. 6. As seen in Fig. 6a, the high tendency of publishing a paper oneself or with a collaboration of two authors until 1990 is dominated by the tendency of collaborating with two, three or four authors in 2010. This fact is consistent with the rising trends of the average degree (Fig. 3) and the average authors per paper (Fig. 4b) graphs.

The normalized and logarithmic binned data in the upper side of Fig. 6 are presented in the lower side as distributions. Unlike the authors per paper characteristics found by Newman [23], reporting power-law consistent distributions having exponents of 6.2 for Medline, 3.34 for Los Alamos Archive, 4.6 for NCSTRL and finally 2.18 for SPIRES databases, our collaborations per paper distribution in Fig. 6c alters from a power-law fit, which we examined not to have exponential characteristics either.

However, the papers per author distribution (Fig. 6d) seems to fit a power-law distribution with two scaling regimes. The solid lines show how power-law distributions with exponents 1.6 and 2.5 would look on the same axes. The scaling regimes are also evident from the raw data plotted in Fig. 6b. These values are in agreement with Newman's studies stating out the exponents 2.86 for Medline and 3.41 for NCSTRL databases [23], but in a greater agreement with Lotka's dataset compiled by hand in 1926 having an exponent of 2 [21].

An interesting search problem in a social network is the degree of separation (average distance) between two users [17]. Average distance is also referred as the length of the shortest path between two random nodes, pointing out the ability of two nodes to communicate with each other [1]. Stanley and Milgram, in their pioneering work in the 1960s, concluded that people in the United States are approximately three "steps" (distance) away from each other [18]. Today, the average distance between two people on Earth is accepted to be six [19]. This is commonly referred to as "six degree of separation" or "small world phenomenon". To determine this quantity for our network, we applied the breadth-first algorithm that Bakhshandeh and friends [17] suggested to give optimal result if the start and the goal nodes are explicitly defined and the search operators are reversible as if in the social networks like ours. Executing the search algorithm in a three-year resolution, we obtained the graph presented in Fig. 7.

In is also in good agreement with the decaying character of the study of Barabási et al. [1], our network presents lower values (4.14 in 2010) of average distances compared to the majority of the studies [1,7,22,23,26,27]. In the view of spanning the whole scientific sub-disciplines of a country and using a considerably large time window, our study has resemblance to Perc's study [7] of Slovenian scientific collaboration network that map the 50 years of database. However, the resulting average distances in 2010 are in a good agreement (4.14 for Turkey and ~4.6 for Slovenia), so is the Swiss database having the average distance 4.74 in 2006 [26]. We propose that the fake links effect that we mentioned in the beginning of Section 2 (of this paper) is a decaying factor over the average distances, as they sometimes link authors from different sub-disciplines

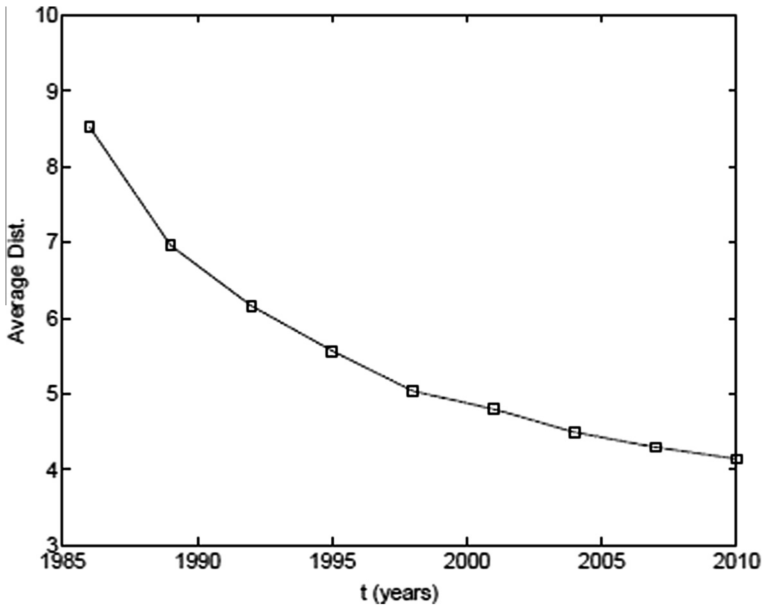

Fig. 7. The average distance graph in the Turkish scientific collaboration network. The dotted line is the nonlinear fit having a minimum about 4.

and shorten the distances between two random nodes. Despite this fact, our network is quite consistent with the small world concept: a large network with small diameter or average path length.

Another quantity, the clustering coefficient, measures network clustering and describes symmetry of interaction among trios of actors. It shows the probability that two of a scientist's coauthors have also coauthored a paper together. Topologically, it shows the density of the triangles in a network, a triangle being formed when two of one's collaborators collaborate with each other [20]. The methodology to achieve this quantity through a network is explained in [1].

Our network has a clustering coefficient graph (Fig. 8) that shows a convergence in time to an asymptotic value about 0.75, yielding a strong interconnectedness between the nodes. This value is of the degree is not in line with any of the mentioned studies above. However, the neuroscience database (~0.76) in [1] seem to produce a match. One extreme of defining a graph network is the regular network which has a high degree of local clustering and the average distance between the vertices is quite large, while the other extreme is the random network which shows negligible local clustering and the average distance is relatively small [31]. Showing a notably small average distance, our network yields random network property. But the clustering coefficient (0.75) and the degree distribution characteristics label our network as "small world", in which the local neighborhood is preserved while the degree distribution decays with a power law tail [33].

4. Getting the advantage of collaborating with a well-known author

Most real networks exhibit preferential attachment. This means that, there is a higher probability that a new node will be linked to a vertex that that already has a large number of connections [15]. This phenomenon has been investigated in several studies performed on complex networks. Some focused on the functional form of attachment rate, while a portion of these studies show that the power-law scaling regimes are governed by preferential attachment [1,7,13,15,35]. The scaling property of our network in Fig. 5 indicates the emergence of preferential attachment, in the perspective outlined above.

In this part of our study, we aimed to show if a new node gets an advantage by collaborating with a well-known author that has already sufficient links to the other nodes. To display the existence of such an advantage, we labeled the new authors connected to the network from 2001 to 2010 as either collaborated with a popular author (i.e. an author that has a degree exceeding the average value of 35, in the year 2000), or not. We considered a new author "collaborated with a popular author" if s/he has collaborated with a popular one in any time between the mentioned time span (not only the collaboration in his/her first paper considered). Our processed database includes the degrees of all 151,745 authors in all discrete years, so visualizing the evolution of the "labeled" authors' degrees is possible as seen in Fig. 9.

The color coded evolution graph provides an interpretation about how the (degrees of) nodes evolve in time, as mentioned in [7]. Comparing the two plots in Fig. 9, one can say that the authors that have collaborated with a popular author (the right side plot) had more collaborators in their network life. This view is also evident in Fig. 10 that we present the degrees of the k-th ranked authors in a Zipf plot. The solid line represents the degrees of the nodes that have connected to high degree nodes, while the dotted line represents the remaining nodes. These figures imply that preferring to collaborate with high-degree authors results in having more collaborators in a real network. To quantify

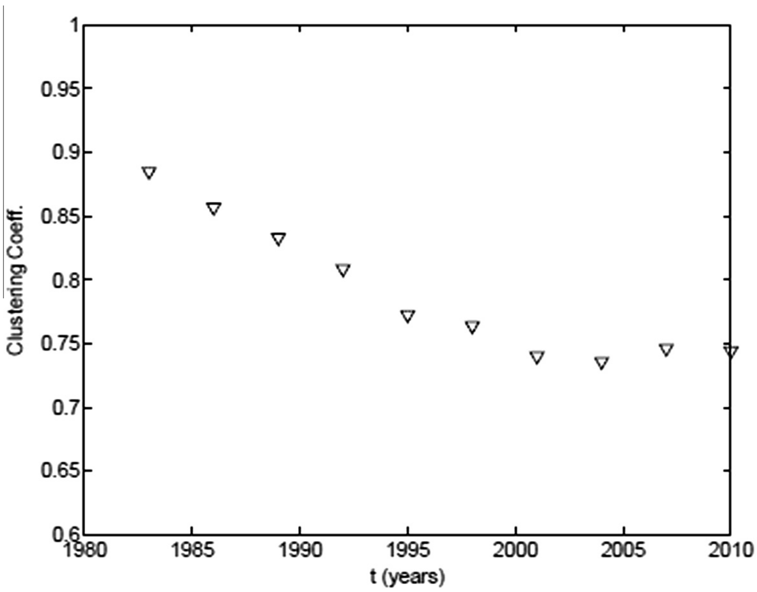

Fig. 8. The clustering coefficient graph, determined by the cumulative data up the indicated year in the x axis.

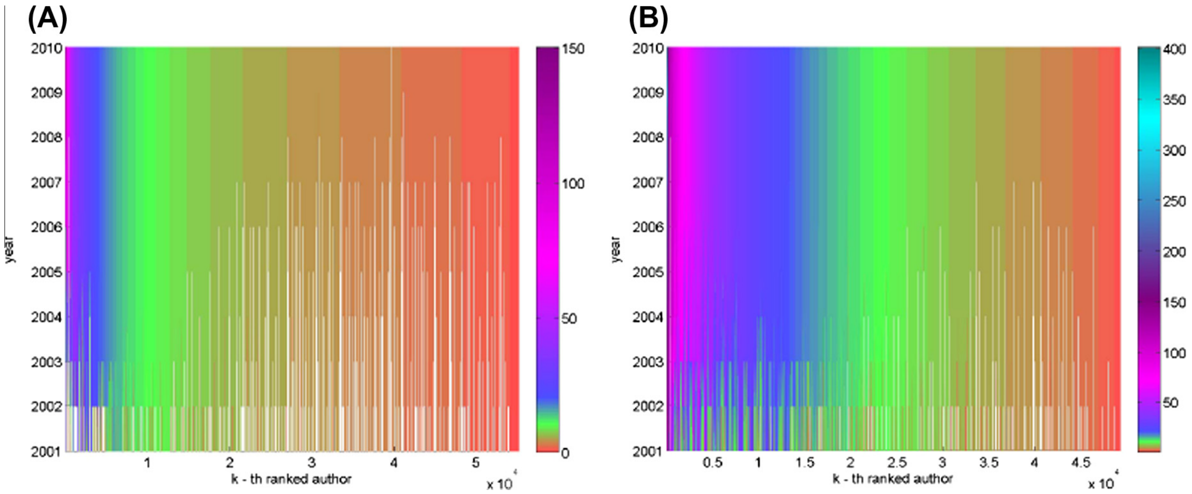

Fig. 9. Color coded evolution of the new authors added to the scientific collaboration network in the time span 2001–2010, The authors in (A) are the 55,144 authors that have not collaborated with the well-known authors, while the 49,246 authors in (B) have collaborated with the well-known authors. Each vertical line refers to a single author, where the authors are ranked according to their degrees (the total number of collaborators) they have in the year 2010. Number one is the scientist that has the highest degree in 2010, author number two has the second-largest degree, and so on. The start of each vertical line corresponds to the year the pertaining author received his/her first collaborator, i.e. when s/he became active and thus a part of the collaboration network. The coloring denotes how the number of collaborators of each author increased over the years (from the time of becoming active till 2010), according to the color bar on the right. The color spectrum is identical in both graphs, i.e. same colors indicate the same degrees in both sides, for comparison purposes. But the right side plot has a larger color spectrum to secure displaying the higher degrees the authors hold.

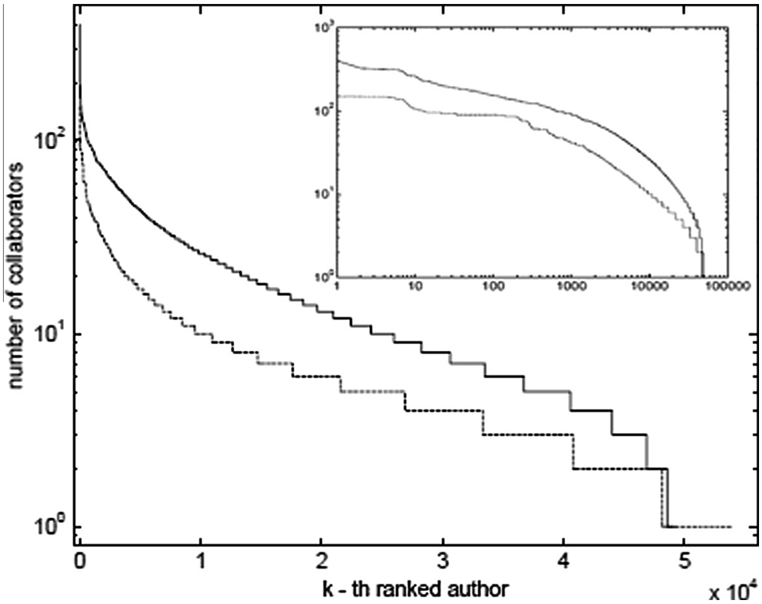

Fig. 10. Zipf plot of the number of collaborators vs. the k-th ranked author on a semi-log (inset shows log–log) scale, as obtained for the year 2010. The solid (upper) line corresponds to the authors that have collaborated with well-known authors, while the dotted line corresponds to the remaining ones.

this issue, we can say that the authors collaborating with the popular authors have an average degree of 18.45 in 2010, while the others have an average degree of 7.43.

Besides enabling the comparison of the two groups of authors, the Zipf plot above is an instrument of examining the expected distribution of the examined quantity [7,36]. If the log–log (inset plot of Fig. 10) plot had a linear outlay of slope β, this would imply a power-law distribution, promoting the linear preferential attachment property indicated by the power-law tail of Fig. 5. But the inset log–log plots show a negative curvature, in contrast with the degree distribution figure, hinting an interesting attachment rate. This issue make necessary to examine the preferential attachment phenomenon for the network by detailed means as in [1,7,13,35], that we propose to include in a further study.

5. Conclusion

Scientific collaboration of people in a country presents many interesting aspects of the community that has been investigated. Narrowing the group to a specific area or university, provides valuable information about that group or university under the investigation. Here, we presented a comparative study about a national scientific collaboration network, formed by Turkish authors' in a 30 year time period. Rather than merely focusing on its final state, we investigated the time evolution of the main parameters identifying the network.

First, we focused on the statistical parameters like cumulative number of authors and papers, average degree, average papers per author and average authors per paper. First two graphs about the network size in yearly resolution showed us that our network grows exponentially in terms of both the authors and papers, where the next graphs about link addition and network velocity stated out that the velocity tends to increase exponentially. This shows that our network is in an accelerating regime. We believe that, this feature is mainly due to the both economic developments in Turkey and the results of higher education reforms causing increases in the number of researchers and capital allocated for scientific research. In Turkey, the number of universities has increased from 76 to 170 over the last decade, where at the same time, the number of academic staff increased from 76,090 to 111,495 [29]. In spite of the high growth rate of the network, we can say that the number of papers per author is still insufficient (1.56 in 2010) for a national scientific collaboration network.

In contrast with the evolving network models, scientific collaboration networks yield nearly linear increase in average degree [1,26]. Our network also promotes this fact. Also, as the years went by, the authors in our network tend to make more collaboration in a separate paper, while they participate in more publications in average.

In parallel with the statistical results above, the empirical measurements also resulted time dependent parameters. The average distance tends to converge slightly below 4, where the clustering coefficient is to converge about 0.75. These small diameter and highly clustered structure classifies our network a strongly interconnected, supported by the average degree characteristics mentioned above. All these properties imply that, our network shows small-world properties, while the degree distribution, with a power-law tail, classifies our network as scale free in agreement with the recent studies. The scaling regime also denotes that node selection is governed by preferential attachment, which would be worth to a further study on this network.

We also tested whether collaborating with a well-known author provides advantage in having more degrees in the later years. Visualizing the author activities for the last 10 years, the last three plots show that connecting a popular node makes an author more popular in later years. This fact defines the other side of the mirror (i.e. preferential attachment provides advantage), while the front side is stated out by most studies, implying that preferential attachment occurs in real time networks.

Acknowledgments

We thank the authorities and the kind staff in the Ankara office of Thomson & Reuters for guiding the retrieval of the raw data from Web of Science.

References

[1] Barabási A-L, Jeong H, Neda Z, Ravasz E, Schubert A, Vicsek T. Evolution of the social network of scientific collaborations. Phys A 2002;311:590.
[2] Albert R, Jeong H, Barabási A-L. The diameter of the world-wide web. Nature 1999;401:130.
[3] Pastor-Satorras R, Vazquez A, Vespignani A. Dynamical and correlation properties of the internet. Phys Rev Lett 2001;87:258701.
[4] Pastor-Satorras R, Vespignani A. Immunization of complex networks. Phys Rev E 2002;65:036104.
[5] Pastor-Satorras R, Vespignani A. Evolution and structure of the Internet: a statistical physics approach. Cambridge: Cambridge University Press; 2004.
[6] Zanette DH, Kuperman M. Effects of immunization on small-world epidemics. Phys A 2002;309:445.
[7] Perc M. Growth and structure of Slovenia's scientific collaboration network. J Informetr 2010;4:475–82.
[8] Perc M. Evolution of cooperation on scale-free networks subject to error and attack. New J Phys 2009;11:033027.
[9] Santos FC, Pacheco JM. Scale-free networks provide a unifying framework for the emergence of cooperation. Phys Rev Lett 2005;95:098104.
[10] Szabo G, Fath G. Evolutionary games on graphs. Phys Rep 2007;446:97.
[11] Gross T, Blasius B. Adaptive coevolutionary networks: a review. J R Soc Interface 2008;5:259.
[12] Perc M, Szolnoki A. Coevolutionary games-A mini review. BioSystems 2010;99:109.
[13] Newman MEJ. Clustering and preferential attachment in growing networks. Phys Rev E 2001;64:025102.
[14] Newman MEJ. The structure of scientific collaboration networks. Proc Natl Acad Sci USA 2001;98:404–9.
[15] Barabási A-L, Albert R. Emergence of scaling in random networks. Science 1999;286:509.
[16] Barabási A-L, Albert R, Jeong H. Mean-field theory for scale-free random networks bio. Phys A 1999;272:173–87.
[17] Bakhshandeh R, Samadi M, Azimifar Z, Schaeffer J. Degrees of Separation in Social Networks. In: Proceedings of the fourth annual symposium on combinatorial search (SoCS). Barcelona, Spain; 2011. p. 18–23.
[18] Milgram S. The small world problem. Psychol Today 1967;2:60.
[19] Kleinberg J. The small-world phenomenon: an algorithm perspective. In: STOC'00. Berlin, New York, USA; 2000. p. 163–170.
[20] Newman MEJ. Proc Natl Acad Sci USA 2004;101:5200–5.
[21] Lothka AJ. The frequency distribution of scientific productivity. J Wash Acad Sci 1926;16:317–23.
[22] Newman MEJ. The structure of scientific collaboration networks. Proc Natl Acad Sci USA 2001;98:404.
[23] Newman MEJ. Scientific collaboration networks. I. Network construction and fundamental results. Phys Rev E 2001;64:016131.
[24] Watts DJ. Small worlds: the dynamics of networks between order and randomness. Princeton, New Jersey: Princeton University Press; 1999. MR 2001a:91064.
[25] Watts DJ, Strogatz SH. Collective dynamics of "small-world" networks. Nature 1998;393:440–2.
[26] Tomassini M, Luthi L. Empirical analysis of the evolution of a scientific collaboration network. Phys A 2007;385:750–64.
[27] Grossman JW. Patterns of collaboration in mathematical research. SIAM News 2002;35:8–9.
[28] Albert R, Barabási A-L. Statistical mechanics of complex networks. Rev Mod Phys 2002;74:47.
[29] http://www.tuik.gov.tr/VeriBilgi.do?alt_id=14, Turkish Institute of National Statistics.
[30] http://www.tuik.gov.tr/IcerikGetir.do?istab_id=158, Turkish Institute of National Statistics.

[31] Yang X-S. Fractals in small-world networks with time delay. Chaos Solitons Fractals 2002;13:215.
[32] Smith DMD, Onnela J-P, Johnson NF. Accelerating networks. New J Phys 2007;9:181.
[33] Amaral LAN, Scala A, Barthelemy M, Stanley HE. Classes of small-world networks. Proc Natl Acad Sci USA 2000;97:11149–52.
[34] Clauset A, Shalizi CR, Newman MEJ. Power-law distributions in empirical data. SIAM Rev 2009;51:661–703.
[35] Jeong H, Neda Z, Barabási A-L. Measuring preferential attachment in evolving networks. Europhys Lett 2003;61:567–72.
[36] Zipf GK. Human behavior and the principle of least-effort. Cambridge: Addison-Wesley; 1949.