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Quantifying the influence of scientists and their publications: distinguishing between prestige and popularity

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Abstract. The number of citations is a widely used metric for evaluating the scientific credit of papers, scientists and journals. However, it so happens that papers with fewer citations from prestigious scientists have a higher influence than papers with more citations. In this paper, we argue that by whom the paper is being cited is of greater significance than merely the number of citations. Accordingly, we propose an interactive model of author–paper bipartite networks as well as an iterative algorithm to obtain better rankings for scientists and their publications. The main advantage of this method is twofold: (i) it is a parameter-free algorithm; (ii) it considers the relationship between the prestige of scientists and the quality of their publications. We conducted real experiments on publications in econophysics, and used this method to evaluate the influence of related scientific journals. The comparison between the rankings by our method and simple citation counts suggests that our method is effective in distinguishing prestige from popularity.
S Online supplementary data available from stacks.iop.org/NJP/14/033033/mmedia

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Contents

1. Introduction

How to measure the scientific influence of scientists and their publications has been a long-term debate. Although many metrics have been introduced, their objectiveness and effectiveness have always been questioned [1–5]. Without clear-cut criteria, nobody can tell whether they are fair enough to reflect the reality. It is well known that the number of citations is the simplest indicator of scientific impact [6–8]. Previous studies showed that the number of citations has a certain correlation with the quality of research [9–11], which has thus been widely used to assess the scientific productions of individuals or institutions as well as the scientists' influence [12–14]. However, the value of each citation is indeed dependent on the *quoters*, i.e. the researchers who cited the paper [15]. If a paper is cited by prestigious scientists, it is probably a gem (i.e. high quality) and is thus highly appreciated. This important perspective is not considered in many citation-based ranking methods. Even the well-known h index, defined as the number of papers with citation number $\geqslant h$, also treats citations equally no matter who are the contributors [16, 17].

In general, if a scientist cites a paper, it indicates that she endorses this paper as well as its authors. This can be considered as a spread of prestige (i.e. quality, will be quantified later) which cannot be reflected merely by the number of citations, since citation counts only reflect the popularity, but not the quality or prestige [18]. Inspired by the success of Google's ranking system for web pages, the popular algorithm PageRank as well as some of its variants have been used to show the prestige in citation networks of journals [19], publications [20–22] and scientists [15, 23]. Since the network analyzed is a particular projection of a citation network, the result depends on how weights are assigned to links. In addition, the choice of the damping factor in PageRank-based methods also affects the results [23]. It has been pointed out that different from the boredom attrition factor 0.15 of web surfers, the appropriate factor is 0.5 in the context of citations, corresponding to a citation chain to two links [20].

All previous studies have focused on the ranking of either scientists or publications, totally neglecting the fact that these two sides are interacting with each other. In other words, the scientists' prestige and the quality of their publications are strongly correlated. It is clear that a paper is expected to be of high quality if it was cited by prestigious scientists; meanwhile, a

Table 1. The journals (and an e-print server) that published more than five papers in our dataset.

Journal	Abbreviation	Paper
Physica A	Physa	1120
Phys. Rev. E	PRE	179
arXiv.org	arXiv	161
Eur. Phys. J. B	EPJB	148
Quant. Financ.	QF	52
Int. J. Mod. Phys. C	IJMPC	47
Phys. Lett. A	PLA	31
Int. J. Theor. Appl. Financ.	IJTAF	24
Europhys. Lett.	EPL	21
Phys. Rev. Lett.	PRL	20
J. Korean Phys. Soc.	JKPS	18
Adv. Complex Syst.	ACS	15
J. Phys. A: Math. Theor.	JPA	14
Proc. Natl Acad. Sci. USA	PNAS	12
Acta Phys. Pol. B	APPB	11
J. Stat. Mech. Theory E	JSM	10
Chin. Phys. Lett.	CPL	7
Int. J. Mod. Phys. B	IJMPB	7

high-quality paper can raise the prestige of its authors. From this perspective, we propose an iterative algorithm to quantify the quality of papers and scientists' prestige via considering their relationship on an author–paper bipartite network. The network is a directed bipartite network with two kinds of links. The link from the author to the paper represents the citing relationship, while the link from the paper to the author indicates the authorship. Our method is parameter-free and can simultaneously obtain the ranking lists of both papers and scientists. We perform our method on a dataset consisting of 1990 scientists in the field of econophysics[6] and their 2012 papers that were published between April 1995 and September 2010, and compare the results with citation counts (CC rank). Although our method has an overlap with the CC rank, it also reveals significant and meaningful differences. The outliers indicate that some scientists or papers with low CC rank have higher influence than their citations indicate, while some others are overestimated by merely counting the number of citations.

2. Data description

Our database consists of a set of papers in the field of econophysics that were published between April 1995 and September 2010 in 78 scientific journals and an e-print server (i.e. arXiv.org). The data are obtained by filtering the whole set of papers with the keywords *econophysics*, *market*, *finance*, *stock*, *price*, *minority game*, *money*, *wealth*, *trade* and *GDP*. Finally, we have 2012 papers and 1990 distinct authors. Actually, these data are an extension of the dataset

[6] Econophysics is an interdisciplinary research field, applying theories and methods originally developed by physicists to solve problems in economics, including uncertainty or stochastic processes and nonlinear dynamics.

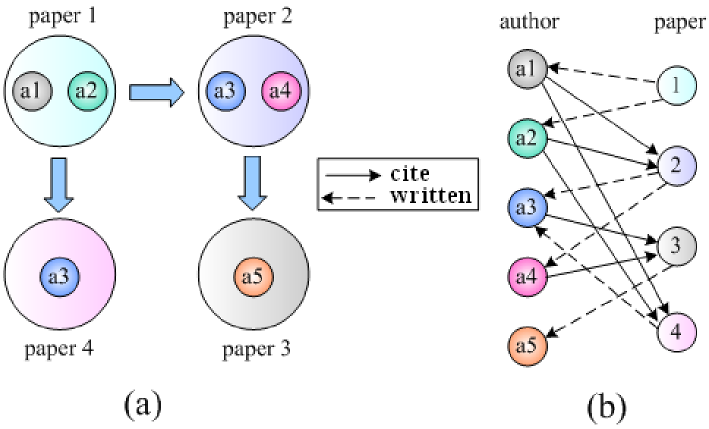

Figure 1. An illustration of how the author–paper bipartite network is constructed. (a) The citation relations between four papers written by five scientists. (b) The corresponding author–paper interactive network of (a), where the directed links from an author to papers indicate that the author cites these papers, and the directed links from a paper to authors mean that this paper is written by these scientists. Here self-citations are not included.

analyzed in [24, 25]. Among the 78 journals, more than half of them contain only one or two papers, and more than half of the papers were published in *Physica A*. Table 1 summarizes the journals that published more than five papers in our dataset. The list of references at the end of each paper is used to construct a paper citation network. Note that only the papers within this dataset are considered in the citation network. Thus the degree of a paper in this citation network is indeed smaller than its actual number of citations according to the *ISI Web of Science*. Unless otherwise stated, *citation* in our context always refers to the case within the paper citation network.

3. Construction of the author–paper interactive network

According to the paper citation relations and the authors of each paper, we can obtain a directed author–paper interactive bipartite network. The directed links from an author to papers denote that this author cites these papers, while the directed links from a paper to authors represent that the paper is co-authored by these scientists. Denote by S and P the sets of scientists and papers, respectively, that exist in total $M = |S|$ scientists and $N = |P|$ papers. A is an $M \times N$ adjacency matrix representing the *cite* relations between authors and papers, with element $a_{i\alpha} = 1$ if author s_i cites paper p_α and 0 otherwise. Similarly, B is an $N \times M$ adjacency matrix representing the *written* relation, with element $b_{\alpha i} = 1$ if author s_i is one of the authors of paper p_α and 0 otherwise. Consider a paper p_α written by n authors $s_1, s_2, \ldots, s_n$, citing paper p_β; then there will be n directed links from paper p_α respectively to n authors of p_α, and n directed links from n authors to paper p_β. Note that self-citations are not included in the network. Figure 1 shows how the author–paper bipartite network is constructed. In this example, there are five scientists and four papers with the citation relation shown in figure 1(a). Paper p_1 cites papers p_2 and p_4 and paper p_2 cites paper p_3. Since p_1 is co-authored by scientists a_1 and a_2, there are two links from p_1 respectively to a_1 and a_2, indicating that a_1 and a_2 are the authors of paper p_1. According to the citation relation between papers p_1 and p_2 (i.e. p_1 cites p_2), there are two links respectively from a_1 and a_2 to p_2. By following the same rules, we finally obtain the author–paper directed bipartite network as shown in figure 1(b).

4. Ranking algorithm

The use of the author–paper bipartite network has a big advantage. It utilizes the interactions between the reputation and the publications of a scientist. Normally, a paper is expected to have high quality if it has been cited by prestigious scientists, while high-quality papers raise the scientists' prestige accordingly. Based on this assumption, we defined an iterative algorithm on the author–paper bipartite network (AP rank) to evaluate the impact and prestige of papers and scientists. Our method can simultaneously obtain the ranking lists of both papers and scientists.

We denote by Q_{s_i} the score of author s_i to quantify s_i's prestige, and by Q_{p_α} the score of paper p_α to evaluate the quality of p_α. For simplicity, we consider the contribution of each author of a paper to be the same, regardless of order. And of course, one can assign weight to an author's importance according to her author rank in the paper. The score of a paper will be evenly distributed to all its co-authors. This implies that if a paper has more authors, each of them obtains less. Thus the score of author s_i is counted by summing over the scores that were distributed by all his papers. Mathematically, it reads

$$Q_{s_i} = \sum_{\alpha \in P} \frac{Q_{p_\alpha}}{k_{p_\alpha}^{\mathrm{out}}} \cdot b_{\alpha i}, \tag{1}$$

where $k_{p_\alpha}^{\mathrm{out}} = \sum_{i \in S} b_{\alpha i}$ is the number of authors of paper p_α. We will show later that Q_{p_α} should be a normalized score. This step is equivalent to mass diffusion from paper to author on the bipartite network, which is indeed a conservative process. We define a process to be conservative if the initial mass of the network is equal to the final mass after the process has taken place. A similar process has been used to design for information recommendation on undirected bipartite networks where the two groups of nodes are, respectively, users and objects [26–28].

Unlike the diffusion process from paper to author, we adopt a non-conservative process from author to paper. We assume that if an author cites a paper, this means that the author votes for (i.e. gives approval to the impact of this paper) this paper with score equal to his score Q_s. Clearly, if two papers have identical citations, the paper cited by prestigious scientists (i.e. authors with higher score) is more significant than the other papers. Here we assume that each paper inherently holds one score. By doing this, we are able to compare the performance of two authors who have zero citation according to their productivity. Accordingly, the score of paper p_α is equal to the summation of its inherent score and the total voting scores from the authors who cite it, namely

$$Q_{p_\alpha} = 1 + \sum_{i \in S} Q_{s_i} \cdot a_{i\alpha}. \tag{2}$$

To avoid the exponential increase of the total score, we normalize the score in the following way:

$$\tilde{Q}_{p_\alpha} = Q_{p_\alpha} \cdot \frac{C}{\sum\limits_{\beta \in P} Q_{p_\beta}}, \tag{3}$$

where C is the initial total score. At the beginning, we assign to each paper one unit of score. Thus $C = N$. Then the scores iterate following the link direction according to the above rules. We define the deviation of the two score vectors of paper between two iteration steps as

$$\Delta(t) = |\tilde{Q}_p(t) - \tilde{Q}_p(t-1)| = \frac{1}{N}\sum_{\alpha\in P}[\tilde{Q}_{p_\alpha}(t) - \tilde{Q}_{p_\alpha}(t-1)]^2. \tag{4}$$

The final scores are obtained when $\Delta(t) < \delta$, where δ represents the *a priori* fixed precision. Here, we set $\delta = 10^{-4}$.

5. Results

When iterating over equations (1)–(3), equation (2) produces new paper quality values Q_{p_α} from new author scores. Since new author scores are obtained by a linear transformation from old paper quality values, we see that in fact $Q_{p_\alpha}(t+1)$ is a function of $Q_{p_\alpha}(t)$ (here the index t denotes the iteration step). Together with the normalization by equation (3), one may view this process as iterated redistribution of Q_p where the total magnitude of Q_p is converged; it is therefore a conservative process and, similarly as for PageRank, a stationary solution is eventually found. The first principle of this algorithm is that the quality of an author is determined by the average quality of papers authorized by him (and, in addition, the quality of each paper authored by a given person is divided by the paper's number of authors, reflecting a proportionally smaller contribution of each of them to the resulting paper's quality). Second, the quality of a paper is given by taking an inherent quality (which is assumed to be one for all papers) and adding the quality of all authors who cite this paper.

To test the above algorithm, we apply it to rank scientists and papers in the field of econophysics. We have tested that the ranking results are the same, no matter whether the iteration starts from the author side or from the paper side. For an author, her citation is the total number of citations received from other papers. Similarly, for a paper, its citation is the number of papers that cite this paper (i.e. the in-degree in the paper citation network). We release the original data together with the executable file of our algorithm. The description of the data and the instruction of the software can be found in the supplementary material, available at stacks.iop.org/NJP/14/033033/mmedia.

5.1. Ranking of scientists

Figure 2 shows the scatter plot of AP rank versus CC rank for authors. If the two methods provide the same ranking, all the points would fall on the diagonal. It shows that AP rank can provide a score that is, in general, proportional to CC rank. However, there are some deviations. We apply Kendall's τ coefficient [29] to measure their correlation, which is defined as

$$\tau = \frac{n_\mathrm{c} - n_\mathrm{d}}{n_\mathrm{t}}, \tag{5}$$

where n_c and n_d are the numbers of concordant pairs and discordant pairs, respectively. n_t is the total number of pairs. The rank correlation between AP rank and CC rank is 0.784. The points below the diagonal are the scientists that have higher scores by AP rank and a smaller score by CC rank, which means that these scientists are more important in this field than merely the number of citations indicates. For example, J D Farmer who owns 19 papers in our dataset has been cited only 224 times and has a CC rank of 26, while his AP rank is 12. The reason is that most of his citations come from prominent scientists and thus his prestige is improved.

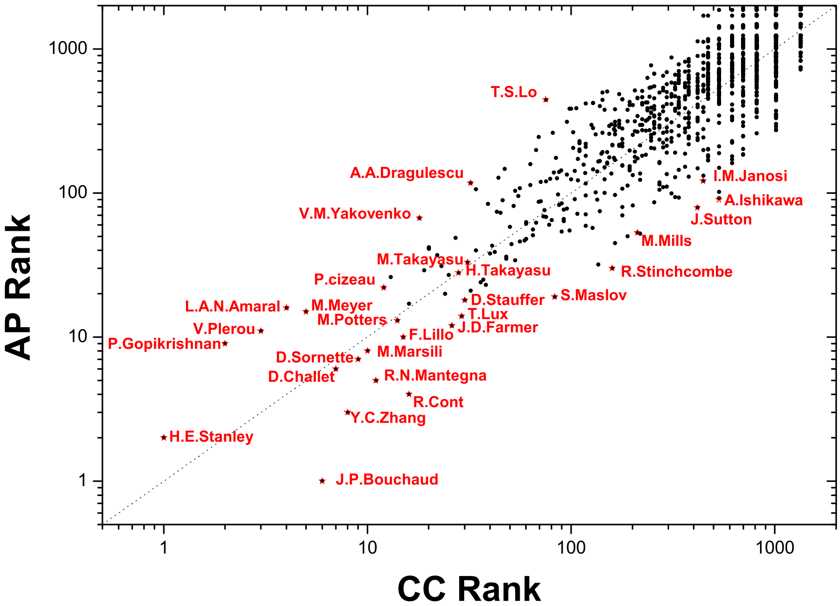

Figure 2. Scatter plot of AP rank versus CC rank for authors. If the two methods provide the same ranking, all the points would fall on the diagonal. The outliers indicate the significant difference between AP rank and CC rank. We label some typical examples in red. Kendall's τ coefficient is 0.784.

The co-authorship network in the field of econophysics is shown in figure 3 where the top 150 scientists ranked by the AP method are presented. The size of the filled circle indicates the AP score of an author. The higher an author's AP score, the larger the circle. The color of the circle represents the number of citations, namely an author's CC score. The higher an author's CC score, the darker the color of the circle. The width of the edge between two nodes is proportional to the number of papers that these two authors collaborated on. From this figure, we can find a very clear community structure. The largest community is led by H E Stanley from Boston University, who coined the term 'econophysics' in the mid-1990s. The corresponding big and red circle indicates that he is a prominent scientist in the field of econophysics.

Another interesting thing is to investigate the role of a scientist in his/her community. Figure 4 shows the author's score as a function of the average score of all his/her co-authors. If an author's score is larger than the average of his/her co-authors (i.e. below the diagonal), it means that his/her overall influence is more than his/her co-authors' and thus he/she may probably play a leading role in the group. In contrast, if an author's score is much lower than the average of his/her co-authors, he/she is more likely to be a follower (e.g. a student). Therefore, this method provides a potential way to identify the supervisor–supervisee relationship.

5.2. Ranking of papers

Figure 5 shows a comparison of the AP rank and CC rank for papers. Kendall's τ coefficient of the AP rank and CC rank is 0.644. Compared with the result on ranking authors, the difference between the results ranked by AP and CC is comparatively larger when ranking papers. Some typical outliers are labeled by stars with their publication information, including the journal, volume and starting page. For example, '*Nature*_397_498' indicates that this paper is published

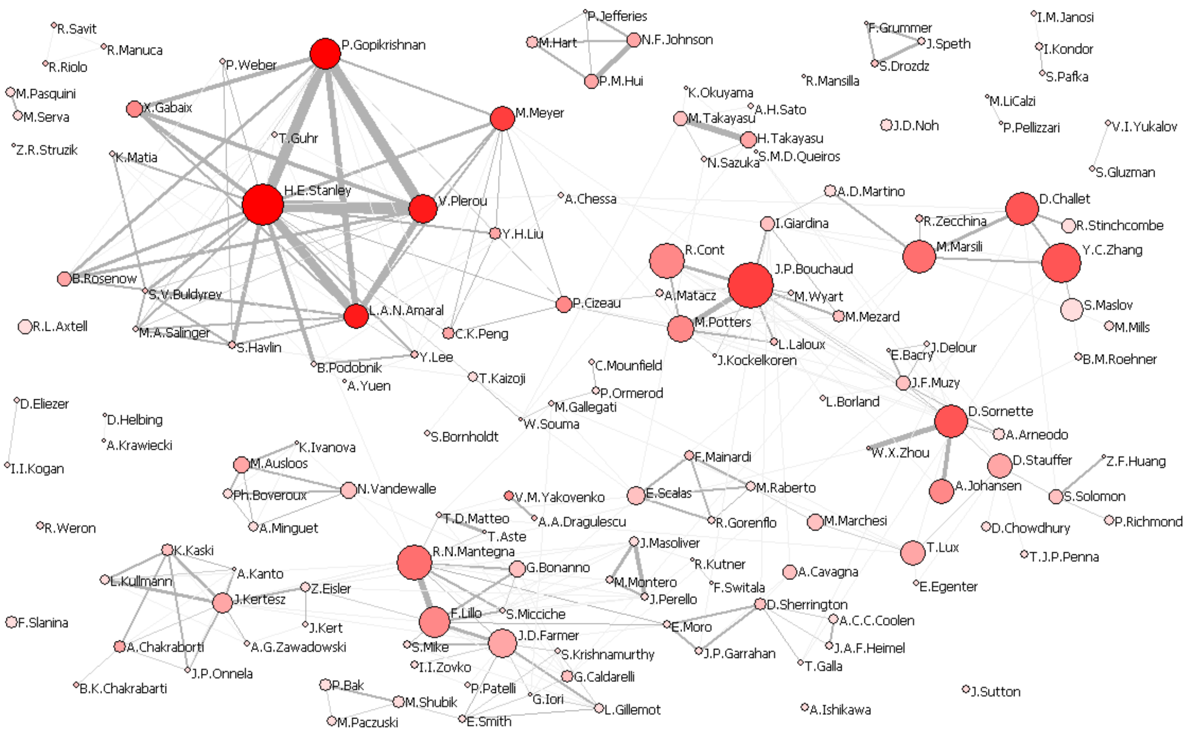

Figure 3. The co-authorship network in the field of econophysics. The top 150 scientists ranked by AP are presented. The size of the filled circle indicates the AP score, while the color of the circle indicates the number of citations (i.e. CC score). The higher an author's CC score, the darker the color of the circle. Two authors are interconnected if they have collaborated at least once. The width of the edge between two nodes indicates the number of papers that they have collaborated on.

in volume 397 of *Nature* and starts from page 498. As the AP algorithm focuses mainly on the interactions between papers and authors, the citations of a paper from some low-score authors have a small influence on the paper's ranking result. In contrast, the citations from the prominent scientists will contribute more to the paper's score. We give two typical examples in figure 6. Although the first paper shown in figure 6(a) (*EPL* **40** (1997) 479) has only been cited 38 times and has a CC rank of 52, we rank it third since it was cited by many high-credit authors indicated by large circles. In contrast, although the paper in figure 6(b) (*Physica* A **299** (2001) 213) has 70 citations and has been ranked 19 by CC rank, most of these citations come from papers written by low-score authors; it is ranked only 158 by AP.

In general, the papers published years ago are more likely to attract attention and to accumulate citations than recently published papers. The most cited papers, which are usually considered as representative or important works in the related field, will further receive more and more citations. As a result, old papers tend to obtain higher ranks than fresh papers due to the cumulative effect as time goes on. We therefore define a time-dependent AP rank method

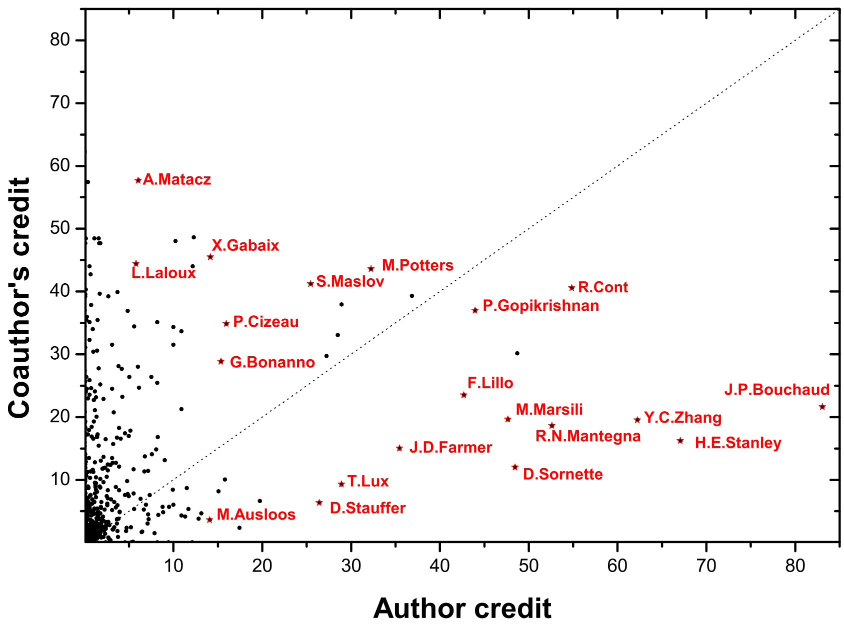

Figure 4. The author's score as a function of the average score of all his/her co-authors.

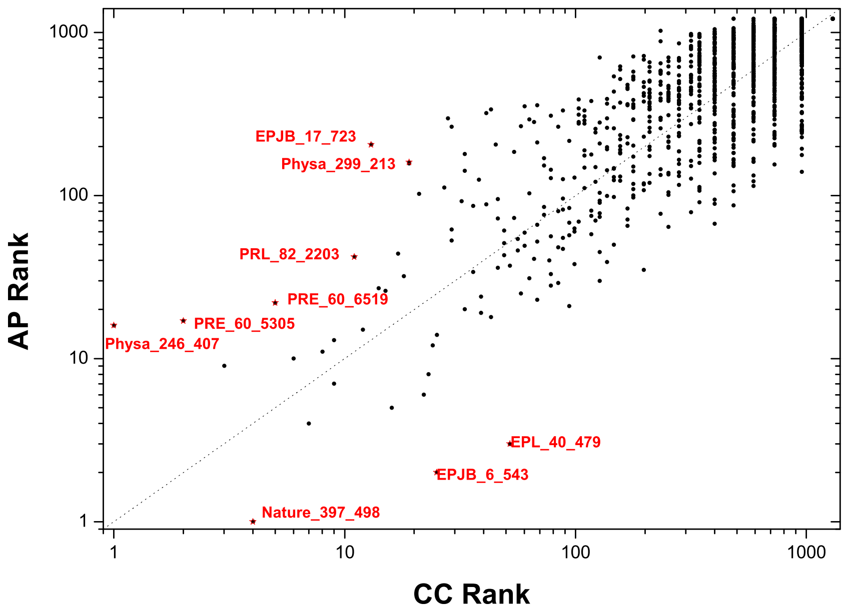

Figure 5. Scatter plot of AP rank versus CC rank for papers. If the two methods provide the same ranking, all the points would fall on the diagonal. The outliers indicate the remarkable difference between AP rank and CC rank. Kendall's τ coefficient is 0.644.

(TAP), with the score of a paper α given by

$$Q^{\mathrm{TAP}}_{p\alpha} = \frac{Q^{\mathrm{AP}}_{p\alpha}}{T_0 - T_\alpha}, \qquad (6)$$

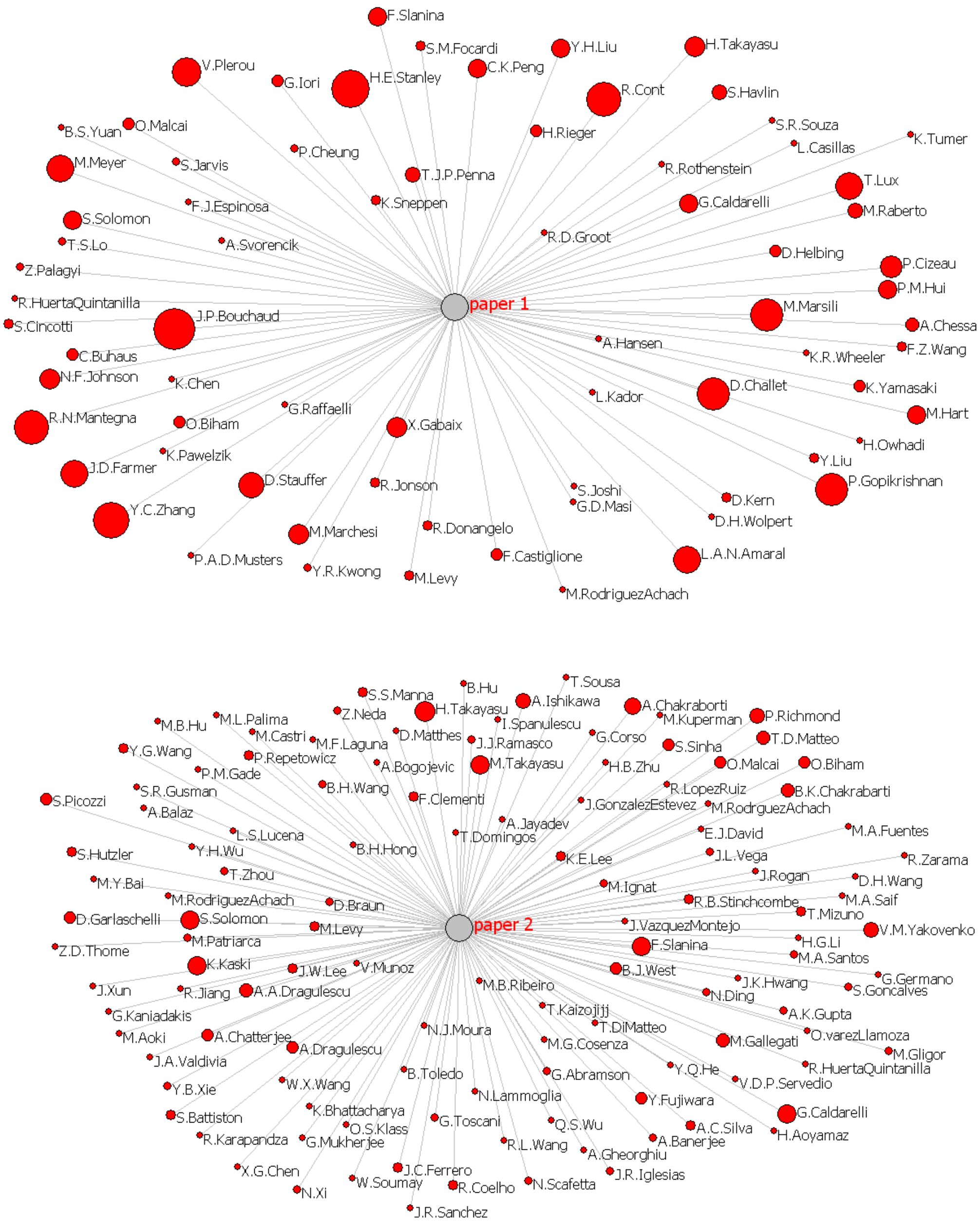

Figure 6. Two typical examples of papers. (a) Paper 1 has 38 citations and yet a very high AP rank. (b) Paper 2 has 70 citations and yet a very low AP rank. The size of the circle indicates the author's AP score. The higher an author's score, the larger the circle.

where $Q^{\mathrm{AP}}_{p\alpha}$ is the final score of paper α obtained by AP rank. The denominator is the number of months between the publication month of paper α (i.e. T_α) and the observing month (i.e. T_0). For our dataset, T_0 is September 2010. Figure 7 shows the scatter plot of AP rank versus TAP rank for papers. Papers of both high AP and high TAP ranks are usually prominent works and have a

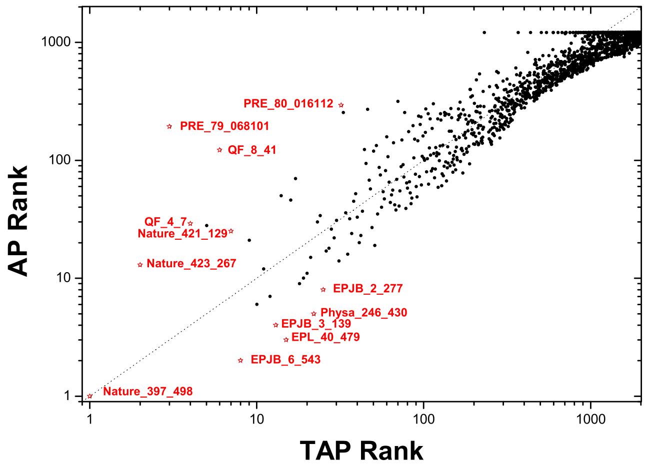

Figure 7. Scatter plot of AP rank versus TAP rank for papers.

long-term influence in the related research field. One typical example is the paper 'Scaling and criticality in a stochastic multi-agent model of a financial market' by T Lux and M Marchesi published in 1999. This paper is the first in both AP rank and TAP rank. Moreover, works with a very high AP rank and a relative low TAP rank are usually pioneer works that were published many years ago with an overall high influence, such as the papers '*EPJB* **6** (1998) 543', '*EPL* **40** (1997) 479', '*EPJB* **3** (1998) 139', '*Physica* A **246** (1997) 430', etc. In contrast, papers with not very low AP rank but very high TAP rank (see the outliers in the top left corner of figure 7) are usually those recently published papers that have potentially high influence in the future. Typical examples are '*PRE* **80** (2009) 016112', '*PRE* **79** (2009) 068101' and '*Quant. Financ.* **8** (2008) 41'. In addition, some works which already have a high AP rank are ranked even higher when publication date is considered. For example, '*Nature* **423** (2003) 267', '*Nature* **421** (2003) 129' and '*Quant. Financ.* **4** (2004) 7' are, respectively, ranked 14, 26 and 29 by the AP method, indicating their high influence in the field of econophysics, and their corresponding TAP ranks are 2, 7 and 4. These works are very promising and may become more influential in the future.

5.3. Evaluation of journals

We further investigate the correlation between the quality of the papers and the quality of their corresponding published journals. As we know, the ISI Impact Factor (IF), which is defined as the mean number of citations a journal receives over a two-year period, is widely used to evaluate the quality, importance or influence of journals. However, we argue that since IF is based solely on the number of citations regardless of the prestige of citing sources, it can only be considered as a metric of popularity, and thus is inappropriate to be used to quantify the quality or prestige of journals [19]. Therefore we consider another metric, the Article Influence$^{\mathrm{TM}}$ Score (AIS) [30], as an indicator to reflect the quality of a journal. Unlike IF, AIS weights each citation by the quality of the citing journals. In figure 8, we compare the five-year IF and AIS of 18 selected journals, including *Nature*, *Science* and the journals listed in table 1. The data shown in table 2 were obtained from Thompson Reuters' *2010 Journal Citation Report* (JCR). IJTAF is

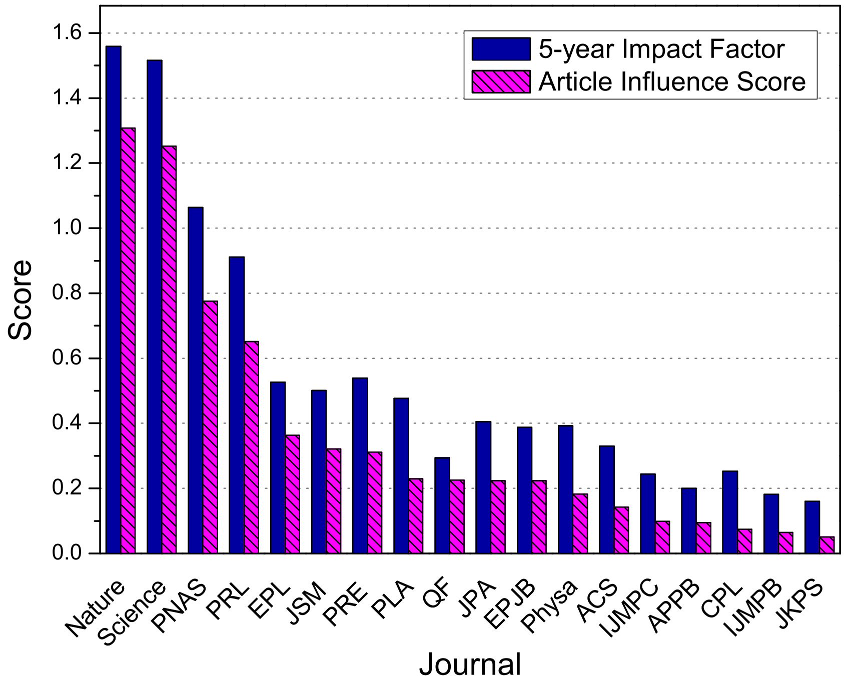

Figure 8. The five-year Impact Factors (IF) and Article Influence Scores (AIS) of 18 journals in our dataset. For better presentation, the scores are modified in the form $\log_{10}(s+1)$, where s is the real value of the five-year IF or AIS.

excluded since it does not have a record in JCR. All the journals are ranked in descending order according to their AIS. For most journals, the five-year IF and the AIS are positively correlated, but there are a few exceptions. PRE has higher five-year IF than EPL and has a lower AIS. Although QF has a low five-year IF, its AIS is even higher than of some journals with a larger five-year IF. In contrast, CPL has a high five-year IF and has a very low AIS. A more detailed comparison and discussion of these two measures can be found in [31].

Figure 9 shows the average rank of the papers in each journal. The 18 selected journals are ranked in descending order by their AIS. Generally speaking, papers published in high-AIS journals tend to be ranked higher than those published in low-AIS journals. The average score of papers in each journal is presented in figure 10. It shows that the average score of papers in high-AIS journals is likely to be higher than that in low-AIS journals. Interestingly, we find that the journal QF has an even lower average rank and a higher average score than some high AIS journals, such as PRE, EPL, etc. This may indicate that *Quant. Financ.* is a mainstream journal of econophysics, and thus its papers are likely to have a larger influence in this field. Finally, we use the product of the average score and the number of published papers to quantify the overall influence of a journal in econophysics, according to which we can find the mainstream journals in this field. The result is shown in table 2, where the journals are ranked by their overall influence scores and their corresponding information on AIS, five-year IF, the number of publications and average scores is also presented. As we can see, the top 5 mainstream journals in econophysics are '*Physica* A', '*Phys. Rev.* E', '*Eur. Phys. J.* B', '*Quant. Financ.*' and '*Phys. Rev. Lett.*'.

Table 2. Mainstream journals in econophysics ranked by their overall influence scores (OIS). Their corresponding information on AIS, five-year IF, the number of publications, average score (AvgS) and OIS is also presented.

Rank	Journal	AIS	Five-year IF	Paper	AvgS	OIS
1	*Physa*	0.522	1.467	1120	0.640	716.845
2	*PRE*	1.047	2.458	179	1.772	317.269
3	*EPJB*	0.674	1.443	148	1.585	234.509
4	*QF*	0.682	0.968	52	3.513	182.669
5	*PRL*	3.486	7.154	20	6.333	126.651
6	*Nature*	19.334	35.241	5	13.205	66.026
7	*EPL*	1.308	2.358	21	2.448	51.410
8	*IJMPC*	0.256	0.753	47	0.4759	22.365
9	*JPA*	0.675	1.542	14	1.456	20.378
10	*PNAS*	4.959	10.591	12	1.534	18.405
11	*Science*	16.859	31.769	1	12.083	102.082
12	*APPB*	0.243	0.586	11	0.577	6.345
13	*ACS*	0.39	1.141	15	0.371	5.561
14	*JSM*	1.094	2.169	10	0.527	5.269
15	*JKPS*	0.124	0.446	18	0.213	3.829
16	*PLA*	0.697	1.995	31	0.046	1.440
17	*CPL*	0.186	0.79	7	0.035	0.246
18	*IJMPB*	0.159	0.519	7	0.031	0.216

6. Discussion

In this paper, we proposed an iterative algorithm named *AP Rank* to quantify the scientists' prestige and the quality of their publications via their inter-relationship on an author–paper bipartite network. The rationale behind this method is that a paper is expected to be of high quality if it was cited by prestigious scientists, while high-quality papers will, in turn, raise their authors' prestige. It is thus clear that AP rank weighs the prestige of quoters more than the number of citations. The former refers to prestige while the latter refers to popularity. We conducted the experiment on a dataset consisting of 1990 scientists and their 2012 papers in econophysics, and compared the ranking results with the citation counts. Although these two methods have an overlap to some extent (for authors, Kendall's $\tau = 0.784$, and for papers, Kendall's $\tau = 0.644$), the outliers reveal remarkable and meaningful differences. We found that some scientists with a lower CC rank may have a higher influence than that indicated by their citations, because they are appreciated by prestigious scientists. Some papers with a large number of citations are ranked lower by AP rank, indicating that they are over estimated by merely counting the number of citations. In other words, these papers are popular but not prestigious. The fact that a paper can only cite earlier papers makes the publishing time an important factor in the paper citation network. Therefore, old papers will have more chances to accumulate more citations than fresh works. With this consideration, we proposed a time-dependent AP rank (TAP rank). The papers can be classified by synthetically considering their AP rank and TAP rank. We further evaluated the influence of journals by the total ranking score

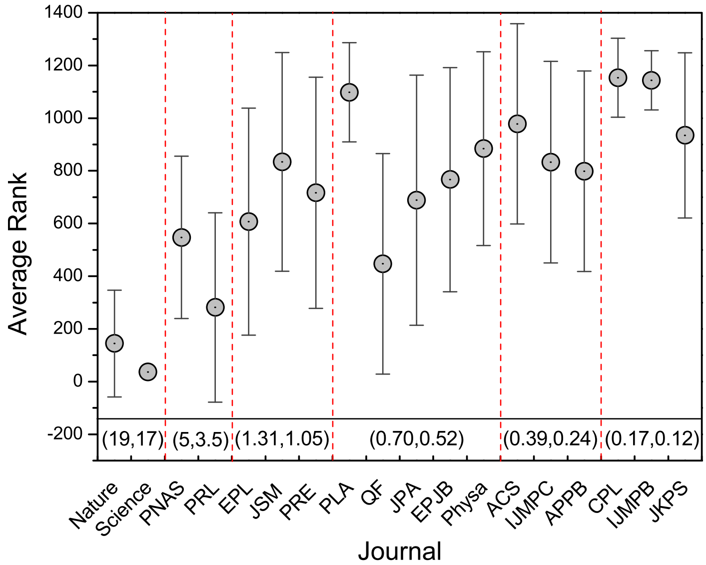

Figure 9. The average rank of the papers in each journal. The journals are ranked from left to right in descending order by their AIS. At the bottom of each region, the left number and the right number indicate the largest and the smallest AIS of the journals in this region, respectively.

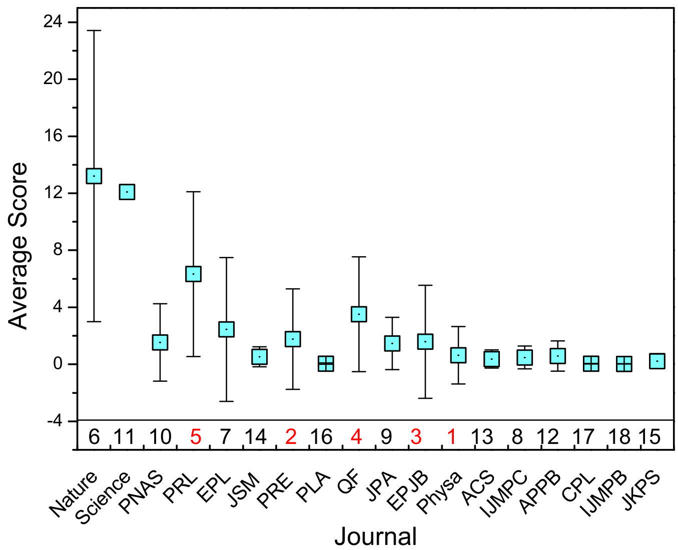

Figure 10. The average score of the papers in each journal. The journals are ranked from left to right in descending order by their AIS. The numbers at the bottom indicate the ranks of journals obtained by overall influence score.

of their publications. The top 5 mainstream journals in econophysics were found: '*Physica* A', '*Phys. Rev.* E', '*Eur. Phys. J.* B', '*Quant. Financ.*' and '*Phys. Rev. Lett.*'. In reality, our method can be directly applied to quantify the journals' quality by constructing a journal–paper bipartite network where the citations between journals are considered.

The main advantages of AP rank are obvious: (i) it is parameter-free; (ii) it considers the interaction between the prestige of scientists and the quality of their publications; (iii) it is effective in distinguishing between prestige and popularity. However, it is not easy to find a benchmark set to validate the advantage of the present algorithm, since finding out how to evaluate the ranking method is a tough task. Radicchi *et al* [15] selected the winners of major prizes and awards as a benchmark set, such as the Nobel prize, Wolf prize and Boltzmann medal. However, these winners are only a tiny fraction of the scientific community and this evaluation method cannot be extended to our dataset. Instead, by analyzing some evident outliers, we can show that the present method is superior to citation counts as a measure of prestige.

Like the PageRank algorithm or its variants for ranking task in other systems ranging from social webs [32] to the ecosystem [33], the AP rank method can also be generalized to applications in a wide range of systems. The modifications and extensions of this method are easy to be implemented. Take the micro-blog web (e.g. Twitter, Sina, etc) as an example; under the framework of AP rank we can build an online reputation system to identify the influential users and evaluate the quality of their blogs (e.g. tweets) via constructing a bipartite network where the forwarding relation between micro-blogs (e.g. retweet) can be considered as a kind of citation.

How to utilize well the available information to devise a good evaluation or ranking method has been a long-lasting challenge. As an issue of ranking metrics, problems arise: is it simple to calculate? Does it reflect the intrinsic value? Is it robust against manipulations? Since every indicator will have its own strengths and weaknesses, it is difficult to design a panacea-like metric that covers all aspects. For instance, citation counts is very simple but not robust against manipulations. The rank can be easily increased by the abuse of self-citations or cross-citations within a small group. This is the shortcoming of all citation-based metrics, including the *h* index and the IF of journals. In addition, how to make a comparison of different scientific fields is also important when designing a metric. Some progress has been made in this direction [34, 35]. Certainly in the near future, with the advance of technology, more information and data can be conveniently obtained and are expected to foster the design of better-ranking metrics to face these challenges.

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