Predicting publication productivity for researchers: a piecewise Poisson model

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Abstract

Predicting the scientific productivity of researchers is a basic task for academic administrators and funding agencies. This study provided a model for the publication dynamics of researchers, inspired by the distribution feature of researchers' publications in quantity. It is a piecewise Poisson model, analyzing and predicting the publication productivity of researchers by regression. The principle of the model is built on the explanation for the distribution feature as a result of an inhomogeneous Poisson process that can be approximated as a piecewise Poisson process. The model's principle was validated by the high quality dblp dataset, and its effectiveness was testified in predicting the publication productivity for majority of researchers and the evolutionary trend of their publication productivity. Tests to confirm or disconfirm the model are also proposed. The model has the advantage of providing results in an unbiased way; thus is useful for funding agencies that evaluate a vast number of applications with a quantitative index on publications.

Keywords: Scientific publication, Productivity prediction, Data modelling.

Introduction

Scientific fields such as informetrics, scientometrics, and bibliometrics establish a range of models and methods to evaluate the impacts of scientific publications, and then to predict the scientific success of researchers [1]. Although publication productivity correlates to scientific success, much attention on this topic has concentrated on citation-based indexes, followed by the h-index provided by Hirsch [2], a popular measure of scientific success. It is the maximum value of h such that a researcher has produced h publications that have each been cited at least h times. The popularity of the h-index is attributable to its simplicity and its addressing both the productivity and the citation impact of publications [3].

The success in the prediction of citation-based indexes and the *h*-index can be thought to result from the cumulative advantage of receiving citations found by Price in the year 1965 [4], which has been extended as a general theory for bibliometric and other cumulative advantage process [5–7]. From the perspective of statistics, the success is due to the predictable components of these indexes that can be extracted via autoregression. In more concrete terms, the current *h*-index, the number of annual citations, and the number of five-year citations are found to be positive predictors to these indexes [8,9].

The cumulative advantage in producing publication is weaker than that in receiving citations. Empirical studies on data display it as the phenomenon that the tail of the quantitative distribution of the publications produced by a group of researchers is much shorter than that of the citation distribution of those researchers [10]. This study also shows the productivity of researchers in the dblp dataset does not have a predictable component that can be extracted via autoregression. The autocorrelation coefficients with a lag larger than 1 of the time series on an individual researcher's cumulative publication quantity are almost smaller than 0.5, suggesting a lack of predictability in a researcher's productivity only by his or her historical publication quantity. Therefore, the critical factor of the success in the prediction of citation-based indexes and the h-index does not exist in the prediction task of publication productivity.

Is there any predictability in publication patterns? Given the factors involved in publishing, such as the intrinsic value of research work, timing, and the publishing venue, finding regularities in the publication history of researchers is an elusive task. Age and achievement probably constitute the most comprehensive attempt to empirically determine the changes in researchers' creativity, reflected by the changes in their publication productivity [11]. In network science, these factors are called the aging phenomenon and the cumulative advantage, dominating the evolution of coauthorship networks [12, 13]. Hence, the productivity has been theoretically expressed as a curvilinear function of age [14]. This theoretical result is suitable for the fruitful researchers that have a long time engaging in research. However, it cannot fit the productivity evolution of many researchers in the dblp dataset analyzed here.

Empirical datasets from several disciplines show that the number of a researcher' publications approximately follows a generalized Poisson distribution with a fat tail [15]. Can this feature be reproducible by dynamical random models? Previous studies show this distribution can be thought as a mixture of Poisson distributions [16]. Samples following the same Poisson distribution means that they would be drawn from the same population. It means researchers can be partitioned into several populations, such that each population has certain homogeneity in publication patterns. Finding such a partition would help to reveal the mystery of publication patterns, which inspires this study.

We partitioned the researchers in the dblp dataset into several subsets, each of which consists of the researchers with the same number of historical publications produced before the current time. This partition eliminates the diversity in publishing experience. For each subset, we found that the number of publications of a member follows a Poisson distribution at the following short time interval. This inspires us to provide a piecewise Poisson model to find significant predictors for publication productivity. The finding is that researchers' publication productivity significantly correlates to time given a historical publication quantity. The relationship allows us to infer researchers' publication productivity in the future. We provided two methods to test the prediction results of our model in terms of the evolutionary trend of researchers' productivity and the quantitative distribution of their publications.

This paper is organized as follows. Literature review and empirical data are described in Sections 2, 3. The model is described in Sections 4-6, where the experiments and comparisons with previous results are also analyzed. The results are discussed and conclusions drawn in Section 7.

Literature review

There are three main aspects to the prediction of scientific success: the h-index, citation-based indexes, and publication productivity. Although our study focuses on predicting the publication productivity of researchers, reviewing the methods in first two aspects contributes to finding the possibility and unavailability of applying those methods to the third aspect.

As a popular measure of scientific success, the h-index of researchers attracts considerable attention on predicting it. Acuna et al analyzed the data of 3,085 neuroscientists, 57 Drosophila researchers, and 151 evolutionary scientists by a linear regression with elastic net regularization. They presented a formula to predict the h-index, and indicated that the current h-index is the most significant predictor, compared with the number of current papers, the year since publishing first paper, etc [8]. Dong et al utilized the standard linear regression and logistic regression to analyze more features, such as the average citations of an author's papers and the number of coauthors [17]. Mccarty et al analyzed the coauthorship data of 238 authors collected from the Web of Science, and showed that the number of coauthors and their h-index also are positive predictors [18].

The number of received citations is a widely-used measure of success for publications and researchers. To predict highly cited publications only based on short-term citation data, Mazloumian applied a multilevel regression model [19], Wang et al derived a mechanistic model [20], Newman defined z-scores [9], Gao et al utilized a Gaussian mixture model [21], Pobiedina applied link prediction [22], and Abrishami et al utilized deep learning [23]. Together with the impact factors of journals, Stern and Abramo applied linear regression models to this prediction task respectively [24,25], and Kosteas introduced the rankings of journals [26]. To improve prediction precision, the information of authors and contents of publications are utilized: Bornmann et al added publications' length [27]; Bai et al applied maximum likelihood estimation, and introduced the aging of publications' impact [28]; Sarigol et al used a method of random decision forests, and introduced specific characteristics of coauthorship networks (e. g. the centrality) [29]; Yu et al provided a stepwise regression model synthesizing specific features of publications, authors, and journals [30]; Klimek et al utilized the centrality measures of term-document networks [31].

Returning to the prediction of publication productivity, one may find that the studies on this aspect are quite few when compared with those on *h*-index and citation-based indexes. Empirical studies found the cumulative advantage in producing publications and the aging of researcher' creativity [32,33]. Laurance et al analyzed the publications of 182 researchers by using the Pearson correlation coefficient, and found that Pre-PhD publication success strongly correlated to long-term success [34]. In the aspect of theoretical research, Lehman concluded that achievement tends to be a curvilinear function of age. From the onset of a researcher's career, productivity tends to rapidly increase, then reaches at the peak productive age, and thereafter slowly declines with aging [11]. Simonton provided a formula to model this process [14].

The aforementioned methods of citation-based indexes and h-index all refer to the positive correlation between the current indexes and their history. Essentially, the mechanism underlying their success is the cumulative advantage on those indexes. However, the effect of cumulative advantage in producing publications is not so strong. The tail of the quantitative distribution of the publications produced by a group of researchers is much shorter than that of the citation distribution of those researchers. Therefore, the prediction methods of publication productivity would be different from those of citation-based indexes and the h-index.

The data

Due to its nature of regression, the provided model needs a training dataset containing enough productive researchers. Therefore, the model needs a large training dataset, spanning a long time interval. Mean-while, name ambiguities exist in bibliographic data, which manifest themselves in two ways: one person is identified as two or more entities (splitting error); two or more persons are identified as one entity (merging error) [35, 36]. Merging errors would generate names with a number of publications far more than ground truth, invalidating the prediction results of the model. Therefore, a training dataset with limited errors is required.

The dblp computer science bibliography provides a dataset satisfying above requirements, which consists of the open bibliographic information on major journals and proceedings of computer science (https://dblp.org). The dataset has been cleaned by several methods of name disambiguation and checked manually. For example, the ORCID information has been utilized regularly to correct numerous cases of homonymous and synonymous. We extracted parts of the data at certain time intervals as training and test datasets (Table 1). These parts totally consist of 220,344 publications in 1,586 journals and proceedings, which are produced by 328,690 researchers at the years from 1951 to 2018.

Sets 1 and 2 are used to extract the historical publication quantities of test researchers in Sets 3 and 4 respectively. Set 5 is used as a training dataset. Sets 6 and 7 are used to test the prediction results for the researchers in Sets 3 and 4 respectively. Due to the size and the time span of the analyzed dataset, this study would not be treated as a case study. The provided model is at least suitable for the community of computer science. Note that the term "researcher" in this paper refers to an author of the dblp dataset.

Dataset	a	b	С	d	e	f
Set 1	1951 - 1995	20,781	$20,\!666$	346	1.556	1.565
Set 2	1951 - 2000	$38,\!149$	$35,\!643$	542	1.571	1.681
Set 3	1995	3,709	2,268	160	1.137	1.859
Set 4	2000	5,741	$3,\!600$	257	1.184	1.888
Set 5	1995 - 2009	87,140	$62,\!636$	931	1.538	2.139
Set 6	1996 - 2013	$116,\!231$	$80,\!193$	$1,\!150$	1.557	2.257
Set 7	2001 - 2018	$301,\!741$	184,701	$1,\!495$	1.733	2.831

Table 1. Certain subsets of the dblp dataset.

The index a: the time interval of data, b: the number of researchers, c: the number of publications, d: the number of journals, e: the average number of researchers' publications, f: the average number of publications' authors.

Motivation

This study is a data-driven one, inspired by the features of the quantitative distributions of researchers' publications. Consider the researchers in the training dataset who have publications at the year y and no more than 10 publications at [1951, y]. Consider the quantitative distribution of their publications produced at y+1, where y = 1995, ..., 2012. The Kolmogorov-Smirnov (KS) test rejects to regard them as Poisson distributions because of their tail (Fig. 1). One can also find that the quantitative distributions of publications produced by relatively large groups of researchers in the dblp dataset have a fat tail, which also appears in other empirical datasets [16].

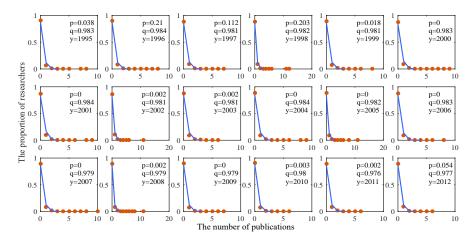


Figure 1. The quantitative distribution of researchers' publications. Consider the researchers of the training dataset who have publications at y and no more than 10 publications at [1951, y]. Index q is their proportion to the total researchers with publications at y. The KS test rejects that the quantitative distribution of these researchers' publications produced at y + 1 (red circles) is a Poisson (blue lines), when $p \leq 0.05$.

The emergence of their fat tail can be explained as a result of the cumulative advantage in producing publications or the diversity of researchers' ability [13]. In more detail, previous studies show that the distributions are featured by a trichotomy, comprising a generalized Poisson head, a power-law middle part, and an exponential cutoff [37]. The trichotomy can be derived from a range of "coin flipping" behaviors, where the probability of observing "head" is dependent on observed events [38].

The event of producing a publication can be regarded as an analogy of observing "head", where the probability of publishing is also affected by previous events. Researchers would easily produce their second publication compared with their first one. This is a cumulative advantage, research experiences accumulating in the process of producing publications. It displays as the transition from the generated Poisson head to the power-law part. Aging of researchers' creativity is against cumulative advantage, which displays as the transition from the power-law part to the exponential cutoff.

The quantitative distributions of researchers' publications can be fitted by a mixture of Poisson distributions [16]. Therefore, we could expect to partition researchers into specific subsets, such that the quantitative distribution of publications produced by the researchers of each subset is a Poisson. When restricting into a short time interval, the effects of cumulative advantage and aging would be not significant. However, the diversity of researchers in publication history cannot be eliminated only by shrinking the observation window in the time dimension. Therefore, we provided a split scheme to eliminate the diversity as follows.

Consider the researchers who produced publications at the two intervals $[T_0, T_1]$ and $[T_1, T_2]$. Partition the latter one into J intervals with cutpoints $T_1 = t_0 < t_1 < \cdots < t_J = T_2$. The half-closed interval $(t_{j-1}, t_j]$ is referred to as the *j*-th time interval, where j = 1, 2, ..., J. Partition the researchers with no more than I publications at $[T_0, t_j]$ into I subsets according to their historical publication quantity at $[T_0, t_{j-1}]$. That is, the *i*-th subset consists of the researchers with *i* publications at $[T_0, t_{j-1}]$.

Let the *i*-th subset at the *j*-th time interval be the subset of the researchers with *i* publications at $[T_0, t_{j-1}]$. Fig. 2 shows that the publication quantity of a researcher of the *i*-th subset (i = 1, ..., 20) at each observed time interval (y + 1 = 1996, ..., 2013) follows a Poisson distribution. This inspires us to provide a piecewise Poisson model.

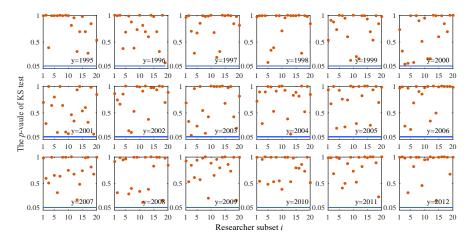


Figure 2. Eliminating the diversity in historical publication quantity induces Poisson distributions. Consider the researchers who produced publications at y and i publications at [1951, y]. The KS test cannot reject the quantitative distribution of the publications produced by these researchers at y + 1 is a Poisson, p-value> 0.05.

The piecewise Poisson model

Our study considers the creativity on producing publications, termed "publication creativity". The provided model gives a method to measure it through researchers' publication quantity. Recall that the *i*-th subset at the *j*-th time interval is the subset of the researchers with *i* publications at $[T_0, t_{j-1}]$. Denote its publication creativity by λ_{ij} . Assume $\lambda_{i1} > 0$ and

$$\lambda_{ij} = \lambda_{i1} \mathrm{e}^{\beta_i (t_j - t_1)},\tag{1}$$

where β_i tunes the effect of time t_j . Given *i*, the formula in Eq. (1) is exactly the Poisson model (see its definition in Appendix A), because the quantity of the publications produced by a researcher in the *i*-th subset at $(t_{j-1}, t_j]$ follows a Poisson distribution (Fig. 2). Therefore, we named the provided model piecewise Poisson model.

Now let us show the calculation of publication creativity. Consider a dataset consisting of the researchers having publications at the time interval $[T_0, t_{L-1}]$ and their publications at the time interval $[T_0, t_L]$, where $1 < L \leq J$. The publication quantity of a researcher at $(t_{j-1}, t_j]$ is his or her publication quantity at that time interval. Then, we defined the publication productivity of the *i*-th subset in the dataset at $(t_{j-1}, t_j]$ to be its average publication quantity at that time interval, and denote it by η_{ij} . It can be calculated as

$$\eta_{ij} = \frac{m_{ij}}{n_{ij}},\tag{2}$$

where n_{ij} is the number of the researchers with *i* publications at $[T_0, t_{j-1}]$, and m_{ij} is the number of publications produced by those researchers at $(t_{j-1}, t_j]$.

Define the publication creativity λ_{ij} to be the expected value of η_{ij} . Therefore, we need a training dataset to calculate λ_{ij} by regression. Taking logs in Eq. (1) and substituting η_{ij} into it, we obtained

$$\log \eta_{ij} = \alpha_i + \beta_i (t_j - t_1), \tag{3}$$

where $\alpha_i = \log \lambda_{i1}$, and j = 1, ..., L. The linear regression is utilized to calculate α_i and β_i . Eq. (3) describes the relationship between η_{ij} and t_j given *i*. The relationship is significant for the majority researchers in the training dataset used here; thus we can let $\lambda_{ij} = e^{\alpha_i + \beta_i (t_j - t_1)}$. Fig. 3 shows an illustration of the provided model.



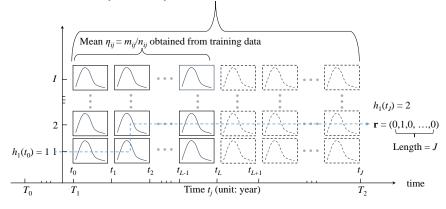


Figure 3. An illustration of the piecewise Poisson model. A training dataset is used to calculate the publication productivity η_{ij} . The publication creativity λ_{ij} is calculated by our model. Vector **r** records the predicted publication quantity of a researcher at each time interval $(t_{j-1}, t_j]$, where j = 1, ..., J.

Algorithm 1 is provided to predict researchers' publication quantity at the time interval $[t_X, t_Y]$, where $t_0 \leq t_X < t_Y \leq t_J$. Denote the publication quantity of researcher s at $[T_0, t_l]$ by $h_s(t_l)$. The algorithm gives $h_s(t_Y)$ the predicted publication quantity of researcher s at $[T_0, t_Y]$. Due to its regression nature, the algorithm cannot exactly predict the publication quantity for an individual, but it can be suitable for a group of researchers.

Note that the training dataset would be not enough for using linear regression given a large *i*. Therefore, the model cannot be applied to productive researchers with a publication quantity more than *I*. Our model can only be used to predict publication quantity for the researchers with a publication quantity at $[T_0, t_X]$ no more than a given integer $I_1 < I$.

Experiments

Now the model is applied to the dblp dataset. The training dataset consists of the researchers in Set 5 and their historical publication quantity from Set 1, Its parameters are I = 40, J = 23, L = 14, $T_0 = 1951$, $T_1 = t_0 = 1995$, $t_L = 2009$, and $T_2 = t_J = 2018$. The test dataset consists of the researchers in Set 4, their historical publication quantity from Set 2, and their annual publication quantity from Set 7. Its parameters are $t_X = 2000$, and $t_Y = 2018$.

The matrix of publication productivity $(m_{ij}/n_{ij})_{I\times L}$ is calculated based on the training dataset. For

Algorithm 1 Predicting researchers' publication quantity.

Require: the $h_s(t_X)$ of any test researcher s; the parameter J; the matrix $(m_{ij}/n_{ij})_{I \times L}$. **Ensure:** the predicted productivity $h_s(t_J)$ of researcher s. for i from 1 to I do calculate α_i and β_i in Eq. (3) by the linear regression; let $\lambda_{ij} = e^{\alpha_i + \beta_i (t_j - t_1)}$ for j = 1, ..., J; end for for each researcher s do initialize $h = h_s(t_X);$ for l from X + 1 to Y do sample an integer r from $\operatorname{Pois}(\lambda_{hl})$; let h = h + r; end for let $h_s(t_Y) = h$. end for

example, n_{11} is the number of researchers with one publication at [1951, 1995], and m_{11} is the publication quantity of those researchers at the year 1996. Then, α_i and β_i are calculated by applying the linear regression to Eq. (3).

The χ^2 test indicates that η_{ij} significantly correlates to t_j given $i \leq 12$ (see the *p*-values in Fig. 4). That is, the significance holds for 99.5% researchers in the training dataset. Thus, we can let $\lambda_{ij} = e^{\alpha_i + \beta_i (t_j - t_1)}$. In the experiment here, we can only predict publication quantity for 98.76% researchers of the test dataset (who have no more than $I_1 = 13$ publications at $[T_0, t_X]$) due to the maximum publication quantity of our model. Two methods are provided to testify the effectiveness of the model as follows.

Firstly, we tested the model by its prediction on the evolutionary trend of researchers' publication quantity. Consider the test researchers who produced *i* publications at $[T_0, t_X]$. Let n(i, y) be the average publication quantity of these researchers at [1951, y], and m(i, y) be the predicted one. Fig. 6 shows their trend about *i* given *y*. The correlation between them is measured by the Pearson correlation coefficient [40] on individual level (s_1) and that on group level (s_2) . Index s_1 decreases over time, whereas s_2 keeps high. It indicates that the model is unapplicable to the long-time prediction for an individual, but can be applicable for a group of researchers.

Secondly, we tested the model by its prediction on the quantitative distribution of researchers' publications. We compared the distribution for the publications produced by the test researchers at $[T_0, y]$

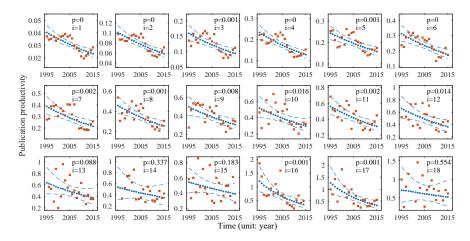


Figure 4. The relationship between publication productivity and time. Consider the researchers who have *i* publications at [1951, y]. Calculate their publication productivity at y + 1 (red squares). The solid dot lines show the predicted results by the Poisson regression, and the dashed lines show confidence intervals. The relationship is significant when p < 0.05.

with the predicted one. Fig. 6 shows that a fat tail emerges in the evolution of the ground-truth distributions, because a small fraction of researchers produced many publications. However, our model cannot predict over-exaggerated productivity due to the maximum publication quantity that can predicted by our model. Therefore, the KS test rejects that the compared distributions are the same with the growth of time (see the *p*-values in Fig. 6), although there is a coincidence in their forepart. It indicates that the prediction precision for productive researchers needs to be improved.

Comparisons with previous results

Firstly, we discussed the possibility of utilizing the prediction formula provided by Simonton [14]:

$$p(t) = c(\mathrm{e}^{-at} - \mathrm{e}^{-bt}),\tag{4}$$

where $a, b, c \in \mathbb{R}^+$. Parameter a is termed the "ideation rate", b is termed the "elaboration rate", c = abm/(b-a), and m represents the maximum number of publications a researcher can produce in his lifespan. This formula theoretically expresses a researcher's publication productivity by a function of time t. With the parameters in Reference [14], the shape of this curvilinear function is shown in Fig. 7.

As aforementioned, the cumulative advantage and the aging of creativity have impacts on researchers'

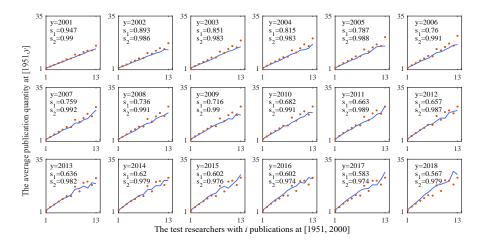


Figure 5. Fittings on the evolutionary trend of researchers' publication quantity. Consider the test researchers who have *i* publications at [1951, 2000]. Panels show the average number of publications produced by these researchers at [1951, y] (n(i, y), red dots) and the predicted one (m(i, y),blue lines). Index s_1 is the Pearson correlation coefficient calculated based on the list of researchers' publication quantity and that of their predicted one. Index s_2 is that based on the sorted lists.

publication productivity. One can think that a researcher's publication productivity is proportional to his publication quantity in his early age of research. The more publications he has, the higher his publication productivity. As his age increases, his creativity decreases and will dry up in his later period of research. The formula in Eq. (5) expresses this evolution of publication productivity.

Consider the test researchers with *i* publications at $[T_0, t_X]$, where i = 1, ..., 18. Fig. 8 shows the average publication quantity of these researchers at each year from 2001 to 2018, which cannot be fitted by the formula in Eq. (5). One possible explanation of this inconformity is the variation of the personnel structure on the researchers who produce publications. Note that the formula is provided at the year 1984. In recent thirty years, the number of academic masters and doctors dramatically increases. They contribute a large fraction of publications during their study periods. Many of them will not do research after graduation, and thus will not continue to produce publications. Therefore, the formula in Eq. (5) is unsuitable for describing the evolutionary process of their productivity. Meanwhile, it can be suitable for the fruitful scientists who have a long research career. However, in the dblp dataset, the number of these researchers is quite small, because more than 99.5% researchers produced no more than 40 publications.

Secondly, we discussed the practicability of utilizing a researcher's historical publication productivity to predict his or her future productivity. Therefore, we should know that is there any predictable components of the productivity that can be extracted via autoregression. Previous studies found that

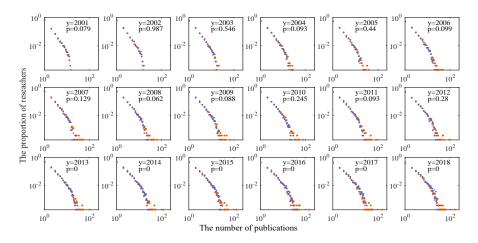


Figure 6. Fittings on the quantitative distribution of researchers' publications. Panels show this distribution for the publications produced by the test researchers at the time interval [1951, y] (red circles) and the predicted one (blue squares). When p > 0.05, the KS test cannot reject the null hypothesis that the compared distributions are the same.

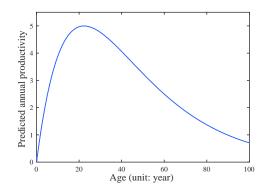


Figure 7. The publication productivity predicted by the formula in Eq. (5). Panel show the curve of this formula with the parameters provided by Simonton: a = 0.04, b = 0.05, and c = 61.

those components are significantly positive predictors to citation-based indexes and *h*-index, constituting the principle terms of the prediction formulae of those indexes.

The mechanism of generating these autoregressive components is the cumulative advantage in receiving citations and in the evolution of h-index. Previous empirical studies show that the number of citations received in the future depends on the number of citations already received [5]. However, the effect of cumulative advantage in producing publications is much weaker than that in receiving citations. It is reflected by the short tail of the quantitative distribution of a group of researchers' publications, compared with that of the citation distribution of the same researchers [10].

In statistics, autoregressive models specify that the response variable depends linearly on its previous

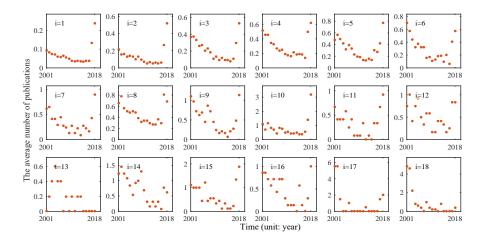


Figure 8. The average annual publication quantity of test researchers. Consider the test researchers with i publications at [1951, 2000]. The red circles show the average publication quantity of these researchers at each year from 2001 to 2018.

values with a stochastic term. The advantage of those model is that not much information is required, only the self-variable series. If the autocorrelation coefficients of the response variable series are smaller than 0.5, autoregressive models are not suitable for prediction task. That is, the coefficients of autoregressive components are not large enough to be significant predictors.

The autocorrelation coefficient of $\mathbf{y} = (y_1, ..., y_T)$ with lag l (where l < T) is defined as

$$r_{l} = \frac{\sum_{t=1}^{T-l} (y_{t} - \bar{y})(y_{t+l} - \bar{y})}{\sum_{t=1}^{T-l} (y_{t} - \bar{y})(y_{t+l} - \bar{y})},$$
(5)

where \bar{y} is the mean of **y**'s elements [41]. We constructed a time series $\mathbf{y}_s = (y_s(t_0), ..., y_s(t_J))$ to record the quantitative information of publications for a researcher s, where $y_s(t_j)$ is the number of his publications produced at $[T_0, t_j]$ for j = 0, ..., J.

We calculated the autocorrelation coefficients of \mathbf{y}_s for any researcher s in the test dataset. We found that these coefficients are almost smaller than 0.5 given a lag> 1. Therefore, the historical publication productivity of an individual is not sufficient to predict his or her future productivity. It indicates that the autoregressive models may not be suitable for the prediction of publication productivity; thus the schemes of those successful prediction methods about citation-based indexes and the *h*-index may also be unfeasible.

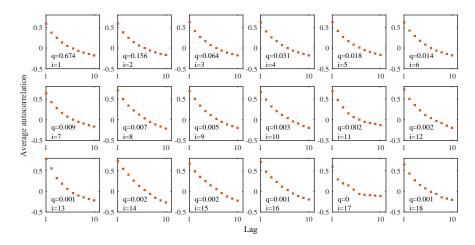


Figure 9. Autocorrelation coefficients of the series on cumulative publication quantity. Consider this series of test researchers from 2000 to 2018. Panels show the average autocorrelation coefficients of the test researchers with i publications at [1951, 2000]. Index q is their proportion to all of the test researchers.

Discussion and conclusions

We provided a model to predict the publication productivity of researchers. The model needs a large training dataset, but there is not much information about researchers required, only their publications' production time. The model's practicability is testified by the dblp dataset, which exhibits its ability in the prediction of publication productivity by the fine fittings on the evolutionary trend of researchers' productivity and the quantitative distribution of their publications. Due to its nature of regression, our model has the potential to be extended to assess the confidence level of prediction results, and thus has clear applicability to empirical research. With its prediction results unbiased, the model may be useful for funding agencies to evaluate the possibility of applicants to complete the quantitative index of publications in their applications.

Our model offers convincing evidence that the publication patterns of many researchers are characterized by a piecewise Poisson process. Even where our model does not provide an exact productivity prediction for an individual, it may still be of use in its ability to provide a satisfactory prediction for a group of researchers on average. The prediction results of our model offer some comfort by showing that the future of a group of researchers is not so random. The occasional rejection of a paper may feel unjust and indiscriminate, but for a group, such factors seem to average out, rendering the trajectories of researchers' publication productivity relatively predictable. Analyzing massive data to track scientific careers would help to advance our understanding of how researchers' productivity evolves. The prediction precision of the model would be improved by utilizing more features of researchers, such as the network features of their coauthorship (degree, betweenness, centrality, etc.), because previous studies showed that research collaboration contributes to scientific productivity [44–46]. However, little is known about the mechanisms governing the evolution of researchers' publication productivity. Predicting the productivity of an individual would not be done only by regression as this study did for a group of researchers, due to the randomness of an individual's research. The randomness is displayed in this study by the relatively small autocorrelation coefficients of the time series on a researcher's cumulative publication productivity. Therefore, advanced algorithms are needed to synthetically analyze more features of researchers, such as journals' annual issue volume, impact factors, and language.

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References

- Sinatra R, Wang D, Deville P, Song C, Barabási AL (2016) Quantifying the evolution of individual scientific impact. Science, 354(6312), aaf5239
- Hirsch JE (2005) An index to quantify an individual's scientific research output. Proc Natl Acad Sci USA 102, 16569-16572.
- 3. Schubert A (2007) Successive *h*-indices. Scientometrics, 70, 201-205.
- 4. Price DJS (1965) Networks of scientific papers. Science 149(3683): 510-515.
- Price DJS (1976) A general theory of bibliometric and other cumulative advantage process. J Am Soc Inf Sci, 27(5): 292-306.

- Barabási AL, Albert R (1999) Emergence of scaling in random networks. Science, 286(5439): 509-512.
- 7. Perc M (2014) The Matthew effect in empirical data. J R Soc Interface, 11: 20140378.
- Acuna DE, Allesina S, Kording KP (2012) Future impact: Predicting scientific success. Nature, 489(7415), 201.
- 9. Newman MEJ (2014) Prediction of highly cited papers. Europhys Lett, 105(2), 28002.
- Xie Z, Xie ZL, Li M, Li JP, Yi DY (2017) Modeling the coevolution between citations and coauthorship of scientific papers. Scientometrics 112: 483-507.
- 11. Lehman HC (2017) Age and achievement (Vol. 4970). Princeton University Press.
- Glänzel W (2014) Analysis of co-authorship patterns at the individual level. Transinformacao 26: 229-238.
- Xie Z, Ouyang ZZ, Li JP, Dong EM, Yi DY (2018) Modelling transition phenomena of scientific coauthorship networks. J Assoc Inf Sci Technol 69(2): 305-317.
- 14. Simonton DK (1984) Creative productivity and age: A mathematical model based on a two-step cognitive process. Dev Rev, 4(1), 77-111.
- 15. Xie Z, Li M, Li JP, Duan XJ, Ouyang ZZ (2018) Feature analysis of multidisciplinary scientific collaboration patterns based on pnas. EPJ Data Science 7: 5.
- Xie Z, Ouyang ZZ, Li JP (2016) A geometric graph model for coauthorship networks. J Informetr 10: 299-311.
- Dong Y, Johnson RA, Chawla NV (2016) Can scientific impact be predicted? IEEE Transactions on Big Data, 2(1), 18-30.
- Mccarty C, Jawitz JW, Hopkins A, Goldman A (2013) Predicting author h-index using characteristics of the co-author network. Scientometrics, 96(2), 467-483.
- 19. Mazloumian A (2012) Predicting researchers' scientific impact. Plos One, 7(11), 1-5.

- Wang D, Song C, Barabási AL (2013) Quantifying long-term scientific impact. Science, 342(6154), 127-132.
- Cao X, Chen Y, Liu KR (2016) A data analytic approach to quantifying scientific impact. J Informetr, 10(2), 471-484.
- Pobiedina N, Ichise R (2016) Citation count prediction as a link prediction problem. Appl Intell, 44(2), 252-268.
- Abrishami A, Aliakbary S (2019) Predicting citation counts based on deep neural network learning techniques. J Informetr, 13(2), 485-499.
- 24. Abramo G, D'Angelo CA, Felici G (2019) Predicting publication long-term impact through a combination of early citations and journal impact factor. J Informetr, 13(1), 32-49.
- 25. Stern DI (2014) High-ranked social science journal articles can be identified from early citation information. Plos One, 9(11), e112520.
- Kosteas VD (2018) Predicting long-run citation counts for articles in top economics journals. Scientometrics, 115(3), 1395-1412.
- 27. Bornmann L, Leydesdorff L, Wang J (2014) How to improve the prediction based on citation impact percentiles for years shortly after the publication date? J Informetr, 8(1), 175-180.
- 28. Bai XM, Zhang LI, Lee I (2019) Predicting the citations of scholarly paper, J Informetr, 13, 407-418.
- 29. Sarigöl E, Pfitzner R, Scholtes I, Garas A, Schweitzer F (2014) Predicting scientific success based on coauthorship networks. EPJ Data Science, 3(1), 9.
- Yu T, Yu G, Li PY, Wang L (2014) Citation impact prediction for scientific papers using stepwise regression analysis. Scientometrics, 101(2), 1233-1252.
- Klimek P, Jovanovic AS, Egloff R, Schneider R (2016) Successful fish go with the flow: citation impact prediction based on centrality measures for term-document networks. Scientometrics, 107(3), 1265-1282.
- Newman M (2001) Clustering and preferential attachment in growing networks. Phys Rev E 64(2): 025102.

- Tomassini M, Luthi L (2007) Empirical analysis of the evolution of a scientific collaboration network. Physica A 385(2): 750-764.
- Laurance WF, Useche DC, Laurance SG, Bradshaw CJ (2013) Predicting publication success for biologists. BioScience, 63(10), 817-823.
- Milojević S(2013) Accuracy of simple, initials-based methods for author name disambiguation, J Informetr 7 767-773.
- 36. Xie Z (2019) A Bayesian model on the merging errors of coauthorship data. Physica A, 527, 121140.
- Xie Z (2019) A cooperative game model for the multimodality of coauthorship networks, Scientometrics, https://doi.org/10.1007/s11192-019-03183-z.
- Consul PC, Jain GC (1973) A generalization of the Poisson distribution. Technometrics 15(4): 791-799.
- Nelder JA, Wedderburn RW (1972) Generalized linear models. J R Stat Soc Ser A-G, 135(3), 370-384.
- 40. Hollander M, Wolfe DA (1973) Nonparametric Statistical Methods. Wiley.
- Box GE, Jenkins GM, Reinsel GC, Ljung GM (2015) Time series analysis: forecasting and control. John Wiley & Sons.
- 42. Cox DR (1972) Regression models and life-tables. J Roy Stat Soc B Met, 34(2), 187-202.
- 43. Dennis W (1954) Predicting scientific productivity in later maturity from records of earlier decades. J Gerontol, 9(4), 465-467.
- Lee S, Bozeman B (2005) The impact of research collaboration on scientific productivity. Soc Stud Sci 35: 673-702.
- 45. Ductor L (2015) Does co-authorship lead to higher academic productivity? Oxford B Econ Stat, 77(3), 385-407.
- 46. Qi M, Zeng A, Li M, Fan Y, Di Z (2017) Standing on the shoulders of giants: the effect of outstanding scientists on young collaborators' careers. Scientometrics, 111(3), 1839-1850.

Appendix A: The Poisson model

The Poisson model is a generalized linear model of regression analysis [39]. It is used to model count data and contingency tables, thus has potential to predict publication productivity. The Poisson model assumes the response variable y follows a Poisson distribution, and assumes the logarithm of its expected value can be expressed by a linear combination of covariates. Let $\mathbf{x} \in \mathbb{R}^n$ be a vector of covariates, and $\Phi \in \mathbb{R}^n$ be a vector of the covariates' effect. The Poisson model takes the form

$$\log(\mathbb{E}(y|\mathbf{x})) = \alpha + \Phi \cdot \mathbf{x},\tag{6}$$

where $\alpha \in \mathbb{R}$, and $\mathbb{E}(y|\mathbf{x})$ is the conditional expected value of y given \mathbf{x} . Note that Eq. (1) can be generalized to deal several characteristics varying with i, namely a vector \mathbf{x}_{ij} . This study only considered the simplest case: one characteristic t_j .

Appendix B: The piecewise exponential model

The formula of the provided model is similar to that of the piecewise exponential model in survival analysis, which is defined as follows [42]. Assume that the duration t of an event is a continuous random variable with probability density function f(t). Let $F(t) = \int_{\tau < t} f(\tau) d\tau$, which is the cumulative distribution function. It is the probability that the event has occurred at duration t. The survival function is defined as S(t) = 1 - F(t), and the hazard function $\lambda(t) = f(t)/S(t)$.

Let \mathbf{x}_i be a vector of covariates for individual i, and Φ be the vector of covariates' effect. The hazard function at t for individual i is assumed to be

$$\lambda_i(t, \mathbf{x}_i) = \lambda_0(t) \mathrm{e}^{\mathbf{x}_i \cdot \Phi},\tag{7}$$

where $t \in [0, T]$, and $\lambda_0(t)$ is a baseline hazard function that describes the risk for individual *i* with $\mathbf{x}_i = 0$, and $e^{\mathbf{x}_i \cdot \Phi}$ is the relative risk.

Subdivide time into reasonably small intervals and assume that the baseline hazard is constant at each interval, leading to a piecewise exponential model

$$\lambda_{ij} = \lambda_j \mathrm{e}^{\mathbf{x}_i \cdot \Phi},\tag{8}$$

where λ_{ij} is the hazard corresponding to individual *i* at time *j*, λ_j is the baseline hazard at *j*. Write Φ as Φ_j and \mathbf{x}_i as \mathbf{x}_{ij} to allow for a time-dependent effect of the predictor vector. Then, we would write

$$\lambda_{ij} = \lambda_j e^{\mathbf{x}_{ij} \cdot \Phi_j},\tag{9}$$

where is the formula of the piecewise exponential model.

Although Eq. (1) and Eq. (9) are similar in formula, they are essentially different. The index j in Eq. (1) is the time, and index i is about researcher subset. The regression is used to calculate λ_{i1} and β_i , which vary with researcher subset i and are free of the index of time j. But in Eq. (9), the baseline λ_j and the effect Φ_j are free of i but depend on j.

Appendix C: An other example

The training dataset is the same as that in Section 6. The test dataset consists of the researchers in Set 3, their historical publication quantity from Set 1, and their annual publication quantity from Set 6. Its parameters are $t_X = 1995$, and $t_Y = 2013$. We only predicted the publication productivity for the researchers with no more than 13 publications at $[T_0, t_X]$, who account for 98.8% of the researchers in the test dataset here. Figs. 10 and 11 show the results of applying the test methods in Section 6 to the researchers' productivity predicted by our model.

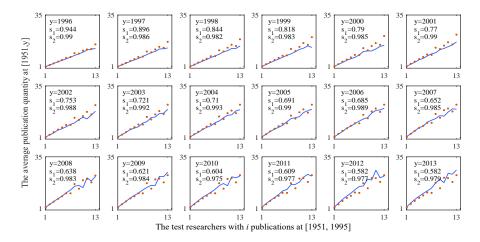


Figure 10. Fittings on the evolutionary trend of researchers' publication quantity. Consider the test researchers who have *i* publications at [1951, 1995]. Panels show the average number of publications produced by these researchers at [1951, y] (n(i, y), red dots) and the predicted one (m(i, y),blue lines). Index s_1 is the Pearson correlation coefficient calculated based on the list of researchers' publication quantity and that of their predicted one. Index s_2 is that based on the sorted lists.

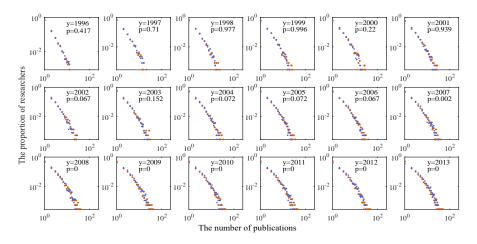


Figure 11. Fittings on the quantitative distribution of researchers' publications. Panels show this distribution for the publications produced by the test researchers at [1951, y] (red circles) and the predicted one (blue squares). When p > 0.05, the KS test cannot reject the null hypothesis that the compared distributions are the same.