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Structure and evolution of co-authorship network in an interdisciplinary research field

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Abstract The structure and evolution of co-authorship networks have been extensively studied in literature. However, the studies on the co-authorship network in a specific interdisciplinary field may be complementary to the mainstream of existing works. In this paper, the interdisciplinary field of "evolution of cooperation", which has been prevalent in the last decades as a promising scientific frontier, is analyzed by extracting its co-authorship network mainly from Web of Science. The results show that the development of this field is characterized by the growth of a giant component of its collaboration network. Originally formed by assembling a few local clusters, the giant component has gradually evolved from a small cluster to a structure of "chained-communities", and then to a small-world structure. Through examining the degree distributions and analyzing the vulnerability, we uncover that the giant component is comprised of the "elite", the "middle-class" and the "grassroots", with respect to the nodes' degrees and their functions in structuring the giant component. Furthermore, the elite and the middle-class constitute a robust cohesive-core, which underpins the modular network of the giant component. The overall results of this work may illuminate more endeavors on the collaboration network in other interdisciplinary fields.

Keywords Evolution of cooperation · Co-authorship network · Giant component · Small world · Cohesive core

Introduction

In the last century, collaboration has gradually become the dominant mode for producing scientific knowledge in many disciplines (Wuchty et al. 2007). The study of scientific

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collaborations has consequently attracted great attention in scientometrics, as well as in various other disciplines such as computer science, sociology and management science (Cronin 2005; Gazni et al. 2012; Wagner et al. 2002; Kouzes et al. 1996; Moody 2004). More recently, scientific collaboration has also become a hotspot in the field of complexity science, especially from the aspect of complex networks (Barabási et al. 2002; Newman 2001a, b, 2004; Guimerà et al. 2005; Hou et al. 2008).

From the perspective of complex networks, the inquiries on the co-authorship networks may be critical to unravel the structural and evolutionary patterns of scientific collaborations. With the boom of complex-network studies since the late 1990s (Watts and Strogatz 1998; Barabási and Albert 1999), the co-authorship networks have been extensively investigated. Two series of pioneering contributions in this direction are respectively given by Barabási et al. (2002) and Newman (2001a, b, 2004). By using the datasets in the disciplines of mathematics, neuro-science, physics, biolomedical studies and computer science, they examined the “small-world” and “scale-free” features in the co-authorship networks. Subsequently, there has been an enormous growth in literature in the last decade to uncover the structure and evolution of the co-authorship networks, especially in their “scale-free” and “small-world” characteristics (e.g., Liu et al. 2005; Tomassini and Luthi 2007; Perc 2010; Yan et al. 2010; Franceschet 2011). The underlying mechanisms for the evolution of the co-authorship networks and patterns of their evolutionary dynamics have also been extensively explored (e.g., Powell et al. 2005; Fenner et al. 2007; Chandra et al. 2007; Evans et al. 2011).

Different from the overwhelming view on the “scale-free” feature of the scientific co-authorship networks, some researches have paid much attention to the property of “social cohesion” (White and Harary 2001) in various disciplines. By analyzing the “*Sociological Abstract*” database from 1963 to 1999, Moody (2004) claimed that the co-authorship network in sociology is characterized by a steadily-growing “cohesive-core”. The existence of disciplinary “cohesive-core” is partly supported by Powell et al. (2005) in terms of the life-science data. Lee et al.’s (2010) work also reveals the increase of disciplinary cohesion during the growth of collaboration networks. By tracking the development of the complex-network-research field, they identified three major processes in the network evolution, i.e., small isolated components, the tree-like giant component with a robust core, and the large-scale loops.

According to the previous brief overview, the co-authorship networks in different disciplines have been intensively pursued, to enrich our knowledge of the social dynamics of scientific collaborations. However, further work is still needed to explore scientific collaborations from a network point of view. Owing to today’s prominent trend of the scientific collaborations that cross disciplinary boundaries, the co-authorship networks in interdisciplinary fields may deserve further research attention. In particular, it is worthwhile to examine what are the structural properties of an interdisciplinary collaboration network. Whether are they with “scale-free” and “small-world” structures? Whether are they structurally cohesive? What’s more, how do the structural properties emerge through their endogenous evolution? The answers of these questions would be valuable to deepen our knowledge on the underlying mechanisms for the growth of the co-authorship network, as well as the development of the corresponding interdisciplinary research field itself.

Accordingly, we in this paper attempt to examine the structural properties and evolutionary patterns of interdisciplinary co-authorship networks by studying an actual case. We choose a typical interdisciplinary research field, i.e. the “evolution of cooperation” (Axelrod and Hamilton 1981), and examine the structure and evolution of the corresponding collaboration network by analyzing the co-authorship data that are mainly extracted from the Web of Science database. With interesting results being obtained in our examination, we expect this case study may bring insightful implications on the collaboration networks on other interdisciplinary research fields.

Data and methods

Data preparation

In this work we choose the interdisciplinary field of "evolution of cooperation" (EOC) as the subject of inquiry and examine the structure and evolution of the co-authorship network of this specific research field. Since Charles Darwin's inquiry on cooperation in animals (Darwin, 1871), many scholars have pointed out that cooperative behaviors are ubiquitous in many social species (Bernasconi and Strassmann 1999; Bshary and Grutter 2006; Partiot et al. 1996). Cooperation has hence become a persistent research issue in theoretical biology. Meanwhile, cooperation is also a fundamental mechanism for the functioning of human society and the formation of social institutions. With the progressive maturity of the game-theoretical tools (Maynard Smith 1982), the studies on the emergence and evolution of cooperation have attracted increasing attention in the context of social science and economics since the 1980s, triggered by the pioneering works such as (Axelrod and Hamilton 1981). More recently, this research field has also flourished in complexity science and the literature has rapidly expanded since the late 1990s. In a special issue of Science magazine to celebrate its 125th anniversary, the evolution of cooperation was selected as one of the top 25 big questions facing science over the next quarter-century (Pennisi 2005). In all, "evolution of cooperation" is a promising research topic that is fast-growing in the last decades. It is also an interdisciplinary topic that crosses the boundaries of biology, economics, sociology, computer science and complexity science (Nowak 2006; Binmore and Samuelson 1992; Boyd and Richerson 1992; Axelrod and Hamilton 1981; Fehr and Gächter 1999; Frank et al. 1993; Bó and Fréchette 2011). This research topic is on one hand focused on a specific subject of inquiry, i.e. the cooperation in humans and animals; and on the other hand, it also incubates a research field that is inherently diverse in its disciplinary origins. The co-authorship network on this *focused-and-diverse* field may then be regarded as a good case to study the interdisciplinary collaboration networks.

In order to construct the co-authorship network on the "evolution of cooperation" (the "EOC network" for short), we use Thompson Reuter's Web of Science (WoS) as the primary source to extract information on authors and their collaborations. We retrieve the core collection of WoS during 1945–2013 by using a few key topical terms, as shown in Eq. 1.

$$\begin{aligned}
&\text{TS} = (\text{``evolution of cooperation''})\ \text{OR}\ \text{TS} = (\text{``indirect reciprocity''})\ \text{OR}\\
&\text{TS} = (\text{``direct reciprocity''})\ \text{OR}\ \text{TS} = (\text{``reciprocal altruism''})\ \text{OR}\\
&\text{TS} = (\text{``complexity of cooperation''})\ \text{OR}\ \text{TS} = (\text{``emergence of cooperation\}})\ \text{OR}\\
&\text{TS} = (\text{``evolution of altruism''})\ \text{OR}\ \text{TS} = (\text{``altruistic punishment''})
\end{aligned} \tag{1}$$

Here we choose very specific topical terms in order to precisely obtain academic papers on this particular field. On the other hand, the topical terms cover the key research themes of "cooperation", "reciprocity" and "altruism" to get an acceptable recall or coverage for the query results. In order to improve the precision of the query results, we retrieve the

Core Collection of WoS, instead of “All Databases”. Through this query, we obtain 2,496 papers, which can be categorized into multiple disciplines and specialties in terms of the categorization system used in WoS. The basic categorization information of the query results is illustrated in Table 1.

Table 1 reveals the interdisciplinary nature of the examined field, as the papers can categorized into very divergent disciplines such as Biology, Mathematics, Physics, Social Sciences, Computer Science, Medicine, and Management and Business. This characteristic may be critical for the structure and evolution of the corresponding co-authorship network.

Besides Web of Science, we also use Google Scholar as a supplementary source to collect relevant papers, so as to incorporate more key publications in this field. The search on Google Scholar via the keywords “evolution of cooperation” can return about 38,500 fits; this result set contains great amount of irrelevant items. Thus, for the precision of the data set, we just extract the papers that are cited more than 100 times and we obtain 42 papers that are non-redundant from the previous WoS query results.

Furthermore, we extract all the references from a recent review paper (Rand and Nowak 2013), which is co-authored by Martin Nowak, a leading scholar in the examined research subject. We add 39 papers that are not included in the result set. In addition, we access the publication list of the homepage of Robert Axelrod at University of Michigan (http://www-personal.umich.edu/~axe/), who is another leading scholar in this field. We add six of his EOC papers that are not included in previous dataset.

Thus we altogether obtain 2,583 papers, including 2,496 from the Core collection of WoS, 42 from Google Scholar, 39 from Nowak’s review paper, and 6 from Axelrod’s homepage. This paper-list does not cover the full range of the research topic under examination. But our prioritized criterion in this work is on the *precision* rather than the *recall* of the retrieved results. On the other hand, by extracting papers from multiple sources, we expect our dataset may have a reasonable coverage for the key contributions in this specific research field.

The number of published papers in the obtained dataset over the calendar year is illustrated in Fig. 1. The earliest work is Charles Darwin’s original contribution firstly published in 1871 (Darwin 1871); and the second earliest work occurred in 1961. Since 1961, the number of published papers non-uniformly grows year by year. During the period

Table 1 Disciplinary categorization of the returned records from WoS Query

Disciplinary category	# of records	Percentage to all records	Disciplinary category	# of records	Percentage to all records
Biology	1,192	46.36	Basic Disciplines of Engineering and Technological Science	60	2.33
Mathematics	301	11.71	Electrics, Communication and Automatic Control	58	2.26
Physics	275	10.70	Environmental Science and Technology	20	0.78
Social science	269	10.46	Mechanics	10	0.39
Computer Science and Technology	191	7.43	Agriculture	3	0.12
Medicine	120	4.67	Fisheries	3	0.12
Management and Business	69	2.68			

The overall number of records is 2,571 instead of 2,496 because some papers are redundantly categorized into multiple disciplines or specialties.

from 1961 to 1999, the scholarly attention on this subject was steadily growing but the overall publications were limited. In comparison, the publications on this topic increase rapidly from 2000 till now and a peak is reached in 2012. These results indicate that this research field is currently at a stage of fast-growth after long incubation.

To study the co-authorship network from the previously-obtained dataset, one important problem is author ambiguity. In order to mitigate this problem, we create an author-name dictionary in two steps. First, we identify authors in terms of their family and first names. For the authors whose full names are same, we check their affiliations, assuming that two authors of the same name but with different affiliations in the same year are two different authors; otherwise they are just treated as one same author. Second, for the identified authors in the first step, we collect all the possible name variants of first names, middle names, and the initials. For example, for author Martin Nowak, we got three forms of "Nowak, M.", "Nowak, M.A." and "Nowak, Martin A.". By adding the variants into the author dictionary, we can basically disambiguate the case of multiple name forms for the same author. Nonetheless, we admit that our treatment does not ensure the elimination of the ambiguity of multiple authors of the same name. Fortunately, by random examination of records, we may assert that this problem seems not severe in our author-list.

Methods

The main method used in this paper is social network analysis. Through checking the key metrics of the co-authorship network of the EOC field, we analyze its structure properties and evolutionary pattern.

Before analysis, we construct the co-authorship network. As shown in Fig. 1, the number of papers before 2000 is generally small. In particular, we do not obtain any single paper between 1871 and 1961. Hence, we exclude the literature in 1871 and aggregate all the obtained papers during the period from 1961 to 1999, regarding all the years before

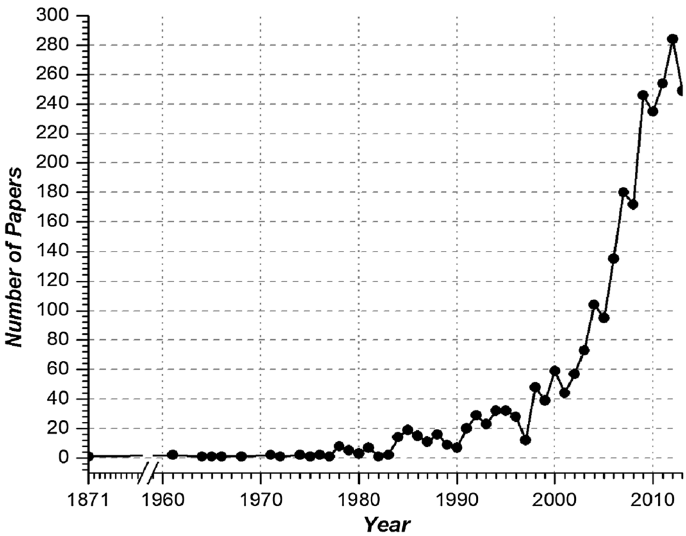

Fig. 1 The number of publications over calendar years

1999 as the incubating stage of the examined EOC field. Thus, we study the structure and evolution of the co-authorship network since the year of 1999, by tracking the change of the cumulative network structure in one-year intervals (i.e., the network from 1961 to 1999, that from 1961 to 2000, and so on). In each period, the authors are the vertexes and the co-authorships between authors are the edges.

Thus, in the constructed network, the network size refers to the number of nodes in the network. The average degree denotes the average number of neighbors of each node, i.e., the average number of collaborators of each author. The size of largest connected-subgraph actually represents the scale of the central cluster of the entire network, as to be elaborately investigated in the later part of this paper. This largest connected-subgraph can be called the "giant component" of the entire network (Guimerà et al. 2005).

Besides the above elementary metrics, we also measure the clustering coefficient, the average shortest-path-length and the modularity, in order to test the "small-world" property and the community structure of the examined network. Furthermore, we measure the distribution of node degrees to examine the "scale-free" property of the network; and the method suggested by Jeong et al. (2003) is used to examine the mechanism of preferential attachment to form the scale-free degree-distribution.

In the previous metrics, the properties of clustering coefficient and modularity may need further explanation. The clustering coefficient is a local property to measure the average cliquishness in the network, reflecting the extent to which the two collaborators of an author also collaborate with each other. In this work, we adopt Watts and Strogatz's (1998) definition, as formulated in Eq. 2. Where Δ denotes the number of triangles in the network; and Λ is the number of connected triples of vertices. The clustering coefficient is important as it is often used, in conjunction with the characteristic path-length, to measure whether the network is a small-world or not (Watts and Strogatz 1998).

$$cc = \frac{3 \times \Delta}{\Lambda} \tag{2}$$

Comparing with the local measure of clustering coefficient, modularity is to measure whether the network is modular at the global level. High value of modularity means that the network has a clear community structure; and the network is comprised of multiple modules or communities with dense intra-communal links but less-dense inter-communal links (Girvan and Newman 2002). In this paper, the well-noted fast community-detection algorithm proposed by Blondel et al. (2008), which is a heuristic method based on modularity optimization, is adopted to detect the communities and meanwhile to obtain the (optimal) modularity.

In addition to examining the network properties, we also give textual analysis on the authors' research topics. To do so, we use the keywords of the papers as the main source of analysis. The terms in paper titles are also extracted and filtered to compensate the absence of author-providing keywords in many papers, e.g., those published in Science, Nature and Proceedings of the National Academy of Sciences of USA. A few terms that are very frequently occurred in almost all the communities are removed from the extracted term-list, including "evolution of cooperation", "cooperation", "game", and "evolution". Based on the obtained terms we build a dictionary of topical terms; and the frequencies of these topical terms are also counted and stored. Then, for the identified communities, we are to count the terms occurring in the keywords and/or titles of the papers in each community during the period under examination; and the top-ten frequent terms are used to characterize the topics of the community. With the analysis of the topical terms, we examine whether the communities are clustered by authors with similar research topics and whether the inter-communal links are also correlated with the topical similarities between the communities, in order to correlating the network evolution with the field growth.

With the previous metrics, subsequently we analyze the structure and evolution of the EOC co-authorship network and its giant component.

Analysis of the structure and evolution of the co-authorship network

The basic characteristics of the entire network

Table 2 lists the basic statistical properties of the previously-constructed cumulative co-authorship networks in different periods, namely the size of the overall network, the average degree, the clustering coefficient, the modularity, and the size of largest connected-subgraph.

Table 2 shows that the EOC network is rapidly expanding in the last decade. Besides, we can also observe a rapid expansion of its largest connected-subgraph. During this process, the proportion of the giant component in the whole network is increasing, revealing the gradual emergence of a core-periphery structure of the co-authorship network. From another aspect, we can find in Table 2 that the network is highly modular in all the years (*Modul* >0.93). This indicates that the whole network is comprised of a number of structurally-cohesive clusters or communities, while the inter-communal links are extremely sparse. The structural characteristics of the whole co-authorship network are further illustrated in Fig. 2.

Figure 2 tracks the yearly changes in the sizes of the entire co-authorship network and its main components. In Fig. 2a, we compare the size of the giant component with the whole network. The curve with hollow-square denotes the growth of the entire co-

Table 2 The basic information of co-authorship network from 1961 to 2013

Period	Network size (number of nodes)	Average degree	Clustering coefficient (*cc*)	Modularity (*Modul*)	Size of largest connected-subgraph
1961-1999	531	1.597	0.393	0.968	20
1961-2000	635	1.723	0.422	0.974	21
1961-2001	695	1.827	0.427	0.976	21
1961-2002	782	1.985	0.446	0.979	21
1961-2003	877	2.169	0.460	0.962	69
1961-2004	996	2.215	0.462	0.959	115
1961-2005	1111	2.457	0.475	0.932	147
1961-2006	1,312	2.802	0.519	0.937	176
1961-2007	1,583	2.892	0.549	0.948	212
1961-2008	1,838	3.004	0.563	0.953	288
1961-2009	2,216	3.029	0.576	0.954	361
1961-2010	2,539	3.108	0.590	0.956	511
1961-2011	2,901	3.206	0.602	0.955	705
1961-2012	3,269	3.309	0.612	0.949	856
1961-2013	3,670	3.409	0.632	0.950	1,127

authorship network, while the curve with solid-triangle denotes the growth of its giant component. These two curves exhibit different growth modes. During the period from 1999 to 2006, the size of the entire co-authorship network steadily expands, while the increasing rate has become sharper since 2006. In comparison, the inflection point occurs in 2009 for the giant component. Another phenomenon shown in Fig. 2a is that the fraction of the giant component to the overall co-authorship network gradually increases in the last decade; and this trend becomes more apparent in the last few years. Up to 2010, the fraction of the size of the giant component to that of the co-authorship network is about 20 %; but up to the year of 2013 this value reaches around 33 %. Such increasing fraction of the giant

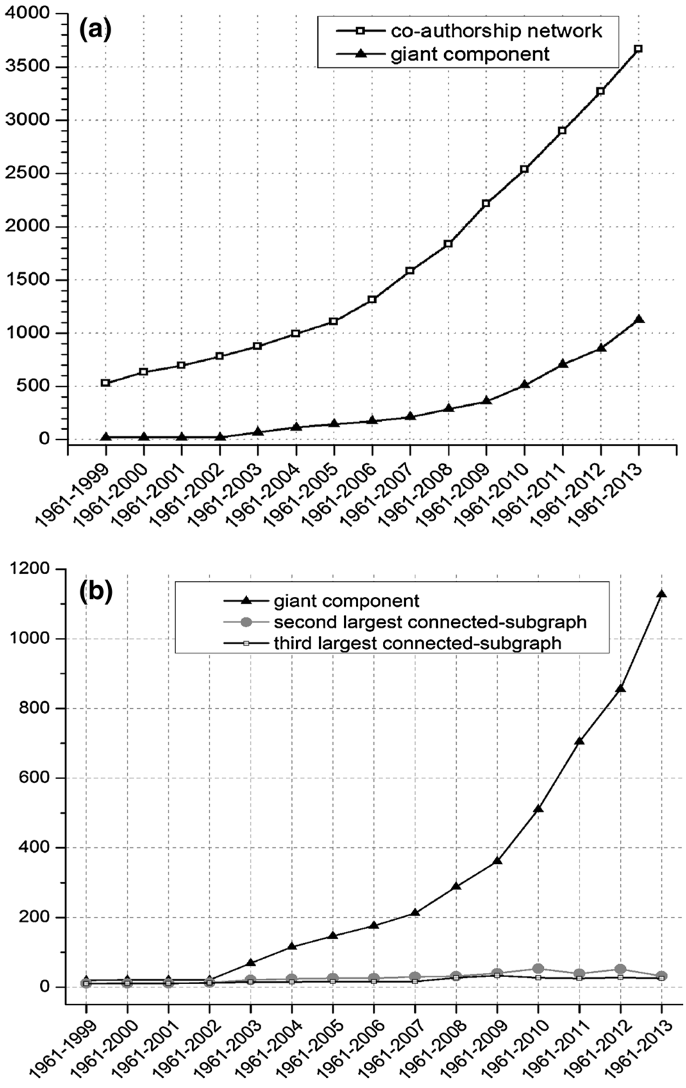

Fig. 2 Sizes of the whole network, the giant component, the second and third largest connected-subgraphs. **a** The sizes of entire network and of its giant component or largest connected-subgraph. **b** The sizes of the giant component, and of the second and third largest connected-subgraphs

component implies the formation and expansion of the "core" of the whole network. The formation of the "core" can also be examined by comparing the size of the giant component with those of the second and third connected-subgraphs. As shown in Fig. 2b, the size of the giant component was not significantly larger than those of the second and third largest connected-subgraphs before the year of 2003. However, the giant component has been rapidly expanding since 2003, while the second and third largest connected-subgraphs remain small-sized. This reveals that a core-periphery structure has gradually formed in the last decade. In this structure, the "giant component" is the "core", while the rest of the entire network is the periphery. The formation of this core-periphery structure can further be illustrated in Fig. 3 by visualizing the network structures in representative years.

Figure 3 exemplifies the structures of the co-authorship network at different development stages of this research field. Up to 1999, the co-authorship network was composed of small clusters and isolated nodes, with the largest cluster containing only 20 authors as illustrated in the lower-left part of Fig. 3. Then, till 2006, as shown in the middle part of Fig. 3, a core-periphery structure had emerged. The entire network contained a giant component that was surrounded by small communities and isolated nodes (i.e., authors). What's more, as shown in the lower-middle part of Fig. 3, the giant component contained a structure of chained-communities, which was actually comprised of three communities interlinked one by one so that the distances between two random nodes could be large.

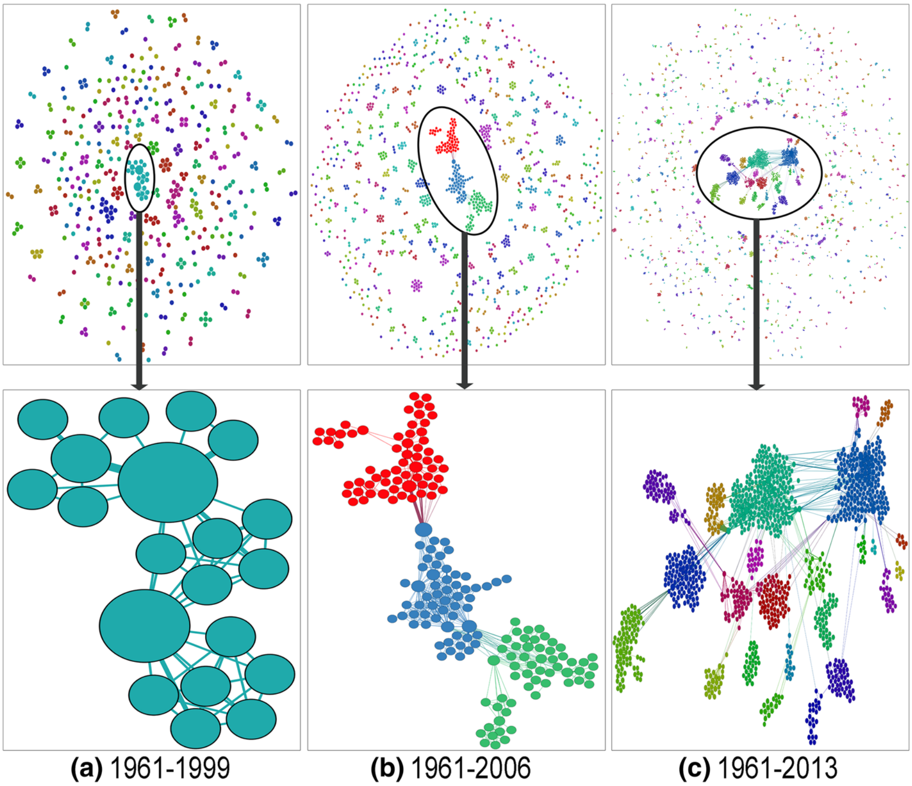

Fig. 3 Topological structures of the cumulative co-authorship network (*upper part*) and the corresponding giant component (*lower part*) in typical years

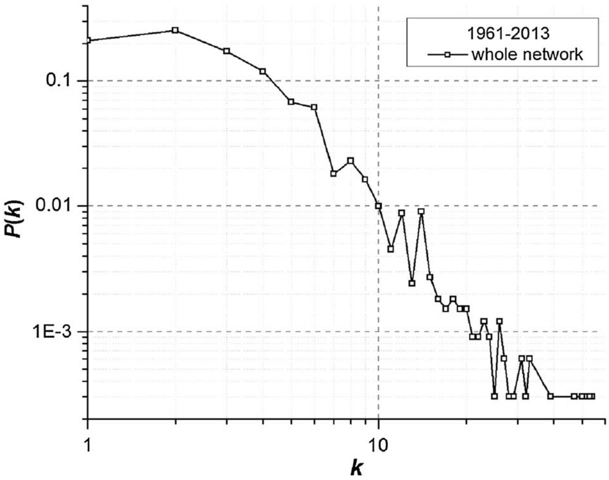

Fig. 4 Degree distribution of co-authorship network (*k* stands for degree)

With the further development of the network, the giant component had remarkably expanded till 2013, as shown in the right part of Fig. 3. At this stage, a small world had emerged within the giant component, as all the local communities were connected through short-cut links. Generally, Fig. 3 depicts a process in which the EOC network evolves from segregation to a core-periphery structure; and the core or giant-component is rapidly expanding in the last decade.

Furthermore, we examine the degree distribution in the EOC network, as shown in Fig. 4.

Figure 4 reveals that the degrees of nodes in the co-authorship network accord with some skewed distribution that resembles the power-law distribution for the nodes whose degrees are greater than 2. It would, then, be interesting to test whether the network grows through preferential attachment (Barabási and Albert 1999). The measure of the preferential attachment mechanism has widely discussed in the last decade (Perc 2014). Here we just adopt the method suggested by Jeong et al. (2003). With this method, we use the network evolution from 2011 to 2012 as an example to measure the preferential attachment mechanism, as shown in Fig. 5.

Figure 5 illustrates the correlation between the node degree (k) and the probability of co-authorship establishment with a k-degree node $\kappa(k)$ in the period between 2011 and 2012. The black solid-line depicts the correlations from the actual network data, while the gray dash-line is the power-law fit generated from the preferential-attachment mechanism. Figure 5 shows that the attachment probability of a node is basically proportional to the degree of this node, indicating the existence of strong preferential attachment in the evolution of the examined network.

The prior analysis of the whole co-authorship network shows two characteristics of the networks. First, the cumulative distribution of node-degrees obeys a skewed distribution. And further analysis indicates that a mechanism of preferential attachment may probably take effect during the growth of the network, i.e. a few "academic stars" or the "attachment kernel" (Perc 2014) play an important role in the development of the examined research field. Second, the network gradually evolves from a set of scattered small clusters to a core-periphery structure which is comprised of a giant component (i.e. the "core") and

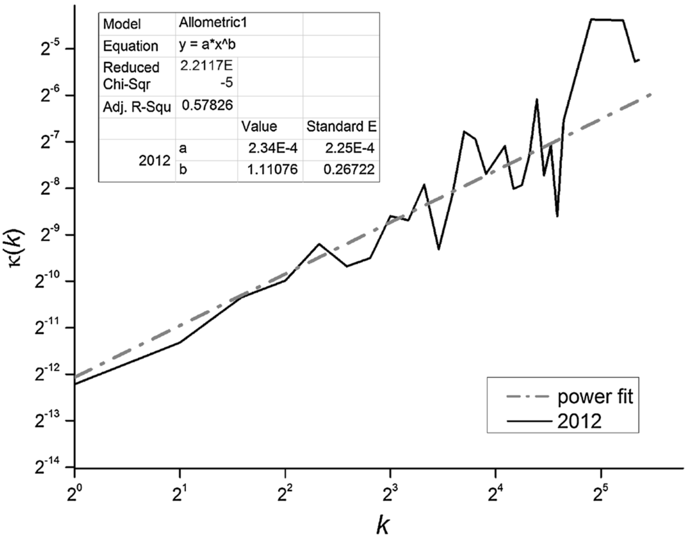

Fig. 5 Examination of preferential attachment for the network from 1961 to 2012

a series of smaller clusters (i.e. the periphery). Further examination on the "giant component" of the network is then deserved, in order to better clarify the key features of this network and the corresponding research field.

Analysis of the giant component

Intuitive illustration of the evolution of giant component

To analyze the giant component, we first examine the overall schemes for its growth by illustrating the year-to-year changes in a few typical years, as shown in Fig. 6.

Figure 6a shows the topological structure of the whole co-authorship network from 1961 to 2002, which is basically comprised of segregated small clusters and isolated nodes. Up to the end of 2002, there was no single prevailing cluster or giant-component. However, further examination shows that a giant component would begin to occur in the succeeding calendar year. The clusters highlighted by circles in Fig. 6a would be interconnected in the year of 2003, to constitute the initial giant-component. Thus, Fig. 6a illustrates the formation of giant component or "core" of the co-authorship network in around 2002 and 2003, by assembling a few previously-separate clusters.

Figure 6b depicts the change of the giant component from 2003 to 2004. We can see that the giant component grew by adsorbing newly-generated small clusters. This is the dominating mode for the expansion of the giant component in the early-stage since its formation. This mode can basically explain the formation of the previously-stated "chain structure

" structure. Analogous to a crystal-growth process, the adsorption of new clusters would commonly generate a long chain of small clusters, which characterizes the early-stage structure of the giant component. In parallel to the expansion of the giant component, some other communities also grew by adsorbing small clusters during the same period.

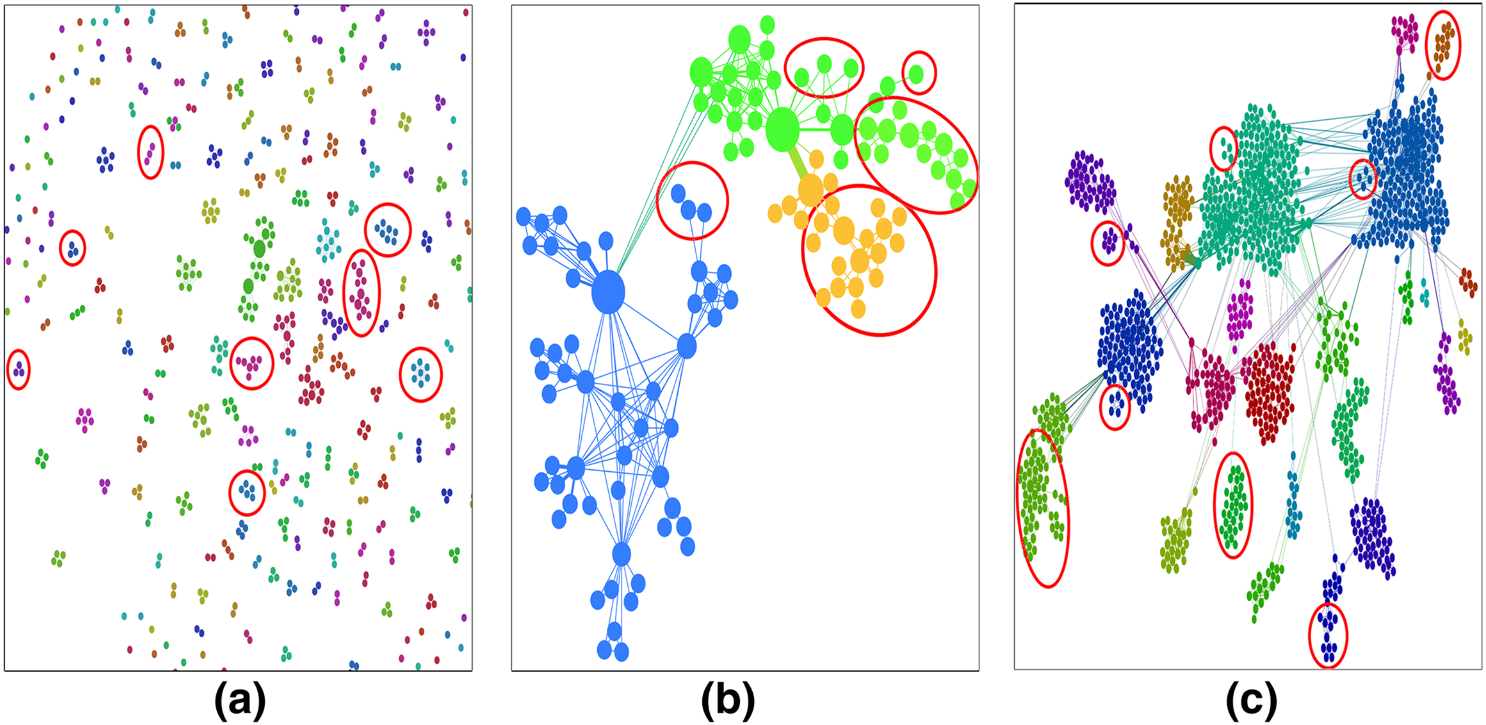

Fig. 6 Illustration of the growth of the giant-component. **a** The cumulative co-authorship network from 1961 to 2002. The *encircled* fragments were to be aggregated to form the initial giant component in 2003. **b** The change of the giant component from 2003 to 2004. The *encircled* fragments are newly added in 2004. **c** The change of the giant component from 2012 to 2013. The *encircled* fragments are newly added in 2013

With the further growth of multiple components, the merging of major components would turn to be the prevailing mode for the expansion of giant component. This trend is exemplified by Fig. 6c, which illustrates the network growth of the giant component from 2012 to 2013. In this period, in addition to the persistent adsorption of small clusters, a few relatively-large clusters were also merged into the giant component. The merging of multiple components speeded up the expansion of giant component. This merging process also helps the giant component to form the small-world structure.

The prior examination shows an overall process for the growth of the giant component. Through this process, the giant component evolves from a small cluster or clique to the structure of "chained-communities", and then to the small-world structure. The recently generated "small-world" is analogous to the structure of "permeable boundaries" as identified in the sociological collaboration network (Moody 2004).

Based on the previous intuitive illustration on the evolution of giant component, we give a more thorough analysis on it, in terms of its degree distribution, modularity, clustering coefficient, and average shortest-path-length. Especially, the "scale-free" and "small-world" properties are accounted for in this analysis.

Degree distribution

The degree distribution of the giant component (1961–2013) is illustrated in Fig. 7. In Fig. 7, the node degree (k) is plotted along the horizontal axis, while the vertical axis displays the fraction or "probability" of the nodes that has a particular degree, denoted by $P(k)$. The black solid line plots the actual degree-distribution, while the gray line with square is the lognormal fit and the gray line with triangle is the power-law fit. The parameters for the two fitting distributions are shown inset.

The degree distribution of the giant component is morphologically similar with that of the whole co-authorship network shown in Fig. 4, both not fully fitting the power-law distribution. Instead, a combination of the lognormal and power-law distributions can fit the actual data well. The majority of authors are in the range of $k < 10$. In this range, the degree distribution basically obeys the lognormal distribution. In comparison, in the range of $k \geq 10$, the power-law distribution roughly fits the actual degree distribution, indicating that a small proportion of authors have significantly larger number of coauthors than the average authors do.

Modularity, clustering coefficient and average shortest-path-length

Figure 8 depicts the changes of modularity (denoted as *Modul*) and clustering-coefficient (denoted as *Cc*) of the giant component from 1999 to 2013. According to Fig. 8, the evolution of the giant component can be divided into three stages. The first stage is from 1999 to 2002. In this stage, the modularity is stable at a low level around 0.4, while the clustering coefficient remains at a high level around 0.8. Correspondingly, the giant component was just a small cluster in which the nodes are densely interconnected with one another. Thus the clustering coefficient is high due to the dense internal connections, but the modularity is low because the giant component can hardly be divided into sub-communities at that stage.

Then, the second stage is from 2002 to 2004, in which we can observe both a rapid ascending of modularity and steep descending of clustering coefficient. Correspondingly, the giant component rapidly expands in this stage and the "core" of the whole co-authorship network begins to occur, as previously-described (Fig. 2). With the expansion

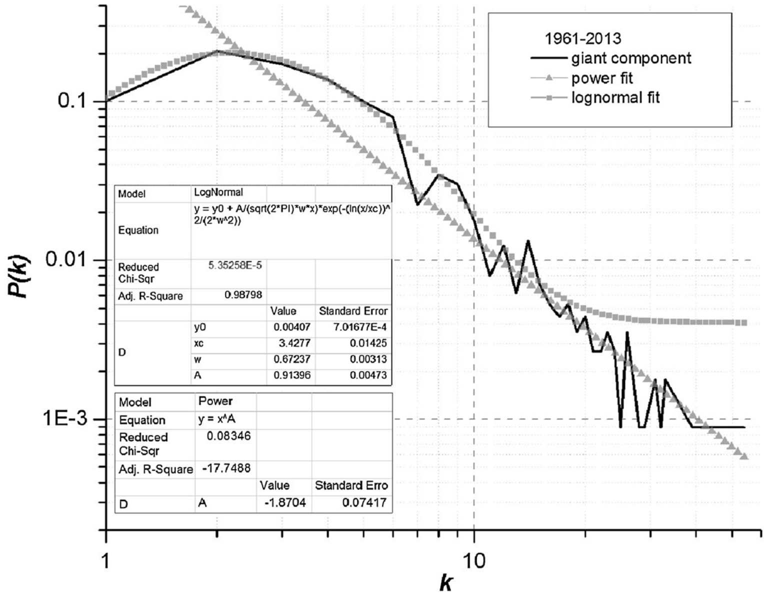

Fig. 7 Fitting of the degree distribution of the giant component

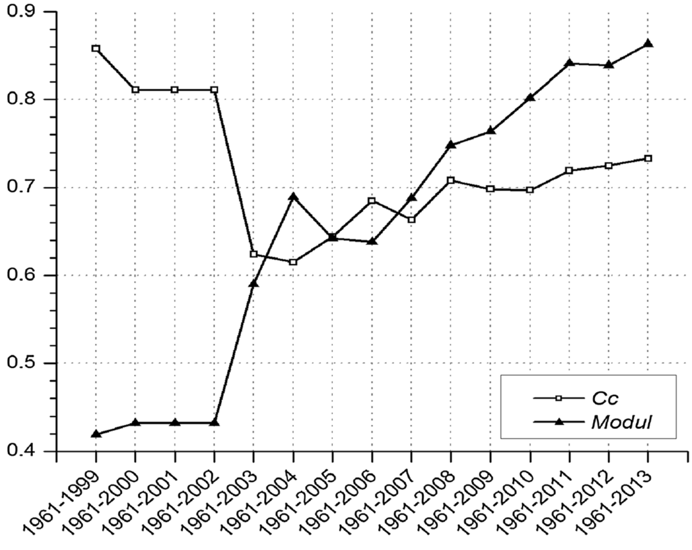

Fig. 8 Clustering coefficient and modularity of the giant component

of giant component by merging external clusters, the local transitivity of links decreases, resulting in the steep dropping of clustering coefficient. Meanwhile, the incorporation of clusters into the giant component remarkably increases the modularity.

The period from 2004 to 2013 constitutes the third stage, in which both the modularity and the clustering coefficient steadily increase. The change mode of modularity and clustering coefficient in this stage reflects the steady expansion of giant component. On one hand, the giant component becomes increasingly modular with the continuous merging of new clusters. On the other hand, nodes become more densely connected within local clusters, leading to the steady increase of the clustering coefficient during this period.

From the previous examination we can see that the giant component evolves into a highly-modular structure of multiple communities that are densely clustered. It would be interesting to examine whether this network (i.e., the core of the whole co-authorship network) can be regarded as a small-world. Thus, we further measure the average shortest-path-length of the giant component.

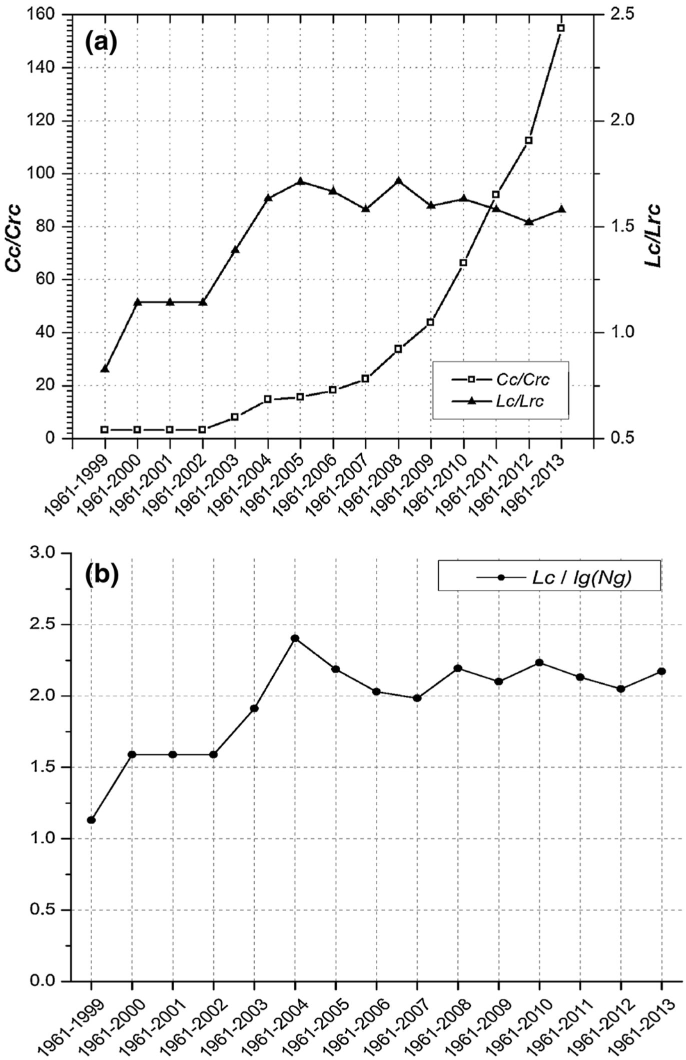

Fig. 9 Clustering coefficient and average shortest-path-length of the giant component. **a** Illustration of clustering coefficient and average shortest-path-length of the giant component. **b** Comparison of the average shortest-path-length with the logarithm of the giant component size

Figure 9a illustrates the clustering coefficient and the average shortest-path-length of the giant component. The horizontal axis displays the calendar year. On the vertical axis, the clustering coefficient and the average shortest-path-length are respectively displayed, dividing by the corresponding values of the random network of same scale. The clustering coefficient of the giant component is denoted as *Cc*, while that of the corresponding random network is denoted as *Crc*. The average shortest-path-length of the giant component is denoted as *Lc*, while that of the corresponding random network is denoted as *Lrc*. As shown in Fig. 9a, the value of *Cc/Crc* has remarkably been increasing since 2004, while the increase of the corresponding average shortest-path-length is insignificant in the same period (e.g., $Lc/Lrc < 1.7$ in 2008 and $Lc/Lrc < 1.6$ thereafter). The remarkable increase of *Cc/Crc* and the relatively stable value of *Lc/Lrc* indicate the giant component evolves into a small-world.

What's more, we compare the average shortest-path-length with the logarithm of the size of giant component (denoted as N_g), with respect to Boccaletti et al.'s (2006) measure of the small-world property. The result is shown in Fig. 9b. We observe that *Lc* is approximately proportional to $lg(N_g)$ during the period from 2005 to 2013 and the proportional value is between 2.00 and 2.25. Hence, the giant component can be regarded as a small-world during the period from 2005 to 2013.

Identifying the "cohesive core" within the giant component

The previous examination shows that the giant component exhibits a small-world structure, which is comprised of multiple communities that are with dense internal edges and meanwhile linked with one another by sparser inter-communal connections. From another aspect, as shown in Fig. 7, this network of giant-component (i.e., the sub-graph of the entire co-authorship network) has a skewed degree distribution, in which a small proportion of nodes hold large numbers of edges while the majority of nodes have arbitrarily $1 \sim 10$ co-authors. It would then be worthwhile to examine whether it is those high-degree nodes that play a critical role to bridge different communities.

In order to identify the key nodes that bridge different communities, a vulnerability analysis is given by continuously removing nodes from the giant component and examining the connectivity of the remaining network. Here a simple measure of the connectivity is used, in which the connectivity of a network is equal to the proportion of the largest connected-subgraph in the whole network.

First we remove the nodes in an ascending mode. In other words, we begin the node-removal process by removing the one-degree nodes and consequently obtaining the remaining network as the more-than-1-degree sub-graph of the original giant component (1961–2013). We denote this remaining network as "$k > 1$ sub-graph". Then the $k > 2$ sub-graph is obtained by removing the nodes whose degrees are equal to 2 (i.e., $k = 2$); and the remaining nodes are step-by-step removed from low to high degrees. This node-removal process continues until the $k = 52$ nodes have been removed and the giant component has been completely broken. The decrease of the network size and the change of connectivity in the remaining network are illustrated in Fig. 10a, while Fig. 10b illustrates the topological structures of a few typical remaining networks.

We measure the decrease of the network size by plotting the ratio of the remaining network to the original giant component. A steep decrease of the size of the remaining network is observed when removing the nodes whose degrees are less than 10. Comparably, the descending slope is remarkably flattened after degree 10. This result indicates

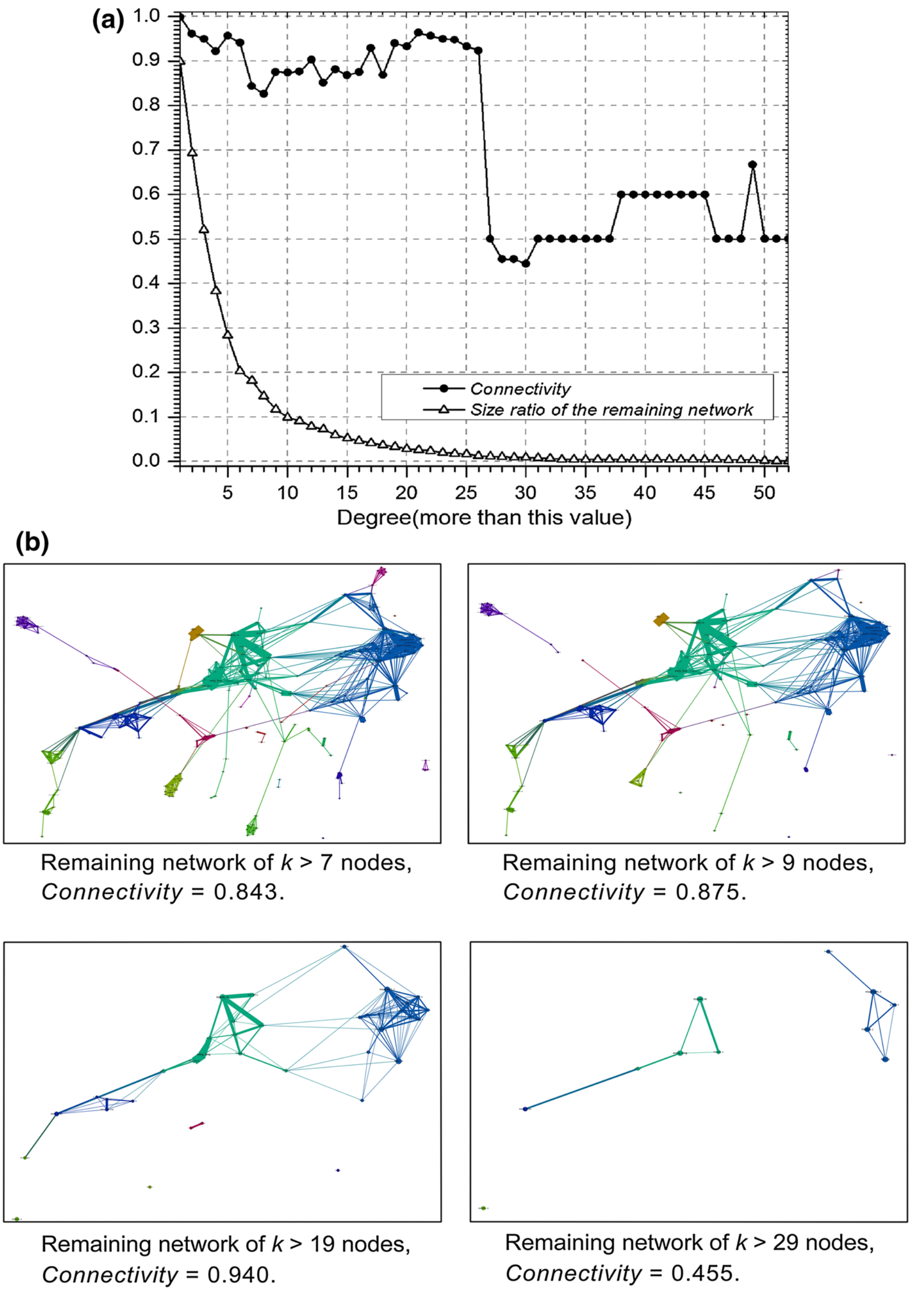

Fig. 10 Connectivity of the remaining network through node removal and the illustrations of network topologies with typical connectivity value when removing nodes ranging from degree 1 to 52. **a** The decrease of the network size and the change of connectivity in the remaining network. **b** The topological structures of typical remaining networks

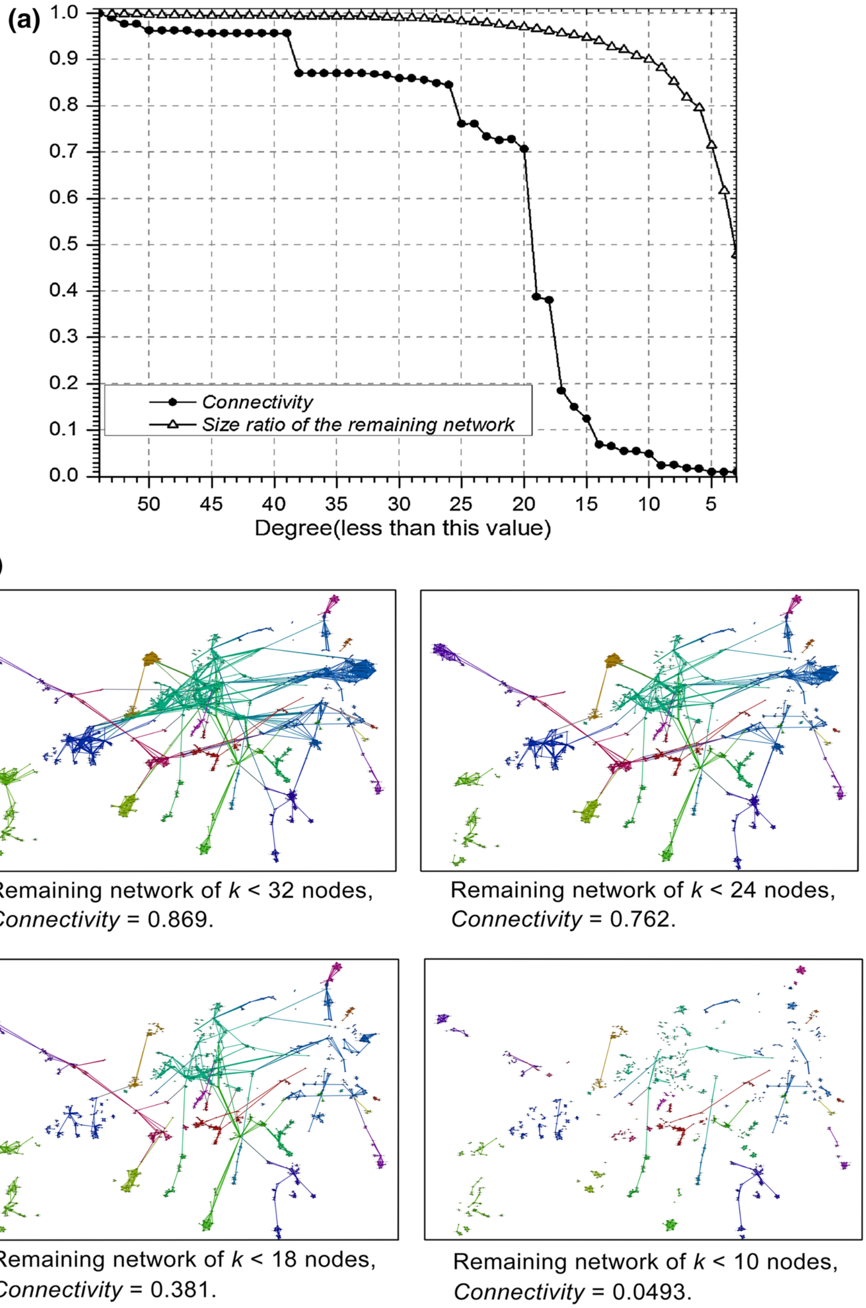

Fig. 11 Connectivity of sub-graphs and illustration of sub-graph topologies with typical connectivity value when removing nodes ranging from degree 54 to 3. **a** The decrease of the network size and the change of connectivity in the remaining network. **b** The topological structures of typical remaining networks

that the majority of nodes are with less than 10 neighbors, providing a good support for the previous divide of the lognormal and power-law distributions at degree 10.

Nevertheless, the connectivity of the remaining network changes in a tremendously different mode. As shown in Fig. 10a, the connectivity gently decreases when removing the nodes whose degrees are less than 10. The connectivity of the remaining network is greater than 0.8 during the removal of the $k < 10$ nodes. This indicates that the giant component basically remains connected through the removal of the low-degree nodes. As exemplified in Fig. 10b, the structural difference between the remaining networks of "$k > 7$" nodes and "$k > 9$" nodes is indistinct. The communal structure of the original giant component is largely retained.

During the further removal of the nodes whose degrees range from 10 to 27, a slight increase of the connectivity can be observed. In this stage of node removal, the local clusters gradually diminish but the connectivity of the remaining network remains high. As illustrated in the "$k > 19$" sub-graph in Fig. 10b, a connected "stem" or "backbone" of the original giant-component is retained although many "leaves and branches" (i.e., local clusters) that appear in "$k > 7$" and "$k > 9$" networks are cut off. This result reveals that the "middle-class" nodes play an important role for gluing the local clusters but they might not be the critical "bridge" nodes to establish global connectivity.

The removal of the nodes of $27 \le k \le 29$ constitutes the third stage of the node-removal process. In this stage, there is a steep descending of the connectivity from 0.9 to 0.45. As further illustrated by the remaining network of "$k > 29$" nodes in Fig. 10b, the giant component is split into two tiny-sized groups. These two groups are basically retained during the further removal of the $k > 29$ nodes; simultaneously the connectivity of the remaining network keeps stable too, largely ranging from 0.44 to 0.67. This implies the existence of a "rich club", which is roughly comprised of the "$k > 26$ nodes". This rich club furthermore contains two local cliques of high degree nodes ($k > 29$), which are redundantly interlinked by the $27 \le k \le 29$ nodes.

In order to further examine the structural characteristics identified in the prior node-removal process, we execute a reverse process to remove nodes in a descending mode (i.e., from high to low degrees). In other words, the $k = 54$ nodes are firstly removed to obtain the remaining network of "$k < 54$ nodes". The $k = 53$ nodes are then removed, followed by the removal of the $k = 52$ nodes. Such process proceeds until the removal of $k = 3$ nodes and the remaining network of "$k < 3$ nodes" becomes completely separated. Under this node removal strategy, the decrease of the network size and the change of connectivity in the remaining network are illustrated in Fig. 11a, while Fig. 11b displays topological structures in typical remaining networks.

The curve for the ratio of the size of the remaining network to the original giant component in Fig. 11a does not provide much additional information other than what we can get from Figs. 7 and 10a, as this result is basically consistent with the identified skewed-distribution of node-degrees as shown in Fig. 7. In comparison, the change of the connectivity of the remaining network may be more informative to enrich the understanding of the structural characteristics of the giant component.

From the curve of connectivity change in Fig. 11a, we can find that the downward removal of high-degree nodes does not significantly decrease the connectivity of the remaining network. For example, in the illustration of the remaining network of "$k < 32$ nodes" shown in Fig. 11b, the remaining network is largely connected. In the remaining network of "$k < 24$ nodes", the detachment of the local clusters from the giant component can be observed; but the overall connectivity is still reasonably high. In fact, during the downward removal from 39- to 20-degree nodes, the connectivity of the remaining network steadily decreases. The connectivity of the remaining network of $k \leq 20$ nodes is about 0.7. In the prior upward removal-process, we observe the existence of self-connected "main stem" of the $k > 19$ network. The reverse removal reveals an interesting phenomenon that the remaining network of giant-component would still keep high connectivity even if this "main stem" were near-completely removed. This phenomenon depicts that the majority nodes of the giant component do not solely rely on the "main stem" to retain its overall connectivity.

However, the continuing removal of the "$10 \leq k < 20$ nodes" would remarkably decrease the connectivity of the remaining network. In particular, the decrease of connectivity is extremely steep during the removal of the "$15 < k < 20$ nodes". As shown in the illustrations of Fig. 11b, in the remaining network of $k < 18$ nodes, a number of local clusters have been detached from the major community. This phenomenon indicates that the "$10 \leq k < 20$ nodes" are critical to glue the "grassroots" participants (i.e., the $k < 10$ nodes) onto the "main stem" of the giant-component.

The removal of the $k < 10$ nodes is the third stage of downward removal-process. In this stage, the decrease of the connectivity becomes flattened but simultaneously the network size dramatically drops down. As consistent with the prior ascending process of node removal, this result reveals that the low-degree nodes may not be critical for the global connectivity of the giant components. For example, although the ratio of the network size to the giant component is around 90 % at $k = 10$, the remaining network of $k < 10$ nodes

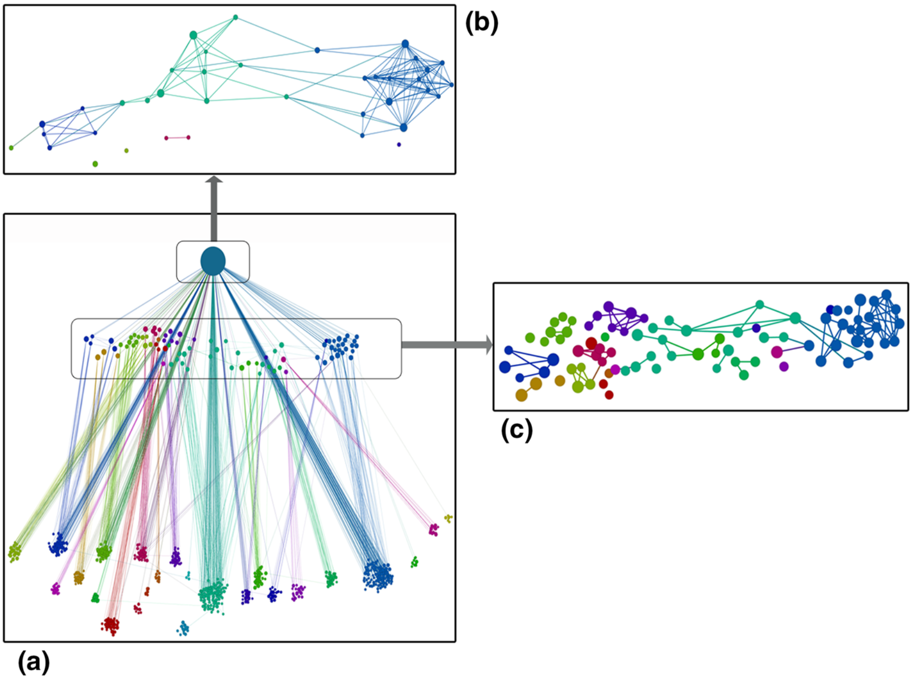

Fig. 12 Illustration of the structure of the giant component (In part (**a**), the $k \geq 20$ nodes are shrunk into a single clustered node). **a** The overall picture for the structure of the giant component. **b** The "elite" nodes ($k \geq 20$) constitute the "main stem" which accounts for about 3 % of the size of giant component. **c** The "middle-class" nodes ($10 \leq k < 20$) who account for about 8 % of the size of giant component play an important role to glue the local cliques of the lower-degree nodes

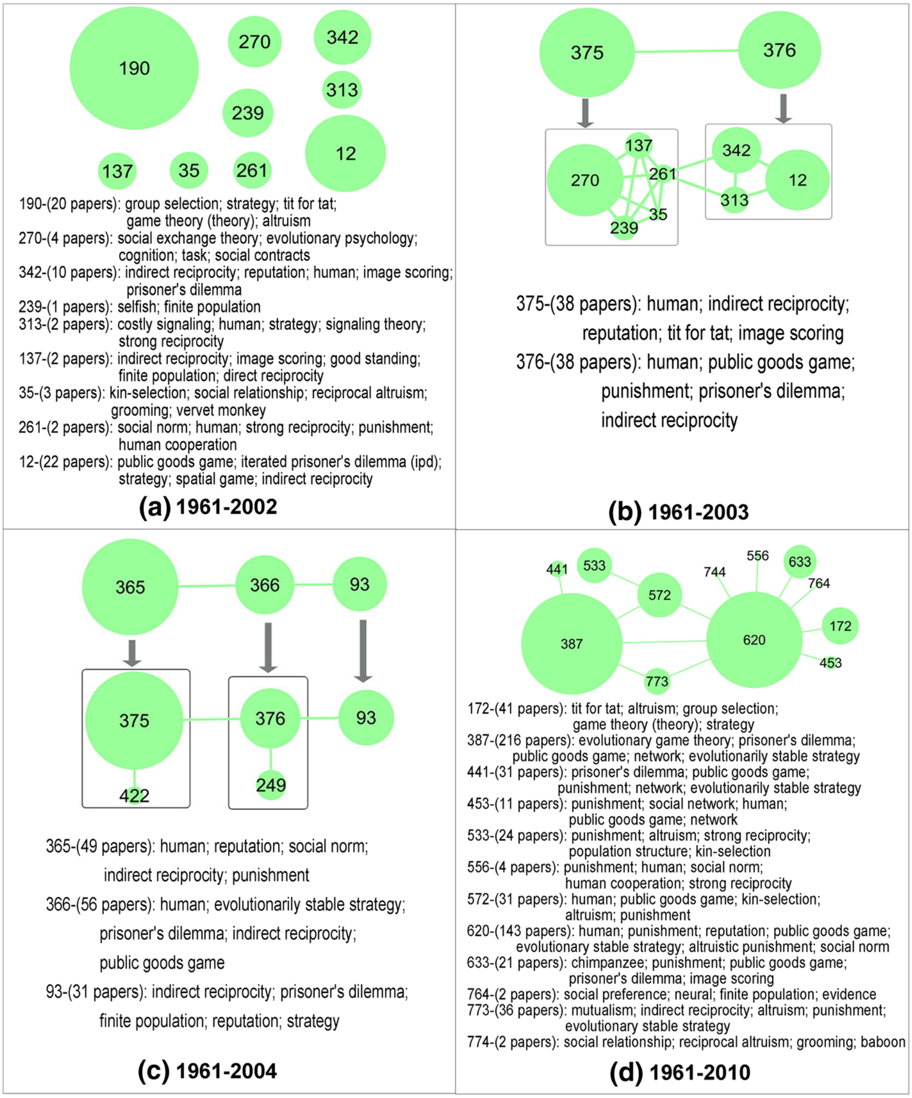

Fig. 13 Illustration of the distribution of research topics within the giant component

has been separated into small clusters and isolated nodes, as shown in the "remaining network of $k < 10$ nodes" illustration of Fig. 11b.

By combining the upward and downward node-removal processes, we observe an intriguing overall picture for the structure of the giant component, as illustrated in Fig. 12. The nodes in the giant component can roughly be classified into three categories, in terms of their degrees and functions in establishing connectivity. The $k < 10$ nodes are basically the "grassroots" nodes; the $10 \leq k < 20$ nodes roughly constitute the "middle-class nodes"; and the $k \geq 20$ nodes can be regarded as "elite" nodes. These three types of nodes generally construct a hierarchical structure of the giant component.

Essentially, the "grassroots" nodes are the subsidiary participants, which constitute the bottom layer in the hierarchy shown in Fig. 12a. These nodes are not the critical "bridges" or "hubs" for the global connectivity of the giant-component. In other words, they are close to the periphery of the whole co-authorship network. Although around 90 % of the nodes in the giant component belong to the "grassroots", removing these nodes does not have severe effect on the connectivity of the remaining network.

To the opposite side, the "elite" nodes are interlinked to form the "main stem" of the giant component, i.e. the top layer of the hierarchy. From the perspective of degree distribution, these "elite" nodes may also serve as the "attachment kernel" (Perc 2014). This "main stem" is self-sustaining as it keeps connected in the removal of all the lower-degree nodes, as shown in Fig. 12b. However, a somehow counterintuitive observation from the prior node-removal processes is that the global connectivity of the giant component is not fully dependent on this "main stem" of elite nodes. This reveals that the elite nodes do not necessarily serve as the "bridges" or "hubs" to establish the global connectivity. Instead, as shown in Fig. 12a, c, the "middle-class" nodes (i.e., the "$10 \leq k < 20$ nodes") play an important role to glue the abundant local cliques of the low-degree nodes (i.e. $k < 10$ nodes). Thus, we can see that the "elite" nodes, together with the "middle-class" nodes, form the "cohesive core" of the giant component. Within this "cohesive core", nodes are redundantly linked with one another so that this "cohesive core" is robust to partial removal of its members. This "cohesive core" accounts only for about 11 % of the size of giant component; but it is this "cohesive core", as a whole, that serves as the hub to interconnect a bunch of local cliques that are otherwise dispersed.

Correlating network evolution with field growth

The previous analyses show the structural properties and evolutionary patterns of the co-authorship network, particularly those of its giant component. In this subsection we give a primitive examination on how the structure and evolution of the co-authorship network is related to the growth of the EOC academic field, in order to deepen the insights on the evolutionary mechanisms of the examined network. Text analytics is focused on the keywords and titles of the extracted papers. The major results are illustrated in Fig. 13, which represents the primary communities and their key topical terms in the years of 2002, 2003, 2004 and 2010, respectively.

In Fig. 13, each circle represents a key community or cluster, labeled by an integer number. The community labels are auto-generated by the software we use to process the data, i.e. Gephi, which is freely-available at http://gephi.github.io/. The diameter of each circle denotes the relative amount of authors. In the same sub-figure, more authors are clustered in the community, the corresponding circle becomes larger. Then, the count of papers and the primary topical terms of the communities are listed. For example, community No. 190 contains 20 papers; and its primary topical-terms are "group selection", "strategy", and "tit-for-tat". For the sake of simplicity, in Fig. 13 we just list the most frequently occurring topical-terms and leave the more information of each community in "Appendix".

Figure 13a shows the key communities in the year of 2002. Up to the end of this year, there had been no giant component to form. However, the communities No. 12, 35, 137, 239, 261, 270, 313, and 342 were to be interconnected to form the initial giant component in the subsequent year, as shown in Fig. 13b.

In the year of 2002, the identified communities are topic-focused and they can largely be grouped into three categories in terms of the topics of the papers. The first category is comprised of communities No. 190 and No. 12; and a focal topic shared by the two communities is gaming strategies. However, these two communities are different from one another in more detailed research topics. Community No. 190 is largely on the "strategy" for the prisoner's dilemma game, especially on the Tit-For-Tat strategy, which is a key research subject of the EOC field since Axelrod and Hamilton's (1981) groundbreaking work. Community No. 12 is more focused on the topics around the mechanisms of direct and indirect reciprocity and the spatial game. Nowak and May's (1992) work plays a critical role in the formation and growth of this community. The second category, which is comprised of communities No. 261, 270 and 342, is basically bounded in the social and behavioral sciences. The third category, which is comprised of communities No. 239, 313,137, and 35, is with a strong background of the biological discipline. These communities were separate from one another in 2002 due to the immaturity of this research field. The collaborations, particularly interdisciplinary collaborations, had not been widespread till 2002. However, some of these communities share common topics such as "reciprocity"; and some of them are disciplinarily proximal. Such intersection of research topics and the disciplinary proximity between communities propels the establishment of the inter-communal links and the formation of the initial giant component in 2003.

As shown in Fig. 13b, the communities No. 270, 137, 26, 239 and 35 were merged into community No. 375, and the communities No. 342, 12 and 313 were merged to form community No. 376. Community No. 375 shares the topical terms "indirect reciprocity" and "human" with community No. 376. But the other most-frequent terms in the two communities are quite different, revealing the differences in subject areas and research methods of the two communities. As previously-described, community No. 375 is more focused on the social and behavior aspect of cooperation in human society, while community No. 376 is more focused on the game-theoretic and biological aspects. What's more, Fig. 13b also reveals the rudimental "chained-communities" structure of the giant component. As shown in the lower graph in Fig. 13b, the sub-community No. 261 in community No. 375 is the key community to bridge to community No. 376, while the other sub-communities are not directly connected to community No. 376. The distance of co-authorship is correlated with the separation of the topical areas of the different cluster. For example, to examine two sub-communities with no direct connection (No. 270 and 12), the topical distance between them is relatively far, with the former focusing on "social exchange" and the latter focusing on "spatial game". In the stage of 2003, the social and behavioral research circle and the game-theoretic and theoretic-biological research circle were basically interconnected by the researchers who studied the cooperative collective actions in human society from the game-theoretic perspective.

Figure 13c illustrates the further growth of the "chained-communities" structure in 2004. In this period, community No. 422 was adsorbed into community No. 375 to form a new community No. 365; community No. 249 was adsorbed into community No. 376 to form a new community No. 366; and community No. 93 was attached to community No. 366. In this process, the proximity in research topics still plays a vital role for community adsorption and attachment. Community No. 93 is clustered by game-theory and evolutionary-dynamics researchers who are mostly from Japan. The research topics of this community are proximal to those of community No. 366. At the end of 2004, these two communities were just loosely-connected via the collaboration between M.A. Nowak and A. Sasaki (Nowak et al. 2004). But these two communities were to be merged later on. For example, as listed in "Appendix", one key contributor of community No. 93, H. Ohtsuki, has co-authored a number of papers with M. A. Nowak in community No. 366, since around 2006, e.g. (Ohtsuki et al. 2006). As shown in Fig. 13d, communities No. 366 and 93 were to be merged into community No. 387. Community No. 365, by contrast, still has a strong disciplinary background in social and behavioral sciences, especially in economics and social psychology. The disciplinary boundaries might play some role in the formation and maintenance of the "chained-communities" in this period, along with other factors such as nationality and affiliation that are not examined in this paper. On the other side, by examining the top topical-terms, we can find that the trend of topic convergence in different communities had become apparent in 2004.

Figure 13d shows the community structure of the giant component in 2010. The giant component in this year is selected in illustration because the small-world structure had been clear till the end of 2010. In this stage, the giant component was comprised of two large communities (i.e. No. 387 and 620) and a set of smaller communities attaching to the two largest. Community No. 387 grew from community No. 366 in Fig. 13c. The development of this community reflects the growth of the researches in spatial games, especially the combination of EOC and complex networks. Correspondingly, community No. 387 is the largest community in Fig. 13d, with 162 authors and 216 papers. Community No. 620 is another major community of the giant component, containing 137 authors and 143 papers. As the successor of community No. 365 in Fig. 13c, this community's primary topical terms contain "reputation" and "social norm", revealing its background in the social and behavioral sciences. These two major communities, as well as various other communities, share quite some common topical-terms in this stage. This on one hand indicates the growing convergence of the research topics in the EOC field and the blurring of disciplinary edges to some extent; on the other hand, this also explains the structuring of the small-world of the giant component. Besides the still-increasingly-dense intra-communal collaborative ties, the collaborations that span the community boundaries became more common in this stage; and the previously "distant" communities become more likely to be connected through "short-cut" paths, as a result of research topic convergence.

Combining the previous description together, Fig. 13 illustrates the overall process of the co-evolution of the co-authorship network and the corresponding research field. Viewing from the research field, the general trend is from disciplinary diversity to topic convergence and fusion. This trend is inherently correlated with the evolution of the co-authorship network from isolated clusters to chained-communities and then to a small-world with cohesive core. More specifically, from Fig. 13a–c we can correlate the early-stage growth of the giant component and the development of the EOC field. At this stage, the researches and collaborations were basically disciplinarily bounded; but some common topics had emerged. Through the merging and adsorption of the communities with similar research topics and disciplinary backgrounds, the giant component emerged from the previous isolated-clusters and a "chained-communities" structure was gradually formed. Simultaneously, the EOC field largely developed within the disciplinary boundaries; but the interdisciplinary collaborations had begun to appear around some shared interests. Reflecting to the network structure, this stage is characterized by the rapid scaling-up of the giant component. The steep descending of the clustering coefficient during the period from 2002 to 2004 in Fig. 7 is owing to the attenuation of triadic-closures during the expansion of the giant component, while the interconnection of multiple communities into the giant component significant increases the modularity. Figure 13d illustrates the stage for the convergence of common topics from multiple disciplines in the examined research field. In the same period, the network evolved from the chained-communities to the small-world, with the steadily increasing of the modularity and clustering coefficient and the relative stability of the average shortest-path-length.

Discussion

Overall view on topological and temporal properties

Based on the previous examination, we can figure out the topological and temporal properties of the co-authorship network in the interdisciplinary field of "evolution of cooperation". The key findings can be summarized as follows.

First, after a long incubation period, this co-authorship network has explosively grown in the new millennium. Meanwhile, the proportion of the giant-component in the whole network increases in the last decade. Consequently, the co-authorship network gradually evolves into a core-periphery structure, in which the giant component is the core and the rest of the network is the periphery.

Second, focusing on the giant-component, three stages can be identified in the evolution of the co-authorship network, namely "segregation", "chained-communities", and "small-world". In other words, the giant component has gradually grown from a small cluster towards a modular structure. In the early period for the modular structure to shape, the modules or communities were linked one by one to form a "chain". Lately, with the increase of the "short-cut" links between the theretofore remote communities, the giant component has evolved into a "small-world".

Third, in the "small-world" stage, the giant component is not just a small-world; richer topological structures can also be clarified. Generally, the node degrees obey a skewed distribution that combines lognormal and power-law distributions. This reveals that the giant component inherently contains a hierarchical structure in which the upper level is comprised of a small-proportion of highly-connected authors and the lower level is comprised of the majority of contributors, who are just with a small number of co-authors. To some extent, the giant component has the characteristic of the "star-production" model of scientific collaboration. But the "permeable boundary" or "structural cohesion" model, as discussed in Moody's (2004) work for the sociological collaboration network, can better fit the structure of the giant component (1961–2013) of the examined network.

Furthermore we give a short explanation on the previously-observed growth of the co-authorship network, especially the successive emergence of the "chained-communities" and the "cohesive-core" in its giant component. As the examined field is rooted in diverse disciplines ranging from biological science, social science, and complexity science, the collaborations crossing disciplinary boundaries would be rare at the initial "segregation" stage. Hence, the initial merging of the local collaborative clusters is largely limited within the disciplinary boundaries. At this stage, the collaboration network is characterized by small clusters that are basically separated with one another. However, at this stage some small clusters may become "nuclei" for the further growth of the network, which gives rise to the formation of the structure of "chained-communities". This stage is basically characterized by the growth of multiple communities from the previously-generated "nuclei" and the formation of a chain to link the communities. At this stage, one community would be likely to connect with another community which is disciplinarily-proximal to the first one, while the links between two disciplinarily-remote communities are rare. The multiple communities would then be better interconnected through the further rise of interdisciplinary collaborations and convergence of research themes in later periods, leading to the emergence of the modular and cohesive structure of the giant-component, in which the multiple "nuclei" are redundantly interconnected with one another to form the cohesive core.

The above-described evolutionary mode of the co-authorship network has close connection to the interdisciplinary nature of the examined research field. On one hand, the field of “evolution of cooperation” grows almost-simultaneously in multiple disciplines and specialties. The diversity in disciplinary origins leads to the multiple “nuclei”. On the other hand, the trend of inter-disciplinary permeation and convergence propel the successive emergence of the “chained-communities” and “cohesive-core” structures in the giant component. The convergence of research subjects leads to the increase of trans-disciplinary collaborations so that the disciplinary boundaries become “permeable”. The successive emergence of “chained” and “cohesive” structures is essentially the result of joint function of the disciplinary diversity and the topic convergence. This evolutionary mode has partially been examined in the previous correlation analysis on the network evolution and the field growth.

Comparison with related work

As noted in the introduction section, the structure and evolution of scientific collaboration networks have been extensively investigated in the last decade. Among them, Moody’s (2004) and Lee et al.’s (2010) respective examinations on the collaboration networks in Sociology and the “complex network research” field are particularly similar with this work, as both contributions are focused on the structural cohesion in collaboration networks. However, substantial differences exist between our work and these two contributions.

Moody’s work is on the collaboration network in “Sociology”, which is a broad discipline that covers many specialty areas. Thus, containing 197,976 unique collaborators, the network studied by Moody is much larger-scaled than the EOC network studied in this paper. Despite the differences in disciplinary coverage and network size, it is noticeable that both networks exhibit a steadily growing cohesive core. For the underlying mechanisms, Moody speculatively ascribes the formation and growth of the cohesive core to Abbott’s (2001) “competitive mixing” model. In contrast, we in this work examine the asymptotic trail of the examined network. By tracking the structural evolution of the co-authorship network from “separation” to “chained-communities” and then to “cohesive-core”, we hypothesize that the formation of cohesive structure is essentially driven by the trans-disciplinary permeation and merging of research subjects. The dynamic view presented in this work may deepen the understanding on the formation of “permeable boundaries” in interdisciplinary research fields.

For the network size and the scope of subject area, our work is more comparable to Lee et al.’s (2010) work, which is on the co-authorship network in the field of “complex network research”(CNR). In the evolution of the CNR network, three stages are identified, namely, “small isolated components”, “tree-like giant component”, and “large-scale loops”. The stage of “small isolated components” in the CNR network is quite similar with the early “segregation” stage in the EOC network of our work. Nevertheless, in the second stage of network evolution, we find a structure of “chained-communities” in the giant component, rather than the “tree-like giant component” as exhibited in the CNR network. In the third stage, the giant component of the EOC network evolves into a modular and structurally-cohesive network, in which we do not find clear large-scale loops. It is, therefore, evidential that the two networks evolve in different modes. The CNR network studied by Lee et al. is basically constructed in terms of the papers that cite two pioneering papers and three early review papers. In this sense, the constructed CNR network are more focused, while the EOC network studied in this paper is more disciplinarily-diversed. Thus, the represented differences provide partial evidence that an interdisciplinary co-authorship network may evolve in different mode from a more disciplinarily-homogenous co-authorship network. Essentially, the interdisciplinary network is more-likely to form a multi-centered structure; in comparison, the disciplinarily-homogenous field may tend to have fewer “neclei” upon which a “tree-like” structure emerges.

Conclusion

In this paper, we study the structure and evolution of the co-authorship network in the interdisciplinary field of “evolution of cooperation”. Through structural and longitudinal analysis, we find that this examined network gradually evolves into a “core-periphery” structure and that the “core” evolves from a small cluster (corresponding to the “segregation” state of the whole network) to a structure of “chained-communities”, and then to a modular structure that contains a growing cohesive-core. When the giant-component evolves into the structure of “cohesive core”, it is generally a small-world which is simultaneously modular, hierarchical, and cohesive, as summarized below.

First, the giant component can be considered as a small-world network, as it is highly modular (i.e., with a clear community structure), highly transitive (i.e., with high clustering coefficient), and small average shortest-path-length (i.e., logarithmic to the size of the giant component).

Second, the giant component inherently contains a hierarchical structure, owing to the skewed distribution of the node degrees; and the preferential attachment mechanism plays a vital for the formation of the skewed distribution.

Third, the hierarchy of the giant component can roughly be classified into two layers; and the upper-layer form the “cohesive core”, which is structurally comprised of redundantly-interlinked clusters.

The previous structure may reflect the overall collaboration pattern in a typical interdisciplinary field. It is common that an interdisciplinary research field is both diverse and focused. The disciplinary diversity often causes the formation of multiple collaboration clusters, whereas the focused research topics may give rise to the permeation and interconnection of the different clusters. The interdisciplinary nature of the examined EOC field may provide partial explanation for the observed structural properties and evolutionary patterns. The results in this work may, therefore, provide revealing implications for the structure and evolution of other interdisciplinary co-authorship networks, as well as the corresponding collaboration modes of the fields themselves.

In all, in this paper we present a primitive attempt to deepen our understandings on the collaboration modes in interdisciplinary research fields. Through the analysis of the structural and temporal properties of the EOC co-authorship network, we have obtained a few interesting and perhaps revealing points. But the present work, which is limited to the data-analysis of a single case, is still far from a solid theory for explaining the social dynamics of interdisciplinary co-authorships and the growth of the interdisciplinary fields. A few ongoing endeavors to extend the present work are listed below. Firstly, in order to extend the examination of the co-authorship network in the present work, we are to examine the multiplex network that combines the co-authorship network with the corresponding paper-citation network and keyword co-occurrence network. We expect such extensive study may provide a more comprehensive view on the developments of the examined interdisciplinary research field. Secondly, to complement the data-driven study conducted in this work, we are to develop agent-based simulative models to further investigate the social mechanisms that underlie the evolutionary schemes examined in this paper. Finally, it can be conjectured that the phenomena shown in this work may reveal some generic properties that can also be identified in some other interdisciplinary fields. Further scholarly inquiries are deserved to examine other interdisciplinary fields, so as to test the generality of the structural characteristics and evolutionary trails observed in the examined EOC field.

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Appendix

The basic information of communities in the giant component during typical periods.

In the following table, we list the communities and their major topical and belonging authors for the communities identified in the years of 2002, 2003, 2004, and 2010, as discussed in the subsection "correlating network evolution with field growth". To avoid the table to be verbosely long, we just select the top 10 for the topical terms in each community and the top 30 for the authors, given that the community is with more topical-terms and more authors.

Period	Community			Major topical terms (top 10 in terms of the occurrence frequency)	Authors with (top 30 in terms of author degree)
	ID	Size	Number of papers		
1961–2002	12	12	22	Public goods game; iterated prisoner's dilemma (ipd); strategy; spatial game; indirect reciprocity; heterogeneous population; agent-based simulation; tit for tat; social insect; reactive strategies	Nowak, M.; Sigmund, K.; Hauert, C.; May, R.M.; De monte, S.; Hofbauer, J.; Bohoeffer, S.; Page, K.M.; Krebs, J.; Schuster, H.G.; Wahl, L.M.; Stenull, O.
	190	21	20	Group selection; strategy; tit for tat; game theory (theory); altruism; reciprocal altruism; unrelated individual; population structure; iterated prisoner's dilemma (ipd); genetic kinship	Dugatkin, L.A.; Crowley, P.H.; Wilson, D.S.; Alfieri, M.; Sargent, R.C.; Provencher, L.; Sloane, S.; Spohn, B.; Rogers, L.; Cottrell, T.; Garcia, T.; Hatch, M.; Stokes, B.J.; White, J.M.; Farrand, L.; Wilkens, R.T.; Mestertongibbons, M.; Pollock, G.B.; Houston, A.I.; Sober, E.; Mitteldorf, J.
	239	7	1	Selfish; finite population;	Clutton-brock, T.H.; O'riain, M.J.; Brotherton, P.N.M.; Gaynor, D.; Kansky, R.; Griffin, A.S.; Manser, M.
	270	7	4	Social exchange theory; evolutionary psychology; cognition; task; social contracts; selection; role; relevance; reciprocation; game theory (theory)	Cosmides, L.; Tooby, J.; Stone, V.E.; Kroll, N.; Knight, R.T.; Fiddick, L.; Sugiyama, L.S.
	342	7	10	Indirect reciprocity; reputation; human; image scoring; prisoner's dilemma; tit for tat; direct reciprocity; strategy; public goods game; human cooperation	Milinski, M.; Semmann, D.; Bakker, T.C.M.; Krambeck, H.J.; Wedekind, C.; Kulling, D.; Braithwaite, V.A.

Period	Community			Major topical terms (top 10 in terms of the occurrence frequency)	Authors with (top 30 in terms of author degree)
	ID	Size	Number of papers		
	313	5	2	Costly signaling; human; strategy; signaling theory; strong reciprocity; social interaction; hunting; human behavioral ecology; handicap models; finite population	Smith, E.A.; Gintis, H.; Bowles, S.; Bird, R.B.; Bird, D.W.
	35	3	3	Kin-selection; social relationship; reciprocal altruism; grooming; vervet monkey; social organization; reciprocity; primate group; papio cynocephalus ursinus; genetic kinship	Seyfarth, R.M.; Cheney, D.L.; Silk, J.B.
	261	3	2	Social norm; human; strong reciprocity; punishment; human cooperation; altruistic punishment; game theory (theory); finite population; enforcement	Fehr, E.; Gachter, S.; Fischbacher, U.
	137	3	2	Indirect reciprocity; image scoring; good standing; finite population; direct reciprocity	Leimar, O.; Enquist, M.; Hammerstein, P.
1961–2003	375	39	38	Human; indirect reciprocity; reputation; tit for tat; image scoring; social exchange theory; punishment; social norm; coalition; reciprocal altruism	Fehr, E.; Tooby, J.; Clutton-brock, T.H.; Milinski, M.; Silk, J.B.; Hammerstein, P.; Hagen, E.H.; Mcelreath, R.; Fessler, D.M.T.; Kosfeld, M.; Wilson, M.I.; Cosmides, L.; O'riain, M.J.; Brotherton, P.N.M.; Gaynor, D.; Kansky, R.; Griffin, A.S.; Manser, M.; Stone, V.E.; Kroll, N.; Knight, R.T.; Leimar, O.; Semmann, D.; Bakker, T.C.M.; Krambeck, H.J.; Seyfarth, R.M.; Cheney, D.L.; Connor, R.C.; Wedekind, C.; Gachter, S.
	376	30	38	Human; public goods game; punishment; prisoner's dilemma; indirect reciprocity; costly signaling; strategy; spatial game; iterated prisoner's dilemma (ipd); reputation	Sigmund, K.; Bowles, S.; Smith, E.A.; Richerson, P.J.; Young, H.P.; Hopfensitz, A.; Henrich, J.; Boyd, R.T.; Weissing, F.J.; Boyd, R.; Hauert, C.; Nowak, M.; Gintis, H.; May, R.M.; De monte, S.; Hofbauer, J.; Bohoeffer, S.; Schuster, H.G.; Page, K.M.; Bird, R.B.; Bird, D.W.; Choi, J.K.; Brandt, H.; Krebs, J.; Richerson, P.; Foster, D.; Wahl, L.M.; Stenull, O.; Traulsen, A.; Panchanathan, K.

Period	Community			Major topical terms (top 10 in terms of the occurrence frequency)	Authors with (top 30 in terms of author degree)
	ID	Size	Number of papers		
1961–2004	365	52	49	Human; reputation; social norm; indirect reciprocity; punishment; tit for tat; reciprocity; kin-selection; image scoring; human cooperation	Fehr, E.; Silk, J.B.; Tooby, J.; Clutton-brock, T.H.; Milinski, M.; Hammerstein, P.; Hagen, E.H.; Mcelreath, R.; Fessler, D.M.T.; Kosfeld, M.; Wilson, M.I.; Griffin, A.S.; Fischbacher, U.; Cosmides, L.; O'riain, M.J.; Brotherton, P.N.M.; Gaynor, D.; Kansky, R.; Manser, M.; De quervain, D.J.F.; Treyer, V.; Schelthammer, M.; Schnyder, U.; Buck, A.; Stone, V.E.; Kroll, N.; Knight, R.T.; Leimar, O.; Semmann, D.; Bakker, T.C.M.
	366	46	56	Human; evolutionarily stable strategy; prisoner's dilemma; indirect reciprocity; public goods game; punishment; continuous prisoner's dilemma; spatial game; heterogeneous population; direct reciprocity	Sigmund, K.; Bowles, S.; Smith, E.A.; Richerson, P.J.; Young, H.P.; Hauert, C.; Hopfensitz, A.; Henrich, J.; Boyd, R.T.; Weissing, F.J.; Nowak, M.; Boyd, R.; Killingback, T.; Mueller, U.G.; Bull, J.J.; Doebeli, M.; Knowlton, N.; De monte, S.; Hofbauer, J.; Herre, E.A.; Rehner, S.A.; Sachs, J.L.; Wilcox, T.P.; May, R.M.; Schuster, H.G.; Bird, R.B.; Bird, D.W.; Traulsen, A.; Choi, J.K.
	93	17	31	Indirect reciprocity; prisoner's dilemma; finite population; reputation; strategy; repeated game; learning theory; group selection; evolution of altruism; defector	Matsuda, H.; Yamamura, N.; Sasaki, A.; Ogita, N.; Fudenberg, D.; Nakamaru, M.; Iwasa, Y.; Tamachi, N.; Sato, K.; Taylor, C.; Nogami, H.; Maskin, E.; Higashi, M.; Kawata, M.; Wakano, J.Y.; Kobayashi, Y.; Ohtsuki, H.
1961–2010	172	36	41	Tit for tat; altruism; group selection; game theory (theory); strategy; reciprocal altruism; evolutionarily stable strategy; mutualism; punishment; prisoner's dilemma	Crowley, P.H.; Dugatkin, L.A.; Wilson, D.S.; Houston, A.I.; Mcnamara, J.M.; Alfieri, M.; Sargent, R.C.; Provencher, L.; Sloane, S.; Spohn, B.; Rogers, L.; Cottrell, T.; Garcia, T.; Hatch, M.; Stokes, B.J.; White, J.M.; Leimar, O.; Farrand, L.; Wilkens, R.T.; Dall, S.R.X.; Barta, Z.; Fromhage, L.; Stephens, P.A.; Mestertongibbons, M.; Pollock, G.B.; Connor, R.C.; O'gorman, R.; Miller, R.R.; Eldakar, O.T.; Farrell, D.L.

Period	Community			Major topical terms (top 10 in terms of the occurrence frequency)	Authors with (top 30 in terms of author degree)
	ID	Size	Number of papers		
	387	162	216	Evolutionary game theory; prisoner's dilemma; public goods game; network; evolutionarily stable strategy; indirect reciprocity; direct reciprocity; punishment; finite population; spatial game	Nowak, M.; Wang, Long; Traulsen, A.; Sigmund, K.; Hauert, C.; Ohtsuki, H.; Fu, Feng; Pacheco, J.M.; Iwasa, Y.; Chen, Xiaojie; Santos, F.C.; Killingback, T.; Taborsky, M.; Rand, D.G.; Fudenberg, D.; Nakamaru, M.; Doebeli, M.; Pfeiffer, T.; Chu, Tianguang; Dreber, A.; Matsuda, H.; Hauser, M.; Taylor, P.D.; Xie, Guangming; Wu, Bin; Yamamura, N.; Bull, J.J.; Sasaki, A.; Mueller, U.G.; Brandt, H.
	441	16	31	Prisoner's dilemma; public goods game; punishment; network; evolutionarily stable strategy; noise; graph theory; social dilemma; scale free network; impact	Szolnoki, A.; Szabo, G.; Perc, M.; Helbing, D.; Wang, Zhen; Xu, Zhaojin; Zhang, Lianzhong; Stark, H.U.; Huang Jianhua; Song, Hongpeng; Vukov, J.; Danku, Z.; Fath, G.; Yu, Wenjian; Chadefaux, T.; Johansson, A.
	453	11	11	Punishment; social network; human; public goods game; network; dictator game; cooperative behavior; experimental economics; collective action; game theory (theory)	Fowler, J.H.; Dawes, C.T.; Johannesson, M.; Wallace, B.; Cesarini, D.; Lichtenstein, P.; Johnson, T.; Smirnov, O.; Christakis, N.A.; Persson, B.; Kam, C.D.
	533	32	24	Punishment; altruism; strong reciprocity; population structure; kin-selection; human; group selection; genetic and cultural evolution of cooperation; evolution of altruism; biofilm	Thompson, C.R.L.; Feldman, M.W.; Foster, K.R.; Santorelli, L.A.; Villegas, E.; Svetz, J.; Dinh, C.; Parikh, A.; Sucgang, R.; Kuspa, A.; Strassmann, J.E.; Queller, D.C.; Shaulsky, G.; Lehmann, L.; Rousset, F.; Roze, D.; Borenstein, E.; Aoki, K.; Cavallisforza, L.L.; Peck, J.R.; Kerr, B.; Godfrey-smith, P.; Ratnieks, F.L.W.; Kendal, J.; Wenseleers, T.; Parkinson, K.; Ravigne, V.; Nadell, C.D.; Xavier, J.B.; Thomas, E.A.C.
	556	6	4	Punishment; human; social norm; human cooperation; strong reciprocity; gene-culture coevolution; experiment; antisocial punishment; societies; reciprocity	Gachter, S.; Herrmann, B.; Renner, E.; Sefton, M.; Thoeni, C.; Gaechter, S.

Period	Community			Major topical terms (top 10 in terms of the occurrence frequency)	Authors with (top 30 in terms of author degree)
	ID	Size	Number of papers		
	572	39	31	Human; public goods game; kin-selection; altruism; punishment; siderophore; inclusive fitness; strong reciprocity; hamilton's rule; competition	Griffin, A.S.; West, S.A.; Gardner, A.; Keller, L.; Kuemmerli, R.; Buckling, A.; Harrison, F.; Shuker, D.M.; Reynolds, T.; Burton-chellow, M.; Sykes, E.M.; Guinnee, M.A.; Brockhurst, M.A.; O'riain, M.J.; Brotherton, P.N.M.; Gaynor, D.; Kansky, R.; Manser, M.; Vos, M.; Racey, D.; Colliard, C.; Fiechter, N.; Petitpierre, B.; Russier, F.; Floreano, D.; Langer, P.; Van den berg, P.; Inglis, R.F.; Oliver, A.; Perez-uribe, A.
	620	137	143	Human; punishment; reputation; public goods game; evolutionary stable strategy; indirect reciprocity; altruistic punishment; social norm; altruism; strong reciprocity	Fehr, E.; Mcelreath, R.; Henrich, J.; Gurven, M.; Bowles, S.; Hill, K.; Silk, J.B.; Marlowe, F.W.; Barr, A.; Ensminger, J.; Henrich, N.S.; Tracer, D.; Milinski, M.; Boyd, R.; Tooby, J.; Gintis, H.; Clutton-brock, T.H.; Alvard, M.S.; Camerer, C.; Gil-white, F.; Patton, J.Q.; Richerson, P.J.; Ziker, J.; Barrett, C.; Bolyanatz, A.; Cardenas, J.C.; Gwako, E.; Lesorogol, C.; Hammerstein, P.; Fischbacher, U.
	633	32	21	Chimpanzee; punishment; public goods game; prisoner's dilemma; image scoring; ultimatum game; social network; smiling; network; laughter	Dunbar, R.I.M.; Johnson, D.D.P.; Melis, A.P.; Hare, B.; Madsen, E.A.; Tunney, R.J.; Fieldman, G.; Plotkin, H.C.; Richardson, J.M.; Mcfarland, D.; Tomasello, M.; Call, J.; Woods, V.; Hastings, S.; Wrangham, R.; Mcdermott, R.; Tingley, D.; Cowden, J.; Frazzetto, G.; Jensen, H.J.; Marriott, A.; Duncan, N.D.C.; Stopka, P.; Bell, J.; Stopka, P.; Macdonald, D.W.; Burnham, T.C.; Russell, Y.I.; Fedurek, P.; Kudo, H.
	764	4	2	Social preference; neural; finite population; evidence	Camerer, C.F.; Tricomi, E.; Rangel, A.; O'doherty, J.P.

Period	Community			Major topical terms (top 10 in terms of the occurrence frequency)	Authors with (top 30 in terms of author degree)
	ID	Size	Number of papers		
	773	27	36	Mutualism; indirect reciprocity; altruism; punishment; evolutionary stable strategy; interaction; cleaner fish; partner control; kin-selection; image scoring	Bshary, R.; Noe, R.; Wright, J.; Hamilton, I.M.; Palmer, C.T.; Wright, S.A.; Cassidy, C.; Vanpool, T.L.; Coe, K.; Bergmueller, R.; Johnstone, R.A.; Russell, A.F.; Voelkl, B.; Heg, D.; Fruteau, C.; Van damme, E.; Jutzeler, E.; Mitchell, J.S.; Schuerch, R.; Vanschaik, C.P.; Vanhooff, J.; Grutter, A.S.; Raihani, N.J.; Bronstein, J.L.; Cant, M.A.; Kasper, C.; Bshary, A.
	774	5	2	Social relationship; reciprocal altruism; grooming; baboon; vervet monkey; social organization; papio cynocephalus ursinus; kin-selection; finite population; female social relationships	Seyfarth, R.M.; Cheney, D.L.; Moscovice, L.R.; Heesen, M.; Mundry, R.

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