Selected contributions, resulting from presentations at the workshop "Modeling Science-Understanding, Forecasting and Communicating the Science System," held in Amsterdam, October 6–9, 2009

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Scientometrics (2011) 89:347–348
DOI 10.1007/s11192-011-0429-3

Modeling science: studying the structure and dynamics of science

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Received: 1 June 2011 / Published online: 28 June 2011

Mathematical models of the science and technology (S&T) system have a long tradition in scientometrics. They entail models of statistical properties such as the cumulative advantage model for citation patterns by Derek de Solla Price (1976) or models of scientific processes such as the epidemics of scientific ideas by William Goffman (1966). Frequently, new modeling attempts "echo" major breakthroughs in mathematical modeling. For example, models developed in physics, economics, or the social sciences are frequently applied to the science system itself, validated using S&T data, and interpreted by the authors of these models and their collaborators. This special issue aims to establish models of the science system as a promising area of research in scientometrics enabled by high-quality and high-coverage data, advanced data mining and modeling approaches, and new means to visualize the structure and dynamics of science at multiple levels. Models of science aim to answer questions regarding the basic mechanisms behind emergent structures such as scientific disciplines, scientific paradigms and cross-disciplinary research fronts, or the career trajectories of researchers.

The issue comprises six selected contributions, resulting from presentations at the workshop "Modeling Science—Understanding, Forecasting and Communicating The Science System," held in Amsterdam October 6–9, 2009.

- *Peter Mutschke, Philipp Mayr, Philipp Schaer, and York Sure* Science Models as Value-Added Services for Scholarly Information Systems
- *Serge Galam* Tailor Based Allocations for Multiple Authorship: A Fractional gh-Index

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- *Timothy S. Evans, Renaud Lambiotte, and Pietro Panzarasa* Community Structure and Patterns of Scientific Collaboration in Business and Management
- *M. Laura Frigotto and Massimo Riccaboni* A Few Special Cases: Scientific Creativity and Network Dynamics in the Field of Rare Diseases
- *Hanning Guo, Scott Weingart, and Katy Börner*: Mixed-Indicators Model for Identifying Emerging Research Areas
- *Christopher Watts and Nigel Gilbert*: Does Cumulative Advantage Affect Collective Learning in Science? An Agent-Based Simulation

The papers in this special issue span a wide range: the possible use of information retrieval as a test-bed for models (Mutschke, Mayr, Schaer, Sure), the study of properties of new indicators such as the h-index (Galam), or measuring and modeling scientific collaboration (Evans, Lambiotte, Panzarasa), scientific creativity (Frigotto, Riccaboni), newly emerging research areas (Guo, Weingart, Börner), and learning (Watts, Gilbert). Different datasets at different scales are used to design and validate the models. In-depth, field-specific analyses as well as generic statements about the nature of scientific activity are made. Globalization and increasing specialization accompanied by interdisciplinary research, and changing institutional conditions (such as funding and tenure schemes) impact the structure and dynamics of science and models of the science system. Triangulation of methods (narratives, survey and bibliometrics indicators) is one possible answer to tackle complexity (Frigotto, Riccaboni); combining different indicators and visual analytics is another one (Guo, Weingart, Börner). Simulation models allow testing different scenarios in the space of theoretical assumptions as well as in the empirical space (Watts, Gilbert).

Many challenges remain: The majority of existing models remain unconnected. There are very few attempts to compare, synthesize, or interconnect existing models (Tabah 1999; Morris and Van der Veer Martens 2008; Scharnhorst et al. 2011). Future work should aim to integrate modeling approaches and results from different disciplines to arrive at a more comprehensive understanding of the science system.

Acknowledgments We would like to thank the authors for their professional contributions to multiple rounds of discussions and revisions, the anonymous reviewers for their expert comments, and the journal *Scientometrics* for editorial advice and support. This work was supported by the COST (European Cooperation in Science and Technology) action MP0801—“Physics of Competition and Conflicts,” the Royal Netherlands Academy of Arts and Sciences (KNAW), in particular the Virtual Knowledge Studio for the Humanities and Social Sciences, the James S. McDonnell Foundation, the Cyberinfrastructure for Network Science Center (http://cns.iu.edu) at Indiana University, USA, and the Rathenau Institute, The Netherlands.

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Scientometrics (2011) 89:349–364
DOI 10.1007/s11192-011-0430-x

Science models as value-added services for scholarly information systems

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Received: 3 June 2011 / Published online: 19 June 2011

Abstract The paper introduces scholarly Information Retrieval (IR) as a further dimension that should be considered in the science modeling debate. The IR use case is seen as a validation model of the adequacy of science models in representing and predicting structure and dynamics in science. Particular conceptualizations of scholarly activity and structures in science are used as value-added search services to improve retrieval quality: a co-word model depicting the cognitive structure of a field (used for query expansion), the Bradford law of information concentration, and a model of co-authorship networks (both used for re-ranking search results). An evaluation of the retrieval quality when science model driven services are used turned out that the models proposed actually provide beneficial effects to retrieval quality. From an IR perspective, the models studied are therefore verified as expressive conceptualizations of central phenomena in science. Thus, it could be shown that the IR perspective can significantly contribute to a better understanding of scholarly structures and activities.

Keywords Retrieval system · Value-added services · Science models · IR · Re-ranking · Evaluation

Introduction

Science models usually address issues in statistical modeling and mapping of structures and scholarly activities in science. As a further dimension, that should be considered in science modeling as well, the paper focuses on the applicability of science models in scholarly Information Retrieval (IR) with regard to the improvement of search strategies in growing scientific information spaces. Introducing an IR perspective in science modeling is motivated by the fact that scholarly IR as a science of searching for scientific content can be also seen as a special scholarly activity that therefore should also be taken into account in science modeling. Moreover, as scholarly Digital Libraries (DLs) can be

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considered as particular representations of the science system, searching in DLs can be seen as a particular use case of interacting with exactly that system that is addressed by science modeling. From this perspective, IR can play the role of a validation model of the science models under study.

From the perspective of IR, a further motivation point is the assumption that traditional IR approaches fail at points where the application of science models may help: (1) the vagueness between search and indexing terms, (2) the information overload by the amount of result records obtained, and (3) the problem that pure term frequency based rankings provide results that often do not meet user needs (Mayr et al. 2008). This strongly suggests the introduction of science models in IR systems that rely more on the real research process and have therefore a greater potential for closing the gap between information needs of scholarly users and IR systems than conventional system-oriented approaches.

While, in this paper we mainly focus on how to use science model-enhanced IR as a test bed for different science models, we would also like to point out that there is a further interface between IR and scientometrics which is currently underexploited. One of the problem solving tasks shared by IR and scientometrics is the determination of a "proper" selected set of documents from an ensemble. In particular for newly emerging interdisciplinary fields and their evaluation the definition of the appropriate reference set of documents is important. Glänzel et al. (2009) have discussed how bibliometrics can be also used for the retrieval of "core literature". Bassecoulard et al. (2007) and Boyack and Klavans (2010) proposed sophisticated methods to delineate fields on the basis of articles as well as journals. However, due to the interconnectedness of research streams and different channels of knowledge transfer, it remains a complex problem how "hard boundaries" in continuously changing research landscapes can be found.

In their paper on Bibliometric Retrieval Glänzel et al. (2009) apply a combination of methods. They start from bibliographic coupling and keyword-based search and continue with a step-wise process to filter out the final core set from potentially relevant documents. Hereby, they make use of methods that are standard techniques in traditional IR as well (such as keyword-based search or thresholds). But, as already stated by Glänzel et al., "the objectives of subject delineation in the framework of bibliometric (domain) studies essentially differ from the goals of traditional information retrieval". In principle, this requires the application of different methods.

The bibliometric retrieval approach, in particular in an evaluative context, aims at defining a reference set of documents on the basis of a firm methodological canon, in order to justify the application and interpretation of standardized indicators. In traditional IR, in contrast, the application of bibliometric models and approaches has the primary goal to enhance the search from the perspective of the user by combining a wider search space with a particular contextualization of the search. The overall aim here is to help the user to get a grasp about the size and structure of the information space, rather than forcing him to precisely define the search space.

Correspondingly, the goal of the DFG-funded project "Value-added Services for Information Retrieval"[1] (Mayr et al. 2008) presented in this paper therefore is to improve retrieval quality in scholarly information systems by computational science models that reason about structural properties of the science system under study. Accordingly, the overall assumption of the IRM project is that a user's search should improve when science model driven search services are used. The other way around, the extent to which retrieval quality can be improved by performing science models as search services is seen as an

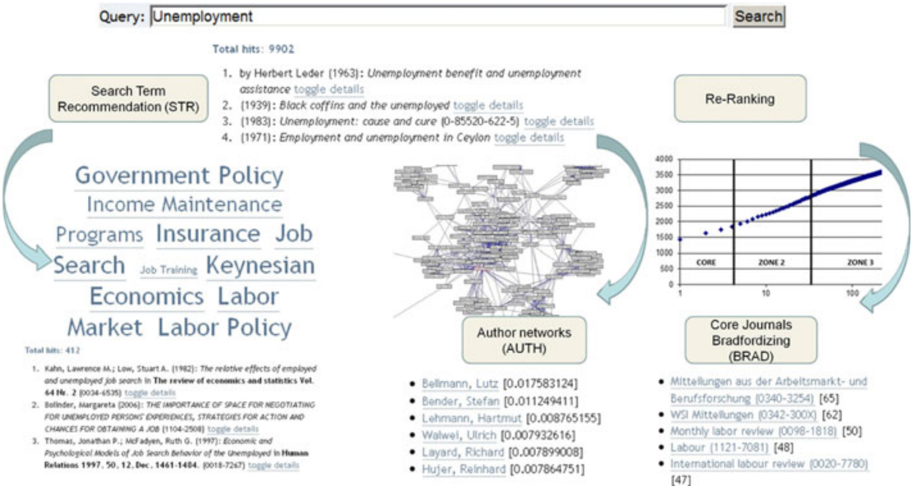
[1] http://www.gesis.org/irm/.

indicator for the adequacy of the models taken in representing and predicting scholarly activities in the science system under study.

In the following, we will at first introduce the models proposed. After that, the evaluation study is presented. The paper closes with a discussion of the observed results and the conclusions to be drawn for the models studied.

Models

Computational science models, to our understanding, are particular conceptualizations of scholarly activities and structures that can be expressed in algorithms (to be operationalized in systems that—more or less—reason about science, such as IR systems). The paper proposes three different kinds of science models as value-added search services that highlight different aspects of scholarly activity (see Fig. 1): (1) a co-word model of science addressing the cognitive structure of a field by depicting the relationships between terms in a field (STR), (2) a bibliometric model of re-ranking, called Bradfordizing, representing the publication form of research output and its organization on a meso-level in terms of journals (BRAD), and (3) a co-authorship model of re-ranking examining the collaboration between the human actors of knowledge flow in science (AUTH). STR addresses the problem of the vagueness between search and indexing terms by pointing to co-related terms that are more appropriate for searching, BRAD and AUTH the problem of large and unstructured result sets by ranking a given document set according to the coreness of journals (BRAD) or according to the centrality of authors (AUTH) in a scientific community. Thus, the three models address very different dimensions of structural properties in the science system. Moreover, they are also heterogeneous as regards the methods applied. The STR uses co-word analysis, BRAD bibliometric statistics, and AUTH methods taken from social network analysis, graph theory respectively.



Total hits: 9902

1. by Herbert Leder (1963): *Unemployment benefit and unemployment assistance* toggle details
2. (1939): *Black coffins and the unemployed* toggle details
3. (1983): *Unemployment: cause and cure* (0-85520-622-5) toggle details
4. (1971): *Employment and unemployment in Ceylon* toggle details

Total hits: 412

1. Kahn, Lawrence M.; Low, Stuart A. (1982): *The relative effects of employed and unemployed job search* in **The review of economics and statistics Vol. 64 Nr. 2** (0034-6535) toggle details
2. Bolinder, Margareta (2006): *THE IMPORTANCE OF SPACE FOR NEGOTIATING FOR UNEMPLOYED PERSONS' EXPERIENCES, STRATEGIES FOR ACTION AND CHANCES FOR OBTAINING A JOB* (1104-2508) toggle details
3. Thomas, Jonathan P.; McFadyen, Ruth G. (1997): *Economic and Psychological Models of Job Search Behavior of the Unemployed* in **Human Relations 1997, 50, 12, Dec, 1461-1484.** (0018-7267) toggle details

- Bellmann, Lutz [0.017583124]
- Bender, Stefan [0.011249411]
- Lehmann, Hartmut [0.008765155]
- Walwei, Ulrich [0.007932616]
- Layard, Richard [0.007899008]
- Hujer, Reinhard [0.007864751]

- Mitteilungen aus der Arbeitsmarkt- und Berufsforschung (0340-3254) [65]
- WSI Mitteilungen (0342-300X) [62]
- Monthly labor review (0098-1818) [50]
- Labour (1121-7081) [48]
- International labour review (0020-7780) [47]

Fig. 1 A simple search example (query term: "Unemployment") and typical structural attributes/outputs of implemented science models in our retrieval system. From *left*: search term recommendation (STR) producing highly associated indexing terms, Author Networks (AUTH) with centrality-ranked author names and Bradfordizing based on core journals (BRAD) with highly frequent journal names/ISSNs

However, to the same extent as different science models emphasize different aspects of scholarly activity we expect that different kind of searches are best served by relying on corresponding science models. This approach meets the fact that the frequency of many structural attributes of the science system (such as co-authorships) usually follows some type of power law distribution. These highly frequent attributes which are produced when applying the science models have a strong selectivity in the document space which can be utilized for IR. In the following the three models, which are descriptive models of science so far, are discussed on a general conceptual level.

A co-word model of science: relevance of co-terms

Search in textual information systems only works when a user can find the right search terms describing his information need and the terms used in the information system. This mapping problem is known as the Language Problem in IR (Blair 1990, 2003). While formulating queries a user is in an "Anomalous State of Knowledge" (Belkin 1980)—by trying to map the words and concepts describing his problem to the terms of the system wasting much effort in trying to fight ambiguity and vagueness of language. This problem especially occurs in highly specialized scientific literature databases where often only literature reference with spare bibliographic metadata is available. Another source of vagueness evolves from special discourse dialects in scientific communities. These dialects are not necessarily the same dialects an information specialist would use to describe a document or a concept using his documentation language.

Therefore, an instrument is needed to map the user's query terms to the document terms of the system. Especially in digital libraries searchers are confronted with databases that contain merely short texts which are described with controlled vocabularies. User studies in digital libraries have shown that most users are not aware of the special controlled vocabularies used in digital libraries (Shiri and Revie 2006). Hence they are not using them in their query formulation.

Co-word analysis (Callon et al. 1983) can be used to reduce the problem of language ambiguity and the vagueness of query. Petras (2006) proposed a search term suggestion system (STR) which relies on a co-word model of science that maps query terms to indexing terms at search time on the basis of term-term-associations between two vocabularies: (1) natural language terms from titles and abstracts and (2) controlled vocabulary terms used for document indexing. The associations are weighted according to their co-occurrence within the collection to predict which of the controlled vocabulary terms best mirror the search terms (Plaunt and Norgard 1998; Buckland et al. 1999). The weights are calculated with the aid of a contingency table of all possible combinations of the two terms A and B: AB, $A\neg B$, $\neg AB$ and $\neg A\neg B$ where "$\neg$" denotes the absence of a term. Indexing terms having a high association with a query term are then recommended to the user for searching.

Thus, the science model proposed focuses on the cognitive structure of a field depicting the cognitive contexts in which a term appears. Accordingly, highly associated terms are not just related terms or synonyms. Terms that strongly appear together (in the sense of the model) rather represent the cognitive link structure of a field, i.e. they represent the co-issues that are discussed together within the research context in question. Thus, the STR is not a dictionary pointing to related terms. To what the STR really points are scientific discourses in which the user's term appears such that the user is provided by the research issues related to his/her term, i.e. the cognitive structure of the field in which the initial term is embedded. In the information system this cognitive structure is described by a controlled vocabulary, used systematically for indexing the documents in the system, such that a high probability of precise retrieval results is expected when these terms are used (instead of natural language terms of the user). In an IR environment a STR can be used as a query expansion mechanism by enriching the original query with highly relevant controlled terms derived from the special documentation language. Query expansion is the process of reformulation an initial query to improve retrieval performance in an information retrieval process (Efthimiadis 1996) and can be done in two ways: manually/ interactively or automatically. Done interactively this kind of reformulation help may improve the search experience for the user in general. Suggesting terms reduces the searcher's need to think of the right search terms that might describe his or her information need. It effectively eases the cognitive load on the searcher since it is much easier for a person to pick appropriate search terms from a list than to come up with search terms by themselves (White and Marchionini 2007).

A further effect of the STR is that it may point the user to different expressions for the concept the user has in mind. A new or different view on a topic may ease the user to change the search strategy towards related issues of the field (which are represented in the cognitive structure the STR is providing). Thus, in an interactive scenario suggested terms or concepts can even help to alleviate "anchoring bias" (Blair 2002) which describes the human tendency to rely too heavily on one concept or piece of information when making decision. This cognitive effect can be worked against by suggesting terms and encourage a variation in one's initial search strategy and a reconsideration on the query formulation.

A bibliometric model of science: coreness of journals

Journals play an important role in the scientific communication process (cp. Leydesdorff et al. 2010). They appear periodically, they are topically focused, they have established standards of quality control and often they are involved in the academic gratification system. Metrics like the famous impact factor are aggregated on the journal level. In some disciplines journals are the main place for a scientific community to communicate and discuss new research results. These examples shall illustrate the impact journals bear in the context of science models. Modeling science or understanding the functioning of science has a lot to do with journals and journal publication characteristics. These journal publication characteristics are the point where Bradford law can contribute to the larger topic of science models.

Bradford law of scattering bases on literature observations the librarian S. Bradford has been carried out in 1934. His findings and after that the formulation of the bibliometric model stand for the beginning of the modern documentation (Bradford 1948)—a documentation which founds decisions on quantifiable measures and empirical analyses. Bradford's work bases on analyses with journal publications on different subjects in the sciences.

Fundamentally, Bradford law states that literature on any scientific field or subject-specific topic scatters in a typical way. A core or nucleus with the highest concentration of papers—normally situated in a set of few so-called core journals—is followed by zones with loose concentrations of paper frequencies (see Fig. 1 for a typical Bradford distribution). The last zone covers the so-called periphery journals which are located in the model far distant from the core subject and normally contribute just one or two topically relevant papers in a defined period. Bradford law as a general law in informetrics can successfully be applied to most scientific disciplines, and especially in multidisciplinary scenarios (Mayr 2009).

Bradford describes his model in the following:

> The whole range of periodicals thus acts as a family of successive generations of diminishing kinship, each generation being greater in number than the preceding, and each constituent of a generation inversely according to its degree of remoteness. (Bradford 1934)

Bradford provides in his publications (1934, 1948) just a graphical and verbal explanation of his law. A mathematical formulation has been added later by early informetric researchers. Bradford‘s original verbal formulation of his observation has been refined by Brookes (1977) to a cumulative distribution function resulting in a so-called rank-order distribution of the items in the samples. In the literature we can find different names for this type of distribution, e.g. "long tail distribution", "extremely skewed", "law of the vital few" or "power law" which all show the same properties of a self-similar distribution. In the past, Bradford law is often applied in bibliometric analyses of databases and collections e.g. as a tool for systematic collection management in library and information science. This has direct influence on later approaches in information science, namely the development of literature databases. The most common known resource which implements Bradford law is the Web of Science (WoS). WoS focuses very strictly on the core of international scientific journals and consequently neglects the majority of publications in successive zones.

Bradfordizing, originally described by White (1981), is a simple utilization of the Bradford law of scattering model which sorts/re-ranks a result set accordingly to the rank a journal gets in a Bradford distribution. The journals in a search result are ranked by the frequency of their listing in the result set, i.e. the number of articles in a certain journal. If a search result is "Bradfordized", articles of core journals are ranked ahead of the journals which contain only an average number (Zone 2) or just few articles (Zone 3) on a topic (compare the example in Fig. 1). This re-ranking method is interesting because it is a robust and quick way of sorting the central publication sources for any query to the top positions of a result set such that "the most productive, in terms of its yield of hits, is placed first; the second-most productive journal is second; and so on, down through the last rank of journals yielding only one hit apiece" (White 1981).[2]

Thus, Bradfordizing is a model of science that is of particular relevance also for scholarly information systems due to its structuring ability and the possibility to reduce a large document set into a core and succeeding zones. On the other hand, modeling science into a core (producing something like coreness) and a periphery always runs the risk and critic of disregarding important developments outside the core.

A network model of science: centrality of authors

The background of author centrality as a network model of science is the perception of "science (as) a social institution where the production of scientific knowledge is embedded in collaborative networks of scientists" (He 2009, see also Sonnewald 2007). Those networks are seen as "one representation of the collective, self-organized emerging structures in science" (Börner and Scharnhorst 2009). Moreover, because of the increasing complexity of nowadays research issues collaboration is becoming more and more "one of the key concepts in current scientific research communication" (Jiang 2008). The increasing

[2] Bradfordizing can be applied to document types other than journal article, e.g. monographs (cf. Worthen 1975; Mayr 2008, 2009). Monographs e.g. provide ISBN numbers which are also good identifiers for the Bradfordizing analysis.

significance of collaboration in science not only correlates with an increasing amount (Lu and Feng 2009; Leydesdorff and Wagner 2008) but also, and more importantly, with an increasing impact of collaborative papers (Beaver 2004; Glänzel et al. 2009; Lang and Neyer 2004).

Collaboration in science is mainly represented by co-authorships between two or more authors who write a publication together. Transferred to a whole community, co-authorships form a co-authorship network reflecting the overall collaboration structure of a community. Co-authorship networks have been intensively studied. Most of the studies, however, focus mainly either on general network properties (see Newman 2001; Barabasi et al. 2002) or on empirical investigation of particular networks (Yin et al. 2006; Liu et al. 2005). To our knowledge, Mutschke was among the first who pointed to the relationship between co-authorship networks and other scientific phenomena, such as cognitive structures (Mutschke and Renner 1995; Mutschke and Quan-Haase 2001), and particular scientific activities, such as searching scholarly DLs (Mutschke 1994, 2001, 2004b).

From the perspective of science modeling it is important to note that, as co-authorships also indicate the share of knowledge among authors, "a co-authorship network is as much a network depicting academic society as it is a network depicting the structure of our knowledge" (Newman 2004). A crucial effect of being embedded in a network is that "some individuals are more influential and visible than others as a result of their position in the network" (Yin et al. 2006). As a consequence, the structure of a network also affects the knowledge flow in the community and becomes therefore an important issue for science modeling as well as for IR (cp. Mutschke and Quan-Haase 2001; Jiang 2008; Lu and Feng 2009; Liu et al. 2005).

This perception of collaboration in science corresponds directly with the idea of structural centrality (Bavelas 1948; Freeman 1977) which characterizes centrality as a property of the strategic position of nodes within the relational structure of a network. Interestingly, collaboration in science is often characterized in terms that match a particular concept of centrality widely used in social network analysis, namely the betweenness centrality measure which evaluates the degree to which a node is positioned *between* others on shortest paths in the graph, i.e. the degree to which a node plays such an intermediary role for other pairs of nodes. Yin et al. (2006) see co-authorship as a "process in which knowledge flows among scientists". Chen et al. (2009) characterize "scientific discoveries as a brokerage process (which) unifies knowledge diffusion as an integral part of a collective information foraging process". That brokerage role of collaboration correlates conceptually to the betweenness measure which also emphasizes the bridge or brokerage role of a node in a network (Freeman 1977, 1978/1979, 1980; cp. Mutschke 2010).

The betweenness-related role of collaboration in science was confirmed by a number of empirical studies. Yan and Ding (2009) discovered a high correlation between citation counts and the betweenness of authors in co-authorship networks. Liu et al. (2005) discovered a strong correlation between program committee membership and betweenness in co-authorship networks. Mutschke and Quan-Haase (2001) observed a high correlation of betweenness in co-authorship networks and betweenness of the author‘s topics in keyword networks. High betweenness authors are therefore characterized as "pivot points of knowledge flow in the network" (Yin et al. 2006). They can be seen as the main driving forces not only for just bridging gaps between different communities but also, by bringing different authors together, for community making processes.

This strongly suggests the use of an author centrality model of science also for re-ranking in scholarly IR (cf. Zhou et al. 2007). Our model of author centrality based ranking originates from the model initially proposed by Mutschke (1994) which has been re-implemented for a real-life IR environment, to our knowledge before anyone else, within the Daffodil system (Mutschke 2001; Fuhr et al. 2002) and the infoconnex portal (Mutschke 2004a, b). Currently, the ranking model is provided by the German Social Science portal sowiport[3] as a particular re-ranking service. The general assumption of the model is that a publication's impact can be quantified by the impact of their authors which is given by their centrality in co-authorship networks (cp. Yan and Ding 2009). Accordingly, an index of betweenness of authors in a co-authorship network is seen as an index of the relevance of the authors for the domain in question and is therefore used for re-ranking, i.e., a retrieved set of publications is re-ranked according to the betweenness values of the publications' authors such that publications of central authors are ranked on top.

However, two particular problems emerge from that model. One is the conceptual problem of author name ambiguity (homonymy, synonymy) in bibliographic databases. In particular the potential homonymy of names may misrepresent the true social structure of a scientific community. The other problem is the computation effort needed for calculating betweenness in large networks that may bother, in case of long computation times, the retrieval process and finally user acceptance. In the following an evaluation of the retrieval quality of the three science model driven search services are presented.

Evaluation

Proof-of-concept prototype

All three proposed models were implemented in an online information system[4] to demonstrate the general feasibility of the three approaches. The prototype uses those models as particular search stratagems (Bates 1990) to enhance retrieval quality. The open source search server Solr[5] is used as the basic retrieval engine which provides a standard term frequency based ranking mechanism (TF-IDF). All three models work as retrieval add-ons on-the-fly during the retrieval process.

The STR module is based on a commercial classification software (Recommind Mindserver). The term associations are visualized as term clouds such that the user can see the contexts in which the terms the user has in mind appear in the collection. This enables the user to select more appropriate search terms from the cloud to expand the original query.

The Bradfordizing re-ranking model is implemented as a Solr plugin which orders all search results with an ISSN number such that the journal with the highest ISSN count gets the top position in the result set, the second journal the next position, and so forth. The numerical TF-IDF ranking value of each journal paper in the result set is then multiplied with the frequency count of the respective journal. The result of this computation is taken for re-ranking such that core journal publications are ranked on top.

The author centrality based re-ranking model computes a co-authorship network on the basis of the result set retrieved for a query, according to the co-authorships appearing in the result set documents.[6] For each node in the graph betweenness is measured, and each

[3] www.gesis.org/sowiport.

[4] www.gesis.org/beta/prototypen/irm.

[5] http://lucene.apache.org/solr/.

[6] Actually, the author–author-relations are computed during indexing time and are retrieved by the system via particular facets added to the user's query.

document in the result set is assigned a relevance value given by the maximum betweenness value of its authors. Single authored publications are captured by this method if their authors appear in the graph due to other publications they have published in co-authorship. Thus, just publications from pure single fighters are ignored by this procedure. The result set is then re-ranked by the centrality value of the documents' authors such that publications of central authors appear on the top of the list.

Methods

A major research issue of the project is the evaluation of the contribution of the three services studied to retrieval quality: Do central authors, core journals respectively, actually provide more relevant hits than conventional text-based rankings? Does a query expansion by highly associated co-words of the initial query terms have any positive effects on retrieval quality? Do combinations of the services enhance the effects? By measuring the contribution of our services to retrieval performance we expect deeper insights in the structure and the functioning the science system: As searching in a scientific information system is seen as a way of interacting with the science system, retrieval quality evaluation might also play the role of a "litmus test" for the adequacy of the science models taken for understanding, forecasting and communicating the science system. Thus, the investigation of science model driven value added services for scholarly information systems might contribute to a better understanding of science.

The standard approach to evaluate IR systems is to do relevance assessments, i.e. the documents retrieved are marked as relevant or not relevant with respect to previously defined information need (cf. TREC,[7] CLEF[8]). Modern collections usually are large and cannot be assessed in total. Therefore, only subsets of the collection are assessed by a so-called pooling method (Voorhees and Harman 2005) where the top *n* documents returned by the different IR systems are taken. The assessors have to judge just the documents in the subsets without knowing the originating IR systems.

Data and topics

In our study, a precision test of the three proposed models was conducted by performing user assessments of the top ten documents provided by each of the three services. As a baseline, the initial TF-IDF ranking done by the Solr engine was taken and therefore also judged. As regards STR, the initial query was expanded automatically by the four strongest associated co-words.

The precision test was carried out with 73 participants for ten different predefined topics from the CLEF corpus. Each assessor had to choose one out of the ten topics. The judgments were done according to the topic title and the topic description. The assessors were instructed how to assess in a briefing. Each of the four evaluated systems (AUTH = re-ranking by author centrality, BRAD = re-ranking by Bradfordizing, STR = TF-IDF ranking for the expanded query, and SOLR as the baseline) returned the $n = 10$ top ranked documents, which formed the pool of documents to be assessed. Duplicates were removed, so that the size of the sample pools was between 34 and 39 documents. The assessors had to judge each document in the pool as relevant or not

[7] http://trec.nist.gov/.

[8] http://www.clef-campaign.org/.

relevant (binary decision). In case they did not assess a document this document is ignored in later calculations.

The retrieval test was performed on the basis of the SOLIS[9] database that consists of 369,397 single documents (including title, abstract, controlled keyword etc.

The 73 assessors did 43.78 single assessments on average which sums up to 3,196 single relevance judgments in total. Only 5 participants didn't fill out the assessment form completely, but 13 did more than one. Since every assessor could freely choose from these topics the assessments are not distributed evenly.

Results

Overall agreement and inter-grader reliability

The assessors in this experiment were not professionals and/or domain experts but students (mainly library and information science). However, according to findings in TREC where a rather high overall agreement between official TREC and non-TREC assessors was observed (Al-Maskari et al. 2008; Alonso and Mizzaro 2009), we also assume not a significant difference between domain experts and students in information science since all topics are every-day life topics.[10] The 73 assessors in our study judged a total of 3,196 single documents with an overall agreement over all topics and among all participants of 82%. 124 of 363 cases where perfect matches where all assessors agreed 100% (all relevant and non relevant judgments matched). To rate the reliability and consistency of agreement between the different assessments we applied the Fleiss's Kappa measure of inter-grader reliability for nominal or binary ratings (Fleiss 1971). All Kappa scores in our experiment range between 0.20 and 0.52 which indicates a mainly acceptable level of overall agreement (for more details see Schaer et al. 2010).

Precision

The precision P of each service was calculated by

$$P = \frac{|r|}{|r + nr|} \tag{1}$$

for each topic, where $|r|$ is the number of all relevant assessed documents and $|r + nr|$ is the number of all assessed documents (relevant and not relevant). A graph of all precision values including standard error can be seen in Fig. 2.

In our experiment the Solr standard relevance ranking algorithm (based on TF-IDF) was taken as the baseline to which each of the three value-added services proposed had to compare. The average precision of TF-IDF over all topics and assessors was 57%, where values range between 17 and 75%. Ignoring the 17% value all other values are stable around the baseline. For two topics (83 and 84) the baseline was also the best judged result.

STR used the same SOLR ranking mechanism as the baseline but with the addition of automatically expanded queries. By expanding the query with the $n = 4$ suggested terms with the highest confidence the average precision could be raised from 57 to 67% which is an impressive improvement in precision, despite that fact that a larger recall is obtained

[9] http://www.gesis.org/solis.

[10] However, a retrieval study with experts from different domains is currently carried out.

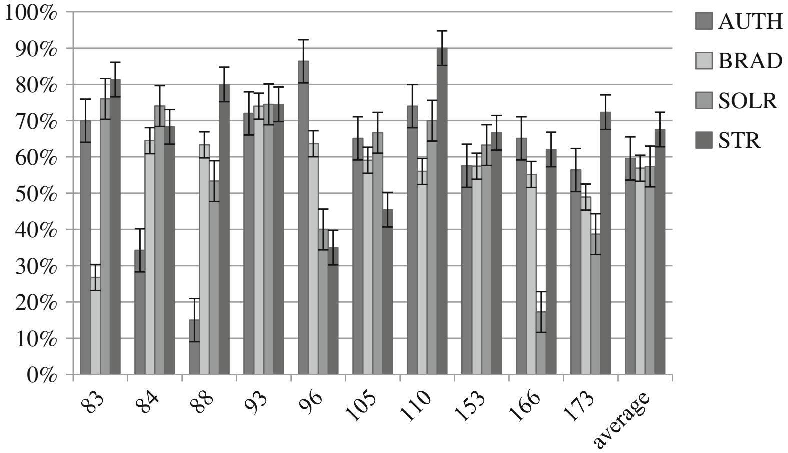


Fig. 2 Precision for each topic and service (relevance assessments per topic/total amount of single assessments), including standard error

(due to OR-ing the query with the four additional terms). In three cases precision drops below the baseline (topic 84, 96 and 105). If we take standard error in consideration only topic 105 is a real outliner (45% vs. a baseline of 66%).

Looking at the four topics where STR performed best (88, 110, 166 and 173 with an improvement of 20% at least compared to the baseline) it can be seen that this positive query drift was because of the new perspective added by the suggested terms. STR added new key elements to the query that were not included before. For topic 88 ("Sports in Nazi Germany"), for instance, the suggested term with the highest confidence was "Olympic Games". A term that was not included in title or description in any way. Of course, sports in Nazi Germany is not only focused on the Olympic Games 1936, but with a high probability everything related to the Olympic Games 1936 had to do with sports in Nazi Germany and was in this way judged relevant by the assessors. Other topics showed comparable phenomena.

The two alternative re-ranking mechanisms Bradfordizing and Author Centrality achieved an average precision that is near the baseline (57%), namely 60% for Author Centrality and 57% for Bradfordizing. Author Centrality yielded a higher, but not significantly higher average precision than Solr as a conventional ranking mechanism.[11] Both re-rank mechanisms showed a stable behavior (again, expect some outlier, cp. Fig. 2).

Overlap of top document result sets

However, a more important result as regards the two re-ranking services is that they point to quite other documents than other services. This indicates that the science models behind them provide a very different view to the document space. A comparison of the intersection of the relevant top 10 document result sets between each pair of retrieval service shows that the result sets are nearly disjoint. 400 documents (4 services × 10 per

[11] Moreover, we observed a high range of re-rankings done by Author Centrality. More than 90% of the documents in the result sets were captured by the author centrality based ranking.

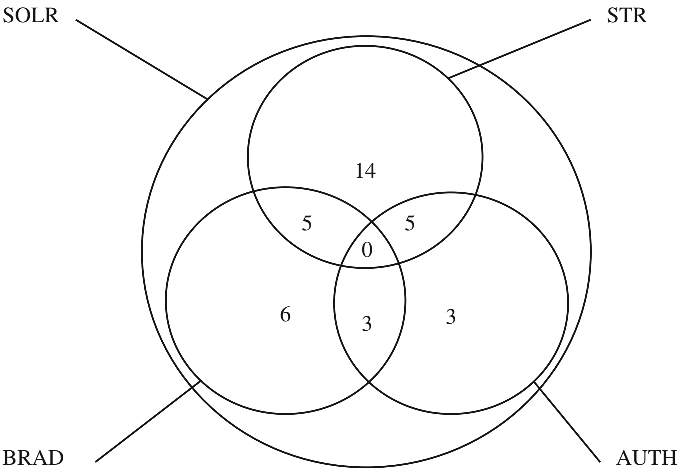


Fig. 3 Intersection of suggested top $n = 10$ documents over all topics and services (total of 400 documents)

service × 10 topics) only had 36 intersections in total (cp. Fig. 3). Thus, there is no or very little overlap between the sets of relevant top documents obtained from different rankings.

AUTH and SOLR as well as AUTH and BRAD have just three relevant documents in common (for all 10 topics), and AUTH and STR have only five documents in common. BRAD and SOLR have six, and BRAD and STR have five relevant documents in common. The largest, but still low overlap is among SOLR and STR which have 14 common documents. That confirms that the models proposed provide views to the document space that differ greatly from standard retrieval models as well as from one another. This can be also seen as a positive validation of the adequacy of the science models taken for representing relevant and quite different scientific activities.

Discussion

Two important implications emerge from the evaluation results: (1) The science models proposed provide beneficial effects to information retrieval quality. The precision tests turned out a precision of science-model driven search services which is at least as high as the precision of standard rankings. The more important effect of the models however is that they provide a particular view to the information space that is quite different from traditional retrieval methods such that the models open up new access paths to the knowledge space in question. (2) The science models studied are therefore verified as expressive models of science, as an evaluation of retrieval quality is seen as a litmus test of the adequacy of the models investigated. Moreover, it turned out that the results provided by the three science models investigated differ to a great extend which indicates that the models highlight very different dimensions of scientific activity. This also demonstrates that the models properly address the diversity of structures and dynamics in science.

The evaluation of retrieval quality achieved by a co-word model approach of query expansion, as performed by the STR, turned out significantly that a “query drift” (Mitra et al. 1998) towards terms that better reflect the scientific discourse(s) actually tends to retrieve more relevant documents (cp. Petras 2006). It is important to note that this positive effect is not only achieved by just mapping query terms to controlled terms from the indexing vocabulary, but mainly by linking the original query to the right research context the user has in mind, i.e. to research issues that are strongly co-related to the original term. The STR maps a query term to the cognitive structure of a field allowing the user to identify and select related topics and streams which obviously leads to more precise queries. Thus, the co-word model of science is verified as an expressive model of accessing the cognitive structure of a field and its various dimensions.

As regards the two re-ranking methods some added-values appear very clearly. On an abstract level, the re-ranking models can be used as a compensation mechanism for enlarged search spaces. Our analyses show that the hierarchy of the result set after re-ranking by Bradfordizing or Author Centrality is a completely different one compared to the original ranking. The user gets a new result cutout containing other relevant documents which are not listed in the first section of the original list. Additionally, the re-ranking via structure-oriented science models offer an opportunity to switch between term-based search and structure-oriented browsing of document sets (Bates 2002). On the other hand, modeling science into a core and a periphery—the general approach of both re-ranking models—always runs the risk and critic of disregarding important developments outside the core (cp. Hjørland and Nicolaisen 2005). Both models, however, imply the principle possibility to turn round the ranking in order to explicitly address publications of less central authors or publications in peripheral journals. Moreover, and probably more interesting, might be the ability of the models to point to items that appear between the top and the “midfield” of the structure, for instance publications in zone 2 journals or publications of “social climbers” in co-authorship networks (who seem to have a strong tendency of addressing innovative topics instead of mainstream issues, see Mutschke and Quan-Haase 2001).

Thus, it could be shown how structural models of science can be used to improve retrieval quality. The other way around, the IR experiment turned out that to the same extent to which science models contribute to IR (in a positive as well as negative sense), science-model driven IR might contribute to a better understanding of different conceptualizations of science (role of journals, authors and language in scientific discourses). Recall and precision values of retrieval results obtained by science model oriented search and ranking techniques seem to provide important indicators for the adequacy of science models in representing and predicting structural phenomena in science.

As regards the relationship between bibliometric-aided retrieval and traditional IR it turned out that, although the different perspectives aim at different objectives, on a generic level they share questions of the determination of the relevant information space and boundary setting in such a space. Thus, we could imagine that a future systematic comparison of bibliometric-aided retrieval and traditional IR approaches could be of relevance both for the questions “what is a scientific field?” as well as for “what is the scientific field relevant for my search?”. In such a study, the different models of science could be explicitly addressed and compared, together with the different selection criteria as applied by the two retrieval approaches.

A further point that might be interesting from the perspective of science modeling is the degree of acceptance of science models as retrieval methods by the users of a scholarly IR system. The degree to which scientists are willing to use those models for finding what they are looking for (as particular search stratagems, as proposed by Bates 2002) is a further relevant indicator for the degree to which the models intuitively meet the real research process. Thus, the major contributions of IR to science modeling might be to measure the expressiveness of existing science models and to generate novel models from the perspective of IR. In addition, the application and utilization of science model enhanced public retrieval systems can probably be a vehicle to better explain and communicate science and science models to a broader audience in the sense of public understanding of science.

However, a lot of research effort needs to be done to make more progress in coupling science modeling with IR. We see this paper as a first step in this area. The major challenge that we see here is to consider also the dynamic mechanisms which form the structures and activities in question and their relationships to dynamic features in scholarly information retrieval.[12]

Acknowledgments We would like to express our grateful thanks to Andrea Scharnhorst for her valuable comments. Special thanks go to the students in two independent LIS courses at Humboldt University (guided by our former colleague Vivien Petras) and University of Applied Science in Darmstadt. These students took part in our first IRM retrieval test in the winter semester 2009/2010. We thank Hasan Bas who did the main implementation work for our assessment tool. The project is funded by DFG, grant No. INST 658/6-1.

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[12] See Huberman and Adamic (2004) and Mutschke (2004b) for first attempts in that direction.

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Scientometrics (2011) 89:365–379
DOI 10.1007/s11192-011-0447-1

Tailor based allocations for multiple authorship: a fractional *gh*-index

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Received: 30 May 2011 / Published online: 26 August 2011

Abstract A quantitative modification to keep the number of published papers invariant under multiple authorship is suggested. In those cases, fractional allocations are attributed to each co-author with a summation equal to one. These allocations are tailored on the basis of each author contribution. It is denoted "Tailor Based Allocations (TBA)" for multiple authorship. Several protocols to TBA are suggested. The choice of a specific TBA may vary from one discipline to another. In addition, TBA is applied to the number of citations of a multiple author paper to have also this number conserved. Each author gets only a specific fraction of the total number of citations according to its fractional paper allocation. The equivalent of the *h*-index obtained by using TBA is denoted the *gh*-index. It yields values which differ drastically from those given by the *h*-index. The *gh*-index departs also from $\bar{h}$ recently proposed by Hirsh to account for multiple authorship. Contrary to the *h*-index, the *gh*-index is a function of the total number of citations of each paper. A highly cited paper allows a better allocation for all co-authors while a less cited paper contributes essentially to one or two of the co-authors. The scheme produces a substantial redistribution of the ranking of scientists in terms of quantitative records. A few illustrations are provided.

Keywords Multiple authorship · Fractional allocations · *h*-Index

Introduction

Individual bibliometry is today a major instrument to allocating research funds, promoting academics and recruiting researchers. The existence of the *h*-index (Hirsch 2005) has boosted the use of quantitative measures of scientist productions. In particular its incorporation within the Web of Science via a simple button have just turned upside-down the

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world of evaluation. The use of the *h*-index is now widespread and unavoidable despite all the associated shortcomings and biases.

To restrict an individual evaluation to only quantitative figures combining the number of articles, the total number of citations and the *h*-index allow at a glance to rank two competing scientists within a given field. Nevertheless qualitative evaluation is still of a considerable importance to approach a scientist career.

It is also worth to emphasize that in addition to the institutional use of these indexes and numbers, watching at one's own *h*-index as well as those of friends or competitors has became a ludic and convivial game to place a researcher in the social perspective of its community out of it absorbing lonely state of doing research.

As expected for any index, the *h*-index was shown to exhibit a series of shortcomings and weaknesses prompting a series of modifications like a weighting by citation impact (Egghe and Rousseau 2008) and the bursting of novel proposals with the *g*-index (Egghe 2006). For a review focusing on the the *h*-index variants, computation and standardization for different scientific fields see (Alonso et al. 2009) and (Van Raan 2006) for a comparison with standard bibliometric indicators. Complements to the h-index (Jin et al. 2007; Hu et al. 2010) as well as generalizations (Van Eck and Waltman 2008) and variants (Guns and Rousseau 2009) of both the *h* and *g*-indexes have proposed. A comparison of nine different variants of the *h*-index using data from biomedicine has been conducted in (Bornmann et al. 2008).

On this basis it is of importance to emphasize that there exists no ultimate index to be self-sufficient. Only combining different indexes could approach a fair and appropriate evaluation of the scientific output of a researcher.

However, the question of multiple co-authorship has not been given too much of interest although several suggestions have been made recently. For instance it was suggested to rescale a scientist *h*-index dividing it by the mean number of authors of all its papers which belong its *h*-list (Batista et al. 2006). Combining citations and ranking of papers in a fractional way was also proposed (Egghe 2008) as well as a scheme to allocate partial credit to each co-author of a paper (Guns and Rousseau 2009). It was also proposed to count papers fractionally according to the inverse of the number of co-authors (Schreiber 2009). Last but not least the initiator of the *h*-index has also proposed to consider a modified $\bar{h}$-index (Hirsch 2010) to account for multiple authors.

It is rather striking to notice that while science is based on the discovering and the use of conservation laws, scientists have been applying the myth of "Jesus multiplying bread and fish" for decades by multiplying for themselves published articles. Indeed, when an article is published with *k* authors, each co-author adds one paper to its own list of publications. It means that for one paper published with *k* authors, *k* authors add one to their respective number of publications. Accordingly, a single *k*-author papers contributes to *k* papers while aggregating the total number of papers published by all scientists from their respective publication lists. The same process applies for the citation dynamics with one single citation for one *k*-author paper contributing to an overall of *k* citations since each one of the *k* authors includes the citation in its personal *h*-index evaluation.

A few proposal were made previously to conserve the number of articles but prior to the introduction of the *h*-index (Zuckerman 1968; Cole and Cole 1973; Price 1981; Cronin 1981; Vinkler 1987; Van Hooydonk 1997; Oppenheim 1998; Egghe et al. 2000) and stayed without much application besides a recent suggestion to define an adapted pure *h*-index (Chai et al. 2008). Fractional counting was also suggested recently to evaluate universities (Leydesdorff and Shin 2010; Leydesdorff and Opthof 2010).

In this paper I propose a new scheme to obey the conservation law of published articles at all levels of associated indexes. One paper counts for a single unit independently of the number of co-authors. This unit must then be divided among the authors. Any fraction used by one of the author is definitively withdraw from the unit. Accordingly, for a multiple author paper fractional allocations are attributed to each co-author with a summation equal to one. These allocations are tailored on the basis of each author contribution. It is denoted "Tailor Based Allocations (TBA)" for multiple authorship.

The total number of citations given to one paper must be also conserved within the sum of all credits given to each one of its authors. Any part taken by one author is subtracted from the total. To be consistent the same TBA must be used with respect to all figures attached to a given paper. Each author gets only a specific fraction of the total number of citations according to its fractional paper allocation. Using TBA for citations yields a new equivalent of the *h*-index, I denote the *gh*-index. Contrary to the *h*-index, the *gh*-index is a function of the total number of citations of each paper. A highly cited paper allows automatically a better allocation for all co-authors while a less cited paper contributes essentially either to one or two of the co-authors or little to all authors.

Several protocols to TBA are suggested and compared. The choice of a specific TBA may vary from one discipline to another. In each case, the *gh*-index yields values which differ drastically from those given by the *h*-index. The *gh*-index departs also from $\bar{h}$ recently proposed by Hirsh to account for multiple authorship. The scheme is found to produce a substantial redistribution of the ranking of scientists in terms of quantitative records. A few illustrations are provided.

Designing the perfect author allocations

According to the principle of conserved number of papers, given a single *k*-authors paper only a fraction $g(r, k)$ is allocated to each one of the *k* authors under the constraint

$$\sum_{r=1}^{k} g(r,k) = 1 \tag{1}$$

where $r = 1, 2, \ldots, k$ denotes the respective position of each author in the sequence of co-authors. The respective values of the set of $\{g(r, k)\}$ are determined following a "Tailor Based Allocations", the TBA.

All quantitative figures attached to an author at position *r* of a given *k* authors paper must then be scaled by $g(r, k)$. Accordingly, the total number of publications of a researcher must be calculated adding the series of the respective fractional TBA for all the papers it authored. Henceforth one paper does not count for one any longer unless it is authored by a single scientist. Given an author with a list of *T* publications, its total number of articles becomes

$$T_g \equiv \sum_{i=1}^{T} g_i(r,k) \tag{2}$$

instead of *T* with the property $T_g \leq T$.

Similarly, considering the total number of citations of an author, the same rescaling applies. Given a number n_i of citations for paper *i* in the author list of T publications, the TBA for the paper citations is

$$g_i(r,k)n_i, \tag{3}$$

instead of n_i. Each co-author is granted a different number of citations from the same paper with for a given paper,

$$\sum_{r=1}^{k}[g_i(r,k)n_i] = n_i \tag{4}$$

using Eq. 1. On this basis, the total number of citations of an author becomes

$$N_g \equiv \sum_{i=1}^{T} g_i(r,k)n_i, \tag{5}$$

instead of $N \equiv \sum_{i=1}^{T} n_i$ with the property $N_g \leq N$.

Using Eq. 3 produces naturally novel values for the corresponding *h*-index denoted *gh*-index. To implement the procedure the next crucial step is to select a criterium to allocate the various values $g(r, k)$ with $r = 1, 2, \ldots, k$ for a specific paper. In principle, this set may vary from one paper to another even for the same value of k.

Clearly, the best scheme will eventually become a specific allowance decided by the authors themselves for each paper prior to have it submitted. For each name, in addition to the affiliation, a quantitative fraction $g(r, k)$ will be stated to denote the fraction of that peculiar paper to be attributed to author r. The distribution of numerical values of a series $g(1, k)$, $g(2, k)$, …, $g(k, k)$ would thus reflect the precise contribution of each one of the authors determining an exact TBA. That will be the most accurate and fair setting. However, an implementation could start only in the near future. In the mean time, we need to adopt one fixed standard in order to make a practical use of our proposal to treat all existing publication data. However, the choice of a protocol must incorporates the tradition of each discipline in co-signing papers. At this stage, each field should adopt its own TBA.

How to choose a tailor based allocations?

In physics, and in particular in condensed matter physics, the smallest team, i.e., a group of two persons is composed of one researcher who has performed most of the technical work while the other one has defined the frame and or the problem. Usually the first one is a junior scientist (J), either undergraduate or graduate student or a postdoctoral researcher whose supervisor is the second one, a senior researcher (S). The associated pair author sequence is then $J - S$. In case we have additional $(k - 2)$ authors A_r with $r = 2, 4, \ldots, k - 1$, the paper becomes a k author paper. The corresponding name sequence follows their respective contributions yielding the series $J - A_2 - A_3 - \cdots - A_{k-1} - S$. However, in terms of decreasing weights of their respective contributions most often we have $A_1 - A_k - A_2 - A_3 - \cdots - A_{k-1}$ for k authors with $J = A_1$ and $S = A_k$, which is different form the name sequence put in the paper.

While Hirsh advocates a specific scientific policy incentive in designing the $\bar{h}$-index (Hirsch 2010) to favor senior researchers, I focus on trying to incorporate into the ranking of authors the reality of the production of papers. The question of what part of return should be attributed to each contribution is open to a future debate within each discipline to set a standard. The standard could vary from one discipline to another. I consider that in the making of current research the “technical part” is the one to receive the larger slice of the output. Simultaneously, the “conceiving part” should be granted with the second larger slice. It follows somehow the spirit of the financial setting of the American National Science Foundation grant attribution. There, the grant pays the full salary of the researcher who does the work against a summer salary for the leading researcher of the grant. That is somehow how it works at least in condensed matter physics, the field I am familiar with.

I do not intend in promoting one specific policy to favor or discourage conducting collaboration but to build a frame to both capture the current practice and to exhibit some flexibility to allow adaptation to fit different policies. Various protocols should be first tested in different fields by different researchers, and then it will become possible to elaborate a standard, which may differ from one field to another. But everyone will thus get its due within the conservation law of published papers applying the TBA. Last but not least, any choice will have the effect to discourage the current inflation of multiple authorship, which automatically increases the ranking of involved scientists. With any TBA, adding an author to a paper will have a “cost” paid by the others, and in particular to the one who in the current situation is getting credit without doing much work.

Homogeneous versus heterogeneous TBA

At this stage to implement our scheme we need to determine an explicit TBA associated to a sequence of authors $A_1 - A_2 - A_3 - A_4 - \cdots - A_{k-1} - A_k$. Previous schemes which did conserve allocation are uniform with respect to ranking as illustrated with the following three main cases:

- The simplest equalitarian fractional allocating (Price 1981; Oppenheim 1998) where each of the k authors receives an allocation $1/k$. However if the output of a paper is equalitarian the input is not making this scheme rather unfair for the author who did the main part of the work.
- The arithmetic allocating (Van Hooydonk 1997) sounds well-balanced with $g(r,k) = \frac{2(k+1-r)}{k(k+1)}$. The higher part is allocated to first author with $g(1,k) = \frac{2}{(k+1)}$, last author receiving the smaller part $g(k,k) = \frac{2}{k(k+1)}$. This scheme favors the first author at the expense of the last one. In other words, most credit is given to the junior scientist as shown in Fig. 1. We could conceive the opposite arithmetic allocation with $g(r,k) = \frac{2(r)}{k(k+1)}$ to heavily benefit to senior researchers as wished by Hirsch. My stand is to favor junior researchers not because they are young but because they do most of the work.
- Similarly one can consider a geometric allocating (Egghe et al. 2000) with $g(r,k) = \frac{2^{1-r}}{2(1-2^{-k})}$. The higher part is still allocated to first author with $g(1,k) = \frac{1}{2(1-2^{-k})}$, last author receiving the smaller part $g(k,k) = \frac{1}{2^{k-1}}$. Figure 2 illustrates the variation of $g(r, k)$ a s function of k.
- An earlier proposal was a rather awkward combination of equalitarian fractioning where each one of the authors receives the same slot $\frac{1}{2(k-1)}$ besides the last author, usually the senior researcher, who gets $\frac{1}{2}$ (Zuckerman 1968).

While above TBA are homogeneous with respect to ranking we now propose an heterogeneous TBA to favor, although differently, both the junior and the senior scientists.

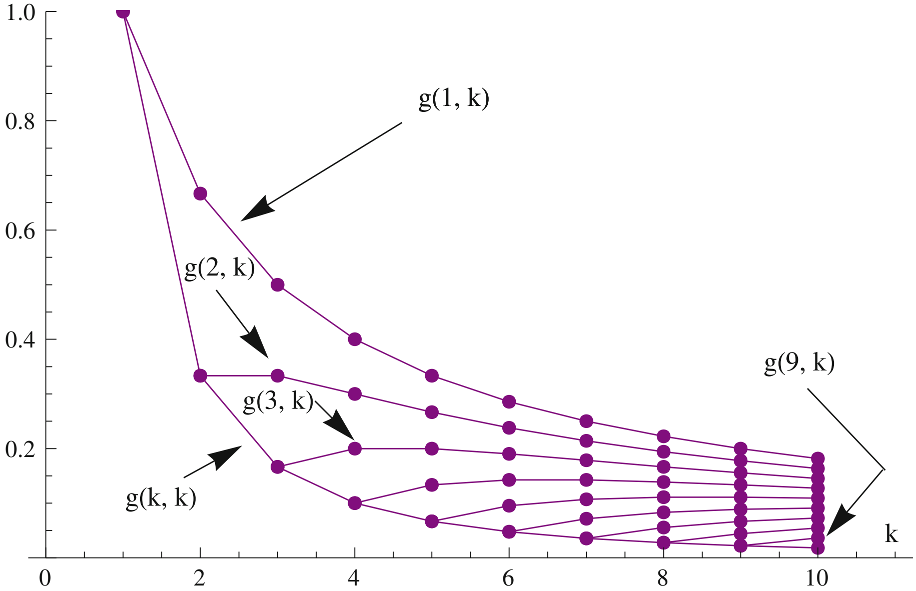

Fig. 1 The various $g(r, k)$ in case of a decreasing arithmetic allocation to favor junior scientists at the expense of senior ones. The function $g_{k,\,k}$ represents the slot allocated to the last author of the list. This TBA yields two third one third at $k = 2$

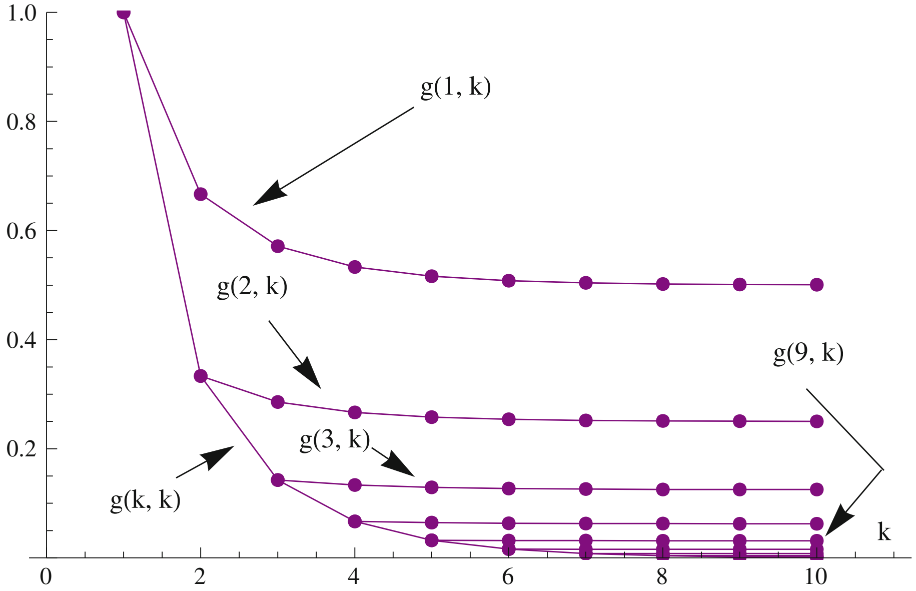

Fig. 2 The various $g(r, k)$ in case of a decreasing geometric allocation to favor junior scientists at the expense of senior ones. The function $g(k, k)$ represents the slot allocated to the last author of the list. This TBA yields two third one third at $k = 2$

I suggest to allocate extra bonuses, δ to first and μ to last authors in addition to the use of a modified non-linear arithmetic allocation to the other authors. Considering k co-authors the formulas are obtained starting from a decreasing arithmetic series $k, k-1, k-2, \ldots, 2, 1$. The first value k is attributed to the first author to which a bonus δ is added. The second value ($k - 1$) is given to the last author with a bonus μ. The remaining terms of the series $k-2, \ldots, 2, 1$ are allocated respectively to authors number $2, 3, \ldots, k-1$. The sum of all terms yields $Sk = \frac{k(1+k)}{2} + \delta + \mu$, which allows to explicit the various fractional allocations as

$$g(1,k) = \frac{k+\delta}{S_k} \tag{6}$$

$$g(k,k) = \frac{k-1+\mu}{S_k} \tag{7}$$

$$g(r,k) = \frac{k-r}{S_k} \tag{8}$$

where $g(1, k)$ and $g(k, k)$ are defined only for $k \geq 2$ and $g(r, k)$ only for $k \geq 3$ with $r = 2, 3, \ldots, k-1$.

Next step is to choose the values of the extra bonuses δ and μ. One hint is to have them determined from setting the case of two authors. At $k = 2$ Eqs. 6 and 7 yield $g(1,2) = \frac{2+\delta}{S_2}$ and $g(2,2) = \frac{1+\mu}{S_2}$ with $S_2 = 3 + \delta + \mu$. For the case of two author three choices of allocations appear quite naturally with either two to one third, three to one quarter or one to one half. First case is achieved under the constraint $\delta = 2\mu$, second one with $\delta = 1 + 3\mu$ and the last one with $\delta = -1 + \mu$. Imposing the $k = 2$ TBA leaves one degree of freedom for the choice of the overall part attributed to the bonuses when $k > 2$. Let us now compare these various choices.

- The case "two to one third"
  Taking $\delta = 2\ \mu$ yields $g(1,2) = 2/3$ and $g(2,2) = 1/3$. Table 1 exhibits all $g(r, k)$ when $\delta = 2$ and $\mu = 1$ for $1 \leq k \leq 10$ with $1 \leq r \leq k$. For each value of k from 1 to 10 a line gives the various weights $g(r, k)$ calculated from Eqs. 6, 7 and 8 for $1 \leq r \leq k$. To visualize the variation of each $g(r, k)$ as a function of k as reported in Table 1, the values are plotted in Fig. 3. Last author of the list received $g_{k,\ k}$. It yields two third one third at $k = 2$. Every weight $g(r, k)$ starts from $k = r + 1$.
- The "case three to one quarter"
  The same as for the case (2/3, 1/3) but with $\delta = 1 + 3\ \mu$ to ensure the $k = 2$ repartition $g_{1,2} = \frac{2+\delta}{S_2} = 3/4 = 0.75$ and $g_{2,2} = \frac{1+\mu}{S_2} = 1/4 = 0.25$ with $S_2 = 3 + \delta + \mu$. We select $\delta = 1$ and $\mu = 0$. The various set of $g(r, k)$ are listed in Table 2 and plotted in Fig. 4.
- The case "one to one half"
  The same as for the case (2/3, 1/3) but with $\delta = -1 + \ \mu$ to ensure the $k = 2$ repartition $g(1,2) = \frac{2+\delta}{S_2} = 1/2 = 0.50$ and $g(2,2) = \frac{1+\mu}{S_2} = 1/2 = 0.50$ with $S_2 = 3 + \delta + \mu$. We select $\delta = 0$ and $\mu = 1$. The various set of $g(r, k)$ are listed in Table 3 and plotted in Fig. 5.
- The inhomogeneous arithmetic case
  Putting both bonuses equal to zero $\delta = \mu = 0$, Eqs. 6, 7 and 8 recover an arithmetic series where the second term is attributed to the last author. Associated values are reported in Table 4 and shown in Fig. 6, which is almost identical to Fig. 1 but yet with

Table 1 The various $g(r, k)$ when $\delta = 2$ and $\mu = 1$ for $1 \leq k \leq 10$ with $1 \leq r \leq k$

k/*r*	1	2	3	4	5	6	7	8	9	10
1	1	xxx	xxx	xxx	xxx	xxx	xxx	xxx	xxx	xxx
2	0.67	0.33	xxx	xxx	xxx	xxx	xxx	xxx	xxx	xxx
3	0.56	0.11	0.33	xxx	xxx	xxx	xxx	xxx	xxx	xxx
4	0.46	0.15	0.08	0.31	xxx	xxx	xxx	xxx	xxx	xxx
5	0.39	0.17	0.11	0.05	0.28	xxx	xxx	xxx	xxx	xxx
6	0.33	0.17	0.12	0.08	0.04	0.25	xxx	xxx	xxx	xxx
7	0.29	0.16	0.13	0.10	0.06	0.03	0.23	xxx	xxx	xxx
8	0.26	0.15	0.13	0.10	0.08	0.05	0.02	0.20	xxx	xxx
9	0.23	0.15	0.12	0.10	0.08	0.06	0.04	0.02	0.19	xxx
10	0.21	0.14	0.12	0.10	0.09	0.07	0.05	0.03	0.02	0.17

At $k = 2$ we have two third for the first author and one third for the second one

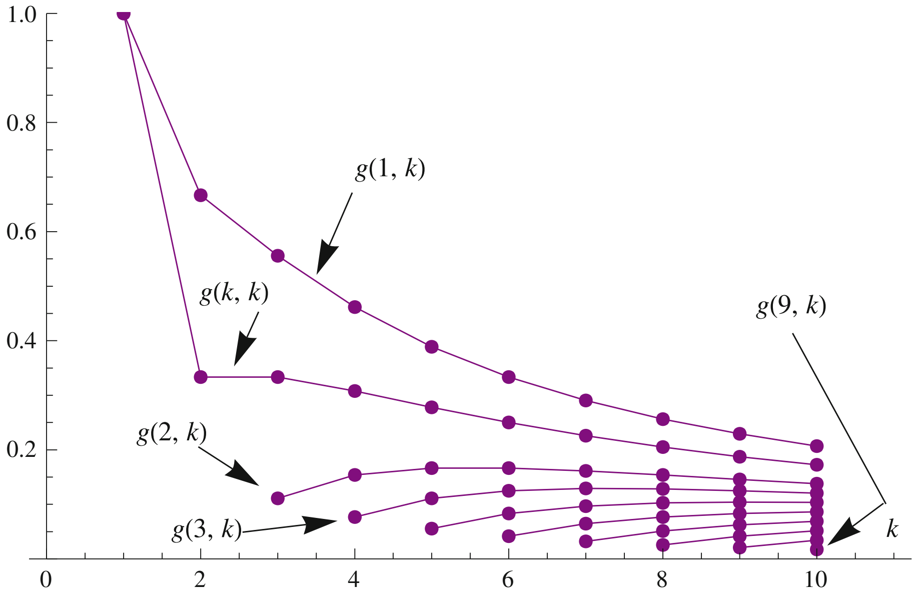

Fig. 3 The various $g(r, k)$ when $\delta = 2$ and $\mu = 1$ for $1 \leq k \leq 10$ with $1 \leq r \leq k$ from Table 1. The function $g(1, k)$ represents the slot allocated to the first author of the list and $g(k, k)$ the slot allocated to the last author. The bonuses are defined to yield respective allocations of two third and one third at $k = 2$. Given a value r the weight $g(r, k)$ is defined starting from $k = r + 1$

subtle differences. Here $g(k, k)$ stands instead of $g(2, k)$ and $g(2, k)$ stands instead of $g(3, k)$. In addition $g(9, k)$ at $k = 10$ is the last lower point while it is the one before last in Fig. 1. Depending on which situation has been selected either Tables 4 or 1 the strategy of the senior scientist in adding authors will be totally opposite.

Table 2 The various $g(r, k)$ when $\delta = 1$ and $\mu = 0$ for $1 \leq k \leq 10$ with $1 \leq r \leq k$

k/*r*	1	2	3	4	5	6	7	8	9	10
1	1	xxx	xxx	xxx	xxx	xxx	xxx	xxx	xxx	xxx
2	0.75	0.25	xxx	xxx	xxx	xxx	xxx	xxx	xxx	xxx
3	0.57	0.14	0.29	xxx	xxx	xxx	xxx	xxx	xxx	xxx
4	0.45	0.18	0.09	0.27	xxx	xxx	xxx	xxx	xxx	xxx
5	0.37	0.19	0.12	0.06	0.25	xxx	xxx	xxx	xxx	xxx
6	0.32	0.18	0.14	0.09	0.04	0.23	xxx	xxx	xxx	xxx
7	0.28	0.17	0.14	0.10	0.07	0.03	0.21	xxx	xxx	xxx
8	0.24	0.16	0.13	0.11	0.08	0.05	0.03	0.19	xxx	xxx
9	0.22	0.15	0.13	0.11	0.09	0.06	0.04	0.02	0.17	xxx
10	0.16	0.14	0.12	0.11	0.09	0.07	0.05	0.04	0.02	0.16

At $k = 2$ it yields three to one quarter for respectively the first and second authors

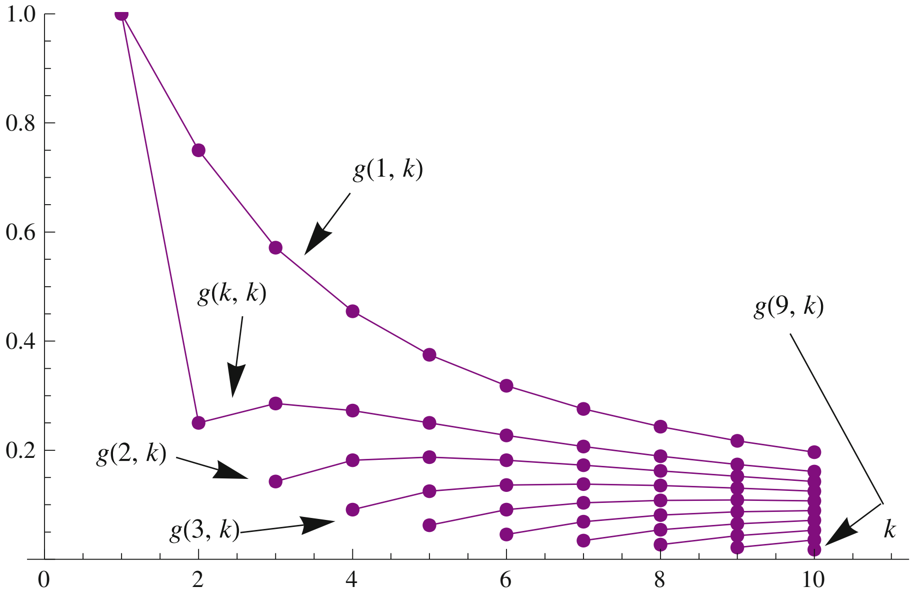

Fig. 4 The various $g(r, k)$ when $\delta = 1$ and $\mu = 0$ for $1 \leq k \leq 10$ with $1 \leq r \leq k$ from Table 2. The function $g(1, k)$ represents the slot allocated to the first author of the list and $g(k, k)$ the slot allocated to the last author. The bonuses are defined to yield respective allocations of three to one quarter at $k = 2$. Given a value r the weight $g(r, k)$ is defined starting from $k = r + 1$

Calculating the *gh*-index

While applying a TBA clearly modifies drastically the number of publications of authors, it also modifies the associated *h*-index by extending the TBA to the paper citations. For a *k* author paper, the author at position *r* in the name sequence now receives $g(r, k)\ n$ for its own part of citations instead of the total number *n*. Using this fractional number of citations

Table 3 The various $g(r, k)$ when $\delta = 0$ and $\mu = 1$ for $1 \leq k \leq 10$ with $1 \leq r \leq k$

k/r	1	2	3	4	5	6	7	8	9	10
1	1	xxx	xxx	xxx	xxx	xxx	xxx	xxx	xxx	xxx
2	0.50	0.50	xxx	xxx	xxx	xxx	xxx	xxx	xxx	xxx
3	0.43	0.14	0.43	xxx	xxx	xxx	xxx	xxx	xxx	xxx
4	0.36	0.18	0.09	0.36	xxx	xxx	xxx	xxx	xxx	xxx
5	0.31	0.19	0.12	0.06	0.31	xxx	xxx	xxx	xxx	xxx
6	0.27	0.18	0.14	0.09	0.04	0.27	xxx	xxx	xxx	xxx
7	0.24	0.17	0.14	0.10	0.07	0.03	0.24	xxx	xxx	xxx
8	0.22	0.16	0.13	0.11	0.08	0.05	0.03	0.22	xxx	xxx
9	0.20	0.15	0.13	0.11	0.09	0.06	0.04	0.02	0.20	xxx
10	0.18	0.14	0.12	0.11	0.09	0.07	0.05	0.04	0.02	0.18

At $k = 2$ it yields one to one half

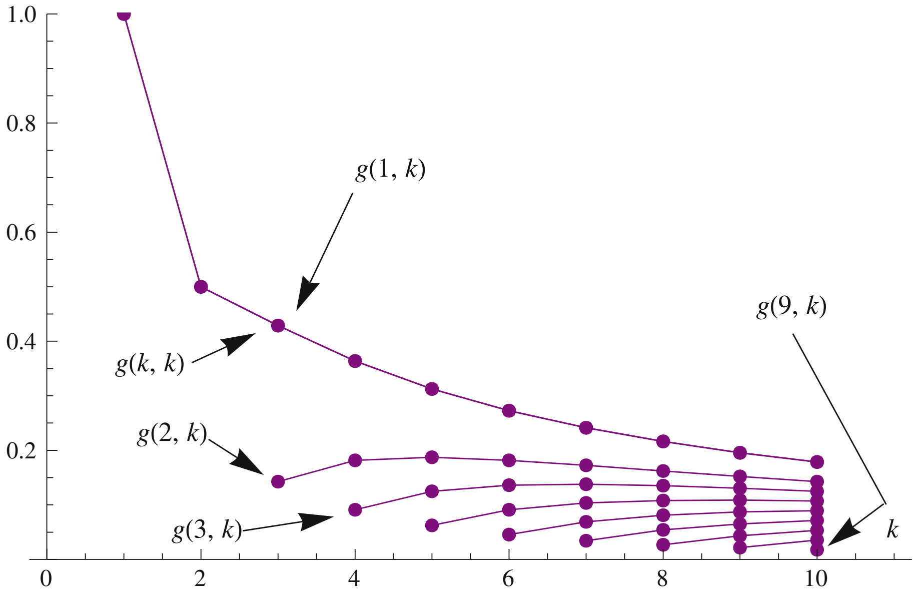

Fig. 5 The various $g(r, k)$ when $\delta = 1$ and $\mu = 0$ for $1 \leq k \leq 10$ with $1 \leq r \leq k$ from Table 3. The function $g(1, k)$ represents the slot allocated to the first author of the list and $g(k, k)$ the slot allocated to the last author. The bonuses are defined to yield respective allocations of one to one half at $k = 2$. Given a value r the weight $g(r, k)$ is defined starting from $k = r + 1$

to calculate the k-index according to the same definition yields a new lower gh-index. The rescaled value does depend on the choice of the bonuses δ and μ.

While the choice of these bonuses should be the result of a consensus among researchers, I choose here one arbitrary set to illustrate how the h-index is changed. I selected one physicist with a h-index equal to 33 to apply my procedure. It names is not disclosed to maintain individual privacy. I also report only its forty first papers of its complete list of articles which is much longer. They are shown in Table 5 where each

Table 4 The various $g(r, k)$ when $\delta = \mu = 0$ for $1 \leq k \leq 10$ with $1 \leq r \leq k$

k/*r*	1	2	3	4	5	6	7	8	9	10
1	1	xxx	xxx	xxx	xxx	xxx	xxx	xxx	xxx	xxx
2	0.67	0.33	xxx	xxx	xxx	xxx	xxx	xxx	xxx	xxx
3	0.50	0.33	0.17	xxx	xxx	xxx	xxx	xxx	xxx	xxx
4	0.40	0.30	0.20	0.10	xxx	xxx	xxx	xxx	xxx	xxx
5	0.33	0.27	0.20	0.13	0.07	xxx	xxx	xxx	xxx	xxx
6	0.29	0.24	0.19	0.14	0.09	0.05	xxx	xxx	xxx	xxx
7	0.25	0.21	0.18	0.14	0.11	0.07	0.04	xxx	xxx	xxx
8	0.22	0.19	0.17	0.14	0.11	0.08	0.06	0.03	xxx	xxx
9	0.20	0.18	0.16	0.13	0.11	0.09	0.07	0.04	0.02	xxx
10	0.18	0.16	0.14	0.13	0.11	0.09	0.07	0.05	0.04	0.02

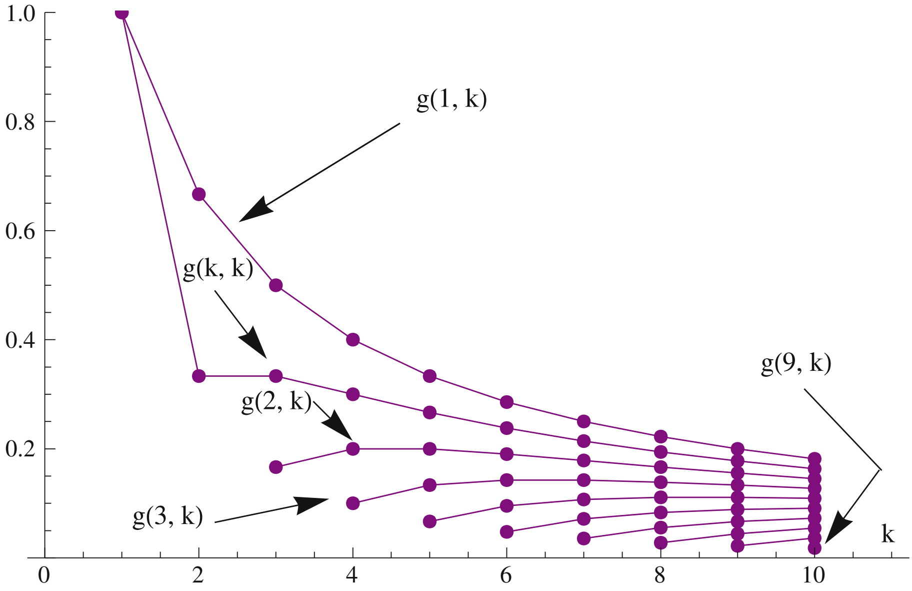

Fig. 6 The various $g(r, k)$ when $\delta = \mu = 0$ for $1 \leq k \leq 10$ with $1 \leq r \leq k$ from Table 4. The function $g(1, k)$ represents the slot allocated to the first author of the list and $g(k, k)$ the slot allocated to the last author

paper is ranked with $i = 1, 2, \ldots, 40$ according to its associated total number of citation n_i following a decreasing order. The second column (r, k) indicates respectively the number of authors and the researcher rank of each paper. The last four columns report the rescaled numbers of citations allocated to the author using the precedent four different choices of slot allocations at $k = 2$. We have $g(r,k;2/3)$ for the case "two to one third", $g(r,k;3/4)$ for the case "three to one quarter", $g(r,k;1/2)$ for the case one to one half and $g(r,k;0)$ for zero bonuses.

Indeed the selected author has published 9 times alone, 4 times as first author for two authors, 13 times as second author for two authors, 1 time as first author for three authors, 3

Table 5 An author h-index list of publication revisited by four different TBA

i	(r, k)	n_i	$g(r, k; 2/3)n_i$	$g(r, k; 3/4)n_i$	$g(r, k; 1/2)n_i$	$g(r, k; 0)n_i$
1	(2, 2)	187	61.71	46.75	93.5	61.71
2	(1, 1)	181	181	181	181	181
3	(3, 3)	179	59.07	51.91	76.97	30.43
4	(1, 1)	145	145	145	145	145
5	(1, 1)	145	145	145	145	145
6	(2, 3)	132	14.52	18.48	18.48	43.56
7	(1, 1)	132	132	132	132	132
8	(2, 3)	120	13.20	16.80	16.80	39.60
9	(1, 2)	104	69.68	78.00	52.00	69.68
10	(3, 1)	98	54.98	55.86	42.14	49.00
11	(1, 2)	94	62.98	70.50	47.00	62.98
12	(3, 3)	90	29.70	26.10	38.70	15.30
13	(3, 3)	81	26.73	23.49	34.83	13.77
14	(1, 1)	75	75	75	75	75
15	(2, 2)	72	23.76	18	36	23.76
16	(3, 3)	71	23.43	20.59	30.53	12.07
17	(3, 3)	68	22.44	19.72	29.29	11.56
18	(3, 3)	66	21.78	19.14	28.38	11.22
19	(2, 2)	63	20.79	15.75	31.50	20.79
20	(3, 3)	55	18.15	15.95	23.63	9.35
21	(1, 1)	51	51	51	51	51
22	(2, 2)	50	16.5	12.5	25	16.5
23	(2, 2)	48	15.84	12	24	15.84
24	(1, 1)	45	45	45	45	45
25	(1, 1)	43	45	45	45	45
26	(1, 2)	42	28.14	31.50	21.00	28.14
27	(1, 1)	39	39	39	39	39
28	(2, 3)	38	4.18	5.32	5.32	12.54
29	(2, 2)	38	12.54	9.5	19	12.54
30	(2, 2)	35	11.55	8.75	17.5	11.55
31	(2, 2)	35	11.55	8.75	17.5	11.55
32	(2, 2)	34	11.22	8.50	17	11.22
33	(4, 6)	33	2.64	2.97	2.97	4.62
34	(1, 2)	31	20.77	23.25	15.50	20.77
35	(3, 3)	30	9.90	8.70	12.90	5.10
36	(2, 2)	30	9.9	7.5	15	9.9
37	(3, 3)	30	9.90	8.70	12.90	5.10
38	(2, 2)	30	9.9	7.5	15	9.9
39	(2, 2)	29	9.57	7.25	14.5	9.57
40	(2, 2)	29	9.57	7.25	14.5	9.57

Table 6 The TBA coefficients used for the author list form Table 5

(r, k)	$g(r, k; 2/3)$	$g(r, k; 3/4)$	$g(r, k; 1/2)$	$g(r, k; 0)$
(1, 1)	1	1	1	1
(1, 2)	0.67	0.75	0.50	0.67
(2, 2)	0.33	0.25	0.50	0.33
(1, 3)	0.56	0.57	0.43	0.50
(2, 3)	0.11	0.14	0.14	0.33
(3, 3)	0.33	0.29	0.43	0.17
(4, 6)	0.08	0.09	0.09	0.14

times as second author for three authors, 9 times as last author for three authors, and 1 time as fourth author for six authors. The associated values of $g(r, k)$ are reported in Table 6. They are used to calculate the rescaled citations of last four columns of Table 5.

Using Table 5 to evaluate the associated *gh*-index, instead of the *h*-index value of 33 we find that $gh(2/3) = 21$, $gh(3/4) = 19$, $g(1/2) = 23$, $gh(0) = 20$. The total number of articles fir the author is respectively 19.91, 18.94, 22.31, 19.13 instead of the inflated value of 40.

While all choices reduce by approximately half the number of articles, the *h*-index is reduced by one third. The differences between the various sets of $g(r, k)$ are significant but not substantial. Clearly the modifications will vary from one author to another depending on its distribution of multiple collaboration and on the author position in the sequence of names.

Conclusion

I have presented a scheme to obey the conservation of both printed papers and given citations. While the principle of a Tailor Based Allocations (TBA) is a scientific prerequisite, the differences between the various sets of fractional coefficients $g(r, k)$ attributed to authors at position r in a list of k names, are significant but not substantial in the cutting of the current inflation of counting of papers driven by the individual counting of multiple authorship.

More applications are needed to figure out which TBA is more appropriate for each discipline. However, our procedure is readable applicable to any individual set obtained from the Web of Science.

From our results, it could appear that the TBA rescaling disadvantages senior authors who usually sit last with several co-authors but indeed it is not quite the case since all indexes are deflated to obey the conservation law of existing articles. Moreover, in contrast to the *h*-index, the *gh*-index takes into account the existence of high citations for a paper since then a large n_i does yield large $g(r, k)n_i$ for all k authors whatever their respective rank is. On the contrary, a low citation paper does contribute mainly to first and last authors.

It is worth to notice that in some disciplines the question of who has contributed the most or least to a paper is uncoupled from the sequence of co-authors in the byline of the paper as traditionally often applied in mathematics and for practical reasons in high-energy physics. In some cases, it is also known that the "senior" co-author did not contribute much to the work but cosigns the paper as a privilege of its status being the professor, director, head of department or project leader. These facts make difficult to adopt one single attribution model, which will be fair for all cases of multiple authorship. In those cases, one possibility could be to apply the 1/*k* allocation for *k* co-authors although the various contributions are rarely equivalent. The situation will be different in the future since then authors will decide which fractions each one gets by having those fractions written along the author affiliations. The sequence of authors could then be at will independent or dependent of the sequence of the authors.

I do not intend to promote a peculiar policy for collaboration but to set a frame in which one paper counts as one paper independently of its number of authors. On this basis the choice of author allocations should integrate the reality of what part everyone did in the building of a paper with the setting a specific TBA for each paper paper having in mind that one paper counts for one no matter the number of co-authors. The focus of the paper is to show explicitly that applying the TBA to obey the rule that one paper counts to one modifies drastically the ranking of scientists. In particular extending the TBA to the number of citations turns useless to be an author of a multiple author paper with a bibliometric return of almost zero. The ranking of scientists is also disrupted substantially even if we select the equalitarian 1/*k* TBA for *k* co-authors since single and pair authors will be favored with respect to larger sets of co-authors.

My proposal does not aim at setting a specific standard to TBA but to trigger novel practice framed by the constraint of a total weight of one to one paper. In particular, within TBA adding an author to a paper has a “cost” paid by the others, and in particular to the ones who in the current situation are getting credit without doing much work.

This principle of reality should not discourage collaborations but on the contrary favor a fair return to multiple authorship. It creates an incentive to stop the current inflation of publications driven by the individual counting of multiple authorship.

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Scientometrics (2011) 89:381–396
DOI 10.1007/s11192-011-0439-1

Community structure and patterns of scientific collaboration in Business and Management

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Received: 7 June 2011 / Published online: 1 July 2011

Abstract This paper investigates the role of homophily and focus constraint in shaping collaborative scientific research. First, homophily structures collaboration when scientists adhere to a norm of exclusivity in selecting similar partners at a higher rate than dissimilar ones. Two dimensions on which similarity between scientists can be assessed are their research specialties and status positions. Second, focus constraint shapes collaboration when connections among scientists depend on opportunities for social contact. Constraint comes in two forms, depending on whether it originates in institutional or geographic space. Institutional constraint refers to the tendency of scientists to select collaborators within rather than across institutional boundaries. Geographic constraint is the principle that, when collaborations span different institutions, they are more likely to involve scientists that are geographically co-located than dispersed. To study homophily and focus constraint, the paper will argue in favour of an idea of collaboration that moves beyond formal co-authorship to include also other forms of informal intellectual exchange that do not translate into the publication of joint work. A community-detection algorithm for formalising this perspective will be proposed and applied to the co-authorship network of the scientists that submitted to the 2001 Research Assessment Exercise in Business and Management in the UK. While results only partially support research-based homophily, they indicate that scientists use status positions for discriminating between potential partners by selecting collaborators from institutions with a rating similar to their own. Strong support is provided in favour of institutional and geographic constraints. Scientists tend to forge intra-institutional collaborations; yet, when they seek collaborators outside

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their own institutions, they tend to select those who are in geographic proximity. The implications of this analysis for tie creation in joint scientific endeavours are discussed.

Keywords Collaboration networks · Community structure · Intra- and inter-institutional collaborations · Geographic distance · Research specialty

Introduction

The idea of using published papers to study collaboration patterns among scientists is not new (Price 1965). In information science, for example, there is a substantial body of literature concerned with co-authorship networks (Ding et al. 1999) and co-citation networks (Crane 1972), where connections between authors are defined, respectively, in terms of collaboration on the same paper or citation of their work in the same literature. Studies of scientific collaborations have even a longer history in the mathematics community, in which one of the earliest attempts to map and investigate the structure of social interaction within a scientific community was formalised through the concept of the Erdös number, a measure of a mathematician's distance, in bibliographical terms, from the Hungarian scholar (De Castro and Grossman 1999). Only recently, however, due to the advent of new technological resources and the availability of comprehensive online bibliographies, have a number of much larger and relatively complete and detailed collaboration networks been documented and analysed (Barabási et al. 2002, Jones et al. 2008, Moody 2004, Newman 2001a, Wuchty et al. 2007).

While most of these recent studies have been interested either in the global structural and dynamic properties of the collaboration networks (Barabási et al. 2002, Moody 2004, Newman 2001a), or in the effects that collaboration has on scientific performance (Jones et al. 2008, Wuchty et al. 2007), only little attention has been given to the micro mechanisms underpinning the way scientists select their collaborators at the local level. For example, while it has been documented that collaborations spanning multiple universities, and in particular, among these, the collaborations involving solely elite universities are more likely to result in more highly cited papers than other forms of collaborations (Jones et al. 2008), it still remains to be explored how in reality scientists assess potential partners and select them for collaborative relations. While consideration of performance will certainly have some impact on the way collaborations are forged, it is also true that only a minority of scientists may be in a position to freely collaborate only with those that can help them achieve the highest levels of performance. For the majority of scientists, there may be structural, disciplinary, institutional, or geographic constraints that restrict their search behaviour to a delimited subset of possible collaborators. Focusing on the principles that are conducive to the highest levels of scientific performance, therefore, does not help understand how ties are actually forged in a collaboration network. To this end, what is needed is an approach to tie creation that uncovers the mechanisms that underlie the selection of scientific collaborators, irrespective of their implications for performance.

In this study, we take a step in this direction, and uncover the role of two fundamental mechanisms of tie creation in collaboration networks: homophily (Lazarsfeld and Merton 1954, McPherson et al. 2001) and focus constraint (Feld 1981). We examine whether scientists adhere to a principle of exclusivity in selecting their collaborators, by choosing only among those with whom they share similar attributes. We focus on two forms of homophily. First, scientists may take the research specialty of potential intellectual partners as cues, and select those with whom there is a substantial overlap of research interests, scientific background, practices, perspectives, and standards. Second, when there is uncertainty on the scientific quality of a joint work, scientists may choose to affiliate themselves with others whose status is similar to their own (Podolny 1994).

We then shift our attention to focus constraint, and examine the extent to which institutional and geographic constraints govern the creation of collaborative ties. First, scientists may be more likely to select collaborators with whom they share the same institutional affiliation than others from different institutions. Second, intra-institutional collaborations may be induced by the tendency of scientists to collaborate with others that are geographically co-located. This tendency would also imply that, when collaborations span different institutions, they are more likely to involve scientists that are in geographic proximity than at long distances from one another.

In our study we also attempt to adopt a broader perspective on collaboration than the one strictly implied by the idea of co-authorship. Co-authorship undoubtedly represents one of the major forms of intellectual cooperation. The literature, however, has long argued in favour of a more permeable concept of collaboration to include other forms of informal interaction among scientists (Katz and Martin 1997, Laband and Tollison 2000). For instance, the published work of an author typically benefits from comments provided by colleagues, journal reviewers and editors. Other forms of informal intellectual collaboration include the mentoring that senior scientists offer to junior ones, and the commentary received during the presentation of papers at conferences, workshops, and professional meetings. Moreover, it is not uncommon that scientists become indirectly connected as a result of collaborative agreements between higher-level units, such as departments, institutions, and research centres (Katz and Martin 1997). For instance, team leaders might agree on a common research agenda that commits their respective groups to a number of collaborative endeavours. In this case, while certain members of the groups may not be directly involved in joint work leading to formal co-authorship, nonetheless their research may indirectly benefit from the transfer of knowledge and skills, cross-fertilisation of ideas, and the establishment of common research standards and goals that the collaborative agreement between their groups has made possible. In cases like these it is not always an obvious task to identify who is collaborating with whom precisely because patterns of co-authorship and collaboration tend to diverge. While a strict bibliometric assessment would count as collaboration only those activities that translate into a joint paper, there are certainly other peripheral or indirect forms of intellectual exchange that are not reflected in formal co-authorship, and yet represent genuine instances of associations that should be taken into account to adequately capture the full extent of scientific collaboration.

To undertake an accurate assessment of collaboration one would therefore need to integrate data on formal co-authorship with details on informal commentary (Laband and Tollison 2000). This would inevitably be an arduous task, especially when conducted on a large scale. Here, we propose an alternative response to the problem of the opaqueness of collaboration. We begin by constructing a collaboration network based on formal co-authorship, in which, as is typically done in similar network studies, two scientists are assumed to be connected when they appear among the authors of the same paper (Barabási et al. 2002, Newman 2001a). However, we move beyond the idea of dyadic direct connections between scientists, and apply recent community-detection methods to partition the network into communities (Fortunato 2010). A scientist belongs to a community when he or she collaborates with other members of that community to a greater extent than with members of other communities. In this sense, communities may be locally dense even when the network as a whole is sparse. Moreover, because within each community scientists are inevitably connected only to a subset of all other members, communities may include scientists that are only indirectly connected with each other.

We study the role of homophily and focus constraint for *all* scientists within each community, even those that are not directly connected with each other. In so doing, we implicitly take on a two-fold perspective on the structure and meaning of collaboration. First, we assume collaboration occurs only within but not across the boundaries of communities. Second, while direct ties clearly reflect formal co-authorship, we regard indirect ties as an indicator of informal forms of collaboration. We seek support in favour of this perspective by examining the collaboration network based on the papers submitted to the 2001 Research Assessment Exercise (RAE) in the UK in the field of Business and Management. Drawing on accurate details on the scientists' attributes, we examine the extent to which the topological boundaries between the uncovered communities reflect some fundamental ways in which scientists collaborate, either formally or informally. We do this by testing the tendency of communities to include pairs of scientists that work in the same research specialties, are affiliated with the same institutions, are associated with the same levels of status, and are located at geographic proximity with each other.

The rest of the paper is organised as follows. In the next section, we place our work within the relevant theoretical context. We then introduce the data and the methods for partitioning the network into communities and assessing homophily and constraint in each community. We then present the results. The final section will summarise and discuss the main findings.

Homophily and focus constraint in collaboration networks

Homophily represents one of the network mechanisms of tie creation with the longest tradition of investigation in the social sciences. This is the principle that similarity breeds connection (Lazarsfeld and Merton 1954, McPherson et al. 2001). A significant body of research has provided supportive evidence in favour of homophily by documenting a positive association between sharing an attribute and some baseline level of interpersonal attraction (McPherson et al. 2001). Attraction could, in turn, be reflected in a heightened probability of similar people to select each other (Kossinets and Watts 2006), or communicate more frequently and develop a stronger social interaction (Reagans 2005).

In this paper, we begin our investigation of homophilous interactions in collaboration networks by examining the extent to which scientists that work in the same research specialty collaborate with one another with a higher likelihood than scientists from different specialties. While research has long been interested in assessing the benefits of conducting research across disciplinary fields and research specialties (Laband and Tollison 2000, Whitfield 2008), the fact that scientists can also develop dense and strong connections within their own fields or specialties has often received scanty attention. Scientists can carefully select their collaborators to draw on different knowledge pools without having to acquire the needed knowledge personally, but they can also aim to strengthen their skills and enhance scientific consensus within their own specialty area. Recent work suggests that scientists embedded in collaboration networks share ideas, scientific standards and technique (Moody 2004, Whitfield 2008). By selecting their collaborators within their own specialty area, scientists can enhance scientific cohesion and embeddedness, receive validation of their own attitudes and beliefs, and facilitate their scientific production through the generation of shared norms of research practice.

A second manifestation of homophilous interactions in collaborative research is related to the role of status similarity in tie creation. In the social sciences, a number of empirical studies have long been interested in the processes and reasons underpinning the creation of connections among economic actors of similar status. Research has shown that processes of competitive isomorphism are likely to lead economic actors of similar status to adopt similar practices and operating systems, which in turn facilitates the coordination of cooperative activities (Chung et al. 2000, Lorange and Roos 1992). Status similarity also aligns the expectations of potential partners about each other's behaviour, and increases their commitment to sharing both the costs and benefits of an interaction (Chung et al. 2000). Moreover, a substantial body of work in sociology has illustrated that economic actors, when considering the choice of creating a connection, assess the status of potential partners (Chung et al. 2000, Podolny 1994). For example, the way in which others perceive the quality of the output of a firm, especially when it cannot be assessed without ambiguity, depends on the status of other firms that interact with the focal firm (Podolny 1994). As a result of the signaling effect of status positions and social interactions, firms with similar status tend to establish connections with one another when there is uncertainty about the output of their transaction.

Sociological research on culture, science and technology has proposed a similar view on the relational foundations and signaling effect of status. For instance, it was found that within artistic genres with limited objective standards and high levels of uncertainty on quality, the perception and judgement of the work of an artist was contingent on the status of other artists with whom the focal artist interacted in the artistic community (Greenfeld 1989). In the sociology of science, it was contended that, when there are pronounced levels of uncertainty about scientific quality, such as during periods of paradigmatic change, the way in which a scientist is regarded depends on the status of those with whom the scientist is associated (Camic 1992, Latour 1987). A similar perspective was also suggested to explain the development of technology, in the sense that when an inventor's technology cannot be evaluated without uncertainty, assessment is fundamentally based on the status of the economic actors that endorse that technology (Podolny and Stuart 1995).

These studies thus suggest that a principle of exclusivity based on status may also govern the selection of partners in scientific collaborations. Challenged by pronounced levels of competitive pressure and uncertainties posed by the need to secure funding and publish in high-quality journals, scientists will become increasingly exclusive in the formation of collaborations. They will generally avoid collaborating with others of a lower status, and instead select collaborators of roughly equivalent status (Jones et al. 2008). In this study, to investigate status-based homophily, we measure the ranking of the institutions with which scientists are affiliated, and then examine whether collaborations tend to span institutions of different ranking or only those with a similar one.

The second ordering principle that we examine is focus constraint (Feld 1981). This refers to the idea that social associations depend on opportunities for social contact. Research has uncovered the tendency of connections to occur among individuals who share activities, roles, social positions, institutional affiliations, and geographic location (Feld 1981, Kossinets and Watts 2006, Monge et al. 1985). Here a special emphasis is placed on institutional and geographic constraint. First, we examine whether scientists are more likely to establish collaborations within their own institutions than across institutional boundaries. Recent studies have investigated forms of collaborations that involve organisations of various institutional profile, such as academic departments, business firms, government and non-government organisations (Leydesdorff and Ward 2005). In particular, research has highlighted the role of these inter-institutional collaborations in sustaining knowledge transfer and creation. There are, however, also benefits associated with intra-institutional collaborations. In principle, scientists can choose their collaborators within their own institutions for a variety of reasons. For instance, joint research may be facilitated by the ease and frequency of face-to-face communication and meetings, and by the common cultural orientations, scientific standards and practices that are typically shared by the members of the same institution. Hiring policies, in turn, can also promote collaborative research within institutions as they tend to emphasise overlapping areas of research interests between applicants and incumbents leading to potential joint work. For these reasons, here we examine the role of institutional constraint in scientific collaboration by testing the tendency of scientists to restrict the choice of their partners within institutional boundaries.

Intra-institutional collaborations may also originate from the benefits that scientists gain from being geographically close to one another. The literature has long investigated the benefits of geographic proximity, and in particular its impact on innovative activities (Jaffe et al. 1993). Even though knowledge could in principle travel through space inexpensively, nonetheless knowledge production tends to be geographically clustered (Braunerhjelm and Feldman 2006). The arguments often proposed to explain this phenomenon include the benefits that geographic proximity offers in terms of knowledge spillovers (Jaffe et al. 1993), opportunities of face-to-face interaction, transfer of tacit knowledge, and the occurrence of unanticipated encounters between individuals (Gertler 2003). While the literature has been concerned mainly with the spatial distribution of economic activities, it may also help gain a better understanding of the geography of scientific collaboration (Jones et al. 2008). When selecting their collaborators, scientists may be encouraged to choose them within short geographic distances because spatial proximity facilitates informal communication and the transfer of complex knowledge, which in turn may lead to an increasing commitment to cooperation (Katz and Martin 1997). This argument thus not only suggests that scientific collaboration may tend to occur within institutional boundaries, but also that, when collaborations span different institutions, they may be more likely to involve scientists from institutions that are geographically close than dispersed.

Data and methods

In this section, we will begin by introducing the RAE network dataset, and then the measures for scientists' attributes that will be used to study homophily and focus constraint. We will then present the community-detection algorithm that will be used to partition the network into groups of indirectly connected scientists. The section will end with a discussion of the statistical methods developed to assess homophily and focus constraint in each community.

The data

For our analysis, we have constructed the collaboration network of the social scientists that authored or coauthored the publications submitted to the RAE 2001 in Business and Management in the UK. The RAE was established in the UK in 1986, when the government introduced the policy of selective funding (Ball and Butler 2004, Cooper and Otley 1998, HERO 2001). The exercise is traditionally carried out by the UK government through Higher Education Funding Councils, and represents a peer-review evaluation process undertaken by panels consisting of members who are chosen by the funding bodies according to their research experience. The RAE that took place in 2001 represents the broader context from which our data were drawn. On the whole, it consisted of 68 units of assessment and around 213,000 publications examined. In this work, we restrict our analysis to the unit of assessment that received the largest number of submissions. This was the Business and Management Studies subject area, which received 97 submissions from 94 institutions (Ball and Butler 2004, HERO 2001). Each institution was invited to put forward within its submission all individuals who were actively engaged in research and in post on 31 March 2001. Each of these individuals was required to submit up to four pieces of research output produced during the period 1 January 1996–31 December 2000.

Panels composed of expert academics were formed to assess the quality of submissions (Baker and Gabbott 2002, Cooper and Otley 1998). Evaluation criteria for each unit of assessment were published by the panels before submissions were made to ensure that academics were informed of the aspects of submissions that the panels regarded as most important as well as the areas on which institutions were required to comment in their submissions (HERO 2001). Ratings were allocated to submissions, and ultimately to universities, on the grounds of their ability to reach national or international levels of excellence. Ratings of research quality were expressed in terms of a standard scale including 7 points ranging from 1 to 5* (i.e., 1, 2, 3b, 3a, 4, 5, and 5*). The RAE aimed to ensure that institutions that produced research of the highest quality were allocated a higher proportion of the available funding than institutions with lower-quality research. In the RAE 2001, for example, institutions that acquired a rating of 1 or 2 did not obtain any funding, while institutions that received a rating of 5* were given four times as much funding as the institutions with a rating of 3b. The allocation of funding according to research quality was therefore intended to act as an incentive both to protect and develop research of excellent quality in the UK.

Our data contain detailed information about each paper that was submitted to the RAE 2001 in Business and Management, including the paper title, the names of author and co-authors, the RAE ratings of their institutions as well as the publication type and publishing details. Among the advantages of this dataset over other sources of data on publications is that disambiguation of institutional affiliations of the authors who submitted to the RAE is relatively straightforward. Our sample includes 9,325 papers submitted to the RAE by 2,609 scientists. These papers were also co-authored by 5,752 scientists that did not submit to the RAE. Thus, the total number of scientists in our sample amounts to 8,361. A tie is established between two scientists if they have co-authored one or more papers. Following Newman (2001b), the weight of a tie between two scientists reflects their contributions in their collaboration: the larger the number of scientists collaborating on a paper, the weaker their interactions. Thus, tie weight increases with the total number of papers co-authored, and is inversely proportional to the total number of co-authors of those papers. In our analysis we looked at the largest connected component of this weighted network which contains 3,338 authors.[1]

Scientists' attributes

To study the role of homophily and focus constraint, we needed a number of additional attributes for the scientists. Because these attributes were available only for the scientists who submitted to the RAE (and not, for example for non-UK scientists or UK PhD students who co-authored with someone who submitted, but did not submit themselves), we then had to extract the subset of these scientists from the largest connected component of the

[1] The next largest component has fewer than 100 authors.

network. Of the 3,338 scientists in the component, only 973 submitted to the RAE. For each of these 973 scientists, we measured research specialty, status, institutional affiliation, and geographic location.

To assess research-based homophily, we assigned each scientist to a research specialty by using the domain statements of the 24 divisions and interest groups identified by the Academy of Management. For each of these divisions and groups, the Academy provides a brief description of the main research topics, objectives and methods.[2] By using an algorithm, we matched the titles of the papers submitted to the RAE with the Academy's statements, and assigned each author to a unique research specialty (Whitfield 2008).

To assess status-based homophily, each scientist was assigned the RAE ranking acquired by the institution with which he or she was affiliated. Two measures of status were obtained by using the RAE ratings that institutions received in 1996 and 2001. To study geographic constraint, we obtained the latitude and longitude values in degrees for each institution, and then calculated the distance in kilometers between any pair of institutions. The geographic distance between any two scientists was then assumed to be equal to the distance between the two institutions with which the scientists were affiliated. Finally, for institutional constraint, scientists were associated with their respective institutions of affiliation.

Community detection

The detection of communities, or modules, in networks has attracted much attention in the last few years. Modules are defined as sub-networks that are locally dense even though the network as a whole is sparse. They have been observed in a variety of networks (e.g., biological networks, brain functional networks, and collaboration networks), where they usually correspond to functional sub-units, namely sets of nodes that have a (usually unknown) property or function in common. This architecture is expected to naturally emerge in groups of interacting scientists (Scharnhorst and Ebeling 2005), as it presents the advantage of combining two types of social organisation (Lambiotte and Panzarasa 2009): *close* networks which foster trust and facilitate the transfer of complex and tacit knowledge, and *open* networks which are rich in structural holes and facilitate knowledge creation and information diffusion. Several methods have been developed to detect modules in large networks, and they cover a broad range of concepts and implementations (Fortunato 2010). In the field of Scientometrics, a division of citation or collaboration networks into communities has been used as a taxonomic scheme in order to map knowledge domains (Börner et al. 2003, Boyack et al. 2005, Chen 2003, Leydesdorff and Rafols 2008, Rosvall and Bergstrom 2008, Wallace and Gingras 2008), but also as way to track their temporal changes and the mobility of researchers (Hellsten et al. 2007).

In this study, we adopt a partitioning-based viewpoint, as we look for non-overlapping communities. Partitions are uncovered by optimising the multi-resolution modularity introduced by Reichardt and Bornholdt (2004):

$$Q(\gamma) = \frac{1}{2m} \sum_{C \in \mathcal{P}} \sum_{i,j \in C} \left[A_{ij} - \gamma \frac{k_i k_j}{2m} \right], \tag{1}$$

where A is the weighted adjacency matrix of the collaboration network, $k_i \equiv \sum_j A_{ij}$ is the strength of node i and $m \equiv \sum_{i,j} A_{ij}/2$ is the total weight in the network. The summation

[2] Descriptions of these divisions and groups are available at the website of the Academy of Management: http://www.aomonline.org/aom.asp.

over pairs of nodes $i, j \in C$ belonging to the same community C of the partition[3] $\mathcal{P}$ counts intra-community links. This quality function measures if links are more abundant within communities than would be expected on the basis of chance, and incorporates a resolution parameter γ allowing to tune the characteristic size of the modules. $Q(1)$ corresponds to Newman-Girvan modularity (Newman and Girvan 2004). The resolution parameter γ is essential in order to get rid of the size dependence of modularity and to uncover the true multi-scale organisation of the network. In what follows, the optimisation of $Q(\gamma)$ is performed by using a reliable greedy algorithm (Blondel et al. 2008).[4]

Statistical significance of module attributes

By definition, uncovered modules consist of groups of scientists that are indirectly connected but are close in a topological sense. Modules thus provide coarse-grained levels of interactions which allow us to go beyond known dyadic connections between scientists present in the data and to uncover intermediate units (building blocks) from the organisation of the collaboration network. It is also important to emphasise that scientists are expected to be driven by antagonistic forces, e.g. geographic distance vs research specialty, in their choice of collaboration. The non-overlapping organisation imposed by the partitioning algorithm is thus expected to highlight the dominant factors, namely it uncovers communities underpinned by one dominant mechanism.

In order to test the effect of homophily and focus constraint on scientific collaborations, we look at two measures of attribute diversity within each community:

$$S_C = -\sum_{v \in \Gamma} p_{c;v} \ln(p_{c;v}) \quad \text{and} \quad R_C = 1 - \sum_{v \in \Gamma} p_{c;v}^2, \tag{2}$$

where $p_{c;v}$ is defined as the density of authors in community C who possess attribute v in the set Γ of possible attributes. S_C and R_C are the Shannon entropy and the Simpson diversity index of $p_{c;v}$, respectively. By construction, S_C and R_C are measures of the diversity of a certain set Γ of attributes within community C. Low values of S_C and R_C correspond to communities whose nodes are affiliated with the same institution, work in the same specialties or are associated with the same levels of status, respectively.

Different sets of attributes are considered in order to assess the salience of different factors for community structure: institution, research specialty and RAE rating. For research specialty, for instance, (2) becomes $S_C = -\sum_{v=1}^{24} p_{c;v} \ln(p_{c;v})$, where $p_{c;v}$ is now the density of authors with research specialty v in community C and the summation is performed over the set of 24 possible research specialties. The significance of these diversity measures is evaluated through a permutation test (Traud et al. 2010), namely by measuring $S_{C;\alpha}$ and $R_{C;\alpha}$ for each community C on 1,000 different instances α where the assignment of the nodes to communities is preserved but where the attributes of the nodes are randomly re-shuffled. The diversity of community C is then assessed by comparing S_C (R_C) to the value of diversity of the null models and by measuring the probability P_c that community C is less diverse than the one observed in the null model (see Fig. 1).

The salience of geographic proximity for community structure is assessed as follows. For each community, we look at two average distances: the average distance d_{UIP} between

[3] Here $\mathcal{P}$ is a partition of the vertices of our graph. That is, $\mathcal{P}$ is a set of communities $\mathcal{C}$ and every author in the largest connected component of our full weighted co-authorship graph is in one but only one of these communities.

[4] The java code used to perform the optimisation of $Q(\gamma)$ is available on request from T. S. Evans.

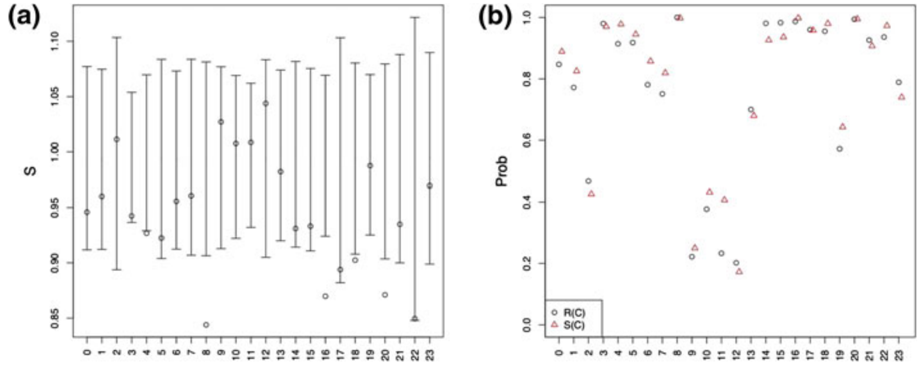

Fig. 1 Statistical significance of the diversity of research specialties in Business and Management for a partition of 24 communities. **a** Points show the entropy S_C of the modules for the research specialty variable. Comparison is against 1,000 different instances of the null model described in the text. The ends of the bars mark the entropies at the quantiles 2.5% and 97.5%. **b** Points show the probability P_C that the diversity found in the null model is greater than the one found in reality

an author and all other authors in the same community provided they are not from the same institution, and the average distance d_{UAP} between an author and all authors in the same community whatever their institution. There is almost no difference in the results obtained from these two distance measures in terms of the comparison of the null models to the actual average distance measured in communities. The important point is that these distances are measured regardless of whether or not scientists co-authored a paper. Moreover, a separation of 100 km when one institution is in a relatively sparsely populated location with few institutions (e.g., Northern Island) may be a short scale whereas 100 km may be a comparatively large distance in a dense urban environment with many institutions. Therefore, these distances have to be compared to an appropriate null model defined as follows. Each author in a community is considered in turn. The locations of all the institutions except for the one associated with the author being considered are shuffled. Authors in the same institution thus remain in the same institution, but the distance from the author under consideration to those in another institution will almost certainly change. We calculate the average distance between all pairs of authors in the same community in 1,000 realisations of the null model and compare the range of average distances found in the null model against the average distance measured for the community with institutions in the real location.

Results

Our analysis was performed on the RAE scientists extracted from the largest connected component of the weighted collaboration network defined in the previous section. Modules at different scales have been uncovered by optimising $Q(\gamma)$ over a broad range of values of γ. In what follows, we will discuss the properties of the partition optimising $Q(0.091)$, keeping in mind that similar conclusions are also obtained for other values of γ. Results are similar for both diversity measures discussed in the previous section, and therefore we will only show entropy in our figures. The obtained partition is made of 24 modules, and has been chosen to coincide with the number of research specialties. Our main purpose is to compare this algorithmically-obtained partition to our information about the scientists, namely their research specialty, RAE rating, institutional affiliation, and geographic distance.

To investigate the mechanisms driving the formation of communities, we measured the diversities S_C and R_C for the first 3 sets of attributes. Community C is said to exhibit a significant uniformity (lack of diversity) for a certain set of attributes if it is less diverse than in 97.5% of the random realisations, i.e., $P_C > 0.975$ in the above notations. In that case, the attributes of C are thus significantly different from a random assignment. On the contrary, the composition of a community is not distinguishable from a random assignment for values of $P_C < 0.975$. Geographic distance is said to be a significant factor underpinning the composition of community C if the average distances d_{UIP} and d_{UAP} between its scientists are smaller than in the null model in 97.5% of the random realisations.

The analysis incorporates four sets of results. The first two test our hypothesis of specialty- and status-based homophily, respectively. As shown in Fig. 1, research specialty is weakly correlated with community structure. Only 5 communities out of 24 exhibit a degree of homogeneity in research specialty that is statistically significant. The rest of the communities are not statistically significantly different from what would be randomly expected. These findings thus provide only partial support in favour of the hypothesis that in Business and Management scientists tend to collaborate with others within their own research specialty. At the same time, results also suggest that scientists do not work across research specialties to a greater degree than by chance. For instance, while Fig. 1b indicates that a few communities have a large probability (close to 1) of exhibiting a greater research similarity than the one found in the null model, there is no community for which the probability that the corresponding null model has a higher research diversity is close to zero.

The second set of results is concerned with status homophily, namely the hypothesis that scientists tend to collaborate with others that are affiliated with institutions with the same RAE rating as their own. As shown by Fig. 2a,b, the salience of status homophily for collaboration depends on which measure of status is used. While the 1996 RAE rating appears to be a statistically significantly strong driver of collaboration for 13 communities, similarity in the 2001 rating is correlated with collaboration only for 6 communities. This should not be surprising. On the one hand, when scientists selected their collaborators, they were aware of the RAE rating that institutions obtained in 1996. In this respect, the results provide support to the hypothesis that scientists in most communities used the 1996 RAE rating as a signal to infer the quality of potential collaborators and discriminate between them. On the other, since the papers in our dataset were published before 2001, the RAE ratings obtained in 2001 were obviously not available to the scientists at the time of their collaboration. Thus, the 2001 RAE ratings could not have been used before 2001 to make inferences about quality, which explains the weaker support that Fig. 2a,b provides to homophily based on the 2001 rating than on the 1996 one. Due to the (weak) correlation between the 1994 and 2001 ratings, some of the scientists that before 2001 chose collaborators with a status similar to their own continued to maintain such similarity when the new RAE ratings were released in 2001. However, Fig. 2a,b suggests that there were also a number of scientists who changed their status in 2001, and as a result some of the similarities based on the 1996 ratings eventually disappeared in 2001.

The last two sets of results test the hypotheses of institutional and geographic constraints, respectively. As can be seen in Fig. 2c, communities are extremely uniform in terms of the institutional affiliation of their UK members. All 24 communities are statistically significantly different from a random assignment, as the probability that the corresponding null model includes scientists with more diverse institutional affiliations than

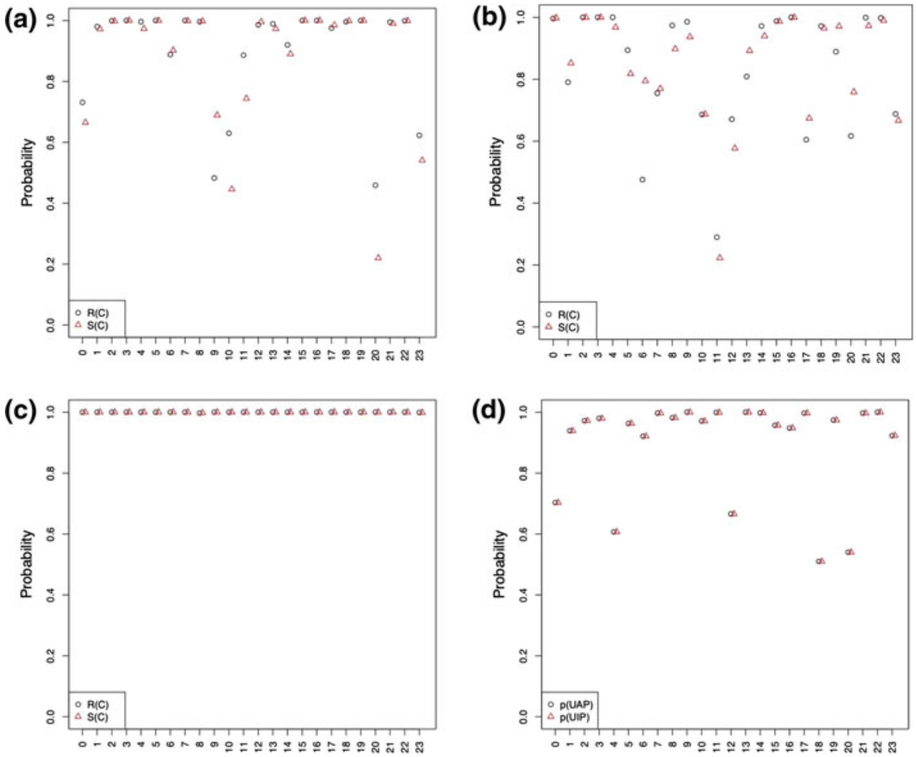

Fig. 2 Statistical significance of the diversity of 1996 and 2001 RAE assignments (**a** and **b**), institutions (**c**) and geographic distance (**d**) for a partition of 24 communities. For each community, we plot the probability that diversity (**a**, **b** and **c**) or average distance (**d**) found in the null model is greater than the one found in reality

the actual community is one. This strongly supports the hypothesis of institutional constraint leading scientists in Business and Management to seek collaborators within institutional boundaries.

Like institutional constraint, geographic distance also plays an important role in shaping collaborations. As shown by Fig. 2d, 10 communities exhibit statistically significantly small distances between their scientists. If the condition for significance is loosened to $P_C > 0.9$, significance is even extended to 19 communities. For a large number of communities, the probability that the average distance between all their UK members is less than randomly expected approaches one. Thus, results also provide support to the hypothesis of geographic constraint within the field of Business and Management: when scientists seek their collaborators outside their own institutions (but within the UK), they are more likely to select those who are in geographic proximity than at long distances.

In summary, the findings show that for the social scientists who submitted to the RAE 2001 in Business and Management in the UK, institutional constraint was the primary organising principle underlying their choice of scientific collaborations within the UK. Geographic constraint and status-based homophily based on the 1996 RAE rating also played a major role in shaping such collaborations, whereas research-based homophily was only marginally significant.

Discussion and conclusions

Prior work established that teamwork production in science is increasingly composed of collaborations that span university boundaries (Jones et al. 2008, Wuchty et al. 2007). Unlike these studies that have typically looked at institutions from multiple countries (and scientists from different disciplinary fields), our analysis has focused only on UK universities (and within a single discipline), and has suggested that scientists in Business and Management in the UK seek their collaborators within their own institutions to a greater extent than randomly expected. In this respect, our study integrates previous work on multi-university collaboration by highlighting that, when scientists' search behaviour is directed toward domestic partners within a single broad disciplinary field, it tends to remain localised within institutional boundaries. Scientists may consider collaborating with international partners (Jones et al. 2008); however, within their own countries and disciplinary borders, they prefer to interact with colleagues from their own institutions.

Our results also supported the role of geography in the selection of collaborators in Business and Management in the UK. Our analysis illustrated that, when collaborations span institutional boundaries, they tend to be geographically clustered. On the one hand, these findings corroborate related studies of multi-university collaborations highlighting how geographic distance can hinder group communication and decision-making (Cummings and Kiesler 2007). The importance of face-to-face contacts has long been reported by the literature. Allen's (1977) rule of thumb, for example, is that collaborators should be no more than 30 metres apart, as longer distances would negatively impact on the effectiveness of their collaboration (Kraut et al. 1990). On the other hand, there is an equally substantial body of literature suggesting a weakening relevance of geographic location for scientific production (Cairncross 1997, Jones et al. 2008). The so-called "death of distance" has been mainly associated with the increasing availability of communication and computer-based technologies in research collaborations (Cairncross 1997, Jones et al. 2008). Our findings complement this argument by suggesting that, when scientists choose their collaborators within their own country and discipline, they tend to favour geographic proximity. In this sense, even though the scientists included in our dataset were only partially affected by the rapid spread of information technologies in the 1990s, our results seem to suggest that technology, at least within national and disciplinary boundaries, is an imperfect substitute for geographic co-location (Cummings and Kiesler 2007).

Previous research on scientific collaboration has also focused on the benefits of interdisciplinarity, and suggested that scientists prefer collaborators from outside their own disciplinary field over those within their field (Laband and Tollison 2000, Whitfield 2008). Since the scope of our analysis was limited only to one disciplinary field, the findings cannot provide evidence either in favour or against the tendency towards collaborations across broad disciplinary fields (e.g., physics and economics). By contrast, what they enable us to assess is the degree to which, within the boundaries of a single disciplinary field, scientists tend to collaborate across the research specialties within that field. In this respect, our results do not provide strong evidence in favour of such inter-specialty collaborations. They only partially support the hypothesis of specialty-based homophily, in that only a relatively small number of communities included scientists that were more similar in their research specialty than by chance. Since individual UK institutions inevitably tend to include only a fraction of all research specialties within Business and Management, and because scientists were found to prefer collaborations within institutional boundaries to those spanning institutions, it is not surprising to find that at least some of these collaborations occurred within the scientific boundaries of distinct specialties.

Moreover, our results provide support in favour of the signaling role of status in the choice of collaborators. In qualitative agreement with a substantial body of literature on status-based homophily (Chung et al. 2000, Lorange and Roos 1992, Podolny 1994), scientists in Business and Management were found to collaborate preferentially with others affiliated with institutions holding an RAE rating similar to the one obtained by their own institution. Similarly, recent work on multi-university research teams indicated that status is a crucial exclusivity principle underpinning scientific collaboration (Jones et al. 2008). These studies, for instance, reported that collaborations between top universities tend to be more common than randomly expected, especially in the social sciences. The same pattern was also found to occur between lower-tier schools, thus further intensifying the social stratification of scientific collaborations. Status therefore acts as a tangible basis for discriminating among opportunities of collaboration. Drawing on related lines of inquiry in the social sciences (Podolny 1994, Podolny and Stuart 1995), it can be speculated that, especially when there is uncertainty about the quality of potential partners' research, the ranking of the institutions to which they belong is an attribution that scientists use to make inferences about the quality of future joint work with them. Thus, they tend to avoid partners from institutions of lower ranking than their own, and forge collaborations only with those affiliated with similarly ranked institutions. This would lead the market for collaboration to take on a "rich-club" structure, in which a core of scientists from top institutions form exclusive relationships with one another (Colizza et al. 2006, Hidalgo et al. 2007, Opsahl et al. 2008).

Taken as a whole, our findings offer important insights on the underlying forces driving collaboration between scientists within a disciplinary field, and have implications for the development of mathematical models of science. Our work provides support for models going beyond a purely network point of view, and motivates the incorporation of competing non-structural factors. The importance of space for network organization is noteworthy and strongly suggests the generalization of gravity-like models (Frenken et al. 2009) in order to properly account for attractiveness over spatial distance as well as the contrary effects of the barriers between disciplines, specialties, and institutions. Similarly, the observed rich-club organization inspires the development of models where research quality across scientists and institutions is heterogeneous and constrains the way in which collaborations are forged. We believe that a precise description of these mechanisms of tie creation is crucial for predicting the emergence of complex structures such as new leading scientific communities and research teams across disciplines and specialties.

Our study is not without its limitations. First, the generalisability of the results is inevitably affected by the dataset used, with a limited geographic scope (the UK) and concerned only with a specific disciplinary field (Business and Management). Most notably, the limited scope of our dataset does not warrant generalisability of our findings to the broader domain of international and inter-disciplinary collaborations. By contrast, our analysis can only apply to collaborations involving scientists and institutions within the scientific boundaries of a single discipline and the geographic boundaries of a single country. Second, for the sake of simplicity the analysis was based only on the largest connected component of the collaboration network. Extending the analysis to other smaller connected components may well provide new insights that our analysis could not reveal. Moreover, we wish to close this section by cautioning about interpretations drawn from our method. One should indeed be careful about how our results might be influenced by the methodology, for instance our choice of community-detection algorithm. As stressed before, there exist numerous, sometimes contradictory, ways to uncover communities in networks, and we have focused here on just one particular method (i.e., optimisation of

$Q(\gamma)$). More definitive conclusions about the relation between topological communities and characteristics of scientists should be drawn by comparing results obtained through different algorithms that partition the network into different communities, or even that allow scientists to belong to multiple overlapping communities. Finally, while our approach takes a purely structural viewpoint, an interesting approach would be to incorporate non-structural attributes in the definition of modules, such as more clearly hidden structural similarities between the nodes (Expert et al. 2011).

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Scientometrics (2011) 89:397–420
DOI 10.1007/s11192-011-0431-9

A few special cases: scientific creativity and network dynamics in the field of rare diseases

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Received: 4 June 2011 / Published online: 21 June 2011

Abstract We develop a model of scientific creativity and test it in the field of rare diseases. Our model is based on the results of an in-depth case study of the Rett Syndrome. Archival analysis, bibliometric techniques and expert surveys are combined with network analysis to identify the most creative scientists. First, we compare alternative measures of generative and combinatorial creativity. Then, we generalize our results in a stochastic model of socio-semantic network evolution. The model predictions are tested with an extended set of rare diseases. We find that new scientific collaborations among experts in a field enhance combinatorial creativity. Instead, high entry rates of novices are negatively related to generative creativity. By expanding the set of useful concepts, creative scientists gain in centrality. At the same time, by increasing their centrality in the scientific community, scientists can replicate and generalize their results, thus contributing to a scientific paradigm.

Keywords Creativity · Co-authorship network · Scientific collaboration · Bibliometric indicators · Biomedical research · Qualitative and quantitative method

Mathematics Subject Classification (2000) 05C82 · 05C90 · 05C65 · 62P25 · 91D30 · 91B82

JEL Classification C63 · L14 · L26 · L65 · O31 · O33

> To create consists precisely in not making useless combinations and in making those which are useful and which are only a small minority […] not that I mean as sufficing for invention the bringing together of objects as disparate as possible; most

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> combinations so formed would be entirely sterile. But certain among them, very rare, are the most fruitful of all.
>
> (Poincaré 1921, p. 386)

Introduction

The evolution of scientific, artistic and economic domains largely depends on the creative *élan* of knowledge communities to attract new talents and to innovate. The centrality of creativity as the engine of social and scientific progress is witnessed by the plethora of research efforts aimed at unveiling its origin and nature. Although such contributions are widespread in various disciplines, it is still possible to identify three main streams of research.

The first approach focuses on the personal or intra-psychic features of individuals revealing a peculiar propensity toward creative thinking and problem-solving (Larkin et al. 1980; Simonton 1988, 2000; Hennessey and Amabile 2010). The fascinating and complex personality of great geniuses, which has often placed them outside the so-called normal science and society, is at the origin of this interest.

Beginning in the 1960s, a growing group of scholars has been studying the social factors of creativity, through the reappraisal of social contexts and social relationships in stimulating or repressing individual creativity (Kuhn 1962; Merton 1973; Latour and Woolgar 1979; Amabile 1983; Csikszentmihalyi 1990; White 1993). Stretching the social perspective, the concept of creativity has been reformulated in terms of a collective activity which derives from the interaction of two or more individual minds (Kurzberg and Amabile 2000; Shalley and Perry-Smith 2008). This view seems better to suit the recent evolution of natural sciences, in which major advances derive from the creative activity of scientific teams, as shown by the great spread of co-authorships and joint research projects (Newman 2001; Guimerà et al. 2005; Barabàsi 2005; Wuchty et al. 2007; Jones 2008). Although several studies have focused on individual creativity in social networks (Burt 2004; Uzzi and Spiro 2005; Fleming et al. 2007) and the importance of the network itself as the locus of innovation (Powell et al. 1996; Lane et al. 1996), the collective dynamics of creative problem-solving are still largely under-explored.

A third stream of literature stems from evolutionary biology (Fontana 2001). According to this approach, novelty emerges from the co-evolution of multiple networks (Padgett and Powell 2011). Once a new concept is created, the constraints and opportunities of interaction in multiple social and semantic networks determine its spread and the possibility of changing the structure of those networks. Creativity is a property of a network of networks.

Early attempts to combine the identification and spread of new concepts in a single model of scientific discovery were based on a two-step process: first, some creative scientists originate new ideas, then those ideas spread through a social network as epidemics (Goffman 1966; Valente 1995; Bettencourt et al. 2006). However, this approach does not consider the combinatorial nature of knowledge creation, the co-evolution of ideas and social contacts and the need for modules and niches in multiple networks to ensure the co-existence of several ideas for the production of further knowledge (Lambiotte and Panzarasa 2009).

In this paper we aim at understanding creativity as a socio-semantic process. In this way, we offer a tentative dynamic combination of the social and semantic domains rather than retracing their traditional separation. We treat creativity as a problem-solving activity characterized by novelty, unconventionality, persistence, and difficulty in problem formulation (Newell et al. 1959). To study creativity, we focus on rare diseases as scientific specialties where problems are *novel* (most of the research started after the genomic revolution in the 1990s), *unconventional* (diseases are frequently misdiagnosed), *persistent* (more than a decade is required, from problem identification to a cure) and *ill-defined* (causes and symptoms of rare diseases are still largely unknown). We draw attention on the process of problem-solving which can be described as a search through a maze (Simon 1962), requiring the activation and teamwork of scientists (the emergence of communities and team assembly) as well as the identification, combination and retention of useful concepts (abstract and general ideas inferred from specific instances). The more difficult and novel the disease, the greater the amount of trial-and-error required to find a solution by recombining individual capabilities and concepts. We hypothesize that new combinations of scientists and concepts which represent progress toward the goal of finding a cure are retained as stable modules in socio-semantic networks; all others are dissolved. To test our research hypothesis, we perform an in-depth case study and develop a theoretical framework for the evolution of scientific creativity.

The paper is structured as follows. In "Knowledge creation and diffusion in scientific networks" section, we locate our research in the literature on creativity. "Empirical protocol, data and methods" section describes our inductive approach and research methodology: from an in-depth case study analysis of a rare disease ("The Rett Syndrome" section) to a model of the co-evolution of social and semantic networks ("A stochastic model of scientific creativity" section). The last section is devoted to a discussion and summary of our main findings.

Knowledge creation and diffusion in scientific networks

Creativity is a complex phenomenon which has been studied from several different perspectives. The socio-economic literature notes that creative activity is accomplished by people who occupy a special position in the social network or the economic system at a certain moment in time (Schumpeter 1934). However, there is no consensus on exactly where creative people can be found: at the periphery of the community, at the center, or in a brokerage position.

In his analysis of the evolution of science, Kuhn argues creative people must be peripheral, to keep some distance from mainstream knowledge and social relations and to gain a different view of the field: "Any new interpretation of nature, whether a discovery or a theory, emerges first in the mind of one or a few individuals. It is they who first learn to see science and the world differently, and their ability to make the transition is facilitated by two circumstances that are not common to most other members of their profession. Invariably their attention has been intensely concentrated upon the crisis-provoking problems; usually in addition, they are men so young or so new to the crisis-ridden field that practice has committed them less deeply than most of their contemporaries to the world view and rules determined by the old paradigm" (1962, p. 143). As novices, they may offer the field their fresh and divergent thinking. The kind of creativity underlying such discoveries displays a generative nature, as it implies the introduction of new concepts and theories on which new scientific achievements become possible (*generative creativity*).

Conversely, as brokers, individuals are at the crossroads of knowledge circulating within different social circles. In this position, they have the best opportunity to produce creative ideas. In this perspective, creativity has typically a combinatorial nature, as it is defined as a link among concepts and perspectives which developed apart, and the creative person is seen as a bridge between communities which were not originally connected (*combinatorial creativity*). Since the work of Schumpeter (1934), several contributions may be ascribed to this view (Brass 1995; Hargadon and Sutton 1997; Weitzman 1998; Perry-Smith and Shalley 2003; Burt 2004; Fleming et al. 2007; Fleming and Waguespack 2007; Cattani and Ferriani 2008). Conversely, cohesive groups may lead to fewer new combinations but can improve information circulation as well as the diffusion, sharing and generalization of ideas (Gould 1991; Watts 2002) through the *replication* of new combinations of concepts (*replicative creativity*).

Both from an individual viewpoint and for the community of scientists as a whole, the benefits of a structural position (novice, broker, leader) and a certain type of creativity (generative, combinatorial, replicative) may change over time. Following Shalley and Perry-Smith (2008), we distinguish three phases: (1) problem identification and formulation, (2) conceptual combination and (3) conceptual expansion.

In the first phase (*problem identification and formulation*) information is insufficient and unordered (Goffman and Harmon 1971; Chen et al. 2009). There are multiple ways of framing the problem, and it is essential to identify its main elements. Novel ideas prosper and the selection forces which normally act on them are still weak (March 2007). In this phase creativity is mainly generative. The second phase (*conceptual combination*) is characterized by the creation of relationships between previously separate concepts across multiple sources, categories and knowledge domains. Creativity here is combinatorial. In the last phase (*conceptual expansion*), new ideas are shared and generalized by means of various techniques such as analogies, metaphors and remote associations. Replicative creativity is prominent at this point.

Apart from a few notable exceptions which reveal the emergence of novelty at various levels of social interaction, few papers try to combine complex phenomena like creativity along more than one dimension, by looking in particular at both the scientific community and the related semantic space (Orsenigo et al. 2001; Taramasco et al. 2010; Roth and Cointet 2010). This paper aims to define a link between the dynamics of creative thought and the social dynamics of the community. Different streams of literature have devoted attention to either one or the other of these dimensions, implicitly declaring an order of relevance. Typically, in the social sciences the focus was on social mechanisms, while in the human sciences more attention was addressed to creative thought. Against this background, we try to restore some of the complexity of the creativity phenomenon and its multifaceted and inevitably intertwined dimensions by considering a co-evolution hypothesis.

To operationalize our approach, we consider three types of change in both semantic and social networks (see Table 1):

- *Generative*: the entry of new nodes (new concepts/authors);
- *Combinatorial*: the creation of new links (new scientific collaborations or new concept associations);
- *Replicative*: the replication of connections (multiple collaborations among the same scientists and repeated use of concept associations).

Here, we first perform a case study of a single specialty to validate our definition of creativity. More precisely, we aim at testing whether the most creative scientists are those who first introduced new concepts or new associations of concepts. Next, we develop a theoretical framework to study the co-evolution of semantic and social networks. Specifically, we analyze the relationships between the creation of nodes, links, and link replication in both semantic and social networks.

Table 1 Creativity in socio-semantic networks

Steps in creative problem-solving	Problem identification	Conceptual combination	Conceptual expansion
Networks events	New nodes	New links	Replication of links
Semantic network of concepts	Generation of new concepts (*generative creativity*)	Generation of new combinations of concepts (*combinatorial creativity*)	Replication of concept combinations, validation and diffusion (*replicative creativity*)
Social network of scientists	Entry of new scientists (novices)	New scientific collaborations	Replication of collaborations

Empirical protocol, data and methods

Research strategy overview

The goal of this paper is to define, measure and model creativity in scientific networks. In the first part of our work ("The Rett Syndrome" section), we conduct an in-depth analysis of a single scientific community. In the second part ("A stochastic model of scientific creativity" section), we develop and test a stochastic model of network evolution.

The case study is designed: (1) to identify the conceptual cores and field boundaries of an epistemic network (Laumann et al. 1983); (2) to explore the possibility of measuring creativity by means of peer evaluation, bibliometric and network indicators; (3) to test whether the most creative scientists, identified by measures at point (2), have introduced new combinations of concepts in the evolution of a rare disease specialty toward a cure. Throughout the case study, we combine both qualitative and quantitative methods, such as archival and bibliometric analysis, to benefit from their complementarities (Denzin and Lincoln 1994) and to achieve reciprocal internal validation of results (Yin 1994).

Our modeling effort builds upon a tradition of stochastic null-models of science dating back to Simon (1955). The model is based on three parameters: the entry of new nodes, the creation of new links, and the replication of existing links (Guimerà et al. 2005). First, we simulate the model for the social network of co-authorships and the semantic network of concept co-occurrence in scientific papers. Then we estimate the maximum likelihood value of the parameters of the model in some rare diseases. Lastly, we check for any relationship between the structural parameters for the semantic and social networks across different domains. The presence of a clear-cut relationship among them implies that the two evolutionary processes of the semantic and social networks are interdependent.

Research setting

In order to be theoretically and methodologically coherent with our research questions, a suitable empirical field of study should display creative problem-solving of different kinds (generative, combinatorial, replicative). It should also provide a moderately sizable and well-defined research topic. In this paper, our first focus is on one rare disease occurring almost exclusively in girls, called the Rett Syndrome (RTT). Next, we test our model on more diseases: Noonan and Horner syndromes, Mesothelioma, Paroxysmal Nocturnal Hemoglobinuria (PNH), and Adenosine Deaminase (ADA) deficiency. We tested the adequacy of RTT, a rare disease, as a research setting so that it could be empirically defined as a creative and closed field. In the following subsections, we describe how this was done, reporting results in "The Rett Syndrome" section. The same method was applied to identifying the other five rare diseases in "A stochastic model of scientific creativity" section.

Empirical closure

According to Csikszentmihalyi (1990), creativity requires dynamic interactions among three subsystems: the *individual* creator, the knowledge *domain* (i.e., the Kuhnian paradigm), and the *field*, which consists of those persons who work in the same domain, and thus have their creativity governed by the same domain-specific guidelines. As a field for our study, we chose a *specialty*, defined as "a group of researchers and practitioners who have similar training, attend the same conferences, read and cite the same body of literature (Fuchs 1993; Chen et al. 2009, p. 3)". This choice was made for two reasons. Conceptually, it is correct to segregate science into subfields displaying cohesive dynamics of both knowledge concepts and scientists working within them. Scientists do select their readings and relations according to their interests, and thus identify a specific reference community and their shared knowledge bases (Börner et al. 2004). In practice, this allowed us to solve the methodological problem of defining the boundary of the epistemic network, by selecting a field which is computationally tractable, but also socially and thematically closed.

To trace the boundary of the RTT specialty, we examined whether any convergence of the field (i.e., important topics and reference people) existed, according to experts' assessment of key scientists and papers collected through questionnaires, lists of topics addressed in specialized conferences, scientific reviews, and numerous descriptions of the field which are available to the general public through the internet and other informational sources. We also mined all papers in PubMed mentioning the term "Rett Syndrome" in the abstract and cross-checked the two lists.

Data availability

Another reason for choosing rare diseases, and RTT in particular, is due to their recent history, which can be traced both on the web and in databases such as PubMed since their early beginnings. Eighty per cent of rare diseases are of genetic origin. Since the Orphan Drug Act was passed in 1983 and the Human Genome Project started in 1990, most research in this field has been carried out in the last 25 years. To sum up, the choice to study rare diseases appeared to be suitable: they are new specialties of tractable dimensions.

Data collection

Data for the case-study analysis on RTT was collected in four steps.

First, we decided to conduct research on existing scientific and informational literature on the evolution of RTT knowledge, in order to extend our understanding of the dynamics of the field, without being a priori guided by the beliefs of RTT experts. We referred to both specialized and non-technical materials published on the web (especially parents' associations websites) and in scientific journals. We also attended the 2009 Meeting of the European Working Group on Rett Syndrome,[1] where we recorded the sessions and checked for the persistence of key concepts/scientists in the discourse (number of times they were mentioned in presentations).

Second, we contacted a set of RTT experts and proposed a questionnaire to scientists working in the field (see Appendix). Our goal was to validate the existence of a social community (*field*) and common semantic space (*domain*) corresponding to the specialty analyzed. In this way, we aimed at ascertaining the existence of a convergence on what they consider their reference context, in terms of both knowledge and people. In addition, we used these data to build our understanding on an endogenously and empirically defined notion of creativity. As regards the identification of interviewees, a primary list of contacts resulted from the combination of the contacts of two Research Foundations on RTT and contact with 78 RTT authors listed in PubMed. The list was integrated with participants in one of the main international conferences in the field (63 names). The questionnaire was structured with open questions, and was sent to contacts by e-mail. We asked the RTT experts to rank at least five authors they considered the most important in the field, and the five most creative.[2] We then asked them to cite at least five key scientific publications in the field and the most important research topics. Our response rate was 11%, including 5 of the top 30 RTT scientists. Although the results are not statistically significant, given the small size of the community and the low response rate, all responders were experts with publications in this field.

Third, we extracted some classical bibliometric indicators from Scopus (Hirsch's *h*-index) and the ISI Web of Knowledge (the sum of the journal impact factor of authors' publications) and compared them with data on creative scientists and contributions collected through the questionnaires.

Fourth, to analyze semantic and social networks, we developed a thesaurus of rare diseases which could be adapted to the great fragmentation of knowledge in the field. We then extracted all the publications on rare diseases in PubMed. We analyzed the dynamics of semantic and social networks and identified the connections between the two, tracing the relationship between authors and their creative concepts. We developed a tool similar to ConceptLink (White et al. 2004) to generate concept maps with the Unified Medical Language System (UMLS) co-occurrence database of MeSH descriptors. Thus, one node in our semantic network is a concept (MeSH term) and links among concepts are computed according to the number of co-occurrences of a pair of concepts in PubMed abstracts. In a similar fashion, we built a co-authorship network based on the number of joint publications of biomedical scientists, and computed three simple measures of author centrality: strength, degree, and *k*-core. Centrality indicators were selected to check whether authors with several joint publications (strength), more co-authors (degree) and members of the inner core of the network (*k*-core members) were the most creative scientists.

[1] www.rettmeeting.org/.

[2] We did not provide our interviewees with a definition either of relevance or of creativity, as the aim of the inquiry was to find a definition embedded in the community.

The Rett Syndrome

Case description

In the field of biomedical sciences, rare diseases are emerging research specialties. According to the European definition, a rare disease is a serious or lethal illness affecting less than one person every 2,000 individuals (75 cases out of 100,000 individuals according to the U.S. definition). Recent estimates show that not less than 30 million Europeans suffer from rare diseases. Nevertheless, the field is far from maturity. In fact, despite rarity, five new rare diseases are discovered every week and, for 8,284 diseases out of 9,471 (87%), there is no information available in public data sources and no ongoing research activity ("orphan diseases"). After the Orphan Drug Act was passed in the United States (1983), research in some rare disease areas has intensified. However, most rare diseases are still specialties in which creativity and novelty are pivotal, for both identification of the disease, and any progression toward a cure.

Our case study focuses on the RTT, a genetic neurodevelopmental disorder which appears in infancy and predominantly affects girls. RTT patients are normal at birth and during early development but, after the sixth month of age, display postnatal deceleration of head growth, psychomotor regression, gait dysfunction, and stereotypic movements such as the so-called "hand-washing". RTT is the second cause of mental retardation in girls throughout the world, with an estimated average incidence of one case every 22,800 girls between 2 and 8 years old. Unfortunately, there is no treatment available for RTT. Several steps have been taken toward identifying treatment[3]: they are based, first, on a clear-cut definition of the disease and, second, on deep understanding of its genetic mechanisms. At present, knowledge of RTT and its genetic causes is still unstable, as it is constantly being revised and refined.[4]

On the question of definition, there is a substantial consensus regarding the descriptive traits of the disease. However, neither the International Classification of Diseases nor the Diagnostic and Statistical Manual of Mental Disorders appropriately classify RTT in line with recent evidence. RTT is not an autistic disorder, although it is categorized among them. As regards identification of genetic causes, 95% of classic RTT cases reveal a mutated gene in the X chromosome, which provides instructions for the over- or under-production of a protein (MeCP2) which is critical for normal brain development. Conversely, only 20–40% of girls affected by a variant form also show a MeCP2 mutation. As a result, other genes, such as CDKL5, have been highlighted as responsible for a set of such RTT manifestations. Nevertheless, in general, such mutations are not one-to-one associated with RTT, but may also occur in other diseases.

[3] The first phase consists of identifying a set of typical characters of the disease (1a) and its association with the genetic disorder which is responsible for its onset (1b). As a second stage, precise understanding of the molecular mechanisms underlying the disease is required (2), which recognizes molecules and therapeutic strategies to be tested in vitro (3), and later in laboratory animals (4). After these four steps (pre-clinical phases), it is possible to test the treatment on humans and results will show whether any treatment for the disease has been found or not.

[4] See, as an example of such a process of redefinition and specification, changes in the topics list concerning the European Working Group on Rett Syndrome First and Second Conferences, which took place respectively in 2007 and 2009: 2007 Topics—The Molecular Cause of Rett Syndrome, MeCP2 Target Genes, Respiration Control and Seizures, Neuronal Plasticity, Future Approaches; 2009 Topics—Basic Molecular Mechanism of MeCP2, Circuit Defects in Rett Syndrome, Behavioral Deficits in Mice Lacking a Functional MeCP2, Modifier Genes and Other Genes Involved in Rett Syndrome, Therapeutic Approaches, Molecular Genetics.

While the causes of the syndrome are challenging researchers, progressive ability to identify and diagnose RTT has enriched the picture of cases[5] and has also added complexity to their potential understanding. For example, not only girls are affected by RTT, as some cases of male phenotypes have also been discovered. Overall, we may state that knowledge of RTT is at a stage in which there are some descriptions of empirical facts, such as clinical evidence, sometimes associated with behavioral traits, and that these facts are sometimes ordered into clearly defined new diseases over time. However, knowledge is far from consolidated. Conversely, continuous growth supported by creative discoveries is acknowledged.

Is Rett Syndrome a specialty?

By the end of 2009, 4,498 researchers had contributed to research on RTT by producing 1,653 scientific articles and 2,243 distinct concepts (MeSH terms). Table 2 lists some key statistics of the top scientists in the RTT research domain. They are the most frequently cited scientists by our responders, ordered by year of entry in the RTT community (last column of the table). We provide in bold those who made the most significant discoveries about RTT. Questionnaire results, bibliometric indices and network statistics are reported. With reference to questionnaire results, for each attribute we show both ranking position and a score proportional to the number of times a scientist was mentioned and the number of scientists the single responder cited in the answer (columns 1–4). Columns 5–6 reflect the frequency with which a paper written by a scientist was mentioned among the key papers. We also provide an average of the first three variables (columns 7–8). With reference to bibliometric analysis, we report overall production (number of papers) and the Hirsch's *h*-index of each author, as well as the number of papers on RTT and the sum of the Impact Factor of RTT publications. As network statistics, we report strength, degree, *k*-core and year of entry into the network.

The set of key scientists, as recognized by peers in questionnaire results, is restricted to the group of authors listed in Table 2. Adrian Bird and Huda Zoghbi are unanimously recognized as the most important scientists in this field; Andreas Rett (the Austrian scientist who first identified the syndrome) ranks fifth. Higher dispersion is displayed with regard to publications; however, a core of four most important works can be clearly identified. All respondents except one cited Guy et al. (2007) among the five most important readings in the field. Only two did not mention MeCP2 as a key concept in the field. On key concepts for research, both questionnaires and analysis of conference topics showed that research is focused on the study of MeCP2, the most probable main cause of RTT. Both informative and specialized literature accounts for the evolution of studies on RTT, citing the same scientists as keys to the field and the same open challenges for research.

Overall, these results support the hypothesis that RTT is a specialty, with a definite reference community (*field*) and knowledge base (*domain*). Scientists display high convergence of perceptions on people and topics (community closure). People in the epistemic community read the same papers, share similar research interests and relate to the same colleagues.

[5] This information is now more easily available to researchers and physicians, as a database on MECP2 mutations (RettBase) and a repository of clinical information (InterRett) are being collected.

Table 2 Creativity in Rett Syndrome scientific community: questionnaire results, bibliometric indicators and network statistics

Key scientist[a]	Questionnaire results								Bibliometric indicators					Network statistics			
									Total		Rett						
	Creativity		Relevance		Key papers		Total		Papers[b]	h index[b]	Papers[c]	IF, total[d]	IF, yearly[d]	Strength	Degree	k-core	Entry
Rett Andreas	**11**	**2.2**	**4**	**15.6**	**6**	**13.3**	**5**	**10.4**	**42**	**n.a.**	**4 (4)**	**4.9**	**0.3**	**9**	**9**	**5**	**1952**
Hagberg Bengt	**10**	**3.3**	**5**	**15.0**	**8**	**6.6**	**8**	**8.3**	**110**	**12**	**46 (21)**	**54.3**	**2.7**	**109**	**60**	**15**	**1983**
Percy Alan[e]	10	3.3	9	3.8	–	–	15	3.6	151	16	43 (25)	101.7	5.1	189	126	16	1989
Zoghbi Huda	**2**	**24.6**	**2**	**61.3**	**2**	**54.7**	**2**	**46.9**	**261**	**64**	**51 (36)**	**279.9**	**14.7**	**247**	**173**	**23**	**1990**
Naidu SakkuBai	–	–	16	1.0	–	–	24	1.0	123	26	45 (18)	150.2	7.9	242	172	20	1990
Kerr Alison	–	–	11	2.2	–	–	16	2.2	57	17	45 (8)	79.6	4.2	271	190	25	1990
Armstrong Dawna	–	–	13	1.7	–	–	19	1.7	37	22	22 (10)	49.5	2.6	82	73	20	1990
Francke Uta[e]	11	2.2	–	0.0	5	14.3	11	5.5	432	36	21 (17)	105.7	5.9	93	68	20	1991
Bird Adrian	**1**	**66.9**	**1**	**70.6**	**1**	**77.1**	**1**	**71.5**	**150**	**50**	**33 (25)**	**313.7**	**18.5**	**113**	**82**	**17**	**1992**
Leonard Helen	9	6.7	12	2.1	–	–	13	4.4	71	16	61 (23)	93.4	5.8	425	205	20	1993
Schanen Carolyn	11	2.2	–	0.0	12	4.0	17	2.1	34	13	14 (6)	65.9	5.5	73	67	13	1997
Wade Paul	–	–	–	0.0	–	–	–	–	64	33	15 (7)	105.0	9.5	40	28	10	1998
Landsberger Nicoletta[e]	10	3.3	–	0.0	–	–	19	1.7	28	11	6 (2)	52.0	4.7	49	39	19	1998
Christodoulou John[e]	13	1.3	–	0.0	–	–	25	0.7	152	27	47 (17)	103.7	9.4	335	176	20	1998
Renieri Alessandra	–	–	13	1.7	–	–	19	1.7	122	25	23 (13)	75.2	8.4	255	108	23	2000
Bienvenu Thierry[e]	–	–	–	0.0	–	–	–	–	148	25	19 (8)	80.4	8.9	166	89	17	2000
LaSalle Janine	6	11.3	7	10.1	15	0.4	10	7.3	45	16	22 (16)	86.4	10.8	75	46	11	2001
Guy Jacky	11	2.2	–	0.0	4	21.6	9	7.9	8	7	4 (0)	43.2	5.4	23	18	10	2001
Jaenisch Rudolph	**7**	**9.7**	**6**	**13.2**	**3**	**26.9**	**3**	**16.6**	**187**	**78**	**12 (6)**	**104.5**	**13.1**	**61**	**47**	**10**	**2001**
Sun Yi	4	18.3	9	3.3	8	8.2	6	10.0	32	21	7 (4)	30.2	4.3	31	25	18	2002
Mandel Gail	5	12.8	8	9.4	10	4.7	7	9.0	28	18	3 (1)	15.1	2.2	18	17	10	2002
Eubanks James	8	8.0	11	2.2	13	2.2	14	4.1	59	14	9 (7)	21.7	3.1	35	20	6	2002
Woodcock C.L.	10	3.3	–	0.0	14	1.1	20	1.5	86	21	6 (4)	35.7	5.9	24	12	5	2003

Table 2 continued

Key scientist[a]	Questionnaire results								Bibliometric indicators					Network statistics			
									Total		Rett						
	Creativity		Relevance		Key papers		Total		Papers[b]	h index[b]	Papers[c]	IF, total[d]	IF, yearly[d]	Strength	Degree	k-core	Entry
Greenberg Michael	**3**	**21.3**	**3**	**16.6**	**7**	**9.2**	**4**	**15.7**	**120**	**64**	**5 (4)**	**36.7**	**6.1**	**28**	**22**	**13**	**2003**
Chang Qiang	13	1.3	–	0.0	11	4.4	18	1.9	13	9	4 (0)	24.4	4.1	26	23	10	2003
Moretti Paolo	11	2.2	–	0.0	–	–	23	1.1	6	4	4 (4)	8.6	2.1	24	20	10	2005
Monteggia Lisa M.	–	–	14	1.3	–	–	22	1.3	53	22	5 (4)	17.9	6.0	13	9	5	2006
Katz David	9	6.7	10	2.7	–	–	12	4.7	94	18	6 (4)	2.2	0.7	24	16	6	2006
Pozzo-Miller Lucas	12	1.7	15	1.1	–	–	21	1.4	45	19	3 (3)	7.4	3.7	15	10	8	2007
Justice Monica	14	1.1	15	1.1	–	–	23	1.1	115	26	–	–	–	–	–	–	–

[a] Scientists ordered by year of entry into RTT (last column). Authors of the most significant discoveries in bold

[b] Total number of papers, *Source* Scopus

[c] PubMed papers on Rett (of which as the last author)

[d] *Source* our computation on ISI Web of Science

[e] Questionnaire responders

How can we measure creativity?

The lists of the most creative scientists and of the most important scholars identified by community members do not perfectly match (see columns 1–4 in Table 2). In addition, interviewees never report the same names and/or rankings for the two questions. This shows that the difference between the two attributes has been carefully weighted by responders. Comparing the ranking of the top ten most creative and most important scholars, we note that creativity is associated with more recent contributors (although their papers are not considered to be references in the field); as regards importance responders recall the "founding fathers" of the field in question: Rett and Hagberg.

The most creative scientist,[6] Adrian Bird, has recently shown the reversibility of RTT, and thus the possibility of finding therapy for patients (Guy et al. 2007). Next in the ranking, Huda Zoghbi has discovered that the mutation of the MeCP2 gene is one of the major causes of RTT Syndrome. Michael Greenberg has directed attention to other genes which may be related to MeCP2 and be the indirect cause of the disorder. Rudolph Jaenisch has contributed to the advances in knowledge of RTT. By introducing mouse models and using transgenic animal experiments as suitable methods for gene research, he has shown that therapeutic cloning can correct genetic defects in mice. He leads a group which has patented a candidate treatment (IGF-1) and has also recently started a clinical trial.[7]

All these contributions lie on the path to definite understanding of the disorder and aim at finding treatment. On this point, it seems that works which approach a cure (i.e., provide an answer to the key research question) are clearly assessed as creative by the scientific community and are very well considered by the community of patient families and donors which socially and financially supports such research. It also seems that creative scientists contribute new concepts or establish new associations between key concepts to find a cure for RTT. Bird introduced the new concept MeCP2 (generative creativity). MeCP2 was then linked to RTT by Zoghbi (combinatorial creativity). Authors who have introduced new concepts or new combinations of concepts are recognized as creative by the scientific community. These two dimensions build up our endogenous definition of creativity, which also reflects its generative and combinatorial nature, as pointed out in the literature.

Although we found a correspondence between descriptions of RTT and experts' evaluation of creativity, it is not easy to find a good measure of creativity from standard bibliometric indicators such as number of papers, Impact Factor (IF), *h*-index and centrality of authors in the community. This is particularly challenging in the case of young scientists. Centrality indicators in the network of co-authorships, such as strength or degree, are only loosely related to creativity ranking provided by peers. For instance, the scientist with the highest strength score was not even mentioned by our responders as being a creative person. The number of years of contributions to the field do not appear to be significant in relation to creativity, whereas IF scores (especially when divided by production time) and the *h*-index can replicate the very top positions (like Bird and Zoghbi), but appear to be highly unsuitable to capture the phenomenon as a whole.[8] As a result,

[6] Cfr. Table 2, scientists in bold.

[7] http://www.disabled-world.com/medical/clinical-trials/rett-trial.php.

[8] Adrian Bird, who was identified as the most creative and important, has the highest IF, but other indicators do not correspondingly highlight such a prominent position in the network. This weak correspondence is lost for other authors who are ranked lower, such as Michael Greenberg or Rudolph Jaenisch. Young researchers, e.g. Monica Justice, were mentioned by peers for their creativity, but are not present in the network yet.

there is no direct mapping of creativity as has been "declared" by experts with a single bibliometric indicator as already pointed out by van den Beemt and van Raan (1995) and Rinia et al. (1998).

Another reason why classical metrics are not effective in signaling creativity may also lie in the evolutionary path which it has taken within the field. Both the deployment of creativity and the involvement of authors on RTT have taken place over time in the form of waves, which have given new impulse to the study of RTT and have enhanced knowledge. The triangulation of narrative, survey results (and analysis of their correspondence, described previously) as well as the average IF per year allows us to claim that there are different generations of creativity within the evolutionary path of RTT knowledge, in which there is one most creative author in each phase, a person who is linked to the introduction of a new concept or a new combination of concepts. If we trace the temporal evolution of the network, we note that, by introducing new (combinations of) concepts, such authors become the most prominent authors of their cohort.

One last consideration must be added with regard to the results of the questionnaires. We noted that the answers to the four simple questions are affected by what could be called a "recency effect" with reference to the behavioral literature. In 90% of cases, the subjects cited scientists, publications and research topics which have appeared in the field in the last decade, whereas the creative contribution, for example, of the scholar who identified RTT as a rare disease is mentioned only once.[9] This supports the hypothesis that there is a thematic and temporal range which scientists implicitly consider to be relevant, which makes them discount creative or influential but "old" contributions, although they were central in the field taken as a whole (Börner et al. 2004). Old contributions and contributors are present in cumulative networks built on data drawn from publication datasets. The understanding of time windows is very important from a methodological point of view, for calibrating the representation of such networks in a dynamic way, so that what is forgotten or remains in the background can be deleted from the picture.

Who are the most creative scientists?

We distinguish two types of creativity: generative and combinatorial. Generative creativity is defined as the introduction of new concepts. Combinatorial creativity is the creation of new relationships among concepts. To measure creativity, we use a paper as the basic unit of analysis. A paper may be seen as a set of authors (a) and concepts (c):

$$p\left(c_1, \ldots, c_i, \ldots, c_n | a_1, \ldots, a_j, \ldots, a_m\right)$$

The collection of papers about RTT defines a socio-semantic or epistemic network. A paper is a hyperlink in the co-authorship network and, at the same time, a hyperlink in the semantic network of concept co-occurrences (Taramasco et al. 2010). More in general, it defines a set of relationships in the socio-semantic network of concepts and authors. This approach may be generalized to the case in which more than two categories are considered (such as citations and research methods). To be published, a paper must contain some

Footnote 8 continued
Conversely, scientists Wade and Bienvenu have a significant position in the community, as reflected by bibliometric and network indicators, but this role is not elicited by the community when directly asked.

[9] The most cited paper of Adrian Rett on MeCP2 is never mentioned among the top readings in the RTT field.

degree of novelty (generative, combinatorial, or both). By analogy, we can identify two changes in the network of co-authorships:

1. A paper contains a new author: a new node is added to the co-authorship network;
2. A paper contains a new combination of authors: a new link is added to the co-authorship network.

In the evolution of the socio-semantic network, new nodes (authors/concepts) enter and new links are formed. New authors can either be already active scientists entering a given specialty from other scientific communities, or new researchers. Thus, we must further distinguish new nodes in the scientific community from new nodes in the specialty. Let us identify new actors in a given specialty s by $n_s(a)$, of which $n(a)$ have never published before, and new scientific collaborations (co-authorships) by $n(a^2)$. Similarly, generative creativity is the entry of new concepts $n(c)$, whereas combinatorial creativity has to do with the creation of new links among previously unrelated concepts, $n(c^2)$. As before, we can distinguish locally new combinations $n_s(c)$ in a given specialty from globally new concepts and concept associations in science. The degree of novelty of a paper may thus be measured as:

$$n_s(p) = \left\{t(c), t_s(c); t\left(c^2\right) | t(a), t_s(a); t\left(a^2\right)\right\}$$

where $t(c)$ is the number of previous occurrences of concept c in the literature (e.g. PubMed); $t_s(c)$ the number of previous occurrences of concept c in a given specialty (e.g. RTT); $t(c^2)$ the number of previous co-occurrences of two concepts; $t(a)$ the number of papers of author a; $t_s(a)$ is the number of papers of author a in a given specialty; and $t(a^2)$ is the number of times two authors have worked together.

For instance, a hypothetical paper p with novelty $n_s(p) = \{(9, 6), (7,2); 0|10, 20; 4\}$ has two concepts and two authors. The first concept has been used 9 times (6 in specialty s), the second 7 times (of which 2 in specialty s), but this is the first time the two concepts are used together. The authors have already published 10 and 20 papers respectively, of which 4 are co-authored. The creativity of a given author can now be measured by looking at the $n_s(p)$ statistics of the papers he wrote.

In PubMed we found 1,653 papers on RTT, with about 4,500 authors and 2,300 concepts. On average, each paper has 4.73 authors and 12.23 concepts. The most central specific concepts in the RTT network are RTT and MeCP2, discovered by Rett and Bird, respectively. The first link between the two concepts was established by Zoghbi. Jaenisch demonstrated the association between Rett and MeCP2 in a mouse model (first Rett-Mice-MeCP2 combination). More recently, Bird has shown the reversibility of the pathology in mice (first Rett-Therapy combination, albeit limited to transgenic mice). The distributions of the share of new combinations of authors/concepts per paper overlap almost perfectly (Fig. 1). This result indicates a positive relationship between the openness of scientific teams to new collaborations and combinatorial creativity at the community level.

The evolution of the RTT network tells us that the centrality of a scientist in a community is associated with the ability to introduce new useful concepts or concept associations. However, we find a negative relationship between seniority and the degree of novelty of the scientific concepts in question (Fig. 2). Conversely, experience has no effect on combinatorial creativity (novelty of concept combinations). Also, as Fig. 3 shows, a positive relationship exists between the authors' centrality and the number of publications which used the new (associations of) concepts they introduced. First, to become central,

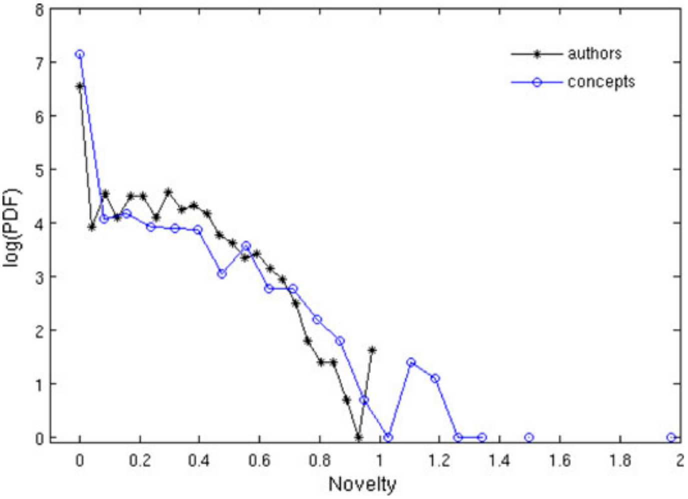

Fig. 1 The distribution of new combinations of concepts/authors in the scientific papers on Rett Syndrome (*source* PubMed, 2009)

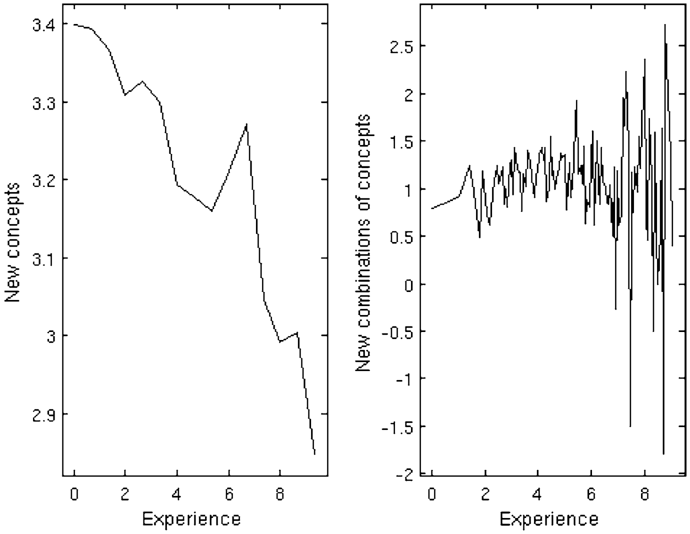

Fig. 2 Average number of new concepts, $n(c)$, and the logarithm of the number of new combinations of concepts $n(c^2)$ by authors' scientific experience as measured by number of articles previously appearing in PubMed

researchers must introduce new (combinations of) concepts. Second, the centrality of creative scientists in the co-authorship network is driven by the replication of concepts they have brought to the field.

In the first stage of emergence of RTT as a specialty (problem identification), the rate of entry of new authors, mainly from other areas of research, was high. The first phase was completed with the introduction of new concepts (e.g., Rett and MeCP2), based on which

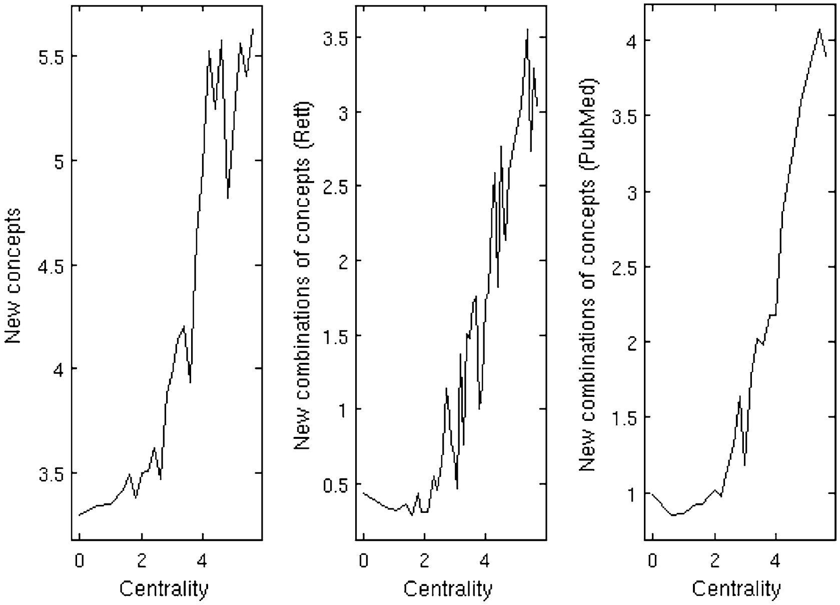

Fig. 3 The logarithm of the number of times newly introduced (combination of) concepts have been replicated versus the logarithm of the centrality of the scientists in the scientific community of Rett Syndrome (*source* PubMed, 2009)

the field has been established. The introduction of new concepts spurred the combinatorial creativity of the community and gave rise to the emergence of a giant component through new scientific collaborations (concept combination and expansion).

A stochastic model of scientific creativity

A baseline model for the co-evolution of socio-semantic networks

The structure of scientific activity has been intensively studied over the last 50 years. On one hand, several empirical regularities of the networks of scientific collaborations have been identified, on the other, simulative and theoretical models able to replicate the main features of scientific networks have been developed. Building on a tradition of science modeling dating back to Simon (1955) we generalize previous stochastic growth models to describe the dynamics of socio-semantic networks. Let us first consider a production function of the form:

$$\dot{C} = f(C,A)$$

where C is the stock of knowledge; $\dot{C}$ the amount of new knowledge produced at time t; and A the number of active researchers.[10] Since one of the principal constraints to

[10] More in general A denotes all rivalrous production inputs, such as labor, and C all non-rivalrous ones, such as ideas.

publication in science is that no two papers which contain the same knowledge may be published, new papers must contain new knowledge. Hence, science as an institution may be described by the production of papers, each proposing a new "quantum of knowledge":

$$P\left(\dot{C}\right) = f(P(C), A)$$

where $P(C)$ is the stock of all papers available and $P(\dot{C})$ are new papers produced at time t. Gilbert (1997) shows that it is possible to generate many of the quantitative features of the present structure of science by looking at scientific activity as a system in which scientific papers generate further papers, with authors playing a necessary but incidental role. Börner et al. (2004) also rely on an author-paper production function to explain the evolution of scientific networks of co-authorship and citations. In our model, we build on the growth process originally presented by Simon (1955) in the version modified by Guimerà et al. (2005) to explain team assembly in science. At any time step t, a new paper, that is a combinatorial set of concepts and authors, is produced. We select authors and concepts at random based on the following probabilistic rules. We start the simulation with an endless pool of new authors and concepts. First m authors are selected.[11] Some authors in the paper may be globally new in science or locally new for a given specialty. A new author in a given field of research (topic) is called a *novice*. Novices become *experts* after their first publication. Each member of the team has probability p_1^a of being a novice ($1 - p_1^a$ of being an expert). If an author is drawn from the experts' pool and there is already another expert in the team, with probability p_2^a, a new combination of experts is established otherwise with probability $1 - p_2^a$, the new author is randomly chosen among the set of collaborators of a randomly selected team member.[12] The probability of an expert being selected is proportional to the number of papers that expert has written. The same procedure is applied to the concept set. We select n concepts. A new concept is added (generative creativity) with probability p_1^c whereas with probability $1 - p_1^c$ a concept which has been already used is selected. In the second case, with probability p_2^c, a new concept association is formed (combinatorial creativity); otherwise an already existing combination of concepts is replicated with probability $1 - p_2^c$. As for authors, the likelihood of selecting an existing concept is proportional to the number of times it has already been used. We apply the same rules for all authors and concepts of a paper, and for all papers. As in the model of Guimerà et al. (2005) this generalized version replicates some of the main topological properties of the co-authorship network: the presence of a giant component encompassing about half the authors, a small-world structure, and a power law connectivity distribution with an exponential cut-off (Lotka 1926; Girvan and Newman 2002; Newman 2004). In our stochastic framework we can also test the relationship between the four main stochastic parameters of the model: p_1^a, new authors; p_2^a, new collaborations; p_1^c, generative creativity; p_2^c, combinatorial creativity.

[11] The number of authors and concepts per paper are positive random numbers with mean m and n respectively.

[12] The probability is $p_1 = 1 - p$ and $p_2 = 1 - q$ in the model of Guimerà et al. (2005). We have modified that model to accommodate teams of different sizes. As in the original model, agents who remain inactive for longer than T time steps are removed from the network. However, our results do not depend on the specific value of T which is usually set to the maximum level, since we are analyzing new fields of research in which the vast majority of authors are still active.

Simulations and model validation

Based on our analysis of RTT, we expect that a relationship is in place between the evolution of the network of scientific collaborations and creativity, as measured by conceptual generation and combination. In particular, we state that, in a given community, new collaborations and combinatorial creativity are positively related.

H1 $p_2^a = p_2^c$. The probability of new co-authorships is the same as the probability of combinatorial creativity. It should be noted that, unlike the case illustrated in Taramasco et al. (2010), this relationship holds in probability for a set of related papers and not for a single paper.

The second relationship is more complex. Figure 2 shows that new authors have a higher probability of introducing new concepts. However, only a few of them will be replicated by others, thus contributing to the solution of the problem and the centrality of creative scientists (Fig. 3). Authors like Bird are recruited in the RTT specialty as the new concept they introduce contributes to the RTT problem-solving activity. These events occur rarely, but they are extremely important. Instead, most novices are recruited to help experts to replicate their findings.

H2 In a scientific community p_1^a and p_1^c are inversely related. The larger is the participation of novices in scientific production, the smaller is generative creativity. However, at individual level, newcomers have a higher chance of working on new concepts and theories. A high turnover of scientists prevents the emergence of the giant component of experts (community closure) which is crucial for the generation of new concepts.

To test our predictions, we selected six rare disease specialties of different sizes and at different stages of evolution, from problem identification to the development of an effective treatment. The stage of development of a research field toward a cure can be identified by looking at the number of active clinical trials and available treatments. Size can be measured by looking at the prevalence rate (i.e., the total number of cases divided by the number of individuals in the population). For all the rare diseases we considered, except PNH, there is no effective treatment available. Horner and Noonan are in a stage of early development (no active clinical trials). ADA and Rett are at an intermediate stage: there is growing consensus about the causes of the pathology and potential intervention strategies, but only a few trials are ongoing. The fields of Mesothelioma and PNH are more mature (several trials are ongoing, and a new drug was launched in 2007 to treat PNH). At each stage of evolution, we selected one relatively large specialty (Noonan, Rett, Mesothelioma) and one small (Horner, ADA, PNH) (see Table 3).

The number of publications ranges from 827 (ADA) to 9,625 (Mesothelioma); the average number of authors and concepts per paper is relatively stable—around 4 and 11 respectively. The topological properties of the co-authorship networks are widely diversified: size in terms of number of papers, the fraction of authors with at least two publications (F_R), repeated co-authorships (f_R) and the share of authors in the giant component of the network (S) range from 5.88 to 28.06 (F_R), 1.36 to 14.07 (f_R) and 2.23 to 59.58 (S), respectively.

We simulated our model for each specialty by taking the average numbers of authors and concepts as inputs (n and m) to generate several random networks for different values of p_1^a, p_2^a, p_1^c and p_2^c, ranging from 0 to 1. For each of them, we fitted four statistics of the simulated network to the same statistics for the real-world semantic and social networks:

Table 3 Creativity and entry in six rare diseases at different stages of evolution (early: Horner and Noonan; middle: Rett and ADA; advanced: PNH and Mesothelioma)

Rare disease	No. of papers	Average number of	Size	F_R	f_R	S	p_1	$p_1^a–p_1^c$	p_2	$p_2^a–p_2^c$
1. Horner No. of trials^A: 0 Prevalence^B: n.a.	1,473	Authors								
		2.85								
		real	3,860	5.88	1.36	2.23				
		sim.	*3,872*	*7.77*	*1.14*	*1.22*	.85		0	
		Concepts								
		9.57								
		real	1,868	51.45	23.61	100				
		sim.	*1,841*	*56.36*	*22.98*	*72.00*	.07	.78	0	–
2. Noonan No. of trials^A: 3(0) Prevalence^B: 50/100.000	985	Authors								
		4.70								
		real	3,466	14.08	7.63	32.60				
		sim.	*3,455*	*20.49*	*5.58*	*22.31*	.75		0	
		Concepts								
		10.40								
		real	1,591	43.87	23.91	100				
		sim.	*1,566*	*45.58*	*21.95*	*100*	.15	.60	0	–
3. Mesothelioma No. of trials^A: 143(45) Prevalence^B: 2.7/100.000	9,625	Authors								
		4.04								
		real	23,748	22.21	18.54	31.54				
		sim.	*23,756*	*27.21*	*19.21*	*29.81*	.62		.05	
		Concepts								
		11								
		real	4,677	60.45	31.65	100				
		sim.	*4,731*	*50.30*	*29.46*	*100*	.04	.57	.05	–

Table 3 continued

Rare disease	No. of papers	Average number of	Size	F_R	f_R	S	p_1	p_1^a–p_1^c	p_2	p_2^a–p_2^c
4. PNH No. of trials[A]: 25(9) Prevalence[B]: .55/100.000	2,476	Authors								
		3.78								
		real	5,849	19.94	11.74	29.71				
		sim.	*5,833*	*29.00*	*11.73*	*31.00*	.72		.02	
		Concepts								
		9.30								
		real	2,344	54.10	26.67	99.87				
		sim.	*2,337*	*52.55*	*25.27*	*100*	.10	.53	.02	–
5. Rett No. of trials[A]: 13(4) Prevalence[B]: 4.15/10000	1,653	Authors								
		4.73								
		real	4,498	24.00	12.15	49.13				
		sim.	*4,496*	*29.81*	*12.40*	*72.06*	.57		.07	
		Concepts								
		12.23								
		real	2,283	52.00	26.81	100				
		sim.	*2,274*	*48.25*	*24.19*	*100*	.11	.46	.07	–
6. ADA No. of trials[A]: 8(3) Prevalence[B]: .22/100.000	827	Authors								
		3.79								
		real	1,618	28.06	14.07	59.58				
		sim.	*1,620*	*32.53*	*14.17*	*77.21*	.52		.15	
		MeSH terms								
		11.63								
		real	1,352	51.85	25.09	100				
		sim.	*1,350*	*47.93*	*23.54*	*100*	.14	.38	.15	–

Structural indicators (number of nodes: size; share of nodes with more than one link: F_R; share of repeated links: f_R; share of nodes in the giant component of the network: S); maximum likelihood estimates of model parameters (p_1^a, p_1^c, p_2^a, p_2^c) based on simulation results (sim., in italics)

[A] *Source* www.clinicaltrials.gov (active trials into brackets)

[B] *Source* www.orpha.net, report series no. 2, November 2009 size, F_R, f_R, S. Lastly, we computed the maximum likelihood values of p_1^a, p_2^a, p_1^c and p_2^c. Results are listed in Table 3.

First, the probability of new combinations of concepts and authors are the same across all the specialties considered. Therefore, combinatorial creativity (i.e., new combinations of concepts) and the openness of the team assembly mechanism to new partnerships among incumbent scientists are closely and positively related.

Second, the lower the entry rate of new authors, the higher the entry rate of new concepts. The generation of new concepts implies closure of the community, repeated collaborations, and the emergence of a specialty (a giant component composed by an "invisible college" of authors focusing on a specific discipline).

Third, generative creativity is partially independent of combinatorial creativity. Our preliminary results indicate that generative creativity precedes combinatorial creativity, but more work is needed to better understand the dynamic interplay between the two forms of creative enterprise.

All in all, combinatorial creativity in a specialty has some preconditions: (1) a domain must be established around a set of new concepts (generative creativity); (2) a field of research composed of a stable nucleus of scientists must emerge (specialty); (3) scientists must be free to enter into new scientific collaborations to explore promising new concept associations.

Concluding discussion

In this paper we aimed at establishing a dynamic relationship between scientific collaborations and creativity. Although we are aware that our results must be further corroborated by testing the model in different disciplines and at different stages of scientific evolution, we believe our findings have several implications.

First, we develop a methodology to identify and measure different kinds of scientific creativity. Many earlier studies compare bibliometric results with the judgments of scholars or experts on the quality of research. Most of them find a reasonable correspondence, although a poor correlation was found between citation indicators and the originality of research proposals in applied research (van den Beemt and van Raan 1995). In our case study of the RTT community, we also find that traditional bibliometric and network centrality indicators do not accurately measure creativity. Hence, we introduce some new indicators, based on counting the new (association of) concepts a scholar contributes to a given domain of study, which match the result of our expert survey on creativity better. More work is needed in this direction to control for the recency effect and to investigate the relationship between generative and combinatorial creativity in scientific careers, teams and communities.

Second, we develop a stochastic model of network evolution. It replicates most of the topological properties of socio-semantic networks, including the rate of generative and combinatorial creativity. In addition, our null-model can be used to measure the expected level of creativity across domains. Unbiased statistical tests to compare the creative performances of teams of scientists in different research areas can be developed.

Third, independently of the peculiarities of each domain, we find that new collaborations among experienced scientists enhance combinatorial creativity. On the positive side, there are several reasons why the increase of spontaneous scientific collaborations must be related to combinatorial creativity rather than to generative creativity. On the negative side, as stated in the initial quotation of Poincaré, most efforts to build scientific networks through centralized public incentive schemes are doomed to failure. The two combinatorial processes of team self-assembly and creative discovery are closely interwoven. Owen-Smith et al. (2002) show that in the United States biomedical innovation system the combination of new concepts is favored by blurring boundaries between basic and goal-oriented research, disciplines and institutions, whereas European research institutes are more frequently organized hierarchically by scientific field. In this paper, we further corroborate their findings by showing that combinatorial creativity is related to the open re-combination of scientific teams. Local closure of a community in space, time and by specialty, and the mobility and collaborations of scientists across disciplines and intuitional boundaries are two sides of the same coin (Cowan and Jonard 2003; David 2003).

Fourth, generative creativity is linked to the emergence of a scientific community (a stable giant component of repeated ties in the co-authorship network). Our analysis of rare diseases reveals that the community closure around a set of relatively stable and shared concepts is a fundamental prerequisite for creativity. Too high a rate of scientific turnover prevents identification of important new problems and concepts (Bruckner et al. 1996).

Further research is needed to better understand the dynamic relationship between generative and combinatorial creativity in the evolution of science. Some of the newly generated (combinations of) concepts are selected by scientists and replicated. The centrality of a scientist in a given field is driven by the replication and validation of the new associations of concepts that he contributed to build in that knowledge domain. In this respect, our study is complementary to that of Bettencourt et al. (2008) regarding the spread of scientific ideas. It would probably be useful to extend our framework to analyze replication dynamics in citation networks and also to examine whether scientists in different disciplines and institutional settings differ in terms of strategies for successful problem-solving: some will leverage social connections to be creative as a consequence of their ability to collaborate and recruit talented scholars, whereas others may focus on combinatorial creativity and collaborate with colleagues to validate and replicate their findings. This relates to the broader problem of distinguishing homophily from contagious diffusion in networks. Lastly, we hope that our work may contribute toward sustaining creative problem-solving in rare diseases.

Acknowledgments The authors wish to thank Rita Bernardelli (ProRett Foundation) and Lucia Monaco (Telethon Foundation) for their support in organizing the Rett survey and field study. We also thank Bernard Munos, Enrico Zaninotto, two anonymous referees, participants at the Sunbelt XXX meeting in Riva del Garda and the ROCK group at the University of Trento for helpful comments.

Appendix: Questions put to scholars on Rett Syndrome

1. Please write the names of the five most influential scientists (except your own) on Rett Syndrome, in order of the importance of their scientific contributions;
2. Please write the names of the five most creative scientists (except your own) on Rett Syndrome;
3. Please rank the five most important scientific publications (except yours) on Rett Syndrome (any citation style, but include at least: first author, year, title, journal/book editor);
4. Please list at least five key concepts which define the most important topics of research on Rett Syndrome.

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Scientometrics (2011) 89:421–435
DOI 10.1007/s11192-011-0433-7

Mixed-indicators model for identifying emerging research areas

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Received: 2 June 2011 / Published online: 21 June 2011

Abstract This study presents a mixed model that combines different indicators to describe and predict key structural and dynamic features of emerging research areas. Three indicators are combined: sudden increases in the frequency of specific words; the number and speed by which new authors are attracted to an emerging research area, and changes in the interdisciplinarity of cited references. The mixed model is applied to four emerging research areas: RNAi, Nano, h-Index, and Impact Factor research using papers published in the *Proceedings of the National Academy of Sciences of the United States of America* (1982–2009) and in *Scientometrics* (1978–2009). Results are compared in terms of strengths and temporal dynamics. Results show that the indicators are indicative of emerging areas and they exhibit interesting temporal correlations: new authors enter the area first, then the interdisciplinarity of paper references increases, then word bursts occur. All workflows are reported in a manner that supports replication and extension by others.

Keywords Burst detection · Prediction · Emerging trend · Temporal dynamics · Science of science (Sci^2) tool

Introduction and related work

The identification of emerging research trends is of key interest to diverse stakeholders. Researchers are attracted to promising new topics. Funding agencies aim to identify

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emerging areas early to encourage their growth via interdisciplinary workshops, solicitations, and funding awards. Industry monitors and exploits promising research to gain a competitive advantage. Librarians need to create new categories and special collections to capture emerging areas. The public at large has a general interest in understanding cutting-edge science and its impact on daily life. While it is not recommendable to "oversell" or "over promise" new research, it is desirable to catch the attention of the media, graduate students, and funding agencies.

Different approaches have been proposed to identify emerging research areas (Lee 2008; Takeda and Kajikawa 2009), their level of maturity (Serenko et al. 2010; Watts and Porter 2003), and their speed of development (Van Raan 2000; Braun et al. 1997). The first and perhaps most difficult task is the delineation of all research areas. Zitt and Bassecoulard (2008) and Lewison (1991) studied how to define research areas. There are various ways to define research areas such as grouping specialist journals, collecting a list of authors, running topical queries according to the field terminology, etc. Hence, much work on emerging areas of research has been done in hindsight—using a set of by then established keywords, e.g., nano, neuro, or highly cited "pioneering" papers to run term based or cited reference searches. Sometimes, all papers published in one or several journals are analyzed. None of these approaches catch *all* work published on a topic, however, their results can be a reasonable proxy for analysis. The method of using established words to refine an emerging research area is taken in this study.

Science indicators have been deployed to examine the emergence or growth of scientific fields, such as Price's index (Price 1970), immediacy index (Garfield and Small 1989) and currency index (Small 2006). Lucio-Arias and Leydesdorff (2007) explore the emergence of knowledge from scientific discoveries and its disrupting effects in the structure of scientific communication. They apply network analysis to illustrate this emergence in terms of journals, words and citations. Work by Leydesdorff and Schank (2008) examines changes in journal citation patterns during the emergence of a new area. Kajikawa et al. (2008) detects emerging technologies by using citation network analysis, finding that fuel and solar cell research are rapidly growing domains. Scharnhorst and Garfield (2010) proposed author- and text-based approaches of historiography and field mobility to trace the influence of a specific paper of Robert K. Merton (1968). The historiograph of the citation flows around Merton's paper of 1968 reveals the emergence of the new field of Science and Technology Studies in the 1970s. They show that studying a research area's origin papers or following a scholar's academic trajectory are pragmatic ways to trace the spread of knowledge.

Many researchers use quantitative models to study how ideas spread within scientific communities and how scientific fields develop over time. Goffman conducted several studies (1966, 1971; Goffman and Harmon 1971; Goffman and Newill 1964) to mathematically model the temporal development of scientific fields. He maintains that an epidemic model can predict the rise and fall of a particular research area. Luís M. A. Bettencourt et al. (2008) analyze the temporal evolution of emerging areas within several scientific disciplines according to numbers of authors and publications using contagion models developed in epidemiology.

Several studies identify emerging topic trends using Kleinberg's (2003) burst detection algorithm. This algorithm employs a probabilistic automaton whose states correspond to the frequencies of individual words and state transitions correspond to points in time around which the frequency of the word changes significantly. Given a set of time stamped text, e.g., abstracts and publication years of papers, the algorithm identifies those abstract words that experience a sudden increase in usage frequency and outputs a list of these words together with the begin and end of the burst and the burst strength that indicates the change in usage frequency. Mane and Börner (2004) applied the burst algorithm to identify highly bursting words as indicators of future trends in a *Proceedings of the National Academy of Sciences* (*PNAS)* dataset covering biomedical and other research in 1982–2001. Chen (2006) applied the same algorithm to identify emergent research-front concepts in datasets retrieved via term search. Later work by Chen et al. (2009) combines burst detection as a temporal property with betweenness centrality as a structural property to evaluate the impact of transformative science and knowledge diffusion.

"Mixed indicators model" section of this paper introduces a mixed model approach to the identification of emerging research areas. "Data acquisition and preparation" section introduces two datasets used to exemplify and validate the model. "Model application to h-Index, impact factor for *Scientometrics* and RNAi, Nano* for *PNAS*" section applies the mixed model approach to four research areas and the interdisciplinarity indicator to the two datasets from section "Data acquisition and preparation" and discusses the results. "Model validation" section compares and validates the different indicators. "Discussion and outlook" section concludes this paper with a general discussion and an outlook to future work.

Mixed indicators model

This paper introduces, applies, and validates a combination of partial indicators to identify emerging research areas. Specifically, the following three hypotheses are examined as indicators:

1. Word bursts precede the widespread usage of words and indicate new research trends,
2. Emerging areas quickly attract new authors, and
3. Emerging areas cite interdisciplinary references.

The first indicator utilizes prior research by Mane, Börner, and Chen (see "Introduction and related work" section). The second indicator was inspired by the work of Kuhn (1970) and Menard (1971). Kuhn argued that scientific revolutions are begun and adopted by new scientists in the field. Menard's work on the growth of scientific areas showed that an area does not grow by "old scientists" accepting and working on new ideas but by attracting new, typically young scientists. The third indicator was inspired by the fact that emerging research areas grow out of existing research, i.e., expertise taught in school and practice, and it cites existing relevant work from diverse lines of research. Intra-area citation is not possible as no research yet exists on the new topic. The two following datasets will be used to introduce, exemplify, and validate the proposed set of indicators.

Data acquisition and preparation

The study uses two datasets: all 75,389 papers published in the *Proceedings of the National Academy of Sciences* in 1982–2009 and all 2,653 papers published in *Scientometrics* from its creation in 1978 to 2009. *PNAS* is highly interdisciplinary and unlikely to capture the entire work of any single author. *Scientometrics* is domain specific, might capture main works of single authors, and is much smaller in size.

PNAS data and statistics

PNAS data was downloaded from Thomson Reuters's *Web of Science (WoS)* (Thomson Reuters 2010) on 2/18/2010 with the publication name query *Proceedings of the National*

Academy of Sciences of the United States of America or *Proceedings of the National Academy of Sciences of the United States of America Physical Science* or *Proceedings of the National Academy of Sciences of the United States of America Biological Science.*

The retrieval resulted in 95,715 records. Using *WoS*'s "Refine Results" function, the dataset was restricted to those 75,389 records published in 1982–2009. It comprises 69,939 articles, 1,892 editorial materials, 1,112 proceedings papers, 1,060 corrections, 770 correction additions, 206 reviews, 181 letters, 157 biographical items, 60 notes, 2 reprints, and 1 tribute to Roger Revelle's contribution to carbon dioxide and climate change studies.

Employing the Science of Science (Sci^2) Tool (Sci^2 Team 2009a), the number of new unique authors per year, unique references (CR), unique ISI keywords, and unique author keywords were calculated (see Fig. 1). As no author or ISI keywords existed before 1991, 184,246 MeSH terms were added using the procedure introduced by Boyack (2004). All terms from the paper titles, author keywords, ISI keywords, and MeSH terms were merged into one "ID" field. The "ID" field was further processed by

- Removing a common set of stop words using the Sci^2 Tool stop word list (Sci^2 Team 2009b), and all individual letters and numbers.
- Removing all punctuations except "-" or "/."

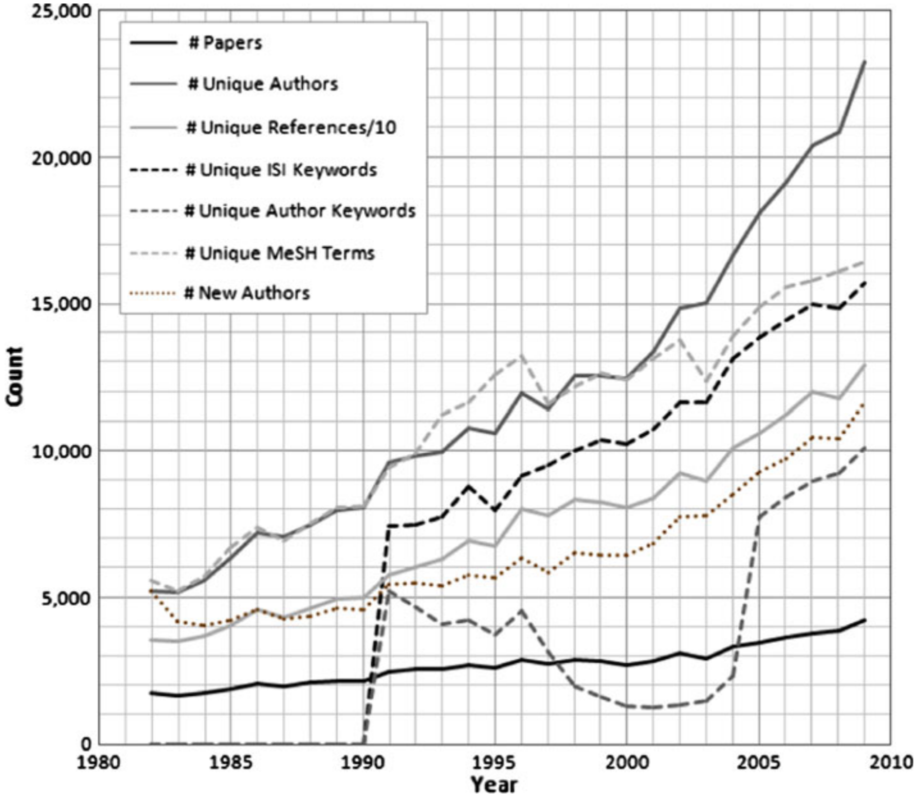

Fig. 1 Number of unique *PNAS* papers, authors, ISI keywords, author keywords, MeSH terms, references/10 and new authors from 1982 to 2009

- Reducing multiple whitespaces to just one space and removing leading and trailing whitespace.
- Lower-casing all words.
- Replacing all "-" and spaces with period separators to preserve compound words.
- Stemming all ID words using the Sci^2 tool. Common or low-content prefixes and suffixes are removed to identify the core concept. For example "emergent" will be replaced by "emerg."
- Normalizing the "AU" author field by uppercasing first letters for more legible labelling.

Two author's names, "Wei-Dong-Chen" and "Yu-Lin," were manually changed into "Chen, WD" and "Lin, Y," and "in vitro" and "in vivo" were replaced by "invitro" and "invivo" respectively.

To understand this dataset's temporal dynamics, bursts, i.e., sudden increases in the frequency of words in titles, new ISI keywords, author keywords and MeSH terms were identified. The top 50 results are shown in Fig. 2. Each bursting word is shown as horizontal black bar with a start and ending time, sorted by burst start year. The bar's area represents burst strength. The words "molecular.weight," "nucleic.acid.hybrid," "dna.restriction.enzym," "rats.inbred.strain," and "genes.vir" (given in the lower left) burst first. The first two words have a higher burst strength, which is indicated by their larger area. Between 1982 and 1991, more words are bursting than in any other period, and the top 3 bursting words ("molecular.sequence.data," "base.sequ" and "restriction.map") appear in this time span. Words "models.molecular" and "reverse.transcriptase.polymerase.chain.react" burst in 2009 and are still ongoing. Figure 2 also shows words that burst multiple times, e.g., "dna.prim" bursts in 1994, 1998 and 2000, "kinet," "reverse.transcriptase.polymerase.chain.react," "time.factor," and "transfect" burst twice over the time span.

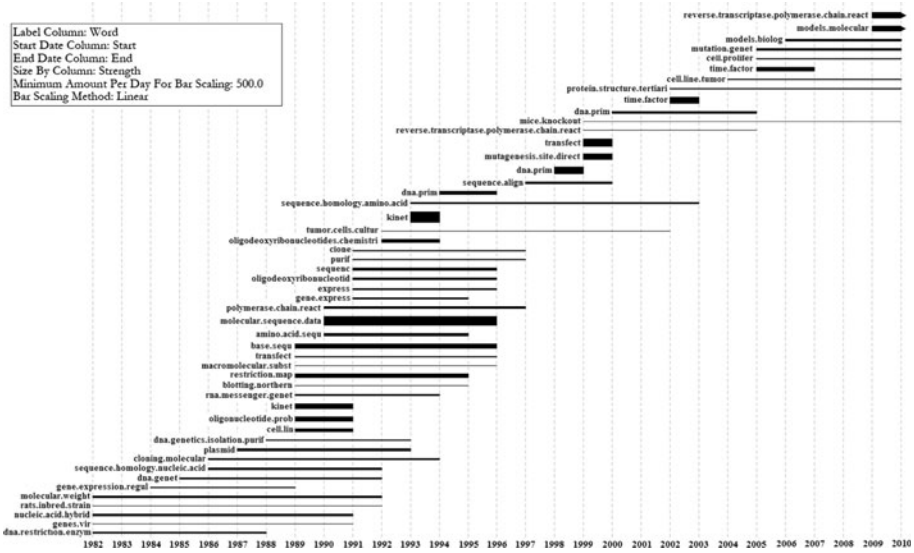

Fig. 2 *Horizontal bar graph* of top 50 bursting topic words from *PNAS*

Scientometrics data and statistics

All papers published in the journal *Scientometrics* from 1978 to 2009 were downloaded from *WoS* (Thomson Reuters 2010) on 3/15/2010. The dataset includes 2,653 records: 1,894 articles, 387 proceedings papers, 93 book reviews, 74 notes, 73 editorial materials, 34 reviews, 27 letters, 22 biographical-items, 17 bibliographies, 11 meeting abstracts, 8 items about an individual, 7 corrections/additions, 4 corrections, 1 discussion, and 1 news item.

The number of unique papers per year, authors, references, ISI keywords and new authors were identified, and unique ISI keywords were further processed as those in "*PNAS* data and statistics" section. Author names "VANRAAN, AFJ," "vanRaan, AFJ," "Van-Raan, AFJ," "Van Raan, AFJ," and "van Raan, AFJ" were manually replaced by "Vanraan, AFJ" and the ISI keyword "Hirsch-index" was replaced by "h-index." Counts per year for all six variables are plotted in Fig. 3.

The same temporal analysis workflows as "*PNAS* data and statistics" section were then run to identify bursts in ISI keywords and results are shown in Fig. 4 (see "*PNAS* data and statistics" section for how to read horizontal bar graphs). In the early 1990s, studies in Scientometrics mainly focused on Scientometrics indicators, especially of relative citation impact. These studies originated from Braun et al. (1987, 1989a, b) and were followed by several publications with "facts and figures" in the titles. The amount of bursting words per year suddenly increased after 2000. Only 10 bursting words appeared from 1991 to 1999, while 50 bursting words appeared in the following 10 years. Studies related to "scienc," "impact" and "journal" are the top three bursting topics in the 2000s. Indicators of scientometric methodologies bursted in this time period, as evidenced by the burstiness of "impact factor," "indic," "index," "h.index," "cocit," "citat" and "self.cit." Figure 4 shows that "h.index" was the burstiest word related to indicators over the entire timespan of the dataset. The h-index, proposed by Hirsch (2005), inspired discussions on its

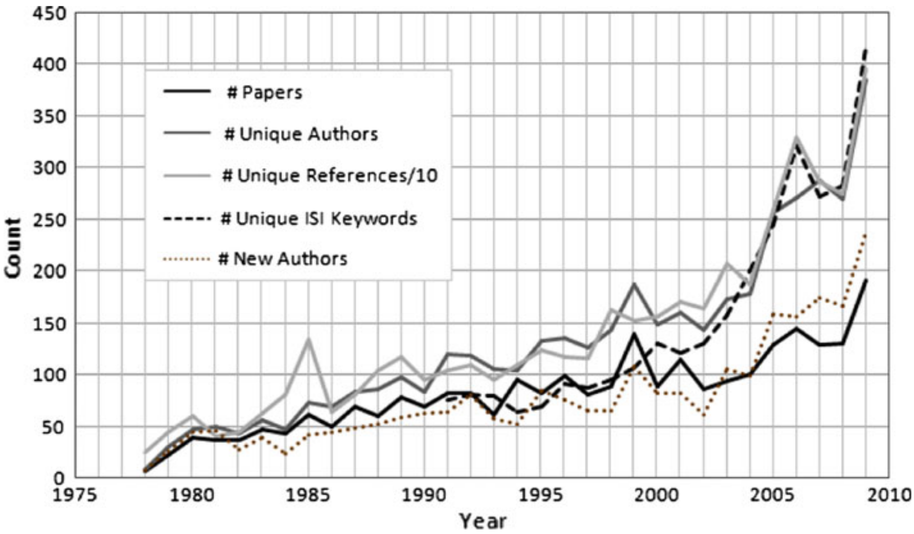

Fig. 3 Number of unique papers published in *Scientometrics*, their authors, ISI keywords, references/10 and new authors for the years 1978–2009

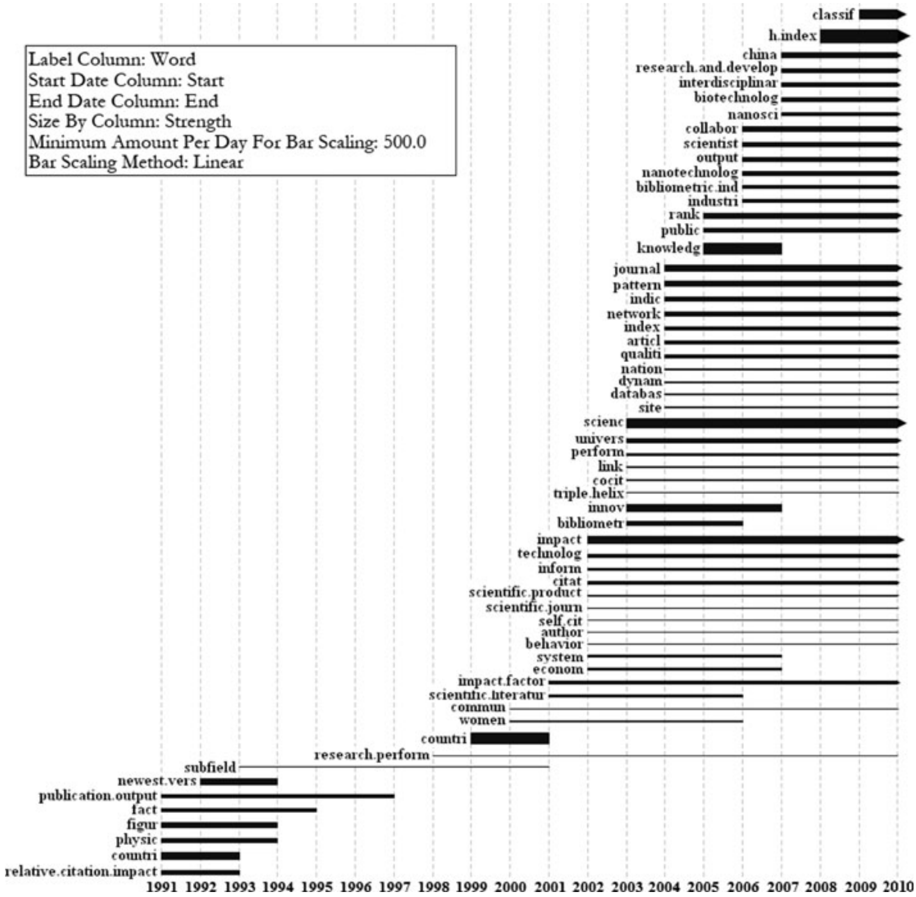

Fig. 4 *Horizontal bar graph* of all bursting ISI keywords from *Scientometrics*

strengths and limitations, as well as research on improved indicators. The word "countri" is the only word that burst twice, from 1991 to 1993 and from 1999 to 2001, indicating the interest in country level, geospatially explicit studies such as Chu (1992), Adamson (1992), Tsipouri (1991), Kim (2001), etc. The Triple Helix innovation model was another bursting topic, as indicated by the burstiness of "triple.helix," and it contributed to the burstiness of "univers" and "innov."

Model application to h-Index, impact factor for *Scientometrics* and RNAi, Nano* for *PNAS*

Construction of datasets

A single journal such as *PNAS* or *Scientometrics* records the (often parallel) emergence of multiple areas of research over time. To understand the structure and temporal dynamics of different indicators for concrete areas of research, publications for four emerging areas

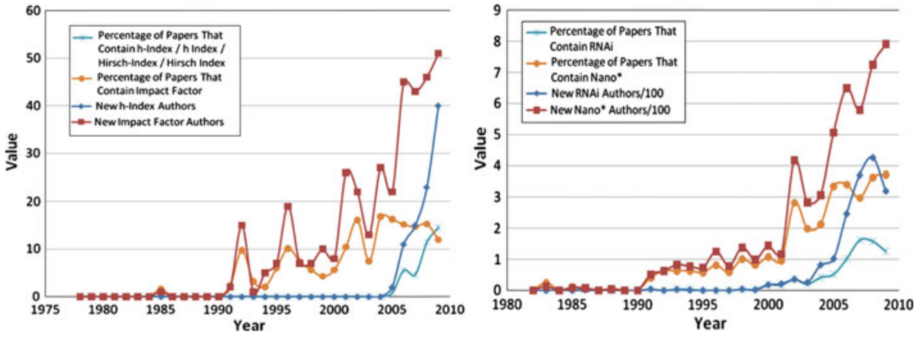

Fig. 5 Papers containing given keywords and the amount of authors publishing papers with those keywords for the first time in *Scientometrics* (*left*) and *PNAS* (*right*)

were extracted: “h-Index” and “Impact Factor” for *Scientometrics*, and “RNAi” and “Nano*” for *PNAS*. Keywords were chosen that represent topically diverse research areas at different stages of their lives in order to account for topic- or time-specific biases.

These four research areas are clearly very different in nature; however, without a clear corpus of every paper in a particular area, keywords were used which were unique and specific enough to encompass a great many papers surrounding a particular topic or method while still avoiding unrelated publications. The keywords “h-Index” and “impact factor” represent specific topics within the larger umbrella of performance indicators a rather active area of research in *Scientometrics*. “Nano*” represents a set of research related by several common factors and RNAi represents the study of or using a single biological system. It is a contention of this study that new and specific vocabulary is a close enough proxy to emerging cohesive research that it can be used in dataset selection. However, the mixed indicator approach presented here can be used with any canonical list of publications representing an area, topic, discipline, etc., and we hope to be able to use these indicators on more accurate lists as they become available.

Figure 5 shows the percentage of papers in *Scientometrics* or *PNAS* which contain each set of keywords. For example, the term “impact factor” appeared in 23 *Scientometrics* paper abstracts or titles in 2009, a total of 192 *Scientometrics* study were published in 2009, and hence the value for that keyword in 2009 is 11.98. The chart also includes the number of unique authors per year who published a paper with that keyword for the first time. The number of new authors from *PNAS* (Fig. 5, right) has been divided by 100 to fit the scale of the chart.

Emerging areas are preceded by word bursts

Table 1 shows all bursting words related to topics of “RNAi,” “Nano*,” and “h-Index”; no bursting words related to “Impact Factor.” All words are sorted by start year. For example, research on h-index is mostly focused on ranking measurements, scientists’ activities, and journal impact factor studies. The h-index was proposed in 2005 and words began bursting the next year. In this case, word bursts help pinpoint topics trends.

Table 1 Bursting topic words for "RNAi", "Nano*", and "h-Index"

Word	Strength	Start	End
RNAi			
messenger.rna	6.36	1993	2002
antisense.rnai	3.11	1994	2002
caenorhabditis.elegan	3.87	2000	2006
functional.genomic.analysi	3.09	2001	2003
double.stranded.rna	5.16	2002	2003
gene	2.96	2003	2005
Nano*			
express	6.73	1991	1999
bind	3.90	1991	2001
sequenc	3.77	1991	2003
rat.brain	4.83	1992	2001
gene	3.90	1992	1997
clone	3.48	1992	1999
site	3.18	1992	1996
inhibit	3.37	1993	2002
identif	3.48	1994	2000
design	4.01	2000	2003
microscopi	3.67	2005	2005
peptid	3.64	2006	2006
h-Index			
rank	2.97	2006	2007
scientist	2.56	2006	2006
journal	2.43	2008	

Emerging areas quickly attract new authors

To understand the attraction of emerging research areas to authors, all unique authors and the year of their first published paper in the dataset was found (see Fig. 6). Topics "RNAi" and "Nano*" experience a noticeable increase in the number of new authors. The number of new authors in "Impact Factor" and "h-Index" also increase remarkably quickly. The sudden increase of new authors to "h-Index" research after 2005 is attributable to the influence of Hirsch's paper published in 2005.

In future work we plan to analyze the origin of new authors (from what areas of science are they coming?) and to study their key features such as career age.

Emerging areas cite highly interdisciplinary references

It is assumed that papers in a new research area cite papers from many areas of research, as no papers yet exist in the nascent area. Thus, sudden increases in the diversity of cited references might indicate an emerging research area. In order to test the interdisciplinarity of the sets of papers containing "Nano*," "RNAi," "Impact Factor," and "h-Index," each set was mapped to the UCSD Map of Science (Klavans and Boyack 2009). This map clusters more than 16,000 journals into 554 disciplines and gives the similarity between these disciplines. An interdisciplinarity score (see Eq. 1) per year was given to "Nano*,"

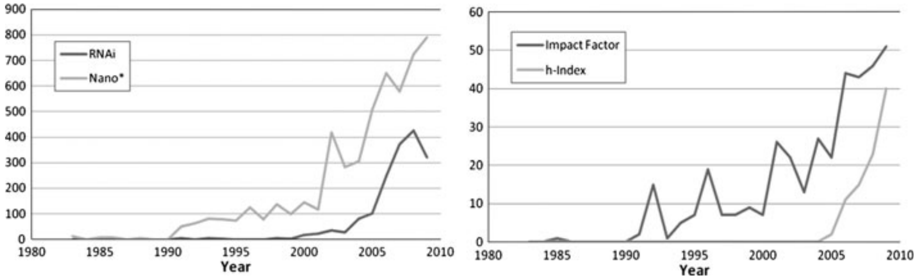

Fig. 6 Number of new authors per year for “RNAi” and “Nano*” research areas (*left*) versus “Impact Factor” and “h-Index” research areas (*right*)

“RNAi,” “Impact Factor,” and “h-Index” using the “Rao-Stirling diversity” (Rao 1982; Stirling 2007). The distribution of references in each paper across the map of science was calculated. Then, the “Rao-Stirling diversity” D was calculated for each pair of referenced disciplines on the map. The probability of the first discipline (p_i) was multiplied by the probability of the second discipline (p_j) and the distance between the two disciplines (d_{ij}), which was then summed for the distribution.

$$D = \sum_{ij(i \neq j)} p_i \cdot p_j \cdot d_{ij} \tag{1}$$

d_{ij} was calculated as the great-circle distance between disciplines, rather than the more standard Euclidean distance, because the UCSD map is laid out on the surface of a sphere. The result is an aggregate measurement of the diversity of individual papers and their references. We define this diversity as interdisciplinarity rather than multidisciplinarity because it measures individual paper references rather than the spread of references across an entire journal or dataset. Porter and Rafols (2009) also used “Rao-Stirling diversity” to measure how the degree of interdisciplinarity has changed between 1975 and 2005 for six research domains.

Figure 7 shows the interdisciplinary distribution of each set of documents per year over time. Several references could not be matched directly with journals in the UCSD Map of Science. If fewer than 50% of a paper’s references mapped onto the UCSD map, the paper was excluded from the analysis. Older papers were more likely to be excluded from the analysis, as the further back in time citations go, the less likely their journal would be represented on the UCSD Map of Science. The newest papers’ references also experienced a dip in their matches on the UCSD map, as they may have been citing journals too new to be mapped. Between 50 and 80% of *Scientometrics* references were not mapped, probably due to the high volume of monograph citations. This is one likely cause of the significantly different internal distributions of interdisciplinarity between *Scientometrics* and *PNAS*, whose references could consistently match to the UCSD map 70% of the time.

Average interdisciplinarity was calculated by taking the average interdisciplinary score across all papers in a given set per year. “Nano*,” “RNAi,” “Impact Factor,” “h-Index” and *Scientometrics* all show an increase in average interdisciplinarity of references over time (see Fig. 8). This may be an indicator that the areas are still expanding in the number and diversity of attracted authors and ideas from different areas. Interestingly, works published in all of *PNAS* since 1982 show virtually no change in their level of interdisciplinarity over time, demonstrating the continuous very high level of interdisciplinarity of papers in this journal.

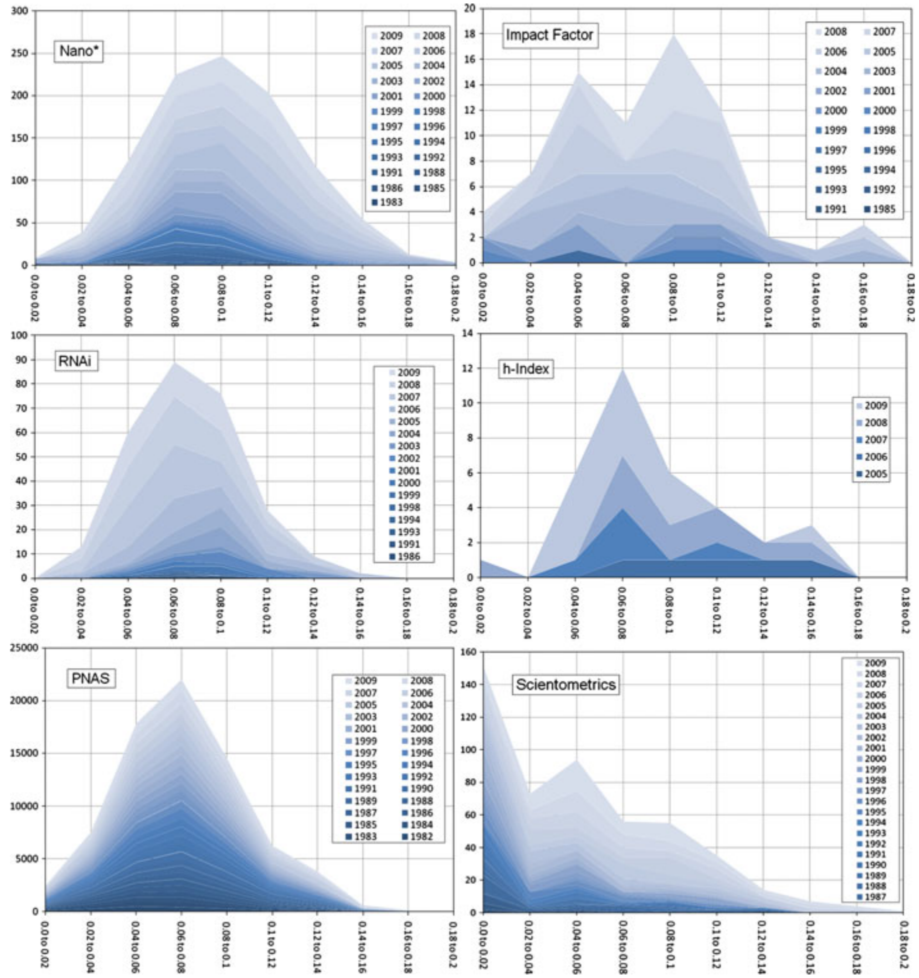

Fig. 7 Interdisciplinarity of references cited in "Nano*" (*upper left*), "RNAi" (*middle left*), "Impact Factor" (*upper right*), "h-Index" (*middle right*), *PNAS* (*bottom left*) and *Scientometrics* (*bottom right*) datasets. *Darker areas* indicate earlier publications, the y axis indicates the number of papers with a certain interdisciplinarity score, where $x = 0$ is the least interdisciplinarity possible

Model validation

Comparison of indicators

The three different indicators provide different insights. The number and type of bursting words is an indicator of the intensity and topical direction of change. The number of new authors an area manages to attract reveals the brain drain from other research areas to itself. The interdisciplinarity of paper references gives an indicator of the diversity and topical origin of the base knowledge from which the new area draws.

Each of the four datasets do have a steady increase in the number of new authors and interdisciplinarity scores which might be an indicator that all four of them are emerging

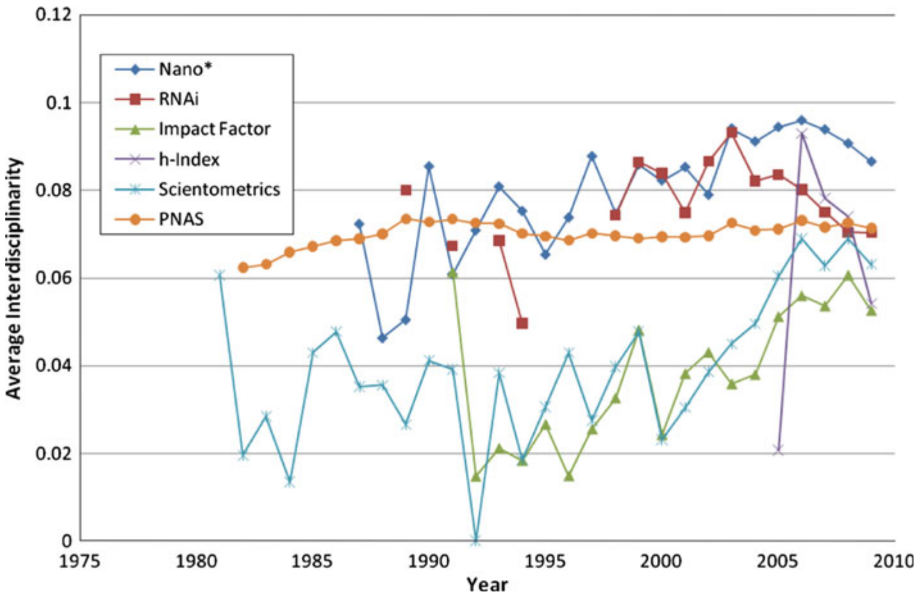

Fig. 8 Average interdisciplinarity of references cited in the six datasets per year

areas of research. More datasets, especially ones representing established or dying research areas, are needed to make more concrete conclusions.

Temporal dynamics

Comparing the temporal dynamics of the three indicators reveals correlations between them, see Fig. 9. The figure shows that the appearance of new authors always signified the beginning of an emerging area. In “Nano*,” “RNAi” and “h-Index” datasets, a sudden increase in the diversity of cited references occurred with the appearance of new authors simultaneously. Word bursts occurred 8 years later for “Nano*,” 7 years later for “RNAi” and only 1 year later for “h-Index.” For “Impact Factor” dataset, a sudden increase in the diversity of cited references occurred 6 years after new authors appeared. The correlation between increasing new authors and diversity of cited references suggests that new authors are coming from diverse established areas rather than some already nascent cohort with a pre-existing body of research.

Discussion and outlook

This paper presented, exemplified, and compared three indicators that seem to be indicative of emerging areas and have interesting temporal correlations: new authors enter the area first, the interdisciplinarity of paper references increases, then word bursts occur. Although the indicators are descriptive, they can be applied to identify new areas of research and hence have a certain predictive power.

The datasets used to validate the model have limitations. With only two journals, journal-specific rather than subject-specific trends might dominate. As *Scientometrics*

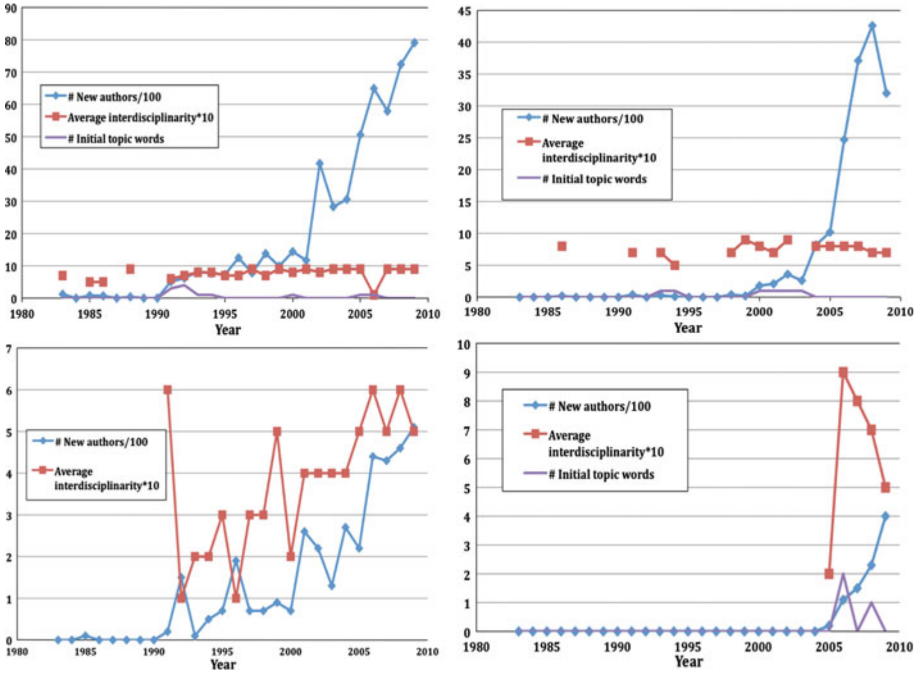

Fig. 9 Temporal dynamics of three indicators for “Nano*” (*upper left*), “RNAi” (*upper right*), “Impact Factor” (*bottom left*), and “h-Index” (*bottom right*)

publishes relatively few papers, keyword filtering resulted in even smaller sets. The use of two largely unrelated journals and two unrelated sets of keywords was an attempt to offset journal-specific or discipline-specific artefacts, as was the use of keywords at different stages of their popularity and use. Future work should use a larger and more diverse dataset of emerging research areas.

Diversity was measured using the UCSD Map of Science covering 2001–2005 data. However, the structure of science evolved continuously since the first paper in this study was published in 1978. Two problems arise: papers that were initially highly interdisciplinary but were part of a larger trend linking multiple disciplines in the future will be seen as less interdisciplinary than they ought to be. This may explain why *PNAS* seems to slowly increase in interdisciplinarity over time (see Fig. 8). Secondly, the UCSD map does not capture journals that ceased to exist before 2001 or did not yet exist in 2005 (see “Emerging areas cite highly interdisciplinary references” section). An updated version of the UCSD map covering the years 2001–2010 will soon become available.

Future work will add additional indicators (e.g., densification of scholarly networks during the maturation of a research area; a combination of lexical and citation based information) but also other datasets (e.g., data of mature or dying areas) to the indicator-by-dataset validation matrix to make sure the indicators are:

- efficient to calculate,
- predictive, i.e., give different results for mature or dying areas, and
- stable, i.e., are robust regarding data errors/omissions.

We welcome replications of this study and suggestions for improvements. The open source Science of Science Tool (Sci^2 Team 2009a) can be downloaded from http://sci2.cns.iu.edu. All workflows used in this study as well as the *Scientometrics* dataset are available online as part of the Sci^2 Tool tutorial (Weingart et al. 2010).

Acknowledgments We would like to thank Joseph Biberstine and Russell J. Duhon for developing custom queries and code and appreciate the expert comments from the three anonymous reviewers. This work is funded by the James S. McDonnell Foundation and the National Institutes of Health under awards R21DA024259 and U24RR029822.

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Scientometrics (2011) 89:437–463
DOI 10.1007/s11192-011-0432-8

Does cumulative advantage affect collective learning in science? An agent-based simulation

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Received: 6 June 2011 / Published online: 21 June 2011

Abstract Agent-based simulation can model simple micro-level mechanisms capable of generating macro-level patterns, such as frequency distributions and network structures found in bibliometric data. Agent-based simulations of organisational learning have provided analogies for collective problem solving by boundedly rational agents employing heuristics. This paper brings these two areas together in one model of knowledge seeking through scientific publication. It describes a computer simulation in which academic papers are generated with authors, references, contents, and an extrinsic value, and must pass through peer review to become published. We demonstrate that the model can fit bibliometric data for a token journal, *Research Policy*. Different practices for generating authors and references produce different distributions of papers per author and citations per paper, including the scale-free distributions typical of cumulative advantage processes. We also demonstrate the model's ability to simulate collective learning or problem solving, for which we use Kauffman's *NK* fitness landscape. The model provides evidence that those practices leading to cumulative advantage in citations, that is, papers with many citations becoming even more cited, do not improve scientists' ability to find good solutions to scientific problems, compared to those practices that ignore past citations. By contrast, what does make a difference is referring only to publications that have successfully passed peer review. Citation practice is one of many issues that a simulation model of science can address when the data-rich literature on scientometrics is connected to the analogy-rich literature on organisations and heuristic search.

Keywords Simulation · Cumulative advantage · Landscape search · Science models · Science policy

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Mathematic subject classification 91D10 (primary) · 91D30 · 90B70

JEL classification C63 · D83 · D85

Introduction

It has long been recognised that academic sciences show evidence of processes of cumulative advantage, or what Merton called 'the Matthew Effect' (Merton 1968, 1988): to those that have, more shall be given. That success breeds success Merton identified from Zuckerman's interviews with Nobel laureates (Zuckerman 1977). Within bibliometric data the telltale sign is a power-law, or scale-free, frequency distribution, as demonstrated for the numbers of papers per author (Lotka 1926; Simon 1955), and the numbers of citations per paper (Price 1976). Opportunities for publishing tend to go to those who already have papers to their name. References in a new paper tend to be made to publications already rich in citations. Most scientists will publish little and be cited little. A tiny minority of authors will enjoy a prolific publishing career, and a minority of publications will become citation classics. With this in mind, it might be asked what this concentration of resources and attention on so few academics and publications does for the advancement of scientific fields. Do collectives of academic scientists perform better for following the practices that generate cumulative advantage patterns? To answer such a question, it is not possible to rerun the course of science using an alternative set of publishing practices. Instead, we show in this paper that an agent-based computer simulation model of academic publication can provide insight into the role played by publication practices.

In what follows, we provide a brief introduction to the idea of modelling scientific publication. In the past this has been attempted through stochastic process models, and so we need to explain why agent-based simulation is called for. Both types of model employ simple micro-level mechanisms to generate macro-level patterns, but agent-based simulations can readily incorporate several such mechanisms in the one model. In particular, to address questions of scientists' performance we combine the mechanisms that lead to cumulative advantage with those of searching for better solutions to problems. These latter mechanisms, called heuristic search algorithms, have already been incorporated in simulations of organisational learning (March 1991; Lazer and Friedman 2007), and so our model connects this field to that of science modelling. We then describe the simulation model, flagging up some issues involved in its design and highlighting where alternative design decisions could be taken. With the help of bibliometric data from a real journal, *Research Policy*, we calibrate the model, and then perform an experiment with it, by varying the mechanism by which references are created for each new paper. This suggests that the cumulative-advantage process operating on citations has little or no effect on search performance, that is, on scientists' ability to find good solutions to scientific problems. This is in contrast to the effects on search performance of filtering papers for publication, achieved through peer review and through a preference for recency when selecting which papers to refer to. However, this paper is only intended to give an indication of the opportunities offered by computer simulation, and we end with some pointers for further research. In spelling out here the structure and issues behind the model we hope to inspire other attempts at designing and validating simulation models capable of providing insight into scientific organisation and performance.

Models of science

Empirical patterns to be explained with stochastic models

Activity by academics and scientists leaves a data trail of their publications that readily lends itself to modelling. In the age of electronic databases of journal publications this kind of data is widely available, but awareness of its patterns predates these. As noted already, Lotka (1926) showed that the numbers of papers per author followed a power-law or scale-free distribution, while Price (1976) found such a distribution for citations per paper. Price (1963) had earlier observed exponential growth rates in papers and authors in the field of physics and reflected on the implications of this.

To explain how these distributions come about, a model of a stochastic process, or *urn model*, is usually employed. Simon (1955) presented a simple stochastic-process model to generate a scale-free frequency distribution, and fitted it to Lotka's data. Items which could be new papers or references in new papers are allocated to selected 'urns' or categories, such as authors. In the case of the power-law distributions, the stochastic process involved growth over time in the number of urns, and some kind of cumulative advantage: those rich in papers or citations were expected to get richer.

Contributions to science modelling since Simon have explored the mathematical implications of such stochastic process models (Schubert and Glaenzel 1984; Glaenzel and Schubert 1990, 1995; Glaenzel and Schubert 1995; Burrell 2001). For example Burrell (2001) relates the citation process to the ageing and eventual obsolescence of papers. Redner (1998) argues for there being at least two mechanisms generating citations in the data he analyses, including one for more highly cited classics. Burrell (2007) employs a stochastic model to estimate the behaviour under different conditions of Hirsch's h-index for measuring research output and impact based on citations.

Beyond simple distributions of papers and citations, bibliometric data have also yielded networks of relations for analysis. Price (1965) relates papers by citations. Newman (2001a, b, c) relates co-authors by their having collaborated together on at least one paper. He then employs social network analysis metrics, including node degree or the number of co-authors, centrality and the shortest path between pairs of nodes, and clustering or the extent to which my neighbours are neighbours of each other. With increased interest in simple processes by which 'small-world' and 'scale-free' networks may be generated (Watts and Strogatz 1998; Barabási and Albert 1999; Watts 2004), it seems desirable to extend science models to explaining network patterns as well as distributions (Boerner et al. 2004).

At this point it becomes desirable to employ computer simulations and so-called 'agent-based', 'multi-agent' or individual-level simulation models in particular (Axelrod 1997; Gilbert and Troitzsch 2005). Mathematical treatments of network formation, like those of distribution formation, are certainly possible (Newman 2003). But for non-specialists, simulation has a number of advantages over mathematical models (Gilbert and Troitzsch 2005), not least that it can model agents as heterogeneous in behaviour rules, attributes and location in pre-existing network structures. When one wants to combine several interacting processes or factors in modelling the behaviour of scientific authors, mathematical analyses become too difficult compared to the programming and exploration of simulation models. In the case of modelling publications, mechanisms that generate the distributions of papers per author, the distributions of citations per paper, the growth over time in numbers of papers and authors, and ideally also the structures in the networks formed by co-authorship and co-citation all need to be combined.

A concept of knowledge seeking as organisational learning

Scientific publications offer the opportunity to inform others of one's findings, obtain validation for one's work through others' responses to it, and provide the starting points and stepping stones for future research. It is hard to represent this aspect of science through stochastic-process models. In the field of organisational studies, however, there is a tradition of constructing computer simulations of humans' collective problem solving, or 'organisational learning' (March 1991; Lazer and Friedman 2007). This offers two additions to the components of a science model: methods of problem solving, and representation of the problems to be solved or the knowledge to be found.

Beginning with Simon's conception of human actors as 'boundedly rational', it has been proposed that problem solving in the workplace involves heuristics (March and Simon 1958; Cyert and March 1963). Psychological studies in the 1970 s and 1980 s bore out this view (Kahneman et al. 1982). Heuristics are simple principles or rules of thumb for seeking solutions to problems that would require impractical amounts of time and other resources to solve by exhaustive search methods. While not guaranteed to find the optimal solution, heuristic search algorithms are used to obtain sufficiently good solutions within a reasonably short number of search steps. It has been proven that no heuristic algorithm will perform well in every situation (the 'no-free-lunch theorem', Wolpert and Macready 1997), but experience has shown several methods perform well on a variety of problems in which different combinations of values must be explored to find a solution.

The use of relatively simple rules to make decisions among combinations of fixed sets of values make heuristic search processes particularly easy to replicate in computer code. Many simulation models of learning in organisations employ combinations of heuristics, including trial-and-error exploration, learning from successful others (either through direct imitation or some more indirect channel for social influence) and recalling past successful ideas. In March's (1991) model of organisational learning, good search performance for a limited amount of search resources requires a balance between the *exploration* of new views, and the *exploitation* of those already evaluated. If the population of searching agents is too diverse, agents will spend much of their time exploring variations of poor solutions, not good ones. If the agents converge in their solutions too soon, however, search comes to an end, with a consensus solution that may not be very close to the optimum. Constraints on the processes that lead to convergence thus become important for search performance (Lazer and Friedman 2007). These have included organising agents into social networks (which then restrict who can imitate whom) and restricting imitation so that imitator agents make only partial copies.

The behaviour of scientists publishing within academic fields has also been compared to heuristic search (Scharnhorst and Ebeling 2005; Chen et al. 2009). Various algorithms offer potential analogies for aspects of scientific publication. By insisting on new papers being original contributions to knowledge, authors are forced to explore more widely, in a similar manner to *tabu search* (Glover 1989, 1990). The combination of ideas from multiple co-authors and multiple references produces both exploration of new combinations, but also the exploitation of past experience, perhaps the main attraction of *genetic algorithms* (Mitchell 1996). The sharing between authors of information about past experiences resembles *particle swarm optimisation* (Clerc and Kennedy 2002). Search performance by swarms of agents can be improved through dividing the agents into *tribes*, whose members only communicate information within their own tribe, and *roles*, where 'managers' maintain a record of the best solution found so far while 'workers' concentrate on further exploration (Clerc 2006; Jin and Branke 2005). There may be scope for clustering and stratification among scientists to produce analogous effects.

Sandstrom (1999) compares information seekers to foraging ants, themselves the metaphor for another heuristic search algorithm, *ant-colony optimisation* (Corne et al. 1999). Recently successful foragers attract others to re-use their paths rather than the paths of the less successful foragers or those that are older and potentially out-of-date. Having attracted more foragers to them, the signals to good paths become renewed more often and with greater strength. Thus under a cumulative-advantage principle, relatively short paths to good sources become increasingly easy to identify from their relative popularity. In like manner when constructing reference lists for a new academic paper a preference for the already well-cited causes some papers to emerge as ‘citation classics’ that other researchers can be relied upon to be familiar with (Merton 1968). This suggests that practices among scientists that generate the Matthew Effect serve to simplify the task of new entrants to a field by selecting the most important texts, and the shortest path to the research frontier. But the organisational learning models also suggest that there may be a need for some balance between exploration and exploitation. Does cumulative advantage operate too fast among scientists?

It may not be possible to answer this question for real scientists. But one *can* begin to answer it for a simulated search of an artificial problem space and then draw an analogy with human systems (Steels 2001).

One analogy is based on the use of *similarity* or proximity. To get accepted by journals, scientists’ publications must satisfy two sources of constraint on their contents: originality and similarity. With respect to similarity, they must be intelligible and relevant to readers, especially peer reviewers. With respect to originality, publications must differ from what has been published before, or at least from what a reviewer has read before, but their contents cannot be *too* unfamiliar. To be recognised as a contribution to the journal’s field certain keywords, paradigm problems or classic references must be mentioned because they are the symbols of membership to this field.

It might be asked, however, whether scientists also face some *extrinsic* source of value and constraint for their work, call it ‘material reality’. In this conception, scientists’ activities have costs in material resources and time, and their publications describe activities and equipment that may be prone to failure and breakages if the science justifying them is in some sense wrong, or out of tune with reality. To simulate problem solving activities addressing this external reality we can borrow the notion of a *fitness landscape*, often used when discussing problem solving using heuristic search methods (Kauffman 1993). The use of various tools and techniques is represented by a set of variables. In the simplest case, these are binary variables, representing presence or absence of some idea, material, technology or practice. The combinations of values of these variables describe the coordinates of a position in some multi-dimensional space. The fitness value of occupying that position, that is, the benefit or cost incurred by employing the particular combination of tools and techniques, can be thought of as the altitude at that point on a landscape. The most desirable combination becomes the tallest peak, but a rugged landscape may have multiple peaks of varying height. A heuristic search method, such as performing a random walk and rejecting any local step that goes downhill, may lead to a nearby peak, but is not guaranteed to find the tallest peak in the whole landscape. The more rugged the landscape, the harder it is to find good peaks. Heuristic search algorithms typically involve many agents each performing searches from various starting positions, sometimes with the sharing of information between search agents about the heights reached.

One fitness landscape suitable for simulating heuristic search is Kauffman's *NK* model. Initially presented as a theoretical model of biological evolution (Kauffman 1993), this has since been reapplied in models of technological evolution (Kauffman 2000), strategic management (Levinthal 1997; Levinthal and Warglien 1999; McKelvey 1999) and organisational learning (Lazer and Friedman 2007). Among its attractions are that it is relatively simple. A solution, or position on the landscape, consists of a string of *N* binary variables. It uses just one other parameter, *K*, the number of interdependencies between binary variables. Using this parameter, one is able to 'tune' the model to produce landscapes of varying ruggedness, and thereby varying degrees of difficulty for heuristic search. The use of this landscape in different models also means that it is possible to transfer code between and compare experiences of programs written for different audiences. Against the use of the *NK* model, however, is the fact that it lacks any empirical foundation. Whether one is interpreting it as a model of biological evolution or of organisational learning, the numbers that go into defining the *NK* fitness landscape are arbitrary and have no empirical referent.

That scientists seek better combinations of tools, techniques and other components is plausible enough. The literature from actor-network theorists contains many examples of scientists and other interested parties negotiating the satisfaction of their varied and often conflicting demands (Latour 1987), a pattern repeated in analyses of technological projects (Latour 1996; Law and Callon 1992). Kauffman (2000) also draws an analogy between technological evolution and constraint satisfaction problems. However, if the effectiveness of scientists' search practices is to be replicated in simulations it will be desirable to match as far as possible the structure of the problems faced by real scientists. Realistic landscapes may be derivable from bibliometric data (Scharnhorst 1998), just as 'maps' of science have been drawn up based on co-citation and co-word relations. Scharnhorst (2002), for example, describes inferring the structure of a 'valuation landscape' from rates of change in the proportion of papers being published in particular areas. So although the *NK* landscape model has sufficed for models of organisation learning, more plausible looking landscapes for science models may yet emerge from future research.

Agent-based science models

Stochastic process models give insight into the generation of the patterns observed in bibliometric data. Models of organisational learning show how heuristic search algorithms applied to fitness landscapes can help with understanding how problem-solving performance in social groups depends upon communication practices, especially those that determine the rate at which past solutions are borrowed. A good science model should aim at combining these processes. It should generate patterns analogous to those seen in real journal publications and it should reflect the fact that scientists' activities serve a purpose, namely that of seeking knowledge or solving problems.

Agent-based simulation models already exist that capture some of these components. Whereas Simon's (1955) urn model simply generated a frequency distribution for papers per author, Gilbert (1997) represented individual academic papers with references to past papers and some contents. Using two continuous variables to represent paper topics, his model depicts an academic field as a two-dimensional plane. Subfields appear within this model as clusters of points. The *TARL* model ('Topics, Aging and Recursive Linking') of Boerner et al. represents both authors and papers, including references and 'topics' for papers, and generates network data. In both of these models, the contents of papers are constrained. For example, papers must be both original, that is, occupy distinct coordinates in the plane, and also sufficiently similar to the papers they refer to, that is, occupy a point within a radius of some given size from their reference papers. But in neither of these models do papers undergo any kind of selection for the extrinsic value of their contents. Drawing on models of organisational learning, we propose to remedy this. Weisberg and Muldoon (2009) also employ landscape search as a model for science. In the 2009 'Modelling Science' workshop at the Virtual Knowledge Studio, Amsterdam, there were several researchers working on simulation models of different aspects of science, including Muldoon on the division of labour among scientists, Payette on modelling 'science as process', and Wouters on the peer review system. (See the presentations available at http://modelling-science.simshelf.virtualknowledgestudio.nl/.) Agent-based models now promise to take the discipline of scientometrics far beyond the scope of stochastic-process models.

Outline of the model

Figure 1 summarises the simulation.[1] At initialisation, a number of 'foundational' publications are written. Being foundational these make no reference to other papers but may be referred to by later papers. Thereafter, at each time step a number of new papers are written. The number added grows geometrically over time at a given rate. For each new paper a number of authors, a number of references to past papers, some contents for the paper and their extrinsic fitness value, and a number of peer reviewers are generated. The paper then undergoes review by the reviewers. The prime determinant of the review's outcome is a paper's fitness as a solution to some extrinsic, complex problem, as defined by a fitness landscape. Papers that satisfy peer review become journal publications. Optionally, the mechanisms for generating authors, references and reviewers can be restricted to publications rather than all papers. Papers compete to become cited through the fitness value of their contents. The selection pressure placed on them is intended to produce ever-fitter solutions or knowledge as the academic field grows.

Generating authors

Every paper needs at least one author. As in Simon's urn model (Simon 1955), there is a given chance that this is a new agent with no previous papers in this field. A new agent has no past papers, but does have opinions concerning this scientific field, represented as a bit string of length $N = 20$. If the author is not new, then one is selected from the stock of existing authors, using one of four methods (Table 1). There are two key distinctions involved. Firstly, we distinguish between using a past journal *publication* (options 2 and 4), and using a past, written *paper*, which may or may not have been published (options 1 and 3). Secondly, we distinguish between selecting authors from recent papers/publications (options 1 and 2), thus showing a preference for *recently prolific authors*, and selecting authors from papers contained in the reference lists of recent papers/publications (options 3 and 4), thus favouring *recently well-cited authors*. So depending on which option is

[1] The simulation model, *CitationAgents1*, was developed initially in *VBA* within *Excel 2003*, and then, after a break of several months, reproduced using *NetLogo 4.1*. Replicating a simulation model in this way helps to verify that the program is working as intended. The extra work involved in replicating the model was worthwhile, as several minor errors in the original version were exposed. A version of it may be downloaded from *OpenABM*: http://www.openabm.org/model/2470.

Fig. 1 Stages in the simulation model

```
Generate foundational publications
For each time step
    For each new paper
        Generate first author
        Generate list of co-authors
        Generate list of references
        Generate contents
        Calculate fitness of contents
        Generate list of peer reviewers
        Decide whether paper becomes journal publication
    Next new paper
    Output periodically statistics on simulation evolution
Next time step
Output final statistics and distributions
```

Table 1 Author-selection options: for choosing which past authors become authors of a new paper

1. Select author from a *recent paper* (published or unpublished)
2. Select author from a *recent journal publication*
3. Select author from *a paper in the reference list* of a recent paper. (If the recent paper has nothing in its reference list, then select from its own authors instead.)
4. Select author from *a paper in the reference list* of a *recent journal publication*. (If the reference list is empty, select author from the authors of the recent publication instead.)

chosen, prolific authors may become more prolific (options 1 and 2, a rich-get-richer principle), or writing opportunities may go to authors with *many publications* (option 2), or to those with *many citations* (options 3 and 4), the last being often suggested as a measure of the quality of a publication.

When selecting authors, preference might be given to the most prolific and recent authors (emphasising recent quantity, not quality), but authors whose output is unread or unrated often command little respect and struggle to attract those resources (doctoral students, research funds, writing sabbaticals) that help in the generation of new papers. Selecting from publications rather than papers is one way to ensure that what is chosen has passed a quality assessment. If instead recent citations are preferred, those whose past works are currently in fashion or well read are rewarded. In addition an author may be spurred into action by a new paper critiquing one of his or her own, for conflict in intellectual social circles is particularly energising (Collins 1998). This points towards using options 3 and 4 in the experiments below.

Real authors also age and the author of a citation classic might not be active in the field anymore. Both Gilbert (1997) and Boerner et al. (2004) represent authors as having an 'age' or duration in the field. Authors' ageing may be added to future versions of the model, but for now it is assumed that even early arrivals last the whole of the simulated period (30 years).

To model the *recency* of papers stratified sampling is used. Past papers are weighted for sampling with a Weibull function of the age of the paper. There are several reasons for choosing the Weibull function for definitions of recency (as well as for numbers of authors and references per papers). It is parsimonious, taking only two parameters: alpha, controlling variability, and beta, controlling basic rate. It is faster to compute than certain other functions such as log normal, yet depending on its parameters it can approximate the bell curve of a normal distribution and the skew of a log normal, and produces the negative exponential when alpha is 1. Analysis of bibliometric data (see the next section) suggested it could be fitted via maximum likelihood estimation to the empirical distributions for authors per paper and references per paper. Boerner et al. (2004) employ it to represent *aging*, and we do likewise, but call it *recency*.

It is, however, based on a *continuous* random variable while time steps come in discrete values, as do the numbers of authors and references. To sample discrete values that are approximately Weibull distributed the continuous space is divided into discrete bands of equal width. So if $\text{Weibull}_{CDF}(x)$ is the cumulative distribution function, the probability of a discrete random variable taking the non-negative integer value x is given by:

$$P(\mathrm{X} = x) = \text{Weibull}_{CDF}(x{+}1) - \text{Weibull}_{CDF}(x).$$

Papers can have more than one author in the model. The number of attempts to add co-authors varies according to a Weibull distribution. After the first, initiating author has been selected, selection of any co-authors employs the same chosen method described above. Although authors may vary in their beliefs or opinions concerning the field, in this version of the model there are no constraints on which authors may write together.

Generating references

The generation of the list of references is similar to generation of authors. A number of attempts are made to add items to a paper's reference list. A Weibull distribution determines this number. Several options are available for the method of selecting papers to become references (Table 2). As well as selecting any past paper or publication without preference (options 5 and 6), there are the options for selecting a paper or publication with preference for recency alone (1 and 2), and selecting with preference for the recently cited (3, 4). Again a Weibull distribution's parameters control the definition of 'recent'.

Two of the options (3, 4) equate to copying references from existing papers. As with Simon's (1955) model and the process for selecting authors, there should be the possibility of introducing new suggestions rather than always copying previous ones. Therefore, for these options, there is a fixed chance that the generated reference is directed at the (recent) paper selected, rather than directed at one of the selected paper's references. This parameter turns out to have some influence over the model's ability to approximate power law distributions of the numbers of citations per paper.

As when authors from past papers were sampled, there are again the options of rewarding the recent or the recently cited, and the publications that satisfied peer review. The organisational learning models (March 1991; Lazer and Friedman 2007) model only the generation of new solutions in one time step using the solution information held in the immediately preceding time step. This is in sharp contrast to science models that allow for copying references to cited papers that are potentially much older than the (recent or otherwise) citing papers. Academic fields vary in their use of older sources, from perhaps

Table 2 Paper-selection options: for choosing which papers become references in a new paper

1. Select a *recent* paper (published or unpublished)
2. Select a *recent* journal publication
3. Select item from the reference list of a *recent* paper
4. Select item from the reference list of a *recent* journal publication
5. Select from all existing papers without preference
6. Select from all existing publications without preference

physics at one extreme, to footnotes-to-Plato philosophy at the other, suggesting that references can play different roles. For this paper, only their role in providing material for new solutions to problems is modelled, not any role that references to classics might play in signalling membership and evoking a sense of belonging to a tradition.

Generating contents and fitness

The authors and references for a paper are employed in the generation of that paper's contents. Each author has a vector of binary variables representing his or her opinions, beliefs or preferred practices within the field. The contents of papers are encoded as a vector of binary variables of the same length, N. When constructing a new paper, for each variable a value is sampled. With a fixed chance (0.01), this comes from a Bernoulli-distributed random process, in which case it represents the possibility of a new discovery or practice entering from outside the field, and hence not obtained from the literature. Otherwise, the value is sampled from the set of contents of all papers in the references and from the opinions of all authors of the new paper. Thus, like genetic algorithms (Mitchell 1996), the production of content involves both mutation and recombination processes.

When values have been sampled for every variable, a fitness value is calculated for the corresponding bit string. Like Lazer and Friedman (2007) in their model of organisational learning, the fitness value is taken from Kauffman's *NK* fitness landscapes using Lazer and Friedman's choice of parameters ($N = 20$; $K = 5$), which generates a moderately difficult landscape to explore. Descriptions of this fitness measure have been given in detail elsewhere (Kauffman 1993, 1995, 2000; Levinthal 1997) but we recap briefly here. For each of the $N = 20$ bits or variables there exists a table of fitness values and dependency relations to other variables. A variable's fitness table has one row for every combination of values (1 or 0) of that bit plus its $K = 5$ dependency variables—i.e. $2^6 = 64$ combinations or rows. The network of inter-variable dependency relations is randomly assigned at the start of the simulation. Given the current state of a variable and its K neighbours, the corresponding row of its table is examined. In each row there is a number, set at the start of the simulation by sampling from a uniform distribution (0, 1). This is the current contribution to total fitness for that variable. The actual fitness value for a paper or author is the mean fitness contribution from all N variables or bits.

Given fitness values, papers may be ordered as more or less fit in their contents or solutions, and authors in their beliefs. The fitness values have two consequences. Firstly, if an author has just co-constructed a paper with a better solution than that represented by the author's own beliefs, then the author updates its beliefs with the paper's contents. Secondly, fitness values are compared when peer reviewers evaluate a new paper.

Generating peer review and publication

A completed paper is evaluated to decide whether it will become a journal *publication*. Peer reviewers are selected for a new paper using a method chosen from the same list as that for selecting authors (Table 1). The choice might be between recently active authors, more likely to be junior researchers building their experience of the field, and well-cited, well-regarded senior academics, confident in their interpretation of what should or should not be accepted. Of course, juniors often collaborate with seniors on a paper so the distinction may not be as significant in the real world as it can be in the simulation. We shall focus on option 2 here: preferring as reviewers the authors of recent publications.

Nine attempts are made to find peer reviewers. Papers are rejected if the number of reviewers recommending the paper is below a threshold (set to 3). These numbers are chosen arbitrarily: although the journal *Research Policy* does claim to send submitted papers to three referees, how its editor chooses these we do not know.

A reviewer recommends a paper if:

- The reviewer is not an author of the paper,
- The paper's contents are not identical to the reviewer's own beliefs,
- The paper's contents are not identical to those of any of its referenced papers, and
- The paper's fitness value is not less than that of the reviewer.

Having non-inferior fitness to that of reviewers is a strong requirement. The simulated authors and reviewers have perfectly accurate estimations of the value of their papers and of their own beliefs. The costs and benefits of real academic papers may be much harder to judge and inferior papers do sometimes creep into print, their errors to be identified later. One solution to this modelling issue would be to introduce softer methods of fitness evaluation using stochastic elements, such as those used by the search algorithm of *simulated annealing* (Kirkpatrick et al. 1983), but this would add more parameters to the simulation and is omitted for the present.

Generating output data

The simulation outputs frequency distribution data: authors, references and citations per paper and per publication, and papers and publications per author. It also plots the growth of the field as the numbers of papers, publications and authors over time. Network data on collaboration (co-authorship) and citation relations can also be generated and analysed. In common with the organisational learning models, statistics concerning the fitness of the solutions currently contained in papers and agents' opinions are calculated. By plotting these over time search performance can be compared with the evolution in the field.

Calibrating the model: the case of *Research Policy*

Validation strategy

A good simulation model should provide knowledge and understanding that one would like to have had from a real-world system, but for practical reasons cannot obtain (Ahrweiler and Gilbert 2005). To address what-if questions about the science system, simulation models should occupy the middle ground between being, on the one hand, a detailed replica of some complex social system, and on the other hand some abstract mathematical construction that is difficult to derive real-world implications from. The former involve too much work in designing, programming, validating and computing to be of practical use. To obtain an answer, things need to be left out of the model. On the other hand, a science model needs to be a plausible representation of scientists' activities, and not just a mathematician's fiction. With this caveat in mind, parameter values can be sought that fit the simulation model to some real bibliometric data. This step is common to previous presenters of science models (Simon 1955; Price 1976; Gilbert 1997; Boerner et al. 2004). The speed of the simulation is such that trial-and-error exploration of the simulation's parameter space suffices for obtaining the following fits. To achieve this, however, the model is simplified in one important respect: agents' problem-solving capabilities are

Table 3 Summary of model parameters, with example values

Parameter description	Example value
Field parameters	
No. of time steps	30
No. of foundational publications	14
No. of papers added in first year after foundation, P_1	16
Field growth, G (# papers to be added at time $t = P_1 * G^{(t-1)}$)	1.067
Authors parameters	
Method for selecting authors	2 or 4 (Table 1)
No. of authors per paper: 2 parameters (alpha, beta) for a Weibull distribution	1.4, 1.3
Chance of author being new to field	0.6
Author Recency: 2 parameters (alpha, beta) for a Weibull distribution	1.3, 1
References parameters	
Method for selecting papers to cite	4 (see Table 2)
No. of references per paper: 2 parameters for a Weibull distribution	1, 4.2
Chance of using recent paper itself rather than copying its reference	0.3
Reference Recency: 2 parameters for a Weibull distribution	1.3, 2
Contents parameters	
Chance of innovation in one bit during contents construction	0.01
No. of bits of information in paper (the *N* in *NK fitness landscape*)	20
No. of interdependencies between bits (the *K* in *NKfitness*)	5
Peer Review parameters	
Method for selecting past authors to be peer reviewers	2 (see Table 1)
No. of attempts to find reviewers for paper	9
No. of recommendations required for publication	3
Reviewer Recency: 2 parameters for a Weibull distribution	1, 4

omitted by setting all fitness values to 1, irrespective of paper contents or author beliefs. This means that peer review is doing nothing more than checking for originality. The *NK* fitness landscape is then reintroduced, but data fitting while using the fitness landscape is a much harder task. A summary of the parameters employed in the simulations is shown in Table 3.

Growth over time

Desiring a small-scale simulation for faster runtimes during experiments, we took data from *ISI Web of Science* for a single journal, *Research Policy*, which sits at the heart of its particular field, innovation studies. Founded in 1974, this journal has shown fairly steady increases in its growth, in terms of both the number of papers per year and the number of authors per year. Taking 1974 to be the model's year 1 (so omitting the foundational papers used for initialisation, which appear in year 0), Fig. 2 shows the number of papers per year for each year thereafter, and the total number of papers for a typical run of the simulation, as well as the real data from *Research Policy* (hereafter *RP*). The results were obtained assuming 14 foundational papers, 16 papers in year 1, and each year thereafter the number of new papers was 1.067 times that of the year before. After 30 simulation iterations the number of papers generated was 1432, comparable with the 1389 papers

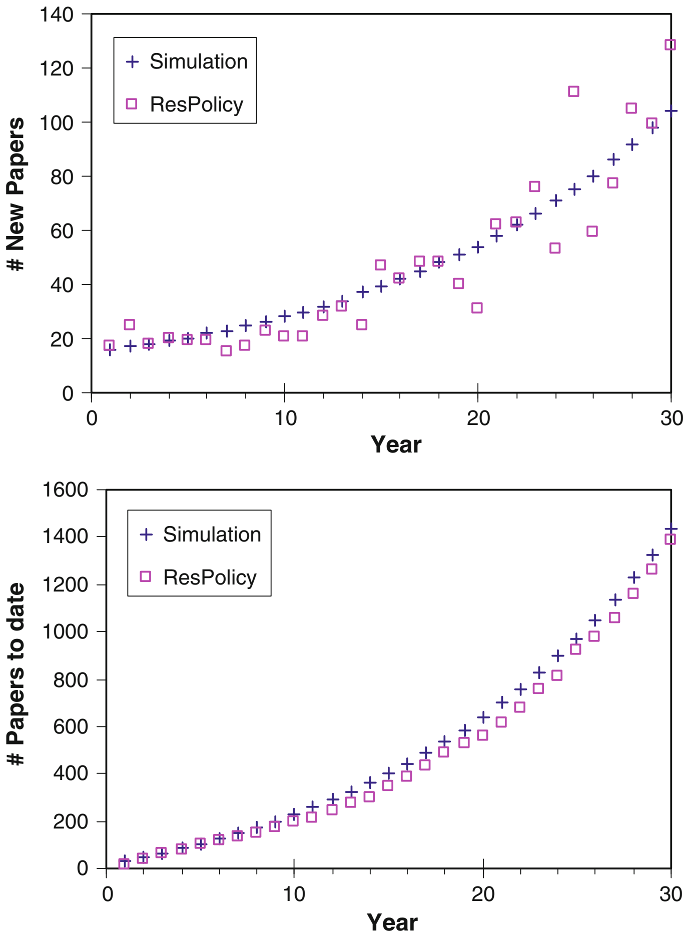


Fig. 2 Field growth: (*top*) the number of papers added to the field each year and (*bottom*) the total number of papers to date. Output from a typical simulation run (*crosses*) is shown with actual data from the journal *Research Policy* (*squares*)

published in *RP* by end of 2003, or model year 30. So far, this shows only that the field is growing exponentially.

Matching the number of authors per year is also straightforward. By 2003, the simulation model's Weibull function approximates the actual distribution of authors per paper for each year (Fig. 3). The mean number of authors per paper rose slightly during the 30-year period for *RP*, but for simplicity constant parameter values were assumed in the simulation: *alpha* = 1.4; *beta* = 1.3. The number of authors available for writing the papers grows over time. Starting with an empty field, all the authors in the journal's volume for 1974 must be new to that journal. However Fig. 4 shows a fall over time in the proportion of authors in a year's volume who are new, that is, publishing in the journal for the first time. Again for simplicity, the simulation assumes a constant chance of an author of a paper being new to the field: 0.6. This assumption of a constant chance is common to the models by Simon (1955); Gilbert (1997) and Bentley et al. (2009). The combination of

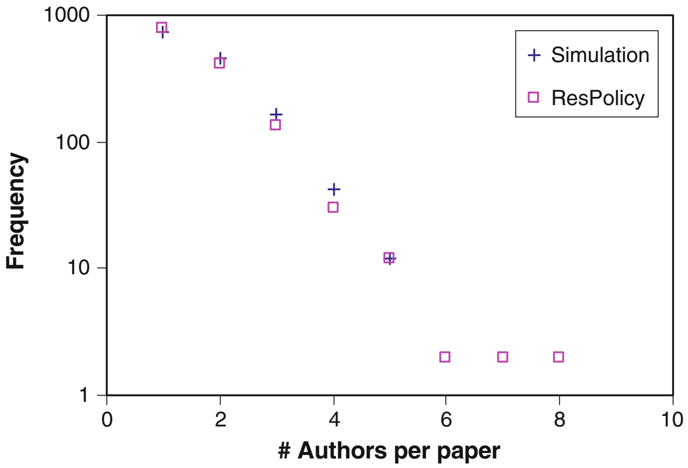
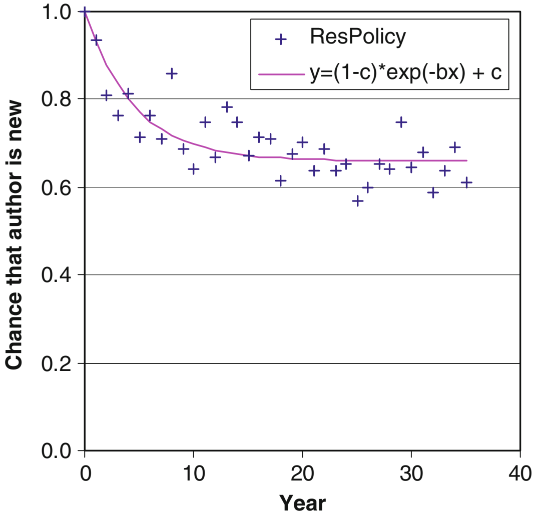


Fig. 3 Number of authors per paper after 30 years: probability density functions fitted for a typical run of the simulation and for *Research Policy*

Fig. 4 Proportion of the authors publishing in each year who are new to the journal *Research Policy*



number of authors per paper and proportion of authors who are new to the field gives the growth in authors seen in Fig. 5, with the corresponding figures for *RP*.

Distributions: authors and papers

When the authors for a new paper are not new to the journal, they can be found from earlier papers. For sampling them, options 2 or 4 from Table 1 will generate a similar distribution. Figure 6 (first chart) shows the distribution from a typical run for option 4, plotted against the empirical distribution from *RP*. In addition, Fig. 6 (second chart) shows a line with an exponent of −3.07, the average exponent from power laws fitted to the results of 20 simulation runs. The exponents for the 20 fits ranged from 2.99 to 3.18.

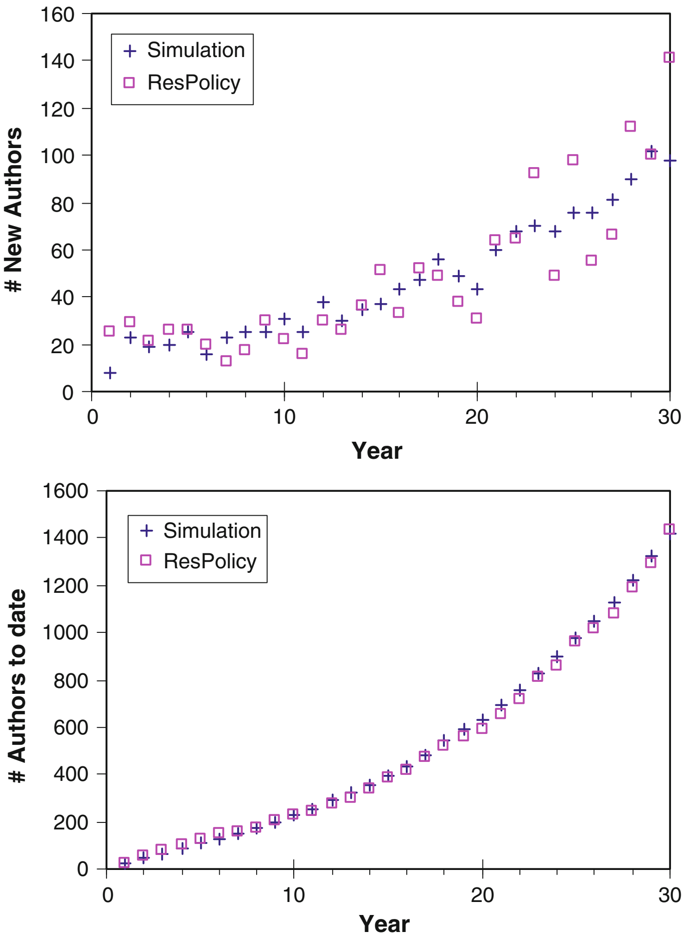


Fig. 5 Growth in authors in a typical run of the simulation and in *Research Policy*: (*top*) new arrivals for each year; (*bottom*) total authors to date

One other aspect of authorship remains to be defined, that of *recency* when selecting publications to obtain authors. To determine this, relations across time between papers having a common author are examined. Taking all pairs of papers that share at least one author and restricting attention to those pairs where the latest paper of the pair was published in year 30, Fig. 7 shows plots for the simulation and *RP* of the distribution of time gaps between these common-author papers. Like the papers-per-author distribution, and unlike the growth curves and authors-per-paper distribution, the simulation's distribution is a non-trivial outcome of its workings. Decisions concerning the method of selecting authors, including the definition of recency, will affect this distribution. The weighting of 'recent publications' used a Weibull function of the time since their publication with parameters *alpha* = 1.3 and *beta* = 1. The simulation output shown is the aggregate results of 20 simulation runs with 95% confidence intervals for each data point.

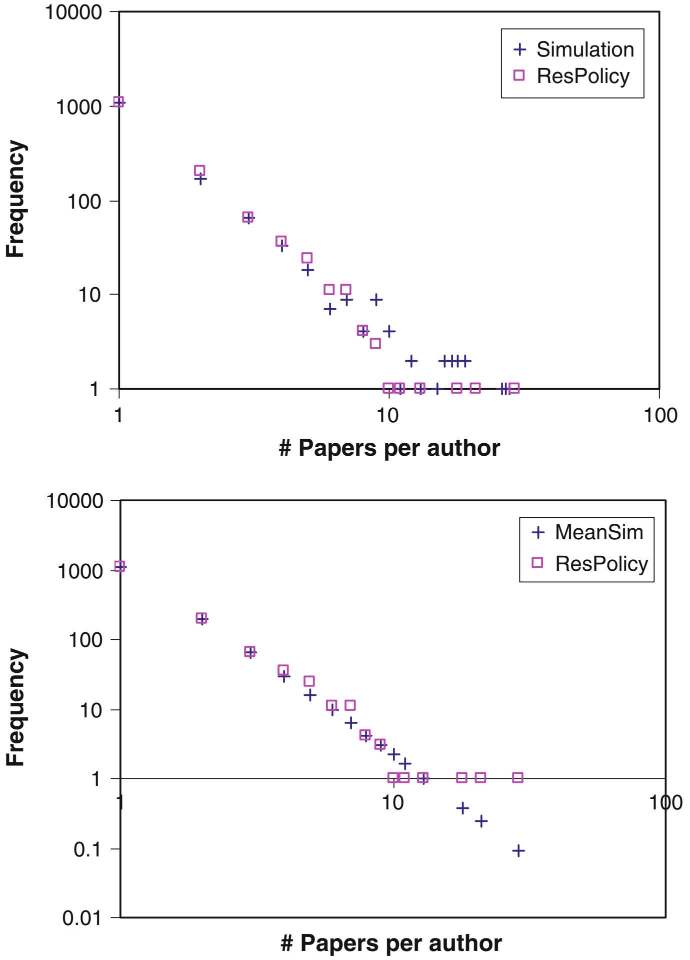


Fig. 6 Frequency distributions of the numbers of papers per author: (*top*) a typical simulation run; (*bottom*) curve taking the mean exponent from power laws fitted to each of 20 simulation runs

Distributions: references and citations

Turning now to the generation of references, there is a problem. The papers of any journal contain references to papers in other journals, including those written prior to the foundation of the target journal. To simulate the journals outside the target would be prohibitively complicated. The solution taken here is to restrict attention to references that point to other papers inside the target journal. Other modellers might try different solutions.

Having made this simplification, there are several data-fitting tasks analogous to those faced for authors-related distributions. The distribution of the numbers of references per paper can be taken straight from the bibliometric data. The Weibull distribution has again been used for this (*alpha* = 1, so equivalent to a negative exponential distribution; *beta* = 4.2). The distribution of time gaps between citing papers in year 30 and the papers cited by their references is used to guide the choice of parameters to define recency, when

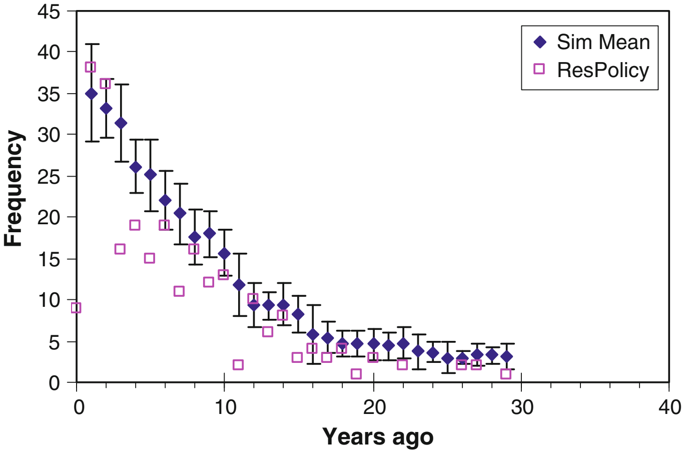


Fig. 7 The time between authorship events. For all pairs of papers one published in year 30 and sharing at least one author, frequency distributions of the ages of the earlier paper: mean results from 20 simulation runs together with 95% confidence intervals for each point, and corresponding data from *RP*

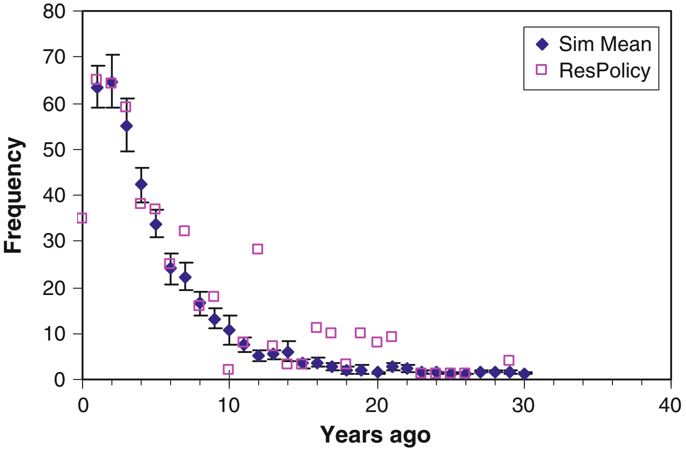


Fig. 8 The time between citing and cited papers. Frequency distributions of the ages of all papers referenced by papers published in year 30 for mean results from 20 simulation runs, with 95% confidence intervals indicated, and corresponding data from *RP*

selecting past papers for their references. To generate the distribution in Fig. 8 'recent publications' were defined using a Weibull function with parameters *alpha* = 1.3 and *beta* = 2. The mean figures from 20 simulation runs suggest papers published more than 20 time steps ago are receiving slightly too few citations, but the simulation has captured the general peak-and-decay pattern.

As in the model of Boerner et al. (2004), the initial or *foundational* papers in the simulation provide a means for representing papers outside the target dataset. An examination of the numbers of citations received by papers in each year (Fig. 9) shows that the papers in the model's year 1 tend to receive slightly more citations than those in the next few years, despite the number of new papers in those years increasing gradually. (For these

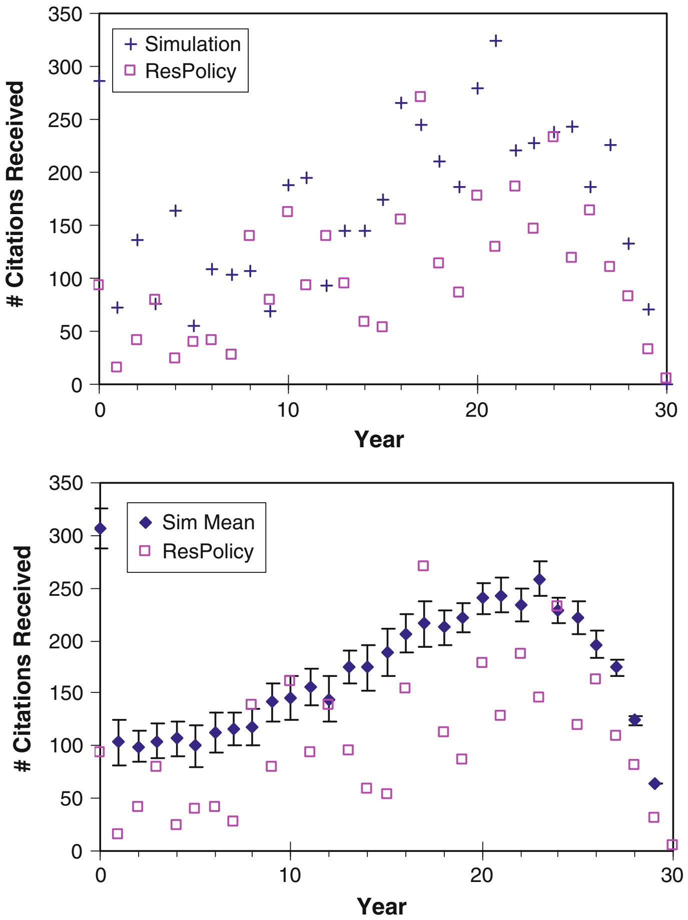


Fig. 9 Citations received by papers in each year: (*top*) a typical simulation run; (*bottom*) mean results from 20 simulation runs, plus 95% confidence intervals

charts foundational papers have been included, and they receive far more citations.) Thereafter the curve rises and falls with the empirical data, though the simulation tends to generate too many citations compared with the empirical case.

The power law for papers per author was obtained with the help of a parameter for the chance of an author being new to the journal. Analogously for references, there is a chance of 0.3 of using a ‘recent’ publication as a reference in a new paper. If the recent paper is not used as the reference, then one of its own references is copied to the new paper. Thus papers that have recently been much cited are likely to be cited again, but there still exists a chance of a, potentially as yet uncited, recent publication gaining a citation. Twenty simulation repetitions were run and power laws were fitted in each case using maximum likelihood estimation (Fig. 10). The exponents ranged from 1.75 to 1.81, with a mean of 1.80, whereas the data from *RP* call for an exponent in the range 1.7–1.8. Compared to *RP* the simulation tends to produce fewer papers with just one citation, and there is more spread in the single papers with high numbers of citations.

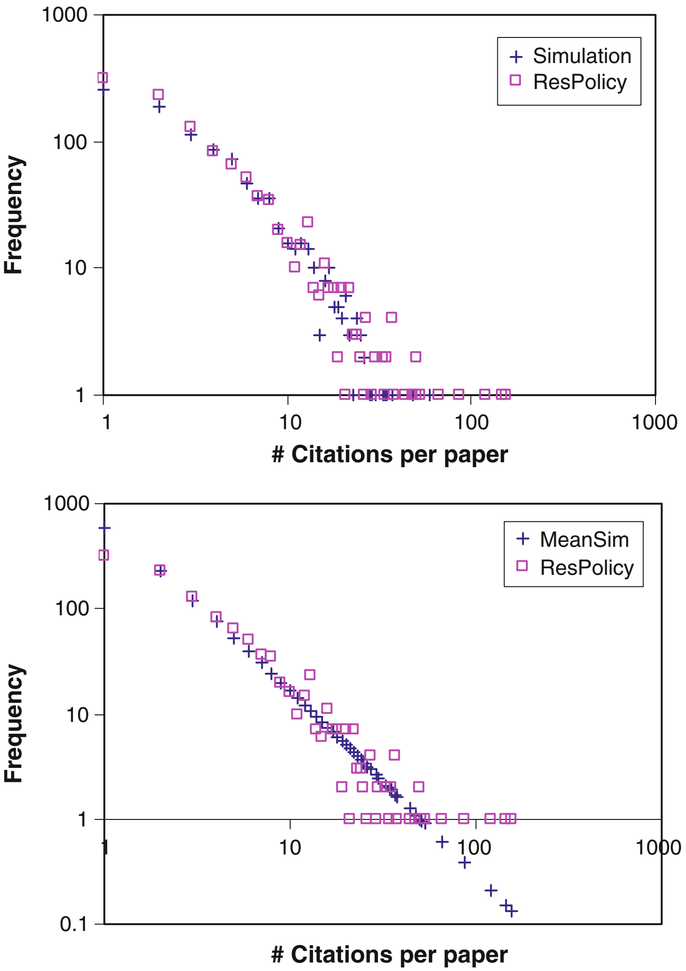


Fig. 10 Frequency distributions for numbers of citations per paper: (*top*) a typical simulation run; (*bottom*) curve taking the mean exponent from power laws fitted to each of 20 simulation runs

The distribution is sensitive to changes in the parameter that sets the chance of references pointing to recent papers rather than to papers referenced by recent papers. With extreme values, the results are far from a power law (Fig. 11). If the recent paper rather than one of its references (equivalent to methods 1 and 2 in Table 2) is selected, then the resulting distribution is exponential, not power law. If the recent paper's referenced paper, never the recent paper itself, is chosen, then the distribution bends away from the kind of power law that would fit *RP*.

To summarise, using empirically grounded assumptions for growth in papers and in authors, and distributions for authors per paper and references per paper, so far the distributions of papers per author, citations per paper, the time gaps between authors' papers, the ages of papers when chosen for references, and the number of citations received per year found in *RP* has been matched closely by the output from the simulation. These fits were achieved through processes for selecting authors and references that included

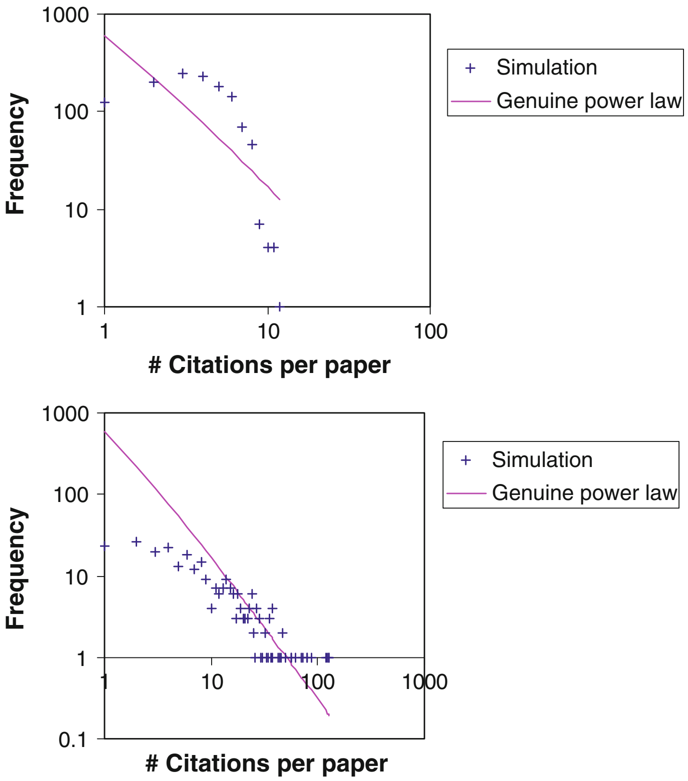


Fig. 11 Citations per paper, but no power law. Results of (*top*) always choosing the recent paper instead of its reference, and (*bottom*) always copying the recent paper's reference, never the recent paper itself. The *lines* indicate what power laws would look like, and have gradients similar to those fitted to *RP*

choosing parameters for the Weibull-distributed weighting of past papers in the definition of what constitutes a 'recent paper' (see Table 3), but also the choice of procedure for sampling papers to become new references. Papers were mostly selected with preference for those with recent citations. This is clearly better than selecting recent papers without regard to their citations, which fails to generate a plausible distribution of citations per paper, but over-concentration on citations would also generate the wrong distribution. So, although there is no guarantee that the former generation mechanism is the best, it is clear that some methods give distributions that clearly fail to fit.

Introducing fitness and peer review

So far, peer review has played little part in the model. Papers may be rejected by reviewers for being unoriginal, but this is a very weak constraint. With $N = 20$ bits of information in the contents of each simulated paper, there are 2^{20}, or over one million, possible combinations of binary values for papers to explore during 30 time steps, and so a paper is rarely rejected for matching a reviewer's beliefs. Once *NK* fitness is introduced, however, peer review places a significant selection pressure on papers. As Fig. 12 shows for a typical simulation run, in most years only about 20% of the generated papers are accepted as publications. If methods for selecting authors or references are restricted to journal

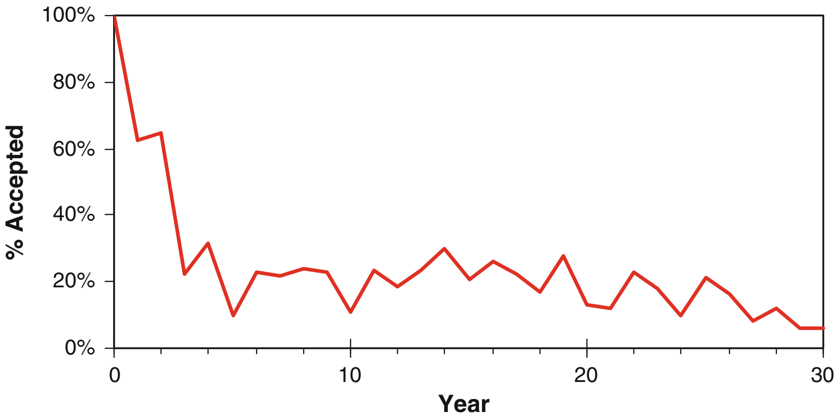


Fig. 12 Percentage of papers being accepted for publication per year in a typical simulation run that includes a fitness function and peer review process

publications rather than including unpublished material (representing working papers, unreviewed conference proceedings, and drafts), reviewing for fitness is likely to have some impact on the model's ability to match the empirical distributions.

This turns out to be the case. The number of publications per year, the number of citations received and the time-gap distributions no longer match the *RP* distributions. To compensate for this, paper production can be increased, by raising year 1's papers from 16, in anticipation of the fact that only 20% will be published. Since each of these extra papers needs authors, the chance of an author being new to the journal and the impact of the recency functions may also have to be changed. However, raising the number of papers increases computation times for the simulation.[2] Instead of results being returned in seconds on a modern PC, they can take minutes, and the simulation no longer encourages user interaction. Further data fitting will have to wait for faster computers, or for the addition of automated methods for searching the parameter space.

We do not know what proportion of papers submitted to *Research Policy* is accepted. We would not expect to match it: the representation of contents and extrinsic fitness value was not intended to be that realistic. But data supplied by the journal *Management Science* suggest that an acceptance rate of roughly 10% is plausible for that journal. It has been found that many papers rejected from one journal eventually make it into print in another journal, typically one of lesser status (Bornmann 2010). Otherwise, bibliometric data do not generally reveal about what happens outside of publication success.

Experimenting with cumulative advantage

We turn next from generating plausible distributions to exploring the impact on search performance of the choice of method for generating reference lists in simulated papers.[3]

[2] The exact relation between computing time and model scale is difficult to state, and differs between the *VBA* and *NetLogo* versions, for reasons internal to those software environments.

[3] The options for generating author lists also include those that produce cumulative advantage (in papers per author), but preliminary testing showed that these mechanisms have smaller effects than those for generating references, perhaps because papers have more references than authors on average.

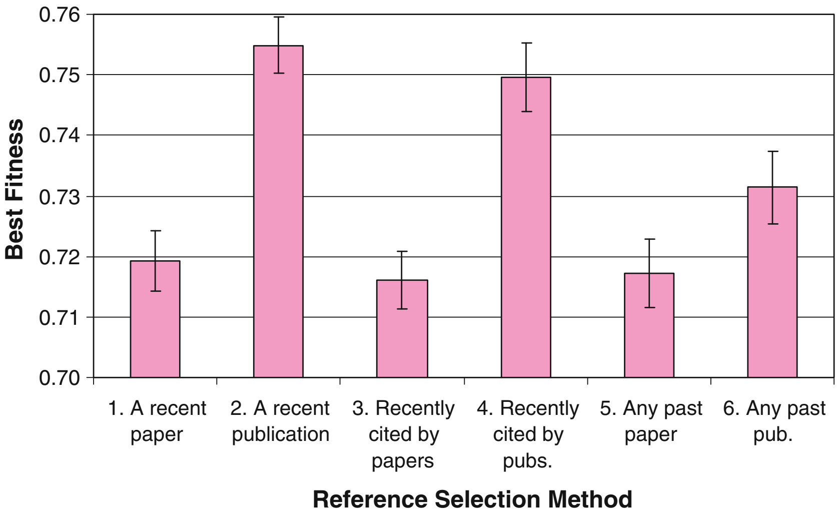


Fig. 13 Best fitness found using various methods for selecting papers for references. Method numbers are those in Table 2. Results shown are the means of 200 simulation runs using each method, with 95% confidence intervals. For descriptions of the methods see the text

Keeping the parameter values found during calibration, we experiment with varying the reference-selection method. The fitness of the best solution found during each simulation run is recorded. Figure 13 shows mean results for 200 simulation runs, with 95% confidence intervals for each mean, for each of the methods in Table 2. It is clear that methods involving publications (even-numbered methods) beat their paper-based equivalents (odd-numbered). Secondly, the method associated with the scale-free distributions of citations per paper (method 4) is not the best, but the difference between it and method 2, which is known to generate a distinct distribution, is not statistically significant. So in this experiment the cumulative-advantage process for generating citations failed to make a noticeable difference to the search performance of the agents. The preference for recency in methods 2 and 4 helps when compared with method 6, which samples from any past publication with no preference for recency. However, the most important aspect of generating references is still the use of publications, that is, the use of filtering provided by peer review.

To test the sensitivity of these results, alternative methods of generating references were tried. For an alternative to methods 1 and 2, instead of sampling papers (or publications) with preference for recency, a recent year can be randomly chosen, then any paper (or publication) from that year selected. This would simulate a reference seeker who went to a particular journal volume simply because it was recent, and who ignored how many papers the volume had in it. This alternative did not differ statistically significantly from methods 1 and 2. As an alternative to methods 3 and 4, sampling stratified by recency and citations received was used, as opposed to stratification by citations received from recent papers. Methods 3 and 4 allow for generating references to 'citation classics' that are not themselves recent, but have recently been in fashion. The alternative method prefers well-cited items that are still themselves recent. Again, the results from the alternative method failed to differ statistically significantly. However, a field with a different growth rate might result in some differences. We leave this investigation for further work.

Discussion and future work

The model described in this paper has the ability to generate distributions and other patterns similar to those found in bibliometric data, including papers per author and citations per paper. Through its simulation of peer review it has the ability to perform searches on fitness landscapes, an analogy for problem solving. As demonstrated here, the pursuit of the second task turns out to disturb that of the first task. Obtaining distributions that fit a particular set of bibliometric data while searching the current, artificial fitness landscape would require further work, not least because of the extra computing time needed as the number of papers increases. Instead, we examined whether searching an artificial fitness landscape was affected by the choice of methods for generating references and citations. As it turned out, the impact on search performance was not *statistically* significant for cumulative-advantage processes. Whether it is significant in the sense of *important* is a question to be asked when we can replace *NK* fitness with landscapes that have some empirical grounding. By contrast, the use of publications rather than papers, that is, choosing to refer only to papers that have passed through peer review, did make a noticeable difference.

Of course, real academic authors and reviewers might not be employing the *optimal* publishing practices. They make choices about their own practices, and there is no guarantee that their attempts to pursue their own individual interests will lead to the best *collective* performance. Nevertheless, simulation models of academic publication can suggest areas in which different practices might come with different costs. These suggestions can then be turned into theories to be investigated in further research, including through other approaches. When the practices that performed best in the simulation are not followed by real scholars, why is this so? What extra utility to those practices is not captured by the theory represent by the model?

Our simulation has a wealth of options and parameters, perhaps inevitably given the need to bring together several different processes from the science system. Even so we omit or simplify aspects of the generation of scientific papers, as well as other activities related to the dissemination of scientific knowledge such as conferences and teaching. But each choice of process or parameter value can be debated, with arguments drawing upon empirical sources, such as ethnographic studies of scientists at work (Latour 1987) and, of course, scientometric analyses. Clearly the exploration of this model has only just begun, but we pick out here a few suggested directions for future research, several of them demonstrating the interplay of endogenous and exogenous influences on the model's workings.

What are the effects on search performance of varying the parameters underlying the generation of recency and the numbers of co-authors, references and reviewers? For example, what would be the impact of a limit on the number of references per paper? At present, most authors can choose the number of references, and those that supply a higher number wield a larger amount of influence in determining which papers will become citation classics, and who among the field will receive the best citation count (Fuller 2000). Work in filtering the list of publications in a field and reducing it to a more manageable size for future researchers and students is not rewarded. Profligate reference creators are not penalised. Is there scope for gaming the system to favour one's own allies or research interests? Do some methods of selecting peer reviewers lead to elites controlling what gets published in a field?

There are several issues to address concerning how a science simulation represents connections to things outside its area of focus. For example, to keep the program fast and responsive, we only simulated the generation of as many papers as are found in a single journal. Generated references in these papers were to previous papers in the simulation. Contents for new papers were largely sampled from these references. The model's sensitivity to the number of foundational papers and the chance of innovation during contents sampling—the only extrinsic sources of information—should be examined, but better approaches to representing a journal's connections to other literature may exist.

The model's sensitivity to different types of landscape should be also investigated, both before and after learning more about the structure of real epistemic landscapes. For the *NK* landscape, increasing *K*, the number of interdependencies between components, is known to lead to more rugged landscapes, and more difficult searches. How does search difficulty affect distributions, and collaboration and citation networks? Will there be an analogue to Whitley's (2000) finding that the social organisation of scientists varied with the degrees of task uncertainty and mutual dependency faced by those scientists? For sufficiently long simulation runs, the difficulty of finding improvements and getting published will increase. Will this lead to identifiable stages of growth in the research field, like those described by Mulkay et al. (1975): exploration, unification and decline/displacement?

As Scharnhorst's (2002) two-landscape conception of science highlights, the value of a particular position in science is dependent on the occupation by others of that and surrounding positions. Our model included one such constraint on where an agent can publish, that of originality. Future work will consider the impact of a requirement for a degree of similarity between publications and authors. Papers will be rejected if their contents are too unlike what has gone before in the referenced papers or in the experience of reviewers and potential co-authors. The evidence from Axelrod's cultural model (Axelrod 1997; Castellano et al. 2000), opinion dynamics models (Hegselmann and Krause 2002) and Gilbert's (1997) science model suggests that homophily (McPherson et al. 2001) or requirements for similarity or proximity, in our case defined as a required number of matching bits, will lead to the formation of clusters among publications and cultural groups among their authors. To be accepted by particular agents will require that many of their cultural practices, such as their terminology, techniques and assumptions, are matched by authors while still presenting them with something at least slightly novel. If originality and similarity are the only constraints on scientific publications, then the value of a paper's contents is endogenous to science and the meaning of a publication event is a social construction generated by the surrounding publication events. This is the situation represented by Gilbert's (1997) model and also by the *TARL* ('Topics, Aging and Recursive Linking') model of Boerner et al. (2004) which arbitrarily assigned 'topics' to each paper and to each author, then used these to restrict who could publish with whom and on what topic. Ideally a science model should combine these endogenous influences with exogenous influences, such as a fitness landscape.

A new, exogenous source of constraint on publishing activity would be social networks among author agents, be they informal, institutional, geographical, linguistic or cultural in origin. For example, authors who do not share a common language are unlikely to co-author a paper together. As Lazer and Friedman (2007) demonstrated, the network structure among agents can affect search performance. The presence of networks, whether endogenous or exogenous, will also raise questions of social capital. Do positions of brokerage and closure in the network (Burt 2005; Chen et al. 2009) lead to different roles in the generation and diffusion of novel ideas in the simulation?

As these proposals make clear, simulation models connecting, on the one hand, science models and bibliometric data, to, on the other hand, organisational learning models and heuristic search on fitness landscapes should provide a fruitful avenue for much research.

By connecting these areas, understanding is gained into the extent to which authoring and publishing practices affect the ability to explore and exploit the range of positions in science.

Acknowledgments This research was supported by *SIMIAN* (Simulation Innovation: A Node), a part of the UK's National Centre for Research Methods, funded by the Economic and Social Research Council.

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