Ranking scientific publications: the effect of nonlinearity

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Ranking the significance of scientific publications is a long-standing challenge. The network-based analysis is a natural and common approach for evaluating the scientific credit of papers. Although the number of citations has been widely used as a metric to rank papers, recently some iterative processes such as the well-known PageRank algorithm have been applied to the citation networks to address this problem. In this paper, we introduce nonlinearity to the PageRank algorithm when aggregating resources from different nodes to further enhance the effect of important papers. The validation of our method is performed on the data of American Physical Society (APS) journals. The results indicate that the nonlinearity improves the performance of the PageRank algorithm in terms of ranking effectiveness, as well as robustness against malicious manipulations. Although the nonlinearity analysis is based on the PageRank algorithm, it can be easily extended to other iterative ranking algorithms and similar improvements are expected.

Many efforts have been made to accelerate the publication of research findings. As a result, hundreds of new journals have been created in the past decade, and thousands of scientific papers are published everyday. Determining how to measure the scientific influence of these publications is not easy and has been a research focus for a long time. So far, many metrics have been introduced, but it remains unclear whether these methods rank papers in an objective way. The number of citations, though simple, is a widely used metric to measure the importance of a paper. The number of citations is now treated as a common indicator to assess the scientific productions of individuals or institutions as well as the influence of scientists. For example, the well-known $H$ index is designed based on the citation number of papers. Recently, a universal property of citation distributions has been found within several science disciplines, making it possible to design an unbiased indicator for citation performance across disciplines and years. From another aspect, comments are found as early indicators of the future impact of criticized papers in research. A mechanistic model for the citation dynamics of individual papers has also been developed to predict the future citation evolution.

To evaluate the scientific impact of a paper, one must consider not only the number of citations that matters but also the means, by which the paper is being cited. This idea is realized by introducing Google’s PageRank algorithm to the citation networks to rank papers. This algorithm takes into account the importance of the citing papers and assigns a high score to a node cited by important papers. The scores of papers are updated in each iteration loop, and the final stable scores are used as the indicator of the significance of the papers. Many variants of the PageRank algorithm were later designed to highlight the prestige in the citation networks of journals, publications and scientists. The so-called CiteRank, for example, accounts for the strong aging characteristics of citation networks by initially distributing random surfers exponentially with age, in favor of the more recent publications. Another variant, called DivRank, makes use of a reinforced random walk on the citation network to diversify the papers in the top of the obtained ranking list.

Malicious activities are common in citation networks, in particular, when researchers manipulate the citations to boost the importance of their papers. One example of the manipulation is to deliberately cite the target papers when researchers or their friends publish new papers. Although, in these cases, the citing papers are usually not extremely outstanding ones, they can still substantially increase the citation number and the PageRank score of the target papers. In PageRank and its variants, the random jump process is used to avoid the sink nodes attracting all scores, so any paper in the network will at least have the score from the random jump process. In each iteration loop of these algorithms, the score of a node equals to the linear summation of the score transferred from neighboring nodes. Therefore, one can always increase the score of the target paper as long as he/she can continue to publish new papers.

In this paper, we argue that the robustness of the iterative ranking algorithms against malicious citations can be improved by introducing nonlinearity to the PageRank algorithm. Specifically, when aggregating the score of the
nodes in each step, we introduce a nonlinear operation that favors the nodes with high-score citing papers but punish the nodes with only low-score citing papers. We refer to our method as NonlinearRank in this paper. In fact, the concept of nonlinearity has recently been introduced to design an algorithm to rank the fitness of countries and complexity of products in international trading networks\(^3\). Our method was validated in the citation network constructed from the data of American Physical Society (APS) journals\(^3\). Simulations indicate that our NonlinearRank algorithm outperforms PageRank in identifying influential papers (examined by real awards, prediction power and spreading ability). Moreover, NonlinearRank is more robust against malicious manipulations.

**Results**

To begin our analysis, we briefly describe the basic concept of the NonlinearRank algorithm. The essential difference between the NonlinearRank and PageRank algorithms is the way a node aggregates the score from its incoming links. The process of these two algorithms is illustrated in Fig. 1. In PageRank, the score of the target node is simply the linear summation of the score distributed from its downstream neighbors (i.e. the papers citing it). However, this procedure is performed in a nonlinear way in NonlinearRank, as shown Fig. 1. The reason to introduce the nonlinearity is twofold. First, the power to the score further separates the contribution of nodes of high score from those of low score, which enables only the papers cited by some high score papers to become important. Second, the root reduces the effect of the number of citations on the final ranking. With this approach, the nodes cited by a large number of low score papers cannot have high score in the end. The power and the root actually work in the same direction: favoring the papers cited by many important ones and punishing the papers cited by a large number of unimportant ones. In fact, PageRank can be interpreted as a diffusion process on networks. It is simply a combination of random walk and random jump processes, with a parameter as a diffusion process on networks. It is simply a combination of many important ones and punishing the papers cited by a large number of low-score citing papers. We refer to our method as NonlinearRank in identifying influential papers (examined by real awards, prediction power and spreading ability). Moreover, NonlinearRank is more robust against malicious manipulations.

Unlike the random walk process, the total score of the new iterative procedure is performed in a nonlinear way in NonlinearRank, as shown Fig. 1. The reason to introduce the nonlinearity is twofold. First, the power to the score further separates the contribution of nodes of high score from those of low score, which enables only the papers cited by some high score papers to become important. Second, the root reduces the effect of the number of citations on the final ranking. With this approach, the nodes cited by a large number of low score papers cannot have high score in the end. The power and the root actually work in the same direction: favoring the papers cited by many important ones and punishing the papers cited by a large number of unimportant ones. In fact, PageRank can be interpreted as a diffusion process on networks. It is simply a combination of random walk and random jump processes, with a parameter as a diffusion process on networks. It is simply a combination of many important ones and punishing the papers cited by a large number of low-score citing papers. We refer to our method as NonlinearRank in identifying influential papers (examined by real awards, prediction power and spreading ability). Moreover, NonlinearRank is more robust against malicious manipulations.

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choose the top-$L$ ranked nodes in the NonlinearRank algorithms and study the dependence of their average spreading coverage on $\theta$. We again select two typical parameter settings $c = 0.15$ and $c = 0.45$ in Fig. 3. Note that when $\theta = 0$, the NonlinearRank degenerates to the PageRank. We can see in both Fig. 3(A) and (B) that when $\theta = 0.3$ the average spreading coverage of the top ranking nodes is larger than that when $\theta = 0$, indicating NonlinearRank outperforms PageRank in ranking the influence of the nodes. Nevertheless, we observe that the improvement of NonlinearRank to PageRank is smaller when $c = 0.15$.

A good ranking algorithm should be effective not only in identifying the influential nodes, but also in predicting the future. Instead of predicting the detailed evolution of the degree of the nodes, here we focus on predicting the most popular nodes. In particular, we pick a testing time $t$ and construct the citation network based on all historical data before $t$ where the PageRank and NonlinearRank algorithms are running. After obtaining the ranking lists, we select the top-$L$ papers and calculate their future degree increment $\langle \Delta k \rangle$ in a future time window $[t, t + \Delta t]$. Naturally, if a ranking algorithm is good at identifying the most popular papers in the future, $\langle \Delta k \rangle$ of the top-$L$ papers in $[t, t + \Delta t]$ will be accordingly large. We tested 40 testing times $t$ from 1960 to 1999 with $\Delta t = 10$ years. For clarification, we selected three representative $L$ papers to present in Fig. 4. By examining the dependence of $\langle \Delta k \rangle$ on $\theta$, we find that there is an optimum of $\langle \Delta k \rangle$ of approximately $\theta = 0.3$. This result indicates that the nonlinearity can indeed improve the prediction ability of the ranking algorithm.

As further support of the proposed approach, we studied $\Delta k$ of papers as a function of $R_p$ (ranks of papers from PageRank) and $R_n$ (ranks of papers from NonlinearRank) in Fig. 4, where $t = 2000$ and $\Delta t = 9$ years. In this scatter plot, the color of each point corresponds to $\Delta k$ of this particular article. Obviously, those articles with high $\Delta k$ are located in the region where $R_p$ is small but $R_n$ is relatively large. This result confirms again that NonlinearRank outperforms PageRank in its prediction performance.

Tolerance of the ranking algorithms against malicious behaviors is crucial, especially when the network structure is subject to manipulations. Here, we consider a common case in a citation network in which some articles deliberately cite one target paper to enhance its ranking. We study the robustness of the ranking algorithms to this situation via the leave-one-out validation. Specifically, we constructed the citation network from the APS data and assumed that it is error-free. A paper with indegree $k = 0$ is randomly picked and considered as the target paper whose rank is intended to be enhanced. $n$ new papers with $m$ links each are then added to the citation network. All of these new papers will cite the target paper and the rest of their links will randomly connect to other nodes. In the original network, the ranks of the target paper from the PageRank and NonlinearRank are denoted as $R_p(A_m)$ and $R_n(A_m)$, respectively. In the modified network, the corresponding ranks from the PageRank and NonlinearRank are denoted as $R_p(A_m)$ and $R_n(A_n)$, respectively. The rank change for the PageRank and NonlinearRank results can be calculated as $\Delta R_p = R_p(A_m) - R_p(A_m)$ and $\Delta R_n = R_n(A_n) - R_n(A_m)$. A smaller $\Delta R$ indicates a higher robustness against manipulations. The relationship between the average rank change $\langle \Delta R \rangle$ and $n$ is shown in Fig. 5, where we study the degree rank, PageRank and NonlinearRank methods. As expected, the degree rank is the most sensitive to such a manipulation. PageRank is better than degree rank in resisting the manipulation. Among these three methods, NonlinearRank enjoys the smallest $\langle \Delta R \rangle$ in different $n$,
indicating the high reliability of the method. Interestingly, the parameter $\theta$ is strongly related to the reliability of the NonlinearRank. One can see in Fig. 5 that $\langle DR \rangle$ generally decreases with $\theta$. Accordingly, we remark that the selection of $\theta$ is a trade-off between ranking effectiveness (i.e. identifying the influential papers) and reliability (i.e. suppressing the manipulated low quality papers). A small $\theta$ of approximately 0.3 enjoys a high ranking effectiveness but leads to only slightly better ranking reliability than that of the PageRank method. A large $\theta$, although very robust against malicious manipulation, does not have a satisfactory ranking effectiveness. In

![Figure 4](image)

**Figure 4** | The dependence of the average future degree increment $\langle Dk \rangle$ of the top-L papers on $\theta$ in NonlinearRank with (A) $c = 0.15$ and (B) $c = 0.45$. The results in both (A) and (B) are averaged over 40 testing times $t$ from 1960 to 1999 with the future time window as 10 years. The future degree increment $\log (\Delta k)$ of papers as a function of $R_p$ and $R_n$ are shown in (C) $c = 0.15$ and (D) $c = 0.45$, with $t = 2000$, $\Delta t = 9$ years.

![Figure 5](image)

**Figure 5** | The average rank change $\langle AR \rangle$ of the manipulated papers when different ranking algorithms are used. In this figure, $n$ is the number of new papers added and each new paper has $m = 20$ links. In both PageRank and NonlinearRank, $c = 0.45$. $\theta$ of NonlinearRank is different in each panel: (A) $\theta = 0.3$, (B) $\theta = 0.5$, (C) $\theta = 1.0$ and (D) $\theta = 2.0$. Results are obtained by averaging 100 times of independent realizations.
practice, one can use a smaller value of \( \theta \) if the ranking effectiveness is the main goal, or a larger value if the resistance to manipulation is a major issue.

**Discussion**

We proposed an iterative ranking algorithm where the nonlinearity is imposed on the aggregation of scores of the nodes in each step. The basic idea is to further enhance the effect of high score papers while suppressing the effect of the low score papers in the iterations of the algorithm. Extensive simulation results indicated that the proposed NonlinearRank method is able to outperform the well-known PageRank method in identifying the influential papers with respect to real awards, spreading ability and prediction. In particular, the NonlinearRank method can resist the malicious manipulation in the citation networks that aims to enhance the rank of low quality papers. Though the NonlinearRank method aims to rank the influence of individual publication, it may contribute to related research in macroscopic level. For example, a more accurate ranking of papers’ quality may help to deepen our understanding of scientists’ career patterns, as well as the scientific production and consumption in different regions. The application of the NonlinearRank method is not restricted to citation networks. The proposed method can be naturally used in many other real systems, such as designing search engines in the World Wide Web and revealing the leaderships in social networks.

In fact, there are many other nonlinearity formulae that can be used for the iterative algorithms. A possible one is to make the random walk on the PageRank algorithm be preferential towards nodes of different degree or similarity. Such preferences can be further adjusted by nonlinear functions. In addition, the random walk process can be nonlinearily hybridized with the heat conduction process. This hybridization has already been shown to enhance the recommendation performance in user-object bipartite networks. Similar nonlinear combination in PageRank might be able to improve its effectiveness as well as the diversity in the top of the ranking list.

Finally, even though a very simple malicious manipulation scheme is considered in this paper, we remark that the cases in real systems are more complicated. For example, the malicious papers in citation networks might form many triangles. This malicious manipulation will largely increase the PageRank score of these malicious papers and subsequently enhance the rank of the target low quality paper. Moreover, the malicious papers might deliberately cite a very small number of papers, making most of the PageRank score of these malicious papers to be transferred to the target low quality paper. Under both manipulation schemes above, the ranking from the iterative algorithms might be influenced more significantly than the degree rank. Therefore, the iterative algorithms resistance to these more realistic manipulation approaches requires future investigation.

**Methods**

**Degree rank.** The most straightforward method to rank articles is to use their citation numbers. In the citation network, the citation is simply the indegree of nodes as

\[
  k_i = \sum_j A_{ij}
\]

where \( A_{ij} \) is an element in the adjacency matrix of the citation network. The final ranking of nodes will be obtained by sorting \( k_i \) in a descending order.

**PageRank.** PageRank is a famous ranking algorithm that forms the basis of the Google™ search engine. In practice, PageRank assigns a score \( s_i \) to denote the attractiveness of the webpage \( i \). Webpage \( i \) obtains a higher score if many other important webpages point to it. From the physical perspective, PageRank describes a random walk process on a directed network, where the score \( s_i \) is proportional to the frequency of visits to a particular node \( i \) by a random walker. In the PageRank algorithm, the parameter \( \epsilon (0 \leq \epsilon \leq 1) \) called return probability is introduced, which represents the probability for a random walker to jump to a random node, and \((1 - \epsilon)\) is the probability for the random walker to continue walking through the directed links. In this way, the node \( i \)'s centrality score at time \( t (t \geq 1) \) is given by

\[
s_i(t) = c + (1 - c) \sum_{j=1}^{N} \frac{A_{ij}}{\sum_{k} A_{jk}} \left( 1 - \delta_{s_j} \sigma \right) + \frac{1}{N} \delta_{s_i} \sigma s_j(t-1),
\]

where \( \delta_{s_j} = 1 \) when \( s_j = b \), and \( \delta_{s_j} = 0 \) otherwise. Initially, we assign each node one random walker, namely \( s_i(0) = 1 \) for \( i = 1, 2, \ldots, N \). The typical value of the return probability in computer science is approximately 0.15\%. The final score of each node is defined as the steady value after the convergence of \( s_i(t) \). The final ranking of nodes in PageRank, denoted as \( R \), will be obtained by sorting \( s_i \) in a descending order when \( s_i \) reaches the stable state.

**NonlinearRank.** NonlinearRank works similarly to PageRank. The only difference is the way it aggregates the score from downstream neighboring nodes. Mathematically, it reads

\[
s_i(t) = c + (1 - c) \sum_{j=1}^{N} \frac{A_{ij}}{\sum_{k} A_{jk}} \left( 1 - \delta_{s_j} \sigma \right) + \sum_{j=1}^{N} A_{ij} \left( 1 - \delta_{s_j} \sigma \right) s_j(t-1) \left( 1 - \frac{1}{k_{in}} \right)
\]

where \( \sigma \) is a tunable parameter. We can control the effect of downstream papers through the adjustment of parameter \( \theta \), so that only papers cited by high score papers get higher score and the paper cited by plenty of low score papers cannot get high score in the end. Notice that NonlinearRank reduces to PageRank when \( \theta = 0 \). The final ranking of nodes in NonlinearRank, denoted as \( R \), will be obtained by sorting \( s_i \) in a descending order when \( s_i \) reaches the stable state. The basic statistical properties of the NonlinearRank method are presented in SI.

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**Author contributions**
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