

# Will This Paper Increase Your $h$ -index? Scientific Impact Prediction

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## ABSTRACT

Scientific impact plays a central role in the evaluation of the output of scholars, departments, and institutions. A widely used measure of scientific impact is citations, with a growing body of literature focused on predicting the number of citations obtained by any given publication. The effectiveness of such predictions, however, is fundamentally limited by the power-law distribution of citations, whereby publications with few citations are extremely common and publications with many citations are relatively rare. Given this limitation, in this work we instead address a related question asked by many academic researchers in the course of writing a paper, namely: “Will this paper increase my  $h$ -index?” Using a real academic dataset with over 1.7 million authors, 2 million papers, and 8 million citation relationships from the premier online academic service ArnetMiner, we formalize a novel scientific impact prediction problem to examine several factors that can drive a paper to increase the primary author’s  $h$ -index. We find that the researcher’s authority on the publication topic and the venue in which the paper is published are crucial factors to the increase of the primary author’s  $h$ -index, while the topic popularity and the co-authors’  $h$ -indices are of surprisingly little relevance. By leveraging relevant factors, we find a greater than 87.5% potential predictability for whether a paper will contribute to an author’s  $h$ -index within five years. As a further experiment, we generate a self-prediction for *this* paper, estimating that there is a 76% probability that it will contribute to the  $h$ -index of the co-author with the highest current  $h$ -index in five years. We conclude that our findings on the quantification of scientific impact can help researchers to expand their influence and more effectively leverage their position of “standing on the shoulders of giants.”

## Categories and Subject Descriptors

H.2.8 [Database Management]: Database Applications—*Data Mining*;  
H.3.7 [Information Search and Retrieval]: Digital Libraries

## Keywords

Scientific impact; Science of science; Citation prediction; Popularity prediction

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WSDM 2015, February 02 - 06 2015, Shanghai, China  
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<http://dx.doi.org/10.1145/2684822.2685314>.

## 1. INTRODUCTION

Integral to the success of scientific research is the publication and dissemination of impactful work and findings.

Every scientific researcher leaves his or her own indelible mark on an ever-expanding body of literature through a personal track-record of academic publications. The impact of each of these publications—both to a field of research and, by extension, to the reputation of the author—can be influenced by a variety of factors. For example, significant research work may start from a small number of exploratory papers that builds up to pioneering work within a field, resulting in a series of less impactful papers that serve as stepping-stones to those of greater impact. Or a researcher may publish in different fields each with differing audiences and levels of popularity, resulting in publications on some topics receiving more attention than those on others. Or, along with many publications that incrementally advance a field, a researcher may produce a groundbreaking work that transforms the field or even stimulates a new research area. As a result of such factors, a researcher’s body of work is likely to be comprised of publications of varying impact. Accordingly, the impact of any particular publication can be difficult to predict.

Yet while the impact of individual publications may vary, a researcher’s influence and productivity is measured by his or her body of work as a whole. Often, the researcher’s total number of citations is used as a measure of impact, while the researcher’s total number of publications is used as a measure of productivity. However, while these simple measures can be useful, they can also have drawbacks. For example, the total number of citations can be skewed by the impact of a solitary well-cited, impactful paper. Similarly, the total number of publications can be increased by a large number of poorly cited papers. Moreover, as citations demonstrate a power law distribution, with the vast majority of publications receiving few citations, these simple measures are difficult to estimate using traditional regression analysis [15, 5]. Thus, answering the question of how many citations a given paper will receive is often ineffective for practical purposes.

In light of these difficulties and limitations, we instead address an analogous question asked by many academic researchers in the course of writing a paper: “Will *this* paper increase my  $h$ -index?”

The  $h$ -index is an index that attempts to measure both the productivity and impact of the published work of a scientist or scholar. The index was suggested in 2005 by Jorge E. Hirsch as a tool for determining theoretical physicists’ relative quality, and is based on the distribution of citations received by a given researcher’s publications. As described by Hirsch: “A scientist has index  $h$  if  $h$  of his/her  $N_p$  papers have at least  $h$  citations each, and the other ( $N_p - h$ ) papers have no more than  $h$  citations each” [8]. In other

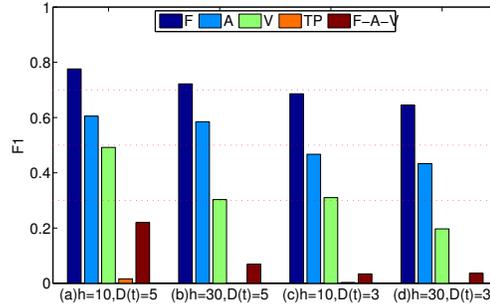
words, a scholar with an index of  $h$  has published  $h$  papers, each of which has been cited in other papers at least  $h$  times. Thus, the  $h$ -index is a function of both the number of publications and the number of citations per publication.

The index is designed to improve upon simpler measures such as the total number of citations or publications. Moreover, because only the most highly cited articles contribute to the  $h$ -index, its determination is a relatively simpler process. Hirsch has demonstrated that  $h$  has high predictive value for whether a scientist has won honors like National Academy membership or the Nobel Prize [8]. As a result of its simplicity and predictive value, the  $h$ -index has become a *de facto* standard for measuring academic performance and scientific impact.

**Contributions.** In this work, we formalize the question of whether a paper will influence an author’s  $h$ -index as a novel scientific impact prediction problem. Our prediction task is to determine whether a given paper will, within a pre-defined timeframe, increase the  $h$ -index of its primary author (i.e., the researcher with the maximum  $h$ -index among the paper’s author list). Factors such as the researcher’s current influence, the publication topic, and the publication venue may, among many other factors, play a role in determining the degree to which the publication contributes to the researcher’s influence. A resulting challenge is the interplay of such factors, which can confound attempts to generate effective predictions. Considerations such as the variability of the  $h$ -index according to the “academic age” of a researcher, the widely differing citation conventions among different fields, and the co-authorship of researchers with differing  $h$ -indices can make it difficult to isolate the nature and degree to which a given researcher’s  $h$ -index is influenced by any particular factor. Our work focuses on addressing and overcoming these issues to generate novel, effective scientific impact predictions and to investigate precisely what role a variety of factors play in these predictions.

Given the task of predicting whether a publication will contribute to an author’s  $h$ -index, we find surprisingly strong performance for the problem of scientific impact prediction. Our results demonstrate that we can predict whether a paper will contribute to an author’s  $h$ -index within five years with an  $F_1$  score of 0.776 as shown in Figure 1. Our study further finds that the most telling factors for determining whether a given paper will contribute to the primary author’s  $h$ -index are the author’s authority on the publication topic and the venue in which the paper is published (see Figure 1 blue bars). In contrast, we find that the popularity of the publication topic and the co-authors’  $h$ -indices are surprisingly inconsequential for determining whether the paper will contribute to the primary author’s  $h$ -index (see Figure 1 orange and red bars). We also find that (1) the contribution of papers to researchers with higher  $h$ -indices is more difficult to predict than it is for researcher’s with lower  $h$ -indices (cf. Figure 1 a vs. b and c vs. d); and (2) the task is more predictable given a long timeframe than a short one (cf. Figure 1 a vs. c and b vs. d). Overall, our findings unveil mechanisms for quantifying scientific impact and provide concrete suggestions to researchers for better expanding their scientific influence and, ultimately, for more effectively “standing on the shoulders of giants.”

A potential concern with this work is that by targeting the  $h$ -index, our findings may result in unintended side effects by a principle referred to by economists as Goodhart’s Law. The law essentially says that once a measure is chosen as a performance indicator it begins to lose value, as measurement can distort the practice being measured. Restated more succinctly by [19], it means that “when a measure becomes a target, it ceases to be a good measure.” Be that as it may, we believe that understanding the characteristics of scientific impact measures is imperative to their informed use,



**Figure 1: Predictability of whether one paper will increase the  $h$ -index ( $\geq h$ ) of its primary author within  $D(t)$  years. F: full factor set; A: only authority factors; V: only venue factors; TP: only topic popularity factors; F-A-V: full factors without authority and venue factors.**

and in no way should our research be construed as advocating the use of the  $h$ -index as a deciding factor in one’s research pursuits.

## 2. DATA AND PROBLEM

In this section, we first describe the academic data we use, then characterize the  $h$ -index from the data, and finally formalize our predictive task—that is, scientific impact prediction.

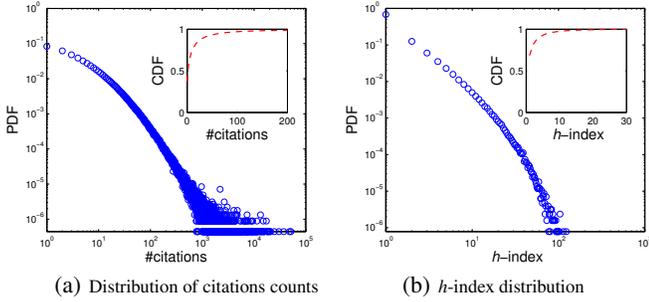
### 2.1 Data Description

In this paper, we use the real-world academic dataset<sup>1</sup> from ArnetMiner [23], which is the world-leading free online service for academic social network analysis and mining. The dataset contains 1,712,433 authors with 2,092,356 papers from computer science venues held between 1960 and 2012. Each paper includes information on the title, abstract, authorship, references, and publication venue and year. In total, the dataset represents 4,258,615 collaboration relationships and 8,024,869 citation relationships.

Next, we briefly explore and report the data characteristics of the author-paper-citation data. Figure 2 shows the distributions of the number of citations for each paper and the  $h$ -index of each author. In our dataset, both metrics follow heavy-tailed distributions (i.e., distributions with a “tail” that is “heavier” than that of an exponential). Moreover, only 6.91% (154,985) of the papers have more than 50 citations, while 0.0125% (159) of the researchers have an  $h$ -index over 60.

**Characterizations of the  $h$ -index.** The  $h$ -index is defined as the number of papers with citation number  $\geq h$ , which is a useful index to characterize the scientific output of a researcher [8]. Figure 3 presents the basic characteristics of scientific impact in terms of  $h$ -index. Positive linear relationships are clearly observed between the  $h$ -index and the number of papers, average number of citations, and number of co-authors in Figures 3(a), 3(b), and 3(c), respectively. Figure 3(b) shows that the average number of citations for each author is larger than her/his  $h$ -index. Figure 3(d) illustrates the ratio between one’s  $h$ -index and the number of papers conditioned on her/his  $h$ -index. This ratio initially decreases, stabilizing after an  $h$ -index of about 20. From Figure 3(e), we see that the  $h$ -indices of one’s co-authors increase as her/his  $h$ -index grows. The reversion point between author and co-author  $h$ -indices occurs when one’s  $h$ -index reaches about 8 or 9, a typical point at which

<sup>1</sup>The dataset is publicly available at <http://arnetminer.org/citation> and <http://arnetminer.org/AMinerNetwork>.



**Figure 2: Distributions of the citation counts of papers and the  $h$ -indices of authors. The heavy-tailed distributions indicate that the prediction of both metrics is not fit for regression problems. In this dataset, 6.91% (154,985) of the papers obtain more than 50 citations and 0.0125% (159) of the researchers have  $h$ -indices greater than 60.**

Ph.D. students graduate. Finally, in Figure 3(f), we examine the interplay between authors’  $h$ -index and the length of time they spend in academia (the date difference between one’s first and last publications). Clearly, we see that the increase of  $h$ -index is initially slow upon first entering academia. As the  $h$ -index increases, the accumulations of influence, resources, connections, and previous papers further drive one’s  $h$ -index and scientific impact expands at an increasingly rapid rate. In other words, the aphorism that “the rich get richer” is demonstrated in academia, whereby the influence of individuals who have already accumulated a great deal of influence increases at a disproportionately quick rate. All characteristics are observed at a 95% confidence interval.

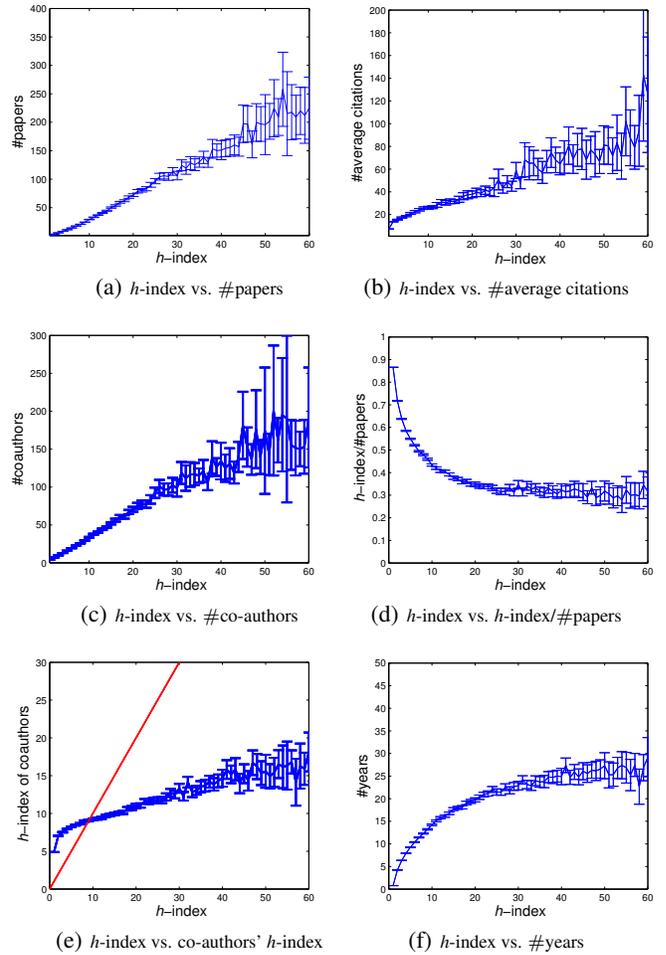
## 2.2 Problem Definition

Traditionally, the task of scientific impact prediction is formulated as a regression problem for predicting citation counts [28]. However, the intrinsically heavy tailed distribution of citation counts, demonstrated in Figure 2(a), make such predictions necessarily skewed [5]. Alternatively, given a threshold  $c$  for the citation count, the task can be formulated as a classification problem—that is, a problem of inferring whether the number of citations for a given paper will reach  $c$ . Even with this formulation, the way in which citation counts are distributed presents inherent challenges, including how to determine the threshold  $c$  and how to avoid the overrepresentation or underrepresentation of different papers. Similar issues also arise for predicting the  $h$ -index of each author.

Our approach is inspired by the work of [5], where the authors consider the problem of Facebook cascade growth prediction. They formulate the problem as a binary classification task where, given the first  $k$  reshares of content within a cascade, they are tasked with predicting whether the cascade will reach  $2k$ . For our work, we formulate an analogous task: Given a paper, we predict whether that paper will increase the  $h$ -index of the authors in the future. We formalize the problem of scientific impact prediction next.

**Problem 1. Scientific Impact Prediction:** Given the publication corpus  $C$  before timestamp  $t$ , each paper (document)  $d \in C$  published in timestamp  $t$ , and the primary author’s  $h$ -index (max- $h$ -index) among the authors of  $d$ , the task is to predict whether the number of citations for each paper  $d$  will reach max- $h$ -index after a given time period  $\Delta t$ .

The primary author is defined as the author of the given paper with the highest  $h$ -index. We address the issues noted above by



**Figure 3: Characterizations of the  $h$ -index. (b) The average number of citations for each author is larger than her/his  $h$ -index. (d) The ratio between one’s  $h$ -index ( $\geq 20$ ) and her/his number of papers stabilize at 0.3. (e) Typically, the author’s  $h$ -index becomes larger than the co-authors’  $h$ -indices at the expected point of the author’s Ph.D. graduation. (f) The rate at which the  $h$ -index increases itself increases as the length of time spent in academia becomes longer (i.e., the rich get richer).**

using a local threshold max- $h$ -index for each paper’s future citation count. For example, according to Google Scholar, as of Nov. 25th, 2014, Dr. Yizhou Sun and Dr. Jiawei Han’s  $h$ -indices are 19 and 125, respectively. By setting  $t = 2014$  and  $\Delta t = 3$  years, we aim to predict whether each of Dr. Sun’s papers (assuming her  $h$ -index is larger than each of her co-authors’) published in 2014 will get more than 19 citations by 2017. But if one paper is co-authored by Dr. Sun and Dr. Han, the task becomes to infer whether this paper’s citation count will reach 125 by 2017. Realistically, the authors’  $h$ -indices may increase during the duration  $\Delta t$ , but it is intractable to capture this evolution in detail. In this sense, we consider the objective of collecting citations for each paper as static and leave the evolving case for future work.

This proposed problem of scientific impact prediction is completely different from the cascade growth prediction problem [5], which needs the observation of the first  $k$  reshares (citations), and further predicts the future reshare counts. Our problem is also fun-

damentally different from the traditional citation count prediction problem [28], which focuses on the regression task to predict scientific impact. In contrast, our problem is to predict each paper’s future impact conditioned on the authors. The chief advantage of this proposed formulation is that it can be leveraged for a variety of real-world applications, such as author  $h$ -index and popularity prediction [18], expert finding [31], and credit allocation [17, 11].

### 3. SCIENTIFIC IMPACT FACTORS

To quantify scientific impact, it is natural to use the number of citations obtained by each paper and its authors. Recall that given a paper  $d$ , our objective is to predict whether the number of citations  $c_d$  obtained within a given time period  $\Delta t$  will be larger than its primary author’s  $h$ -index (denoted as max- $h$ -index). We investigate the factors that drive a paper’s citation count to become greater than its primary author’s  $h$ -index, including the paper’s author(s), content, published venue, and references, as well as social and temporal effects related to its author(s). Table 1 lists the six different groups of factors investigated. Figures 4 and 5 show the importance of different factors as evaluated by correlation coefficients. In Figure 4, we present the changes of factor importance as predicted for scholars with different  $h$ -indices. In Figure 5, the changes of factor correlation are plotted as the time period  $\Delta t$  is varied.

#### 3.1 Author Factors

The predictive task for each paper naturally depends on the authors themselves, including both the primary author and his or her co-authors. Prior work has been devoted to examining the interplay between scientific impact (number of citations) and the average values of authors’ attributes [28, 4]. Given our problem formulation, we also investigate the attributes of the primary author of each paper, such as the ratio of the author’s previous papers contributing to his or her  $h$ -index. Additionally, as the first author usually leads the collaboration, the spread of a paper’s scientific impact also relies highly on the impact of the first author. We thus consider the probability that the number of citations obtained by the first author’s previous publications is greater than the primary author’s  $h$ -index. Further, the overall impact of all co-authors should have the potential to influence a paper’s quality and popularity. Thus the sum of all authors’  $h$ -indices is used to simulate their overall impact. Since each paper has a unique local threshold (max- $h$ -index) in our classification problem, we calculate the relative value of each factor by dividing it by the max- $h$ -index. For example, the first author’s  $h$ -index divided by the max- $h$ -index is designed to model the author’s effect on the success of the paper. Moreover, the author’s productivity, i.e., the number of his or her previous publications, has a positive effect on the future citation counts of the paper due to self-citation behavior [2].

**Significance.** Figure 4(a) and 5(a) clearly show that *A-max-ratio* of one paper—i.e., the ratio between the max- $h$ -index and the number of papers attributed to its primary author—has the highest correlation with the probability that it will collect at least max- $h$ -index citations among all seven author factors. We also observe that the author factor correlations are not sensitive to the two parameters, illustrated by the lower thresholds for the primary author’s  $h$ -index and  $\Delta t$ .

#### 3.2 Content Factors

Aside from the attributes of its authors, another intuitive factor affecting a paper’s success is its content. Topic modeling is a widely used method for extracting and mining the content of literature and can be used to extract “topics” that occur in a collection of documents. One of the most popular topic modeling meth-

ods is known as Latent Dirichlet Allocation (LDA), a generative probabilistic approach that views each document as a mixture of various topics [3]. Similar to previous work on modeling citation counts [28], we run a 100-topic LDA model on the title and abstract of the corpus  $C$  published before time  $t$  and the target papers published at time  $t$ , which returns the probability distribution  $p(z|d)$  over topics  $z \in Z$  assigned for each paper  $d$ . We define the following features based on each paper’s topic distribution, including popularity, novelty, diversity, and authority.

First, we consider that as popular topics attract more attention, it is relatively easy for papers related to such topics to accrue citations. To capture this effect, we quantify the popularity of each topic  $z$  across the overall corpus by

$$popularity(z) = \sum_{d \in C} p(z|d) \times c_d,$$

where  $p(z|d)$  is the probability that paper  $d$  distributes on topic  $z$  and  $c_d$  is the number of citations  $d$  collects until the timestamp  $t$ . Given one target paper  $d_t$  at time  $t$ , its popularity is defined as

$$C\text{-popularity}(d_t) = \sum_{z \in Z} popularity(z) \times p(z|d_t). \quad (1)$$

Second, the novelty of a paper is considered an essential factor in assessing its contribution to the scientific community. Previous work assumes that the novelty of an article can be determined by measuring the difference between its content and that of its references [28]. We utilize the Kullback-Leibler divergence [12] to capture the sum of the difference between  $d_t$ ’s topic distribution and the topic distribution of each of its references. Specifically,

$$C\text{-novelty}(d_t) = \frac{\sum_{d_r \in R} KL(p(Z|d_t), p(Z|d_r))}{|R|} \quad (2)$$

$$KL(p(Z|d_t), p(Z|d_r)) = \sum_{z \in Z} \log \frac{p(z|d_t)}{p(z|d_r)} p(z|d_t),$$

where  $R$  is the set of  $d_t$ ’s references.

Third, the topic diversity of a paper, defined as the breadth of its topic distribution, is able to distinguish between different types of papers, such as between surveys and technical work. We follow the definition of diversity in [28] as calculated by Shannon entropy:

$$C\text{-diversity}(d_t) = \sum_{z \in Z} -p(z|d_t) \log p(z|d_t). \quad (3)$$

Fourth, Kleinberg has pointed out that, in a hyperlinked web environment, a good authority represents a page that is linked by many hubs [10]. Similarly, authority in academia is denoted by being highly cited by others in a specific domain of expertise. To measure the authority of researcher  $a$  on topic  $z$ , we propose the following definition:

$$authority(a, z) = \sum_{d \in C_a} p(z|d) \times c_d,$$

where  $C_a$  is the researcher  $a$ ’s previous publications. Therefore, given the target paper  $d_t$ , the author’s authority is distributed over the topic distribution of  $d_t$ , i.e.,

$$C\text{-authority}(d_t, a) = \sum_{z \in Z} p(z|d_t) \times authority(a, z). \quad (4)$$

This definition of authority comes from the intuition that the correspondence between the paper’s topic distribution and its authors’ expertise help assure its quality.

**Table 1: Factor Definition.** We employ six categories of factors, comprised of author, topic, reference, social, venue, and temporal attributes. *max-h-index* denotes the *h-index* of the primary author (i.e., the author with the maximum *h-index*) of a given paper.

	Factor	Description
Author	<i>A-first-max</i>	The first author’s <i>h-index</i> divided by the <i>max-h-index</i> .
	<i>A-ave-max</i>	The average <i>h-index</i> of all authors divided by the <i>max-h-index</i> .
	<i>A-sum-max</i>	The sum of <i>h-indices</i> divided by the <i>max-h-index</i> .
	<i>A-first-ratio</i>	The ratio between <i>max-h-index</i> and the number of papers attributed to the first author.
	<i>A-max-ratio</i>	The ratio between <i>max-h-index</i> and the number of papers attributed to the primary author.
	<i>A-num-authors</i>	The number of authors of the given paper.
	<i>A-num-first</i>	The number of papers by the first author.
Content	<i>C-popularity</i>	The average number of citations over different topics (see Eq. 1).
	<i>C-popularity-ratio</i>	The average number of citations over different topics divided by the <i>max-h-index</i> .
	<i>C-novelty</i>	The topic novelty of this paper (see Eq. 2).
	<i>C-diversity</i>	The topic diversity of this paper (see Eq. 3).
	<i>C-authority-first</i>	The consistence between the first author’s authority and this paper (see Eq. 4).
	<i>C-authority-max</i>	The consistence between the primary author’s authority and this paper.
	<i>C-authority-ave</i>	The average consistence between each author’s authority and this paper.
Venue	<i>V-ratio-max</i>	The ratio between the number of papers $\geq$ <i>max-h-index</i> citations divided by the <i>max-h-index</i> .
	<i>V-citation</i>	The average number of citations of all references divided by the <i>max-h-index</i> .
Social	<i>S-degree</i>	The number of co-authors of the paper’s authors.
	<i>S-pagerank</i>	The PageRank values of the paper’s authors in the weighted collaboration network.
	<i>S-h-co-author</i>	The average <i>h-index</i> of co-authors of the paper’s authors divided by the <i>max-h-index</i> .
	<i>S-h-weight</i>	The weighted average <i>h-index</i> of co-authors of the paper’s authors divided by the <i>max-h-index</i> .
Reference	<i>R-ratio-max</i>	The ratio between the number of references $\geq$ <i>max-h-index</i> and the total number of references.
	<i>R-citation</i>	The average number of citations divided by the maximum <i>h-index</i> .
Temporal	<i>T-ave-h</i>	The average $\Delta h$ -indices of the authors between now and three years ago.
	<i>T-max-h</i>	The maximum $\Delta h$ -index between now and three years ago.
	<i>T-h-first</i>	The $\Delta h$ -index of the first author between now and three years ago.
	<i>T-h-max</i>	The $\Delta h$ -index of the <i>max-h-index</i> author between now and three years ago.

**Significance.** From Figures 4(b) and 5(b), we find that there is a strong correlation between a paper’s probability of contributing to its primary author’s *h-index* and the authority-based content factors from that paper. Perhaps surprisingly, the current topic popularity and the diversity or novelty of the paper’s content have much lower correlations than its authors’ expertise. This observation suggests that, when authoring a paper, rather than following the current trend or hot topic, it is more important to instead focus on what one is good at. Finally, the increase of the primary author’s *h-index* is accompanied by a corresponding rise in the importance of several authority factors, indicating that highly influential scholars are more easily recognized as the experts and authorities in their respective fields.

### 3.3 Venue Factors

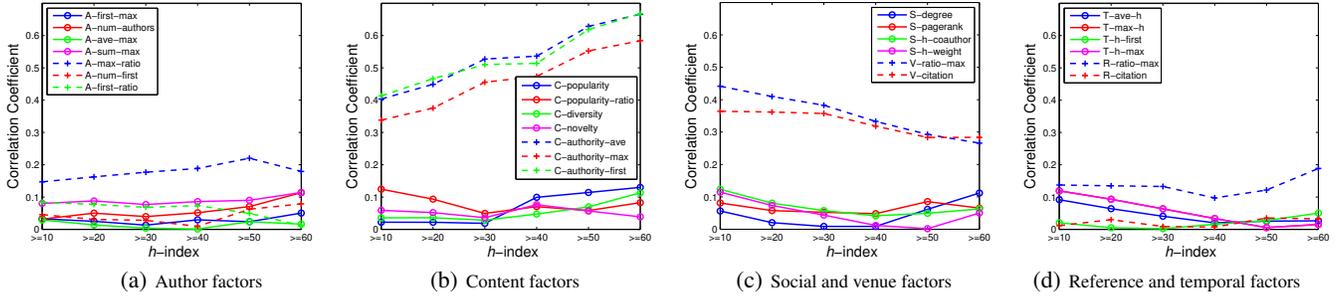
Top venues attract high-quality submissions, and high-quality submissions elevate the reputation of their respective venues. Google Scholar metrics show that different venues have large differences in their *h5-indices*<sup>2</sup>, which is defined as the *h-index* when only considering articles published within the last 5 complete years. For example, in the field of data mining and analysis, the top three

<sup>2</sup>[http://scholar.google.com/citations?view\\_op=top\\_venues&hl=en](http://scholar.google.com/citations?view_op=top_venues&hl=en). Accessed on Nov. 25th, 2014.

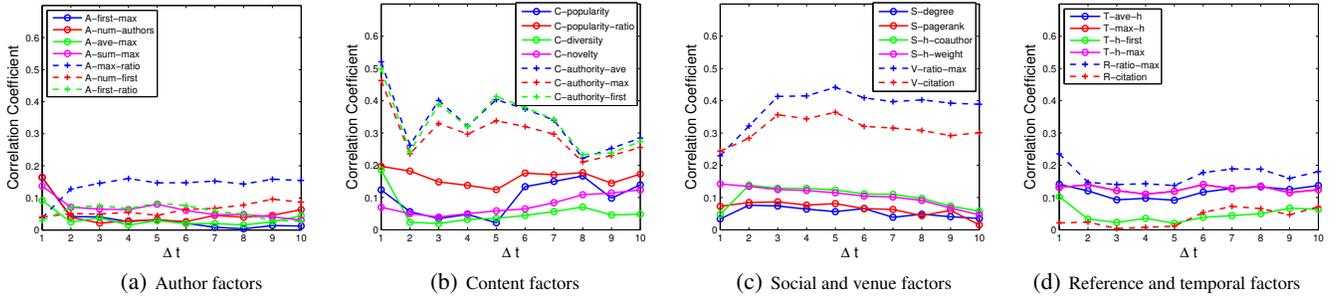
venues are ACM SIGKDD, IEEE TKDE, and ACM WSDM, with *h5-indices* of 69, 57, and 54, respectively. In contrast, most other venues in this field typically have *h5-indices* between 10 and 20. In light of these differences, we engage in the investigation of how different venues influence the probability that a paper contributes to the author’s *h-index*. Two heuristic metrics are examined, namely (1) the average number of citations each paper in the venue collects and (2) the ratio between the number of papers in the venue with at least *max-h-index* citations to the venue’s total number of papers. Every researcher aims to publish scientific results in well-respected journals and conferences, so our intuition is that top venues help researchers spread their scientific impact and, more specifically, to increase the citation counts of their papers, which further offers a large potential to increase their *h-indices*.

### 3.4 Social Factors

Previous studies show that researchers have the tendency to cite their co-authors’ work [2]. As shown in Figure 3(c), our preliminary results show that a researcher’s *h-index* is also positively correlated with his or her total number of collaborators/co-authors. To explore this trend, we extract a weighted collaboration network from the dataset, where each author is denoted as a node, and each link between two nodes is connected if the researchers have col-



**Figure 4: Factor correlation analysis when predicting for scholars with different  $h$ -indices.  $t=2007$  and  $\Delta t=5$  years. Author’s authority on a subject and published venue are the most highly correlated factors.**



**Figure 5: Factor correlation analysis as the time period  $\Delta t$  is varied. Note that  $t=2007$  and a minimum threshold for the primary author’s  $h$ -index is set to 10.**

laborated with each other. The weight of each link is defined as the frequency of collaborations. We then extract four attributes for each node (author) from the collaboration network, including the number of co-authors (degree), the PageRank score, the average  $h$ -index of co-authors, and the weighted average  $h$ -index of co-authors. For a given paper, the highest values among its authors for these four metrics are used as social factors.

**Significance.** The factor correlations of social and venue factors are shown in Figures 4(c) and 5(c). Both subfigures demonstrate the prominently positive correlation of venue factors. This discovery coincides with the fact that the scientific researchers have the highly motivated tendency to publish results in top venues. Perhaps more interestingly, the correlation between several venue factors and researchers’  $h$ -indices decreases as the researchers’  $h$ -indices increase. This indicates that gathering into leading venues can help to initially elevate researchers’ reputations, but it is the researchers’ growing peer-influence itself, rather than the venue, that further increases their prominence. Nevertheless, compared to venue factors, social factors have only a limited correlation with whether a paper will increase its primary author’s  $h$ -index.

### 3.5 Reference Factors

The scientific impact of a scholarly work is often quantified by its respective citation count. In this way, the more times a publication is cited by others, the larger its assumed impact. Conversely, as most scientific research is undertaken by “standing on the shoulder of giants,” we ask whether highly cited papers actually tend to acknowledge the previous “giants” upon whom they stand. Two intuitive factors are used to evaluate this question, namely (1) the ratio of a paper references that have at least max- $h$ -index citations to the paper’s total number of references and (2) the average number of citations accumulated by the paper’s references.

### 3.6 Temporal Factors

As fast-rising phenomena typically attract the attention of crowds more easily, a “rising star” in academia can attract publicity. Previous work has found that temporal information can be a powerful factor in modeling scientific impact [2, 28], so it seems straightforward that the speed at which an author’s  $h$ -index grows should affect the rate at which her/his papers contribute to her/his  $h$ -index. To capture this effect, we examine the increase of authors’  $h$ -indices within the past three years. Specifically, we consider four temporal factors, including the  $h$ -index changes of the first author, the max- $h$ -index author, and the average change and maximum change among all authors. The specific definitions are shown in Table 1.

**Significance.** From Figures 4(d) and 5(d), we can see that among the reference and temporal factors,  $R$ -ratio-max, i.e., the ratio between the number of references that have accumulated at least max- $h$ -index citations and the total number of references, demonstrates the most influence on the success of  $h$ -index contribution. Other important factors are illustrated by the rising trends of both the primary author’s  $h$ -index and all authors’ average  $h$ -index. However, their effects are more pronounced for the young “rising star” (low  $h$ -index) than for the established, highly influential “giants” (high  $h$ -index).

### 3.7 Summary

According to the correlation analysis above, we provide the following intuitions relating to academia:

- A scientific researcher’s authority on a topic is the most decisive factor in facilitating an increase in his or her  $h$ -index. This coincides with the fact that the society follows (e.g., ACM/IEEE fellow or membership of NAS/NAE) or lifetime

honors (e.g., Turing award) are typically awarded for contributions to a topic or domain.

- The level of the venue in which a given paper is published is another crucial factor in determining the probability that it will contribute to its authors’  $h$ -indices. Top venues make one outstanding and expand one’s scientific impact; gradually, one’s impact further helps to increase the venue’s prestige. The suggestion here lies in the every scholar’s aim: *Target and publish influential scientific results in top venues.*
- People in social society often follow vogue trends. However, publishing on an academically “hot” but unfamiliar topic is unlikely to further one’s scientific impact, at least as measured by an increase in one’s  $h$ -index. This reminds us that *one should not turn to follow the vogue topics that are beyond his or her expertise.*

## 4. EXPERIMENTS

In this section, we demonstrate the predictability of whether a paper will contribute to its primary author’s  $h$ -index within a given timeframe.

### 4.1 Experimental Setup

The task is to predict whether the papers published in time  $t$  will contribute to the  $h$ -indices of the authors (the max- $h$ -index author for each paper) within a given time period  $\Delta t$ . For example, by setting  $t = 2007$ ,  $\Delta t = 5$  years, and the minimum max- $h$ -index to 10, we collect all the papers published in 2007, extract the features from the corpus before 2007, and observe whether the number of citations for each paper in 2007 is larger than or equal to the maximum  $h$ -index of its authors in 2012 (the last year represented in our dataset).

**Methods.** As our problem is formulated as a classification task, we use a series of different classifiers, including logistic regression (LRC), random forest (RF), and bagged decision trees (BAG). While we also generated experiments using support vector machines, naïve Bayes models, and neural networks, we found that their performance was very poor compared to the other three methods; thus their results have been omitted. Due to its predictive ability, ease of implementation, and interpretability, we primarily use logistic regression to analyze factor contributions and parameter settings.

**Evaluation.** We employ half of the instances for training and the remaining half for validation. To quantitatively evaluate the predictability of the problem, we report the performance in terms of precision, recall,  $F_1$  score, area under the receiver operating characteristic (AUC), and accuracy. Furthermore, our problem can be viewed as a ranking task, namely ranking all papers of one scholar in the reverse order of probability that each paper will increase his or her  $h$ -index. Therefore, the precision at the top 3 results (Pre@3) and mean average precision (MAP) are also used to evaluate the performance.

### 4.2 Prediction Results

We present the predictability of whether a paper published in 2007 will contribute to the primary author’s  $h$ -index within five years. The prediction is applied on the papers whose primary author’s  $h$ -index is at least 10 in 2007. The resulting set of papers contains 21,519 instances, of which 30.46% successfully contributed to their primary author’s  $h$ -indices. Table 2 lists the predictive performance of different methods.

**Table 2: Predictive results generated by different methods.  $t=2007$ ,  $\Delta t=5$  years, and  $h$ -index threshold is set to 10. LRC — Logistic Regression; RF — Random Forest; BAG — Bagged decision trees; R—Random guess with half predicted positive and half negative. The results of support vector machine, naïve Bayes, and neural network models are omitted due to their poor performance on this task.**

Method	Pre.	Rec.	$F_1$	AUC	Accu.	Pre@3	MAP
R	0.305	0.500	0.375	0.500	0.500	0.674	0.522
LRC	0.854	0.711	0.776	0.938	0.875	0.925	0.965
RF	0.785	0.815	0.800	0.939	0.876	0.957	0.979
BAG	0.802	0.821	0.811	0.951	0.884	0.950	0.978

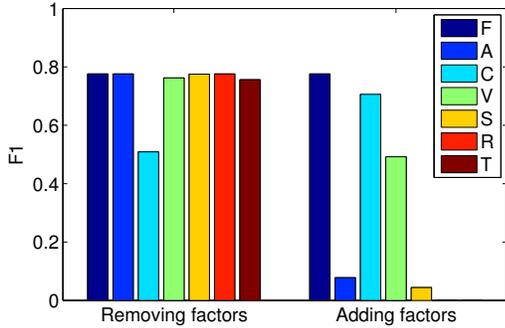
Overall, the random guessing would achieve an  $F_1$  score of 0.375 and an accuracy of 0.5. However, by our methodology, the predictive power significantly outperforms random guessing with an  $F_1$  score of over 0.776 (+107% increase) and an accuracy of more than 0.875 (+75% increase). In terms of precision, recall, and AUC score, the performance is still promising. As the three selected methods achieve similar results, logistic regression is chosen as the primary classifier to examine the remaining experiments

### 4.3 Factor Contribution

To predict whether a paper will increase its primary author’s  $h$ -index, we devise six groups of different factors (see §3) that may drive the growth of scientific impact. To explore the contributions of each group to the prediction task, we employ two methods: (1) we remove each group of factors and keep the remaining five to evaluate the predictive performance; and (2) we add or use only one group of factors to evaluate the predictive performance. Figure 6 shows the  $F_1$  scores for the two cases. The contributions of different groups of factors show a high degree of variability. When removing factor groups, the 30% drop in  $F_1$  score by removing the content factors indicates that they are significantly importance to this prediction task. By contrast, the marginal decreases in performance demonstrated by all other factors imply they provide only limited contributions. When using only one factor group, the content factors still play the most important role (0.70  $F_1$  score) in predicting the growth of scientific impact. Venue factors also achieve a reasonable performance. The contribution analyses are consistent with the factor correlation results elaborated upon in the previous section.

We further examine the contributions of each individual factor. We choose the information gain ratio (IGR) to determine which of the factors are the most important. The information gain for a factor  $x_k$  is the expected reduction in entropy—that is, uncertainty—achieved by learning the state of that factor. For each factor  $x_k$ , then, the IGR of  $x_k$ , denoted  $IGR(x_k)$ , is simply defined as the information gain  $IG(x_k)$  divided by the intrinsic value  $IV(x_k)$  of  $x_k$ , i.e.,  $IGR(x_k) = IG(x_k)/IV(x_k)$ . The higher the  $IGR(x_k)$  for factor  $x_k$ , the greater its importance.

Table 3 lists the information gain ratio and corresponding ranking of each single factor. Clearly, the topic authority of the primary author matters the most ( $C$ -authority-max), followed by the authorities of the other co-authors ( $C$ -authority-ave and  $C$ -authority-first). The following positions, from the 4<sup>th</sup> to the 7<sup>th</sup>, are held by the two venue factors and the two reference factors. The  $IGR$  of the remaining factors decrease to the next lowest order of magnitude, which indicates that they provide relatively limited contributions to the prediction task.



**Figure 6: Factor contribution analysis.** F denotes training a logistic regression model with a full feature set. A—Author factors; C—Content factors; V—Venue factors; S—Social factors; R—Reference factors; T—Temporal factors. The left side of the figure illustrates the effects of removing each group of factors, while the right side illustrates the effects of using only each group of factors for training.

#### 4.4 Predictability of Papers with Different Constraints

Our experimental results provide evidence of the predictability of whether one paper will contribute to the  $h$ -index of its primary author within five years. Two intuitive questions naturally arise: First, is a primary author with a high or a low  $h$ -index more predictable? Second, is a paper more predictable given a long or short timeframe? To answer these questions, we investigate the predictability of papers conditioned on the primary author’s  $h$ -index and the length of the given timeframe  $\Delta t$ .

Figure 7 shows the predictive performance with different constraints. On one hand, it suggests that our prediction task is more difficult for papers with a high  $h$ -index primary author. Recall that the higher the primary author’s  $h$ -index, the higher the local threshold for this paper during classification. Intuitively, then, as we consider authors with higher  $h$ -indices, it becomes increasingly difficult for any particular paper to reach the defined local threshold, which makes the corresponding prediction task increasingly non-trivial. On the other hand, the rising lines as the increase of  $\Delta t$  imply that our prediction task is easier when given a longer timeframe. Intuitively, papers can accrue more citations as time goes on, during which time the authors’ influence may increase, which may further compound the rate at which citations accrue. In this way, it becomes quite likely that the papers will contribute to their respective authors’  $h$ -indices if simply given a long enough timeframe.

Overall, the task of determining which papers will increase one’s  $h$ -index is more predictable when conducted over a relatively long timeframe for those who have relatively low  $h$ -indices.

#### 4.5 Case Studies

We illustrate several case studies to demonstrate the effectiveness of our methodology for quantifying scientific impact. Our case studies include two researchers and two data mining conferences, and conclude with the self-prediction of *this* paper.

**Two anonymous scholars.** We choose two anonymous scholars,  $A_{86}$  and  $A_{33}$ , who in 2007 had substantially different  $h$ -indices (86 and 33, respectively). We examine the difference in the predictability of whether the papers published by each author in 2007 would contribute to his or her respective  $h$ -index by 2012. From

**Table 3: Information Gain Ratio (IGR) of each factor.** IGR is used to decide the relevant extent of features. Here, IGR is between 0 and 1, with higher values indicating greater relevance.

	Factor	IGR	Ranking
Author	$A$ -first-max	0.0028	21
	$A$ -num-authors	0.0021	25
	$A$ -ave-max	0.0021	24
	$A$ -sum-max	0.0044	17
	$A$ -max-ratio	0.0085	9
	$A$ -num-first	0.0031	19
	$A$ -first-ratio	0.0049	16
Content	$C$ -popularity	0.0026	22
	$C$ -popularity-ratio	0.0077	10
	$C$ -diversity	0.0013	26
	$C$ -novelty	0.0089	8
	$C$ -authority-ave	0.0873	2
	$C$ -authority-first	0.0637	3
Venue	$V$ -ratio-max	0.0473	4
	$V$ -citation	0.0463	5
Social	$S$ -degree	0.0022	23
	$S$ -pagerank	0.0051	15
	$S$ -h-coauthor	0.0073	11
	$S$ -h-weight	0.0052	14
Reference	$R$ -ratio-max	0.0127	6
	$R$ -citation	0.0105	7
Temporal	$T$ -ave-h	0.0039	18
	$T$ -max-h	0.0056	13
	$T$ -h-first	0.0028	20
	$T$ -h-max	0.0056	12

Figure 8(a), we can observe the skewed heavy-tailed distributions for the number of citations their papers published in 2007 have obtained by 2012. Back in 2007,  $A_{86}$ ’s and  $A_{33}$ ’s  $h$ -indices were 86 and 33, respectively. In 2012, 8 of  $A_{86}$ ’s 48 publications published in 2007 have obtained at least 86 citations and 9 of  $A_{33}$ ’s 26 publications have obtained at least 33. In other words, while the ratio of the papers that have contributed to  $A_{86}$ ’s  $h$ -index is relatively low (8/48), this is actually a result of the researcher’s high  $h$ -index, which corresponds to a large scientific impact. In contrast,  $A_{33}$ ’s relatively low  $h$ -index compared to  $A_{86}$  makes the ratio of papers that contribute to  $A_{33}$ ’s  $h$ -index higher than those that contribute to  $A_{86}$ ’s. Table 4 shows the predictive results of whether their papers in 2007 would contribute to their  $h$ -indices in 2012, from which we make two observations. First, the performance of the model for both researchers is much higher than random guessing with respect to  $F_1$  score, AUC, and accuracy. Second, the overall performance for  $A_{33}$  is significantly higher than that for  $A_{86}$ , which suggests a greater predictability for researchers with relatively lower  $h$ -indices.

**KDD and ICDM.** Using ACM SIGKDD and IEEE ICDM as examples, we present the effects that different conferences have on spreading scientific impact and contributing to authors’  $h$ -indices. Currently, KDD and ICDM are considered two of the world’s premier research conferences in data mining. Back in 2007, ICDM was in its seventh year, while KDD was in its thirteenth year. Fig-

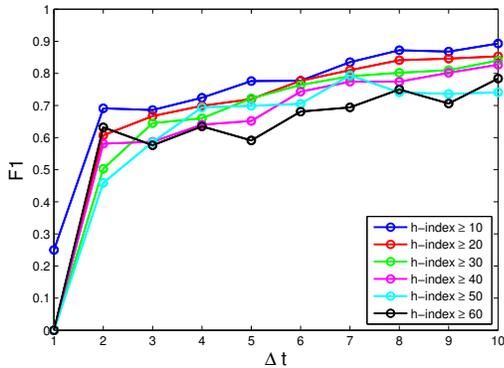


Figure 7: Predictive performance by varying the constraints.

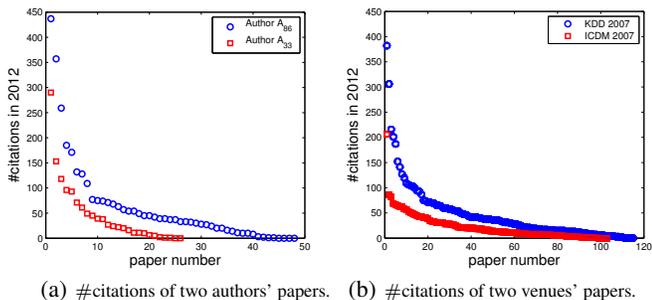


Figure 8: Case studies of citation counts in 2012 for papers published in 2007. In 2012, 8 of  $A_{86}$ 's 48 papers and 9 of  $A_{33}$ 's 26 papers published in 2007 obtained #citations over 86 and 33 ( $A_{86}$ 's and  $A_{33}$ 's  $h$ -indices in 2007), respectively.

ure 8(b) plots the number of citations in 2012 for all papers published in these two venues in 2007. In our dataset, we observe that KDD'07 and ICDM'07 papers contribute to their primary authors'  $h$ -indices in different proportions. We further examine which conference has papers that are, in terms of their contribution to the  $h$ -indices of their respective authors, more predictable. This comparison is illustrated by Table 5. The prediction results for KDD'07 papers are generally better than ICDM'07 in terms of recall and  $F_1$  score, and are competitive with ICDM'07 in terms of precision, AUC, and accuracy. Overall, both venues demonstrate promising predictability in the spread of the scientific impact of their respective publications.

**Self-prediction for this paper.** Finally, we perform a self-prediction on whether *this* paper will contribute to its primary author's  $h$ -index by 2019. Keeping in mind that using the methodology employed in this paper would technically require unavailable training data (i.e., data composed of publications from 2014 and their citation counts in 2019), we instead revert to using the logistic regression model trained on the data from 2007 to generate this prediction. To generate features for this paper, we insert this paper into the 2012 data and make the assumption that it was accepted by the venue to which we have submitted at that time. The author factors, for example, are extracted from their respective author profiles circa 2012. With the approximate model and features, we estimate that the probability that this paper will contribute to the  $h$ -index of the author with highest  $h$ -index within five years is around 76%. With a pinch of optimism, we leave the evaluation of the fidelity of this prediction as an exercise for future readers.

Table 4: Predictive results for two anonymous authors.  $t=2007$  and  $\Delta t=5$  years. Pre@k:  $k=8$  ( $A_{86}$ );  $k=9$  ( $A_{33}$ ).

Authors	Pre.	Rec.	$F_1$	AUC	Accu.	Pre@k	MAP
$A_{86}$	0.500	0.375	0.429	0.584	0.833	0.375	0.346
$A_{33}$	1.000	0.667	0.800	0.856	0.885	0.667	0.849

Table 5: Predictive results for KDD'07 and ICDM'07 papers.  $t=2007$ ,  $\Delta t=5$  years and logistic regression is used. In our dataset, KDD'07 and ICDM'07 papers contribute to their primary authors'  $h$ -indices in different proportions.

Venues	Pre.	Rec.	$F_1$	AUC	Accu.
KDD'07	0.800	0.889	0.842	0.884	0.818
ICDM'07	0.842	0.593	0.696	0.886	0.825

## 5. RELATED WORK

Scientific impact modeling is being extensively explored and has become an important and popular research topic, particularly since the rise of two recent, successive *Science* papers in 2013 [24, 27]. The study of scientific impact by scholarly researchers offers the potential to help scholars more effectively disseminate their work and expand their scientific influence.

Traditionally, the number of citations has been widely used as a measurement of scientific impact for both individual papers and solitary scientific researchers. Several practical metrics are designed based on the number of citations to reflect scientific impacts. Garfield proposed the idea of impact factor for indexing and evaluating the quality of journals [6]. Recently, Hirsch proposed the  $h$ -index, which is able to measure both the productivity and popularity of researchers [8]. In this setting, on the one hand scholars aim to publish results in high-impact journals to collect more citations and increase their  $h$ -indices, while on the other hand the journals attempt to accept solid and potentially influential work to improve their impact factors. Accordingly, both impact factor and  $h$ -index successfully characterize the motivation and behaviors of the scientific community.

Besides measuring scientific impact, a large body of work has been focused on the prediction of scientific impact. The 2003 ACM SIGKDD Cup introduced a competition focused around citation count prediction [7], with the task of estimating the number of citations of one paper given its previous number of citations. Following this, many efforts have been made to predict the number of future citations for scholarly work. Castillo et al. studied the correlation between author reputation and citations [4]. Yan et al. examined a series of features important to future citations [28, 29]. Wang et al. uncovered basic mechanisms that govern scientific impact, which has the power to quantify and predict citation counts [27, 18]. However, the effectiveness of such predictions is fundamentally limited by the power law distribution of citations. Herein we (re)define the impact prediction problem by addressing a question of interest to many academic researchers, namely: "will this paper increase my  $h$ -index?" The major difference between our work and previous work lies in that, rather than solving a regression task in a highly skewed environment, we address the problem by generating a local threshold (the author's  $h$ -index) for each paper's future citation count.

Our work is also related to other mining tasks in academic data such as citation recommendation [16, 22, 30], topic influence [13, 21], collaboration prediction [20, 26], and analysis of citation networks [25] and academic social networks [23]. Furthermore, as the formalization of our predictive task is partly inspired by the cascade growth prediction problem [5], the prediction of scientific impact

has relations with predicting the popularity [9, 14, 1] of online “paper” (e.g., tweet, video, photo) in social media.

## 6. CONCLUSION

In this paper, we examine scientific impact by formalizing a novel problem that can be reduced to the following question: will a paper contribute to its primary author’s  $h$ -index within a given time-frame? Previous, rich work on predicting the number of citations of individual papers is fundamentally limited by the heavy-tailed distribution of citation counts. Our problem definition differs by offering a great potential to quantify scientific impact on the interplay between scientific researchers and publications. We examine six groups of factors from different perspectives that may drive a paper to obtain enough citations to contribute to its primary author’s  $h$ -index.

By experimenting on a large-scale public academic dataset, we find that two factors—(1) the authors’ authority on the publication topic and (2) the publication venue—play the most decisive roles in determining whether a paper will contribute to its primary author’s  $h$ -index. Surprisingly, we notice that the popularity of the publication topic and the co-authors’ influence are not correlated to the prediction target. Our study also demonstrates a greater than 87.5% potential predictability for whether a paper will contribute to its primary author’s  $h$ -index within five years. Overall, our findings unveil mechanisms for quantifying scientific impact and provide concrete suggestions to researchers for better expanding their scientific influence and, ultimately, for more effectively “standing on the shoulders of giants.”

Notwithstanding the extensive and promising results of the present work, there is still much room left for future work. First, while this work is conducted only on literature from computer science, it is necessary to examine the observed patterns in other scientific disciplines, such as physics, mathematics, biology, and so on. Second, since authors’  $h$ -indices evolve within the prediction timeframe, it would be natural to design methodologies that could capture the co-evolution of authors’  $h$ -indices and citation counts.

**Acknowledgments.** This work is supported by the Army Research Laboratory under Cooperative Agreement Number W911NF-09-2-0053, the U.S. Air Force Office of Scientific Research (AFOSR) and the Defense Advanced Research Projects Agency (DARPA) grant #FA9550-12-1-0405, and the National Science Foundation (NSF) Grant OCI-1029584.

## 7. REFERENCES

- [1] M. Ahmed, S. Spagna, F. Huici, and S. Niccolini. A peek into the future: Predicting the evolution of popularity in user generated content. In *WSDM '13*, pages 607–616. ACM, 2013.
- [2] S. Bethard and D. Jurafsky. Who should I cite: Learning literature search models from citation behavior. In *CIKM '10*, pages 609–618. ACM, 2010.
- [3] D. M. Blei, A. Y. Ng, and M. I. Jordan. Latent Dirichlet allocation. *JMLR*, 3:993–1022, 2003.
- [4] C. Castillo, D. Donato, and A. Gionis. Estimating the number of citations using author reputation. In *SPIRE '07*, pages 107–117. Springer, 2007.
- [5] J. Cheng, L. Adamic, P. A. Dow, J. M. Kleinberg, and J. Leskovec. Can cascades be predicted? In *WWW '14*, pages 925–936, 2014.
- [6] E. Garfield. Citation indexes for science: A new dimension in documentation through association of ideas. *Science*, 122(3159):108–111, 1955.
- [7] J. Gehrke, P. Ginsparg, and J. M. Kleinberg. Overview of the 2003 kdd cup. *SIGKDD Explorations*, 5(2):149–151, 2003.
- [8] J. E. Hirsch. An index to quantify an individual’s scientific research output. *Proceedings of the National Academy of Sciences*, 102(46):16569–16572, 2005.
- [9] L. Hong, A. S. Doumith, and B. D. Davison. Co-factorization machines: Modeling user interests and predicting individual decisions in Twitter. In *WSDM '13*, pages 557–566. ACM, 2013.
- [10] J. M. Kleinberg. Authoritative sources in a hyperlinked environment. *Journal of the ACM*, 46(5):604–632, 1999.
- [11] J. M. Kleinberg and S. Oren. Mechanisms for (mis)allocating scientific credit. In *STOC '11*, pages 529–538. ACM, 2011.
- [12] S. Kullback and R. A. Leibler. On information and sufficiency. *Annals of Mathematical Statistics*, 22(1):79–86, 1951.
- [13] L. Liu, J. Tang, J. Han, M. Jiang, and S. Yang. Mining topic-level influence in heterogeneous networks. In *CIKM '10*, pages 199–208. ACM, 2010.
- [14] H. Pinto, J. M. Almeida, and M. A. Gonçalves. Using early view patterns to predict the popularity of youtube videos. In *WSDM '13*, pages 365–374. ACM, 2013.
- [15] F. Radicchi, S. Fortunato, and C. Castellano. Universality of citation distributions: Toward an objective measure of scientific impact. *PNAS*, 2008.
- [16] X. Ren, J. Liu, X. Yu, U. Khandelwal, Q. Gu, L. Wang, and J. Han. ClusCite: Effective citation recommendation by information network-based clustering. In *KDD '14*, 2014.
- [17] H.-W. Shen and A.-L. Barabási. Collective credit allocation in science. *PNAS*, 2014.
- [18] H.-W. Shen, D. Wang, C. Song, and A.-L. Barabási. Modeling and predicting popularity dynamics via reinforced poisson processes. In *AAAI '14*, 2014.
- [19] M. Strathern. Improving ratings: audit in the British university system. *European Review*, 5(03):305–321, 1997.
- [20] Y. Sun, J. Han, C. C. Aggarwal, and N. V. Chawla. When will it happen?: Relationship prediction in heterogeneous information networks. In *WSDM '12*, pages 663–672. ACM, 2012.
- [21] J. Tang, J. Sun, C. Wang, and Z. Yang. Social influence analysis in large-scale networks. In *KDD '09*, pages 807–816, 2009.
- [22] J. Tang and J. Zhang. A discriminative approach to topic-based citation recommendation. *Advances in Knowledge Discovery and Data Mining*, pages 572–579, 2009.
- [23] J. Tang, J. Zhang, L. Yao, J. Li, L. Zhang, and Z. Su. Arnetminer: Extraction and mining of academic social networks. In *KDD '08*, pages 990–998, 2008.
- [24] B. Uzzi, S. Mukherjee, M. Stringer, and B. Jones. Atypical combinations and scientific impact. *Science*, 342(6157):468–472, 2013.
- [25] D. Vu, A. Asuncion, D. Hunter, and P. Smyth. Dynamic egocentric models for citation networks. In *ICML '11*, pages 857–864, 2011.
- [26] C. Wang, J. Han, Y. Jia, J. Tang, D. Zhang, Y. Yu, and J. Guo. Mining advisor-advisee relationships from research publication networks. In *KDD '10*, pages 203–212, 2010.
- [27] D. Wang, C. Song, and A.-L. Barabási. Quantifying long-term scientific impact. *Science*, 342(6154):127–132, 2013.
- [28] R. Yan, C. Huang, J. Tang, Y. Zhang, and X. Li. To better stand on the shoulder of giants. In *JCDL '12*, pages 51–60. ACM, 2012.
- [29] R. Yan, J. Tang, X. Liu, D. Shan, and X. Li. Citation count prediction: Learning to estimate future citations for literature. In *CIKM '11*, pages 1247–1252. ACM, 2011.
- [30] X. Yu, Q. Gu, M. Zhou, and J. Han. Citation prediction in heterogeneous bibliographic networks. In *SDM '12*, pages 1119–1130, 2012.
- [31] J. Zhang, J. Tang, and J. Li. Expert finding in a social network. In *DASFAA '07*, pages 1066–1069, 2007.