

## Abstract

The notion of reputation in academia is critical for taking decisions on research grants, faculty position tenure, and research excellence awards. And the notion of reputation is always associated with the publication track record of the researcher or research group. Thus, it is important to assess publication track records quantitatively. To quantify a publication record, bibliographic metrics are usually adopted. Among these, citation based metrics, such as H-indices and citation counts, are quite popular. In this paper we study the correlation between P-score, a publication record metric we introduced previously, and H-indices. We show that they are correlated with a Kendall-Tau coefficient that exceeds 0.5. Additionally, we noticed that they have important differences. We were able to identify publication venues with high H-indices and low P-scores, as well as venues with low H-indices and high P-scores. We provide interpretations for these findings and discuss how they can be used by research funding councils and committees to better support their funding decisions.

# P-score: a complementary metric to H-index

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February 19, 2018

## 1 Introduction

Academic research evaluation is a topic of interest to universities, research groups, research funding institutions and the public at large. The evaluation of research is usually carried out by comparing journals, conferences or papers through the usage of academic impact metrics. A popular and moderately effective approach is to compute metrics based on the number of citations received by a given piece of research and assume that the number of citations is a good proxy for research quality. However, this approach has multiple shortcomings.

First, in the evaluation and bibliometrics research communities, citations are understood as a measure of attention rather than a proxy for impact or quality. Citations measure the attention to a paper of peers in related fields [18], not the quality of the work produced.

Second, citations can take a long time to happen. To illustrate this, in a recent study that looked at first time to citation in a universe of more than a million papers, half the papers only received their first citation 20 months or more after they were published [20].

Third, citations are not simple to compute and are not always broadly available, particularly at the level of individual researchers. Collecting citation counts requires access to the contents of a large number of publications, of which many are not easily available, and most authors do not have up to date citation information in their public internet profiles.

Despite these limitations, citation based metrics continue to be a popular approach to academic research evaluation. Nonetheless, it is desirable to employ alternative and complementary metrics that tackle the exposed problems without loss of effectiveness.

Academic reputation is an individual or group property strongly associated with academic impact. Reputable venues tend to concentrate the most relevant research papers because that is how they acquire and keep their good reputations. At the same time, reputable authors seek to publish on reputable venues because it gives their research more visibility and accreditation. Therefore, a researcher conveys reputation to a venue proportionally to its own reputation and the reputation of a researcher is proportional to the reputation of the venues where she or he publishes. This relationship between authors and venues constitutes a reputation network in which authors influence venue reputations and vice versa.

Pscore is a graph modeling metric that attributes quantitative reputations to venues based on the publication patterns of a reference group of researchers without having to rely on citation information. It deals with the three problems discussed previously.

First, instead of measuring the amount of researcher attention, Pscore measures reputations, which is presumably a better proxy for academic impact as was shown by Ribas.

Second, while citations can take years to happen, reputations tend to be steady over the time, so the quality of new research can be promptly estimated with pscore by simply complementing the reputation flows graph with the newest publication data.

Third, pscore does not require citation data to perform effectively, thus we can avoid the laborious effort of compiling individual researcher citation information.

The Pscore of computer science venues has shown significant correlation with H-index. Yet, there are important cases where the two metrics diverge considerably. Namely, in venues that belong to an intersection between different domains and in venues of less popular subareas of computer science. These differences appeal to the importance of pscore as a complementary metric.

## 2 P-score: a network-based metric

Contrary to citation counting metrics such as the Impact Factor [13, 31, 1, 2] and H-index [4, 3, 12, 6, 7], P-scores are a graph modeling metric that takes into account the relations among researchers, papers they published and their publication venues. They are based on a framework of reputation flows we introduced previously [28]. Let us review them briefly.

A *reputation graph* in academia is a graph with three node types: (a) *reputation sources* representing groups of selected researchers, (b) *reputation targets* representing venues of interest, and (c) *reputation collaterals* representing entities we want to compare such as research groups and academic departments. Figure 1 provides a generic illustration of our reputation graph and introduces the following notation:  $S$  is the set of reputation sources,  $T$  is the set of reputation targets, and  $C$  is the set of reputation collaterals. We first propagate the reputation of source nodes to target nodes, which allows assigning weights to the target nodes. Following, we propagate these weights to the collaterals. In here we adopt research groups as source nodes and publication venues as target nodes. Further we focus on the weights assigned to the publication venues and do not consider potential collaterals of interest (such as individual researchers).



Figure 1: Structure of the reputation graph.

Our reputation graph for academia can be naturally associated with paper authors, modelled as reputation sources, and papers, modelled as reputation targets. The interac-

tion between reputation sources and reputation targets is inspired by the notion of *eigenvalue centrality* in complex networks [8, 16, 16, 23]. In the reputation graph, if we consider only sources and targets, it is easy to identify reputation flows from sources to sources, from sources to targets, from targets to sources, and from targets to targets. These reputation flows can be modeled as a stochastic process. In particular, let  $P$  be a *right stochastic* matrix of size  $(|S| + |T|) \times (|S| + |T|)$  with the following structure:

$$P = \left[ \begin{array}{c|c} (d^{(S)}) \cdot P^{(SS)} & (1 - d^{(S)}) \cdot P^{(ST)} \\ \hline (1 - d^{(T)}) \cdot P^{(TS)} & (d^{(T)}) \cdot P^{(TT)} \end{array} \right] \quad (1)$$

where each quadrant represents a distinct type of reputation flow, as follows:

$P^{(SS)}$ : right stochastic matrix of size  $|S| \times |S|$  representing the transition probabilities between reputation sources;

$P^{(ST)}$ : matrix of size  $|S| \times |T|$  representing the transition probabilities from reputation sources to targets;

$P^{(TS)}$ : matrix of size  $|T| \times |S|$  representing the transition probabilities from reputation targets to sources;

$P^{(TT)}$ : right stochastic matrix of size  $|T| \times |T|$  representing the transition probabilities between reputation targets.

The parameters  $d^{(S)}$ , the fraction of reputation one wants to transfer among the source nodes themselves, and  $d^{(T)}$ , the fraction of reputation one wants to transfer among the target nodes themselves, control the relative importance of the reputation sources and targets. Assuming that the transition matrix  $P$  is ergodic, we can compute the steady state probability of each node and use it as a reputation score. More formally, we can write:

$$\gamma = \gamma P \quad (2)$$

where  $\gamma$  is a row matrix with  $|S| + |T|$  elements, where each row represents the transition probabilities of a node in the set  $S \cup T$ .

We should note that, while our network model allows modeling citations in the fourth quadrant, it is possible to compute steady state probabilities for the network without consideration to citations. This is accomplished by setting the parameter  $d^{(T)} = 0$ . Thus, it should be clear, in all of our experiments here P-scores are computed without taking citations into account.

## 2.1 Reputation Sources

The choice of the reputation sources is an important part of the method since its composition has a direct impact in the final rankings. There is no definitive way to make it. This choice depends on what we want to measure. In here we use the top CS departments in the US as reputation sources. It is a simple procedure that allows assigning P-scores to publication venues, P-scores that reflect the publication patterns of top CS departments in the US. We then compare how these scores compare with H-indices assigned to the same publication venues.

One way to determine the top CS departments is to adopt the randomization procedure we first described in [27]. A run of that procedure works as follows:

1. randomly select 10 entities from the set of reputation targets and use them as the set  $S$  of reputation sources
2. compute steady state probabilities for all nodes
3. using the steady state probabilities of reputation targets as a score, select the 10 entities with highest scores and use them as a new set  $S_{new}$  of reputation sources
4. if  $S_{new} \neq S$  then  $S \leftarrow S_{new}$  and go back to step 1
5.  $S_{auto} \leftarrow S_{new}$
6. take  $S_{auto}$  as the set of automatically selected reputation sources
7. exit

By applying this randomization procedure 100 times to a set of 126 US graduate programs in Computer Science (CS), exactly the same 126 graduate programs considered by NRC in its 2011 evaluation of CS graduate programs in the USA <sup>1</sup>, we ended up with a subset of 12 CS programs to be considered as reputation sources. These are the CS programs that appeared as least once in the set  $S_{auto}$  of automatically selected reputation sources and they are as follows:

1. Carnegie Mellon University
2. Georgia Institute of Technology
3. Massachusetts Institute of Technology
4. Stanford University
5. University of California-Berkeley
6. University of California-Los Angeles

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<sup>1</sup><http://www.nap.edu/rdp/>

7. University of California-San Diego
8. University of Illinois at Urbana-Champaign
9. University of Maryland College Park
10. University of Southern California
11. University of Michigan-Ann Arbor
12. Cornell University

All the 12 departments above are among the top 5th percentile in the ranking produced by NRC. This suggests that our recursive procedure is able to take advantage of patterns in the publication streams of the various CS departments to determine the most reputable ones in fully automatic fashion. We further observe that this was done while setting the parameter  $d^{(T)} = 0$ . That is, we did not use information on citation counts in the model.

### 3 Correlation with H-indices

**TO WRITE:** explain that distributions are not Normal, show graphs, propose Kendall-Tau, show macro values

### 4 Assessing conferences in CS

Discuss the cone strategy, justify the 10 degrees angle, discuss the problem of positioning the cone vertex at the origin, introduce the (-100,-100) pivot, discuss items above and below the cone

### 5 Related Work

Quantitative metrics of scientific impact have a long history. An influential approach is Garfield’s Impact Factor (1955) [13], a journal-level metric that is defined by the mean number of citations received by articles published in a given journal over a 2-year period. Despite being one of the earliest approaches at measuring scientific impact, it has showed remarkable survivability. Pinski et. al. [24] describe several limitations with the metric. Impact factors also suffered criticism for being misleading [21, 31] and for lacking reliable validation from an independent audit [30]. Riikonen and Vihinen (2008) [29] showed that actual citation and publication counts were better predictors of a scientist’s contribution than impact factors in a study that assessed the scientific contribution of Finnish researchers in biomedicine.

The acceptance rate is another important journal-level metric that attempts to quantify the scientific impact. It is defined by the proportion of accepted papers relative to the

number of submitted papers. Chen et. al. [9] have showed that highly selective conferences (therefore having low acceptance rates) have higher scientific impact, measured in terms of the number of citations received by the published papers.

The H-index is an author-level metric proposed by Hirsch (2005) [15]. Since its formulation, it has been widely adopted as a measure of individual scientific research output. An H-index of  $h$  means that a researcher has published  $h$  papers that were cited at least  $h$  times. The H-index takes into account both the number of publications and the number of citations per publication, achieving higher values when a researcher obtains a consistently high number of citations over multiple publications. The H-index has been criticized for not taking into account field specific citation statistics [33]. The G-index, proposed by Egghe (2006) [11], is a less strict variation of the H-index where the score  $g$  is the largest number such that the top  $g$  articles have received at least  $g^2$  citations.

Citation counts and derived metrics are straightforward to calculate, but they represent only a coarse estimate of academic impact, because they are essentially popularity measures. Some people are popular but not prestigious and vice versa. For example, an author of pulp detectives may sell many books, but may not have earned the respect of literary critics [5]. Citations from prestigious journals are more relevant than citations from peripheral journals, as noted by Pinski et. al. (1976) [24]. To address this issue, some studies distinguish popularity from reputation or prestige with the usage of citation weighting strategies [10, 34] or PageRank based methods [5, 32]. Furthermore, Piwowar (2013) [25] noted that citation based metrics are slow, since the first citation to a scientific article can take years to happen, concluding that the development of alternative metrics to complement citation analysis is not only desirable, but a necessity. As discussed in [17], each metric has advantages and disadvantages deriving from their inherent biases.

Martins et. al. (2009) [19] proposed a method of assessing the quality of scientific conferences through a machine learning classifier that makes use of multiple features in addition to citations. Gonçalves et al. (2014) [14] quantified the impact of various features on a scholar’s popularity. They concluded that, even though most of the considered features are strongly correlated with popularity, only two features are needed to explain almost all the variation in popularity between different researchers: the number of publications and the average quality of the scholar’s publication venues.

The idea of reputation, without the direct use of citation data, was discussed by Nelakuditi et al. [22]. They proposed a metric called *peers’ reputation* for research conferences and journals, which ties the selectivity of the publication venue based upon the reputation of its authors’ institutions. The proposed metric was shown to be a better indicator of the selectivity of a research venue than the acceptance ratio.

In this work, we study the correlation between H-index [15] and *P-score* [26], a novel metric for academic reputation. The *P-score* is calculated with a *reputation flows* model [28] instantiated in an academic setting. The *reputation flows* model exploits the transference of reputation among entities in order to identify the most reputable ones. Particularly, the reputation flows consist of a random walk model where the reputation of a target set of entities is inferred using suitable sources of reputation.

## 6 Conclusions

ZZZ Rewrite entirely.

## ACKNOWLEDGEMENTS

Omitted for blind review.

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