Diffusion of scientific credits and the ranking of scientists

Filippo Radicchi,¹ Santo Fortunato,¹ Benjamin Markines,² and Alessandro Vespignani²,¹

¹Complex Networks and Systems, Institute for Scientific Interchange (ISI), Torino, Italy
²Center for Complex Networks and Systems Research (CNetS), School of Informatics and Computing, Indiana University, USA

Recently, the abundance of digital data enabled the implementation of graph based ranking algorithms that provide system level analysis for ranking publications and authors. Here we take advantage of the entire Physical Review publication archive (1893-2006) to construct authors’ networks where weighted edges, as measured from opportunely normalized citation counts, define a proxy for the mechanism of scientific credit transfer. On this network we define a ranking method based on a diffusion algorithm that mimics the spreading of scientific credits on the network. We compare the results obtained with our algorithm with those obtained by local measures such as the citation count and provide a statistical analysis of the assignment of major career awards in the area of Physics. A web site where the algorithm is made available to perform customized rank analysis can be found at the address http://www.physauthorsrank.org.

PACS numbers:

I. INTRODUCTION

Recently, the recording of social interactions and data in the electronic format has made available datasets of unprecedented size. This is particularly evident for bibliographic data whose study has received a boost from the information technology revolution and the digitalization process. This has led to the definition of ranking measures which are supposed to provide objective and quantitative measures of the importance of journals, papers, programs, people and disciplines [1, 2]. While the validity of these metrics is object of debate [3], it is now standard practice to consider measures such as the impact factor, the number of citations and the h-index [4] to assess the scientific research production of individuals and institutions. In this context the use of multipartite networks as the natural abstract mathematical representation of the data is particularly convenient and several studies have recently focused on the study of co-authorship networks, paper citation networks, etc. [5-9]. In general, each of these networks is an appropriate bipartite or unipartite network projection of the original bibliographic dataset where authors and papers are nodes and citations, authorship and other bibliographic information define the links among nodes [9, 10].

The possibility of a system level study of these networks has opened new possibilities for the bibliometric analysis aimed at evaluating the impact of scientific collections, publications and scholar authors. In particular, the field has leveraged on graph based ranking algorithms developed in the context of the World Wide Web [11-15] to provide the impact and prestige of papers and authors. The final goal of ranking bibliographic data is even more ambitious as it ultimately concerns the possibility of predicting the evolution of impact and ranks on the basis of past data [13].

Criticisms to the ranking mechanism are generally rooted in the fact that the common indicators, like the simple citation counts or the metrics derived from this quantity, do not truly account for the actual merit of a scientist. Citations have different values depending on who is the citing scientist, defining a complicated mechanism of scientific credit diffusion from author to author. Even at the simplest level, this is a very non-local process in which scientists endorse each other through the process of citing each other’s works. In order to take into account this perspective, we have defined an approach that bases the author’s ranking on a diffusion algorithm that mimics the diffusion of scientific credits along time. Here we take advantage of the set of all 407,236 papers published between 1893 and 2006 in journals of the Physical Review (PR) collection (see section II for a detailed description of the set). This collection is surely an exceptional proxy of the activity in the physical sciences and the impact that individual scientists have generated in the field [16]. The PR dataset has been already exploited to analyze paper citation network and measure the impact of a specific paper both with local (individual paper/author) metrics (number of citations) and with graph-based ranking algorithms [10, 15]. Here we propose a system level algorithm with the aim of ranking authors by mimicking the scientific credit spreading process. We first construct an author-to-author citation network that fully accounts for the bibliometric data relative to the credit given from any author to other authors. We then define an appropriate graph-based ranking algorithm that simulates the diffusion of credits exchanged by the authors over the whole network. The algorithm takes into account that citations from more important authors have higher relevance than citations from less important authors and the non-local nature of the diffusion process in which any author can in principle impact the score of far away nodes through the diffusion process. Finally, the proposed ranking technique is compared with other commonly used methods, which are based only on local properties of the citation network.

The paper is organized as follows. We first give a brief description of the PR dataset (section II). In sec-
tion III the weighted citation network between authors is defined and analyzed. The description of the Science Author Rank Algorithm (SARA) is performed in section IV. This algorithm is used for the estimation of the scientific impact of physicists along time. We compare SARA with other ranking schemes like Citation Count and Balanced Citation Count in section V. In section VI, we test SARA by using the list of the winners of the major prizes in Physics. This list of prominent physicists is in fact the best benchmark on which we may test our algorithm. We finally conclude and report final comments in section VII.

**II. DESCRIPTION OF THE DATASET**

Our database is composed of the set of all 407,236 papers published between 1893 and 2006 in journals of the collection of Physical Review (PR). The journals considered here are Physical Review Series I, Physical Review, Physical Review A, Physical Review B, Physical Review C, Physical Review D, Physical Review E, Physical Review Letters and Reviews of Modern Physics. For each paper the editorial office of PR provided an xml file from which we can extract the names of its author(s), date, journal, volume and page of publication, its references, the PACS [22] numbers and other additional information.

The list of references at the end of each paper allows to construct a network of citations between papers. According to our database, the total number of references (obtained by summing all references over all papers) is 9,359,556 of which 3,866,471 [23] are internal references (i.e., references to papers appeared in PR journals).

In this work we have neglected all references of the type “First author et al.” and all references pointing to papers written by authors without any publication in the PR journals. Using these criteria, we identify 8,783,994 total references (including the 3,866,471 internal references).

In the rest of the paper and all our analysis, we consider all 8,783,994 references. As already stated, these references include all papers, published or not in PR journals, referenced by papers published only in PR journals.

**III. CONSTRUCTION OF THE WEIGHTED AUTHOR CITATION NETWORK**

A weighted citation network between authors (WACN) can be easily determined as a particular projection of the paper citation network (PCN) constructed by the list of references described in section II [see Figure 1]. Consider for instance a paper \(i\), written by the \(n\) co-authors \(i_1, i_2, \ldots, i_n\), which cites a paper \(j\), written by the \(m\) co-authors \(j_1, j_2, \ldots, j_m\). A natural way to project the unweighted directed link \(i \rightarrow j\) between papers \(i\) and \(j\) into a WACN is to create \(n \cdot m\) directed connections from each of the \(n\) citing authors to every of the \(m\) cited authors (i.e., \(i_k \rightarrow j_s, \forall k = 1, \ldots, n\) and \(\forall s = 1, \ldots, m\)), where every connection has weight equal to \(w_{i_k,j_s} = 1/(n \cdot m)\). Given a set of references (i.e., directed links between papers), the weight of a directed link between two authors will be the sum of all the weights over all the references in the set.

It is important to stress here that while the list of references does not have ambiguity, the analysis of the author projection opens the issue of names disambiguation. Indeed, common names may refer to different authors and not all authors report their full names in publications. In other words we could have a multiplicity of authors identified by the same identifier. In appendix A we provide a detailed analysis of this and other related problems which are common issues in bibliometry.

As an example of the network construction, in Figure 2 we show the WACN of the top-scientists in the field of “complex networks”. In order to construct this network, we first select out of the PR dataset only papers whose titles contain keywords as “complex network”, “scale-free network”, “small-world network”, etc. We then consider their references and based on this list we project the PCN into a WACN.

**A. Dynamical Representation of the Weighted Author Citation Network**

In principle, a single WACN may be constructed based on the full set of the 8,783,994 total references described in section II. This is however not very informative as very old citations are mixed with new ones, discounting the dynamical information contained in the longitudinal nature of the database. In addition, the rate of citation per unit time is steadily increasing along the years. For this reason, we define dynamical slices of the database containing the same number of citations. We first sort the full list of references according to their date (i.e., the date of the publication of the citing paper). Then
we divide this list in $M_I$ homogeneous intervals, where homogeneous stands for intervals with the same number of references $M_R$. In order to avoid abrupt changes, we consider overlapping intervals, in the sense that the $q$-th interval shares its first $M_R/2$ references with the $(q-1)$-th interval and its last $M_R/2$ references with the $(q+1)$-th interval. It should be noticed that this sharp division may split references of the same citing paper into different contiguous intervals, but this “border effect” may be considered negligible since we consider $M_R$ much larger than the average number of references per paper (all results have been obtained by using $M_I = 39$ and $M_R = 488,000$, while on average each paper has 20–30 references). Moreover, we should remark that we can relate each interval with real time by simply associating the average of the dates of all the references belonging to the interval with the interval itself. However, since the rate of citation per unit of time is increasing almost exponentially with time, the homogeneity of references in each interval does not correspond to homogeneity in time: for instance the first interval spans more than 70 years of publications (1893-1966), while the last interval is representative for the publications of only one year (2006). The choice $M_R = 488,000$ adopted in this paper ensures that intervals are representative of periods of time not shorter than one year.

B. Properties of the Weighted Author Citation Network

We provide in this section a simple statistical analysis of the WACNs. In particular we monitor the number of authors and their indegree and instrength distributions, where for example the instrength of a node $i$ is defined as

$$s_i^{\text{in}} = \sum_j w_{ji},$$

i.e., the sum of all weights of the links pointing to $i$ [17]. First of all, it is interesting to note that quantitatively...
the properties of the WACNs are not constant in time. This is understandable since the production of scientists has strongly changed during the last century.

Figure 3: (Color online) In the main plot, the total number of authors \( N_{\text{tot}} \) (yellow circles), number of authors with outstrength larger than zero \( N(s_{\text{out}} > 0) = \sum_j \theta (s_{\text{out}}^j) \) (green squares) and number of authors with instrength larger than zero \( N(s_{\text{in}} > 0) = \sum_j \theta (s_{\text{in}}^j) \) (red diamonds) are plotted as functions of the number of references (referenced papers), where \( \theta (\cdot) \) is the step function equal to one when its argument is larger than zero and null otherwise. In the inset the same quantities as those of the main plot are considered, but now they are plotted as functions of time. More specifically, each \( x \)-value corresponds to the average publication year of papers belonging to the respective dynamical slice of the main plot.

From Figure 3, one can qualitatively appreciate the former observation: the total number of nodes in the network (i.e., the number of scientists citing or cited in a particular period of time) is an increasing function of time. It should be stressed that this behavior is mainly a consequence of the increment of scientists in physics as one can deduce from the time-increment of the number of nodes with non-zero instrength (i.e., cited authors) that is growing in a much slower fashion.

The indegree distributions calculated on different WACNs are generally different. Nevertheless, if we consider the relative indicator given by the ratio of the citing authors \( (k_{\text{in}}^i) \) to a scientist in a given WACN divided by the average number \( (\langle k_{\text{in}} \rangle) \) of citing authors over all physicists in the same WACN, the distributions of the rescaled variable \( k_{\text{in}}^i / \langle k_{\text{in}} \rangle \) obey the same universal curve [see Figure 4a]. This result is in accordance with the remarkable scaling recently discovered on PCNs [18]. The same is not valid for the instrength distribution since a simple scale transformation does not seem to lead to a universal behavior.

IV. SCIENCE AUTHOR RANK ALGORITHM

The author-to-author network can be used to define a graph based ranking algorithm that uses the global features of the network to account for the impact of each author. Analogously to various ranking algorithms such as PageRank [11], CiteRank [15], the HITS scores [12], etc., we define an iterative algorithm based on the notion of diffusing scientific credits. In practice we imagine that each author owns a unit of credit which is distributed to its neighbors proportionally to the weight of the directed connection. Each author thus receives a credit that is then redistributed to neighbors at the next iteration and so on. In other words, the SARA simulates the diffusion of credits on the global network according to a diffusion probability proportional to the weight of the links.

Let us be more specific. Once the WACN has been defined as detailed in section III, we calculate the SARA score for each node \( i \) according to
\[ P_i = (1 - q) \sum_j \frac{P_j}{s_{j}^{\text{out}}} w_{ji} + q z_i + (1 - q) z_i \sum_j P_j \delta (s_{j}^{\text{out}}). \]  

Here \( P_i \) is the score of the node \( i \), \( 1 \ge q \ge 0 \) is the damping factor, \( w_{ji} \) is the weight of the directed connection from \( j \) to \( i \), \( s_{j}^{\text{out}} \) is the outstrength of the node \( j \) (i.e., the sum of the weights of all the links outgoing from the \( j \)-th vertex, \( s_{j}^{\text{out}} = \sum_k w_{jk} \)) and finally \( \delta(x) = 1 \), if \( x = 0 \) and \( \delta(x) = 0 \), otherwise. The first term on the r.h.s. of Eq.(2) represents the diffusion of credit through the network: scientist \( i \) receives a portion of credit from each citing author \( j \) and each amount of credit is linearly proportional to the weight \( w_{ji} \) of the arc linking \( j \) to \( i \). The second and the third terms stand from the redistribution of credits to all scientists in the network. A portion \( q \) of the credit of each node is redistributed to everyone else (i.e., second term), with the exception of dandling ends (i.e., nodes with null outstrength), which distribute their whole credit (i.e., third term). The meaning of the redistribution of credit is that everyone is in “scientific debit” with the whole scientific community, since a general background is at the basis of the knowledge of every scientist. In particular, the credit is distributed homogeneously among papers in the network. The factor \( z_i \) takes into account the normalized scientific credit given to the author \( i \) based on his productivity. \( z_i \) is calculated according to the formula

\[ z_i = \frac{\sum_p \delta_{p,i} 1/n_p}{\sum_j \sum_p \delta_{p,j} 1/n_p}, \tag{3} \]

where \( p \) represents the generic paper \( p \) and \( n_p \) the number of authors who have written the paper \( p \). Moreover, \( \delta_{p,i} = 1 \) only if the \( i \)-th author wrote the paper \( p \), otherwise it equals zero. The sum runs over all different papers (citing and cited). Basically, each paper receiving a credit is going to redistribute it equally among all co-authors of the paper. The fact that the \( z_i \)'s are not homogeneous (differently from the original formulation of PageRank [11], where \( z_i = 1/N \), \( \forall i \) with \( N \) total number of authors) is of fundamental importance: each paper is carrying the same amount of knowledge independently of the number of co-authors. The denominator of the r.h.s. of Eq.(3) serves only for normalization purposes. The stationary values of the \( P_i \)'s can be easily computed recursively, by setting at the beginning \( P_i = z_i \), \( \forall i \) (but the results are independent of the choice of the initial values) and iterating Eqs.(2) until they converge to values stable within a priori fixed precision [24].

The scores calculated according to Eq.(2) depend on the particular value chosen for the damping factor \( q \). In all results shown in this paper, we always set \( q = 0.1 \). This is the value for which the predictive power of SARA is maximized. An exploration of the dependence of the predictivity of SARA as a function of the damping factor \( q \) is reported in Appendix B.

**A. Ranking Authors**

The SARA is used to provide a ranking of the authors in the PR database. Given an author-to-author network, we calculate the score of each author according to Eq.(2) and assign a rank position to this scientist. The higher is the score of a scientist, the higher is her/his rank. As described in section III, we decided to preserve the longitudinal nature of the PR database and construct WACNs corresponding to dynamical slices of the database containing the same number of citations. In this way we can have a dynamical perspective on the evolution of the merit of authors along the years. As prototypical examples, we show in Figure 5 the evolution of the relative rank of four Nobel Laureates. For each author \( i \) we calculate its relative rank as

\[ R_i = 1/N \sum_{j \neq i} \theta (P_j - P_i), \tag{4} \]

which basically stands as the probability to find an author with better score than author \( i \). \( N \) is the total number of authors in the WACN, while the step function \( \theta(\cdot) \) is equal to one only when its argument is equal to or larger than one, otherwise it is zero. The relative rank in other words defines the top percentile of each scientist. It should be stressed that the relative rank of Eq.(4) works better than the absolute one in the case of comparison of scientific performances in different historical periods,
Figure 6: (Color online) Scatter plots of SARA rank versus CC rank [(a) and (b)] and BCC rank [(c) and (d)]. Plots in (a) and (c) refer to the author citation network based on papers published between 1893 and 1966, while plots in (b) and (d) have been generated by using the author citation network based on papers published in 2005. In all insets, the same data as the ones analyzed in the respective main plots have been logarithmically binned. For each bin we plot maximum and minimum values (error bars), 90% confidence intervals (boxes) and median (horizontal bars inside boxes) of the SARA rank. In all plots, outlier points stress the most significant differences between SARA and the other techniques. Authors badly ranked in CC or BCC methods and well classified in SARA are generally very prominent physicists. By looking at figures (a) and (c) for example, we see scientists of the caliber of “Jordan, P” and “Weyl, H” occupy the top-positions in SARA ranking, while their ranks are two orders of magnitude smaller according to CC or BCC methods. On the other hand, the majority of authors poorly ranked by the SARA technique and well ranked by CC method correspond to poorly defined identifiers referring in general to multiple physical persons [see figure (b)]: names like “Li, J” or “Yu, Z” are very common in China and for this reason their CC score is very high; SARA differently is able to capture the low scientific relevance of all these authors, ranking them at positions about three orders of magnitude higher than the ones obtained with the CC method.

Since the number of authors in the WACN is increasing rapidly in time (see Figure 3).

From Figure 5, we can clearly see that relative rank dynamics of Nobel laureates is qualitatively related in time with the achievement of the prize: top-performances are reached close to the date of the assignment of the honor. Indeed, it is worth remarking that the method naturally accounts for the fact that the rate of citations per unit time is steadily increasing through the years by defining dynamical slices of the database containing the same number of citations. Discounting old citations, the author’s rank becomes a dynamical quantity that changes according to the author’s research activity as well as the success of new research fronts. Thus, rank is related to
the actual impact of the research of an author at a given time and is changing through the years.

V. COMPARISON WITH DIFFERENT METRICS

Assessing the reliability and the results of any ranking method is not easy. The main question is to which extent the SARA algorithm is providing a better rank than other ranking methods commonly used in scientific impact analysis. For this reason, we consider two basic measures which are commonly used to rank authors. The first is the Citation Count (CC) with which authors are simply ranked by the total number of citations received in a given time window (note that the number of citations does not correspond to the indegree of the author in the citation network). CC is traditionally the simplest and mostly used quantity for measuring the scientific impact: popular indicators, as the h-index [4] for instance, are based on this simple metrics. The second measure is the Balanced Citation Count (BCC) that discounts the effect of multiple authored papers in the citation count by normalizing the citation weight by the total number of authors of the cited paper [i.e., authors are ranked on the basis of their instrength as defined in Eq. (1)]. As a first comparison of the rankings obtained with the three different methods, we show in Figure 6 the scatter plot in which each author is identified by its SARA ranking and CC or BCC rank. If the methods provide the same ranking all the points would fall on the diagonal. Fluctuations are indicated by the cloud of the scattered plot about the line indicating the linear behavior. Indeed, it is possible to show that, in the absence of degree-degree correlations in the network, diffusion algorithms such as the SARA are providing a score that is on average proportional to the indegree dependence of the diffusion process [19]. However, important fluctuations appear: some nodes can have for example a low SARA rank despite a modest indegree, whereas some others can have a surprisingly large SARA despite a high indegree, as it is possible to see in Figure 6. We believe that the potential refinement offered by this method is its ability to uncover such outliers. It is interesting to see that most of the outliers corresponding to authors badly ranked with the CC and BCC methods are indeed very important scientists that are highly ranked with our method.

VI. BENCHMARKING THE SCIENCE AUTHOR RANK ALGORITHM

The previous analysis is not an accurate author by author analysis but a procedure to identify the most evident outliers. In order to produce a more refined analysis on the effectiveness of the SARA ranking, we test the predictive power of the three ranking methods by studying the assignment of major prizes and awards (in Ref. [20] it has been already shown that scientists with high CC scores have high probability to earn a Nobel prize in their discipline). We expect that a better performing ranking would identify most of the award winning authors by placing those at very top ranks. In other words we assume that awards and prizes are an outcome of a peer performed rank analysis that singles out the most highly ranked authors. This human ranking process, obtained with the hard work of committees and the help (in many cases) of the whole community can be considered as a benchmark for the ranking algorithms. We expect that the better the algorithm is performing, the more awarded authors will be found in the top rank brackets. In Figure 7, we see how SARA improves the prediction in the assignments of major prizes in Physics with respect to both CC and BCC methods. The probability to earn a prize is consistently higher for authors who have reached top rank positions [25] according to SARA than for scientists who have occupied the same positions in CC or BCC rankings.

Finally, we provide a table [see Table 1] with best ranked scientists at the end of years 1973 (period 1967-
### Table 1: (Color online) Top 20 scientists according to the SARA method. The rankings are determined by considering all papers published in the periods 1967-1973 (left) and 2003-2004 (right). We highlighted in gray scientists, who have not yet earned any of the major prizes [NP=Nobel Prize, WP=Wolfe Prize, BM=Boltzmann Medal, DM=Dirac Medal, PM=Planck Medal]. "Kohn, W" has earned the NP in Chemistry in 1998.

| Rank | Author     | Year 1973 | NP | WP | BM | DM | PM |
|------|------------|-----------|----|----|----|----|----|
| 1    | Gell-Mann, M | 1969      | -  | -  | -  | -  | -  |
| 2    | Weinberg, S  | 1979      | -  | -  | -  | -  | -  |
| 3    | Schwinger, J  | 1965      | -  | -  | -  | -  | -  |
| 4    | Feynman, R.P. | 1965      | -  | -  | -  | -  | -  |
| 5    | Lee, T.D.    | 1957      | -  | -  | -  | -  | -  |
| 6    | Anderson, P.W. | 1977      | -  | -  | -  | -  | -  |
| 7    | Bjorken, J.D. | 1957      | -  | -  | -  | -  | 2004 |
| 8    | Yang, C.N.   | 1957      | -  | -  | -  | -  | -  |
| 9    | Slater, J.C.  | 1957      | -  | -  | -  | -  | -  |
| 10   | Adler, S.L.  | 1977      | -  | -  | -  | -  | -  |
| 11   | Glaser, R.J. | 2005      | -  | -  | -  | -  | -  |
| 12   | Chew, G.F.   | 1963      | -  | -  | -  | -  | 1961 |
| 13   | Wigner, E.P. | 1983      | -  | -  | -  | -  | -  |
| 14   | Lovelace, C. | 1963      | -  | -  | -  | -  | -  |
| 15   | Satchler, G.R. | 1977      | -  | -  | -  | -  | -  |
| 16   | Mott, N.F.   | 1977      | -  | -  | -  | 1985 | -  |
| 17   | Fisher, M.E. | 1980      | -  | 1980 | 1983 | -  | -  |
| 18   | Mandelstam, S. | 1991    | -  | -  | -  | -  | -  |
| 19   | Bethe, H.A.  | 1967      | -  | -  | -  | -  | 1955 |
| 20   | Phillips, J.C. | 1967      | -  | -  | -  | -  | -  |

| Rank | Author     | Year 2004 | NP | WP | BM | DM | PM |
|------|------------|-----------|----|----|----|----|----|
| 1    | Anderson, P.W. | 1977      | -  | -  | -  | 1985 | -  |
| 2    | Witten, E.  | 1979      | -  | -  | -  | -  | -  |
| 3    | Tokura, Y.  | 1985      | -  | -  | -  | -  | -  |
| 4    | Perdew, J.P. | 1985      | -  | -  | -  | -  | -  |
| 5    | Kohn, W.    | 1999      | -  | -  | -  | -  | -  |
| 6    | Kresse, G.  | 1985      | -  | -  | -  | -  | -  |
| 7    | Büttiker, M. | 1985      | -  | -  | -  | -  | -  |
| 8    | Weinberg, S | 1979      | -  | -  | -  | -  | -  |
| 9    | Cioc. A.     | 2005      | -  | -  | -  | -  | -  |
| 10   | Zunger, A.  | 2005      | -  | -  | -  | -  | -  |
| 11   | Barabasi, A.L. | -        | -  | -  | -  | -  | -  |
| 12   | Lee, P.A.   | 2005      | -  | -  | -  | -  | -  |
| 13   | Vanderbilt, D | -        | -  | -  | -  | -  | -  |
| 14   | Sachdev, S. | 2005      | -  | -  | -  | -  | -  |
| 15   | Newman, M.E. | -        | -  | -  | -  | -  | -  |
| 16   | Affleck, I. | 2005      | -  | -  | -  | -  | -  |
| 17   | MacDonald, A.H. | - | -  | -  | -  | -  | -  |
| 18   | Hirsch, J.E. | -        | -  | -  | -  | -  | -  |
| 19   | Zoller, P.  | 2006      | -  | -  | -  | -  | -  |
| 20   | Parisi, G.  | 1999      | -  | -  | -  | 1999 | -  |

VII. CONCLUSIONS

In this paper we propose a new measure for ranking scientists mimicking the spread of scientific credits among authors. The proposed technique, called Science Author Rank Algorithm (SARA), is similar in spirit to the standard ranking procedure implemented for pages in the World Wide Web [11]. SARA is based on a mixed process, where a biased random walk is combined with a random distribution of the credits among the nodes. On a global level, the algorithm takes into account that inlinks from highly ranked authors are more important than inlinks from authors with low rank and measures the non-local effects of the spreading of scientific credits into the network. The non-local characteristics of this algorithm are evident as any author can in principle impact the score of far away nodes through the diffusion process and the fact that the score of an author is more affected by the score of its neighbors than the raw number of inlinks.

We apply SARA on Weighted Author Citation Networks (WACNs) directly constructed from the paper citation network based on articles published in the Physical Review (PR) collection between 1893 and 2006. This large dataset allows the estimation through SARA scores of the scientific relevance of physicists along time. The time behavior can be monitored by simply using the longitudinal nature of the PR database and therefore constructing WACNs representative of different periods of time. A quantitative comparison between rankings obtained via SARA scores or other more popular heuristics shows the great improvement that can be obtained by considering the whole citation network instead of only its local properties.

As practical application of our ranking recipe, we have developed a Web platform ([http://www.physauthorsrank.org](http://www.physauthorsrank.org)) where the evolution of the scientific relevance of all physicists, with at least a publication in PR journals before 2006, can be plotted. The Web site offers several additional features such as the evaluation of the authors’ rank in their specific topical area.

While we believe that the methodology exemplified by our approach entails more information than the simple citation counts or the metrics derived from this quantity, including the h-index and its related measures, we want to be the first to spell out clearly the many caveats
deriving by a non-critical approach to similar ranking approaches. First of all it is worth remarking that the present algorithm takes into account only the PR dataset. While this may be appropriate to rank authors within the physics community, it is clear that it does belittle the rank of authors who have got a large impact in other areas or disciplines. This problem might be mitigated by the inclusion of other databases or very extensive citation repositories. The inclusion of larger repositories however would amplify the disambiguation problem and this endeavour might not be straightforward. For this reason we have added to our web platform the user disambiguation process. The hope is that a collaborative web2.0 approach may help in achieving progressively cleaner datasets. A similar procedure has been recently proposed by Thomson Reuters with the web site http://www.researcherid.com [21], where authors are asked to link their ResearcherID to their own articles. Another issue is the fact that our scientific credit spreading is considering credits and citations just as a positive indicator. While this may be appropriate to rank authors within a specific field, it is clearly wrong since they refer to papers citing newer papers. We cannot exclude the possibility of other wrong internal references, but there is no possibility of other wrong internal references, but there is no fixed precision. Here we set $\epsilon = 10^{-6}$; typically 20 – 30 iterations are needed for convergence.

Actually, the total number of internal references reported by the PR database is 3,866,822, but 351 of them are clearly wrong since they refer to papers citing newer papers (i.e., the year of publication of the citing paper is smaller, in some case even of 30 – 40 years, than the one of the cited paper). We cannot a priori exclude the possibility of other wrong internal references, but there is no other simple method to determine whether a reference is fixed precision. Here we set $\epsilon = 10^{-6}$; typically 20 – 30 iterations are needed for convergence.

The best performance $R_i^{\text{best}}$ of scientist $i$ is calculated according to $R_i^{\text{best}} = \min_t R_i (t)$, where $R_i (t)$ is the relative rank defined in Eq.(4) of the $i$-th author in the WACN corresponding to the $t$-th time slice of the PR database.

Acknowledgments

This work is partially supported by the Lilly Endowment grant 2008 1639-000. to A.V. the grant of the European Community number 238597 ICTeCollective to S.F.. We acknowledge the American Physical Society for providing the data about Physical Review’s journals.

[1] L. Egghe & R. Rousseau, Introduction to Informetrics: quantitative methods in library, documentation and information science, (Elsevier, Amsterdam, 1990).
[2] E. Garfield, Citation Indexing. Its Theory and Applications in Science, Technology, and Humanities, (Wiley, New York, 1979).
[3] R. Adler, J. Ewing & P. Taylor, IMU Report: Citation Statistics, http://www.mathunion.org/Publications/Report/CitationStatistics (2008).
[4] J. E. Hirsch, Proc. Natl. Acad. Sci. USA 102, 16569-16572 (2005).
[5] M. E. J. Newman, Proc. Natl. Acad. Sci. USA 98, 404-409 (2001).
[6] M. E. J. Newman, Phys. Rev. E 64, 016131 (2001).
[7] M. E. J. Newman, Phys. Rev. E 64, 016132 (2001).
[8] A. L. Barabási, H. Jeong, Z. Neda, E. Ravasz, A. Schubert & T. Vicsek, Physica A 311, 590-614 (2002).
[9] S. Redner, Eur. Phys. J. B 4, 131-134 (1998).
[10] P. Chen, H. Xie, S. Maslov,& S. Redner, Journal of Informetrics 1, 8-15 (2007).
[11] S. Brin & L. Page, Computer Networks and ISDN Systems 30, 107-117 (1998).
[12] J. Kleinberg, Journal of the ACM 46, 604 (1999).
[13] C. Castillo, D. Donato & A. Gionis, Lecture Notes in Computer Science, (Springer-Verlag, Berlin, 2007).
[14] A. Sidiropoulos & Y. Manolopoulos, Journal for Systems & Software 79, 1679-1700 (2006).
[15] D. Walker, H. Xie, K. K. Yan & S. Maslov, J. Stat. Mech. P0610 (2007).
[16] S. Redner, Phys. Today 58, 49-54 (2005).
[17] A. Barrat, M. Barthélemy, R. Pastor-Satorras & A. Vespignani, Proc. Natl. Acad. Sci. USA 101, 3747-3752 (2004).
[18] F. Radicchi, S. Fortunato & C. Castellano, Proc. Natl. Acad. Sci. USA 105, 17268-17272 (2008).
[19] S. Fortunato, M. Boguna, A. Flammini & F. Menczer, Proc. WAC 2006 LNCS 4936, 59-71 (2008).
[20] E. Garfield, Essays of an Information Scientist 4, 182-187 (1986).
[21] M. Enserink, Science 323, 1662-1664 (2009).
[22] PACS stands for Physics and Astronomy Classification Scheme. This scheme is nowadays universally adopted by the majority of Physics journals in order to well classify papers. Since 1980, Physical Review’s journals have started to associate a set of PACS numbers (on average three PACS numbers per paper) with every published paper.
[23] Actually, the total number of internal references reported by the PR database is 3,866,822, but 351 of them are clearly wrong since they refer to papers citing newer papers (i.e., the year of publication of the citing paper is smaller, in some case even of 30 – 40 years, than the one of the cited paper). We cannot a priori exclude the possibility of other wrong internal references, but there is no other simple method to determine whether a reference is good or not.
Appendix A: IDENTIFICATION AND DISAMBIGUATION OF AUTHORS

The list of references enables the construction of an error-free network of citation between articles. However, in this paper we are not interested in the analysis of paper citation networks (PCNs), but on one of their particular projections: the Weighted Author Citation Network (WACN). We present a detailed description on the way in which we construct the WACN in section III. Here we would like to focus about possible sources of error, caused by the format of the PR dataset itself, associated with the projection of a network of citation between papers into the correspondent WACN.

Whether authors can be well identified or not is still an open problem. Every author in the database has always a first and a last name. Many of them also have additional names, generically indicated as middle names. First (and middle) names may appear in their full version or they can only be represented by the first letter. Writing first (and middle) names in their complete version is typically more common in recent papers and in papers with short lists of authors. On a total of 1 916 812 repetitions for the authors (this means the sum of all authors, not only different authors, over all the papers) the first names appear 1 564 251 times with just their first letter and the remaining 352 561 times in their full version. The simplest (and actually implemented) way to identify and distinguish authors is to assign to each author an identifier (ID) in accordance with the following rule

\[
\text{LAST-NAME}, \text{FIRST-NAME MIDDLE-NAME} \implies \text{LAST-NAME}, \text{FM}.
\]

This means for example that according to rule A1 “Einstein, Abert” has ID equal to “Einstein, A” while the ID of “Bethe, Hans Albrecht” is “Bethe, HA”. Essentially, the last name is taken in its full version, while for the first and the middle names we consider only the first letters. Proceeding in this way we are able to distinguish 216 623 “different” authors.

This approach is however biased by two main sources of error. First, there is a problem of identification for the authors. Unfortunately, scientists do not always sign their papers using the same name and this has as a consequence the impossibility to automatically relate different names to the same physical person. This fact may happen for several reasons: different order between first and last name; possible presence or absence of middle names; change of last names (this happens especially to ladies after their wedding).

The second problem is basically the reverse of the formerly described source of error: the obvious impossibility to distinguish authors having same initials and the same last name by using only this information. We did not try to perform any kind of more elaborated analysis since this is still an open problem in bibliometrics and mainly because this was beyond the purposes of our paper. Furthermore, a simple analysis revealed that the number of “pathological” cases is expected to be small enough to be considered irrelevant for the results reported in the paper.

In order to evaluate the relevance of the error introduced by the impossibility to disambiguate IDs, we consider only papers of our database signed by authors using the full version of their first and last names (and eventually their middle names). Unfortunately, this happens only in recent papers (from 1980 on) and only when the list of authors is sufficiently short (less than four, in general): this means that is very unlikely to happen. As already mentioned, the total number of “signatures” (i.e., the total number of non-distinct authors who have signed all papers in our database) is 1 916 812, while the number of times in which an author has signed with her/his “full signature” is only 352 561. Based on this subset, we perform the reduction described in rule (A1). We then calculate the probability \(P(d)\) by simply counting the ratio between the total number of IDs shared by \(d\) different scientists and the total number of IDs. The resulting distribution is plotted in Figure 8: in the 92% of the cases an ID corresponds to a single author; the rest of the distribution has a power law decay (i.e., \(P(d) \sim d^{-\delta}\)) as \(d\) increases (the exponent \(\delta \simeq 3\)).
Appendix B: SCIENCE AUTHOR RANK ALGORITHM: DEPENDENCE ON THE DAMPING FACTOR

Science Author Rank Algorithm (SARA) depends on the so-called damping factor $q$ [see Eq. 2]. $q$ is a real number in the interval $[0, 1]$ and the results calculated with SARA for different values of $q$ may differ. As a practical example, we report in Figure 9 some scatter plots between SARA rankings calculated for different values of $q$. As expected, SARA rankings calculated for different $q$ are linearly correlated and the correlation strength decreases as the difference between the $q$s increases.

The decision to set $q = 0.1$ is based on a special analysis which is graphically reported in Figure 10. For each scientist, who earned one of the major prizes in Physics, we computed her/his best performance during her/his scientific history. We then plotted the ratio of prizes assigned to scientists with the best performance falling in a given interval (note that the intervals’ division is totally arbitrary, but the results do not strictly depend on this choice). According to any reasonable measure of scientific impact, the probability that a scientist earns an important prize should be related to her/his scientific relevance. In the case of SARA ranking, we generally observed that the majority of prizes is assigned to scientists who have reached a top position in the ranking. This allows us to justify the use of such measure for the scientific impact of authors. Moreover, as already stated and shown (see Figure 7), SARA is more effective than other well known criteria like Citation Count (CC) or Balanced Citation Count (BCC) if one wants to predict future winners of prizes. Anyway, also in the case of SARA, the predictivity of the algorithm may quantitatively change as function of $q$. Looking at Figure 10, we see for instance that, in the top intervals, the highest ratios are reached for values of $q \approx 0.1$, while values of $q < 0.1$ or $q > 0.1$ give lower ratios in these first two bins. As a consequence, we can say that $q = 0.1$ is the optimal value for SARA since it is the value which maximizes the predictivity of our algorithm.