## Prediction of citation dynamics of individual papers

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### Abstract

We apply stochastic model of citation dynamics of individual papers developed in our previous work (M. Golosovsky and S. Solomon, Phys. Rev. E 95, 012324 (2017)) to forecast citation career of individual papers. We focus not only on the estimate of the future citations of a paper but on the probabilistic margins of such estimate as well.

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#### I. INTRODUCTION

The interest in predicting citation behavior of scientific papers is motivated by the need to forecast the journal impact factor, for early identification of the breakthrough papers, and career considerations [1–3]). Prediction is usually based on a priori and a posteriori factors that, in principle, can determine citation career of a paper. The former factors are set at the moment of publication and these are subject, title, author's previous record and reputation [4–9], venue (journal) [10, 11], the length and the composition of the reference list [8, 11–13], the style of the paper [11, 14, 15], etc. The difficulty of this approach is that the most important attributes, such as novelty, originality, significance, and timeliness of the results are qualitative. In principle, some of them can be quantified but this is challenging. A brilliant example of such quantification is Ref. |12| which managed to characterize the novelty of a paper through diversity (frequency of atypical combinations) of its references. A posteriori factors develop during short time after the paper has been published and these include the "impact factor"- the number of citations during a short period after publication [4, 16–19], and the place that the paper occupies in its community. There are two complementary approaches to predict citation career of a paper basing on these factors.

Computer scientists focus more on a priori factors. They take a large set of papers whose citation career has been evolving for a long time and use it for training, namely, they measure correlation between these factors and the number of citations of a paper in the long time limit. Then, the factors are ranked according to their importance and predictive model is built by machine learning. The general consensus is that predictive algorithm shall use several factors or combination of them [7, 20], whereas the relative weight of these factors for different disciplines can vary. It has been also realized that linear correlations do not tell the whole story [4, 16, 18, 21] and predictive algorithm shall be better nonlinear, similar to that of Ref. [18]. When the predictive algorithm has been validated, it works as follows. For a new paper, one determines all relevant factors and builds a prediction. The result of prediction is the number of citations of a paper after some predetermined time. Although this prediction is probabilistic, the margins of predictability were never studied properly.

The approach of researchers with the background in natural sciences is different. They focus more on a posteriori factors, such as recent citation history of a paper. They construct

empirical models of citation dynamics which are based on some predetermined scheme of the citation process, namely, they assume a certain strategy that the author of a new paper adopts when he cites the previous studies. This model predicts a future citation behavior of a paper basing on its citation history and several paper-specific parameters, the most important of them being fitness, a hidden parameter that can be reliably estimated only after citation career of the paper has been developing for 2-3 years [22]. When the model has been constructed and validated, the prediction is performed as follows. One takes a new paper and, by studying its initial citation history, makes a probabilistic estimate of its fitness and other specific parameters. After such estimate has been made and the corresponding parameters have been substituted into the model of citation dynamics, it predicts the number of citations of this paper in the long time limit. This approach has been most completely embodied in the Wang-Song-Barabasi model [16].

Bibliometric analysis considers both a priori and a posteriori factors. The researchers in this area have long recognized that the early citation history of a paper is a good predictor of its future success. On another hand, they were the first to draw attention to sleeping beauties [16, 23–25], the papers that started to gain popularity long after publication. Many important papers exhibited the sleeping beauty behavior which no model of citation dynamics can predict. Thus, the presence of such papers sets a limit to prediction of the future citation count of a paper. On another hand, this poor predictability is what makes science fun for so many researchers.

Our purpose is to forecast the future citation career of a paper basing on our recently developed stochastic model of citation dynamics [21]. This model includes several empirical parameters, some of them are common to the whole discipline while all individual attributes of the paper are lumped into one parameter- fitness which does not vary with time. Our first goal is to explore the limits of predictability of the citation career of a paper with a given fitness, the uncertainty of prediction being related to intrinsic stochasticity of the citation process. Our second goal is to quantify the ingredients of fitness, in particular, we show how one can quantify such attribute of a paper as timeliness of results.

#### II. STOCHASTIC MODEL OF CITATION DYNAMICS- A SUMMARY

Assume a paper j published in year  $t_j$ . To quantify its citation dynamics, we introduce  $\Delta K_j = k_j(t_j, t_i)dt$ , the number of citations garnered by this paper in the time window  $(t_i, t_i + dt)$  where  $k_j(t_j, t_i)$  is the paper's j citation rate in year  $t_i$ . The model assumes that  $\Delta K_j$  is a random variable that follows a time-inhomogeneous stochastic point process, namely, the probability of having  $\Delta K_j$  citations in a short time interval dt is  $\frac{\lambda_j^{\Delta K_j}}{\Delta K_j!}e^{-\lambda_j}$  where  $\lambda_j dt$  is the paper-specific probabilistic citation rate. The model assumes that this rate consists of the direct and indirect contributions,

$$\lambda_j(t_j, t_i) = \lambda_j^{dir}(t_j, t_i) + \lambda_j^{indir}(t_j, t_i), \tag{1}$$

where the first term captures those papers that cite paper j and does not cite any other paper that cites j; while the second term captures the papers that cite both j and one or more of its citing papers.

The model yields the following expression for  $\lambda_i(t_i, t_i)$ 

$$\lambda_j(t) = \eta_j R_0 \tilde{A}(t) + \int_0^t m(t - \tau) \frac{T(t - \tau)}{R_0} k_j(\tau) d\tau, \tag{2}$$

where, in order to shorten notation, we introduced  $t = t_i - t_j$ , the number of years after publication, and dropped  $t_j$ . The first addend in Eq. 2 stays for the direct citation rate. Here,  $\eta_j$  is the fitness of the paper j,  $R_0$  is the average length of the reference list length of the papers published in year  $t_j$ , and  $\tilde{A}(t)$  is the aging function. The second addend in Eq. 2 captures the indirect citation rate. Here, m(t) is the average citation rate of the papers published in year  $t_j$ , T(t) is the obsolescence function, and  $k_j(\tau)$  is the past citation rate of the paper j.

Our measurements yielded the factors and functions,  $R_0$ ,  $\tilde{A}(t)$ , m(t) and T(t). We shown that they are the same for all papers in the same field published in the same year. Thus, the paper's individuality is captured by the fitness  $\eta_j$  and by its past citation history,  $k_j(\tau)$ . To predict citation dynamics of the paper, we need to measure its past citation dynamics and to estimate its fitness (which is supposed to be constant during paper's lifetime). Then we substitute these numbers into Eq. 2 and run numerical simulation with known functions  $R_0$ ,  $\tilde{A}(t)$ , m(t) and T(t). Technically, Eq. 2 describes a self-exciting or Hawkes process, since there is a positive feedback between the past and present citation citation rate. Hence, the prediction of future citations is inherently probabilistic and its margins increase with time.

# III. PROBABILISTIC CHARACTER OF THE CITATION PROCESS. IMPLICATIONS WITH RESPECT TO PREDICTABILITY OF FUTURE CITATIONS

Citation process is stochastic, the stochasticity imposes limits on the predictability of future citations. Moreover, as we showed earlier [21], citation dynamic of a paper follows a self-exciting (Hawkes) process whereby past fluctuations are amplified. The positive feedback between past fluctuations and future citations renders the task of long-term prediction of citation behavior of a paper almost futile and limits predictive algorithms to the range of 2-3 years. In our previous study [26] we illustrated this by measurements.

We explore here the following question: if we had known paper's fitness - what are the margins of predictability of its citation trajectory? To answer this question, we analyzed the relation between the paper's fitness and the number of citations it garners in the long-time limit. This was done using our calibrated and verified model of citation dynamics. We wish to estimate,  $K^{\infty}(\eta)$ , the expected number of citations after 25 years for the paper with a certain fitness  $\eta$ . To this end, we performed numerical simulations based on Eq. 2 with parameters for Physics papers published in 1984. We considered 4000 papers with the same fitness  $\eta$ , found statistical distribution of their citations after 25 years, and measured the mean  $K^{\infty}$  and the width of this distribution. We consider  $K^{\infty}$  as the expected number of citations in the long time limit.

Figure 1a shows that the expected number of citations,  $K^{\infty}$ , grows nonlinearly with fitness  $\eta$ . Figure 1b focuses on the width of the  $K^{\infty}$ - distribution. We observe that for the papers with low  $\eta$ , citation distribution in the long time limit is wide, while for the papers with high  $\eta$ , citation distribution in the long time limit is narrow. This means that while citation dynamics of a low-fitness paper strongly depends on chance, citation dynamics of the high-fitness paper is more deterministic.

# A. Divergence of citation dynamics of the papers with the same fitness- numerical simulation

In particular, Fig. 1b shows that if expected number of citations in the long-time limit is 3, the actual number of citations can be anything between 0 and 7; if expected number of citations is 10, the actual number can be between 3 and 20, if the expected number is 100,

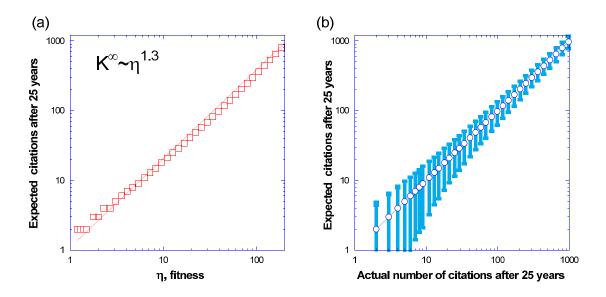


FIG. 1. (a) Expected number of citations after 25 years,  $K^{\infty}(\eta)$ , in dependence of the paper's fitness  $\eta$ . Numerical simulation for 4000 papers with the same  $\eta$ . The simulation is based on Eq. 2 with the parameters for Physics papers published in 1984. Continuous line shows an empirical power-law dependence,  $K^{\infty} \propto \eta^{1.3}$ . (b) Actual number of citations after 25 years versus expected number. The error bars show the width of the distribution,  $K^{\infty} \pm std(K^{\infty})$ . Citation distributions are broad for low  $\eta$  and narrow for high  $\eta$ .

the actual number can be between 50 and 130, if the expected number is 1000, the actual number can be between 700 and 1200. If we compare two papers that garnered 3 and 20 citations in the long-time limit, they can have the same fitness  $\eta$ , namely, they are most probably in the same "quality" league. Two papers that garnered 700 and 1200 citations are probably in the same "quality" league, namely they can have the same fitness. But the papers that garnered 100 and 1000 citations should have different fitness and belong to different "quality" leagues.

Figure 2 shows  $K^{\infty}$ - distributions from a slightly different perspective. We observe that a paper which is worth 10 citations, with 10% probability can garner less than 3 or more than 18 citations; a paper which is worth 100 citations, with 10% probability can garner less than 54 or more than 135 citations; a paper which is worth 1000 citations, with 10% probability can garner less than 680 or more than 1150 citations.

It should be noted that our model assumes constant fitness through the whole citation

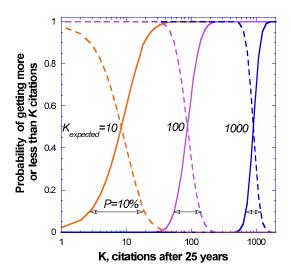


FIG. 2. Statistical distribution of the number of citations after 25 years for the papers with the same fitness  $\eta$ . Numerical simulation based on Eq. 2 for 4000 papers. The mean of the distribution,  $K^{\infty}$ , is indicated at each curve. Continuous lines show cumulative probability of getting more than K citations,  $\int_{K}^{\infty} p(K)dK|_{\eta=const}$ . Dashed lines show complementary probability of getting less than K citations,  $\int_{0}^{K} p(K)dK|_{\eta=const}$ . The intervals of the 10% probabilities of having  $K_{expected}$  citations are shown by arrows.

career of the paper. Similar assumption was adopted by Ref. [27] in their description of Web-pages popularity and it was justified by measurements. This assumption is reasonable for ordinary papers but not for sleeping beauties, that can be dormant for a long time and then become popular.

### B. Fitness estimation

Refs. [16, 28] associate fitness with the ultimate impact of the paper, namely the number of total citations in the long-time limit; Ref. [29] determines paper fitness by ranking; Ref. [30] estimate patent fitness as a combination of attributes found through factor analysis, Ref. [31] associates fitness with the number of citations during a couple of years after publication. We define fitness slightly differently, namely,  $\eta$  is the number of direct citations in the long-time limit. Obviously, this definition cannot be a basis for prediction of future citations

since it can be used only when citation career of a paper is close to completion.

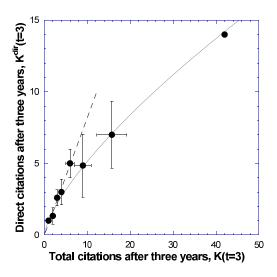


FIG. 3. The relation between direct citations and total citations during first three years after publication for Physics papers published in 1984. Publication year corresponds to t=1. The dashed line shows linear approximation,  $K^{dir}(3) = K(3)$ . This approximation is good only for low-cited papers. Red continuous line shows the empirical approximation  $K^{dir}(3) = [K(3)]^{0.7}$  which shall be used for highly-cited papers. The fitness is estimated from Eq. 2 as  $\eta_j = \frac{K_j^{dir}(3)}{R_0 \sum_{1}^{3} \tilde{A}(t)}$ .

To work out operational definition of fitness that can be used for prediction, we note that the fitness in our sense is related to initial citation rate, since at the beginning of the citation career of a paper citations are predominantly direct. We base our operational definition of fitness on the "magic of three years", well-recognized in bibliometrics. Namely, the number of citations garnered by a paper during first 2-3 years after publication (for computer science papers this initial period is 0.5-1 year) is a basis for fitness estimation. Figure 3 shows that the relation is nonlinear (see also Fig. 1a) and from this calibration plot we estimate fitness.

### IV. FITNESS ESTIMATION BASING ON PAPER'S CONTENT

We believe that  $\eta_i$  is determined by the journal (venue), the number of researchers in the area, reputation of the research group, and last but not least -by the paper's novelty, timeliness, and quality although the latter can be subjective notion. It should be noted,

however, that the paper's fitness and the number of citations gauge not the quality of a paper but its impact. Note, that even erroneous paper can have a great impact. On the other hand, the impact can depend on the factors unrelated to paper's content - institution, reputation of the research group, catchy title, etc.

For example, H. Brot et Y. Louzoun showed [32] that the name of the first author matters for citation count, in particular, the Physics papers whose first author's name starts from the letters A, B, C, in the long time limit have  $\sim 10\%$  more citations than the papers whose list of authors starts from X, Y, Z. (May be, success of the famous Alpher-Bethe-Gamow paper partially derives from the lucky combination of their last names?)

To further demonstrate the importance of the author's name for success of the paper, we consider anectodal evidence based on a couple of papers. Indeed, Richard Lewontin and Jack Hubby made a landmark study in molecular evolution while collaborating in the University of Chicago. To get equal credit for their contribution, their scientific report was published as two companion papers with very similar titles and subjects:

- 1. J.L. Hubby and R.C. Lewontin, "A molecular approach to study of genic heterozygosity in natural populations. 1. Number of alleles at different loci in drosophila pseudoobscura", Genetics 54(2), 577-594 (1966).
- 2. R.C. Lewontin and J.L. Hubby, "A molecular approach to study of genic heterozygosity in natural populations. 2. Amount of variation and degree of heterozygocity in natural populations of drosophila pseudoobscura", Genetics 54(2), 595-609 (1966).

The main difference between these two papers is the order of authors. By 2018, the second paper got around 900 citations while the first paper got only around 500 citations! This difference is explained by the fact that, when the papers were first published in 1966, Lewontin, who was three years older than Hubby, was better known in the scientific community. Thus, researchers preferred to cite the paper in which Lewontin was the first author. Eventually, Hubby became also well-known, the paper in which he was the first author got fair credit and a large number of citations. However, citation count of the Lewontin paper remained bigger due to impressive head start. On another hand, do citation counts of these two papers reflect difference in their "quality"? Our model and Fig. 1 show, that the probability of two papers, which garnered 500 and 900 citations in the long time limit, to have

the same fitness, is  $\sim 10\%$ . This probability is not small, hence it is quite probable that the papers of Lewontin and Hubby are in the same "quality" league.

### V. TIMELINESS OF RESULTS

One of the important criteria, which the editor and reviewers use in their eavluation of submitted papers, is the timeliness of results. This criterion singles out the papers that deal with a hot topic. In our parlance, the paper that focuses on hot topic has enhanced fitness as compared to the paper belonging to the mature research direction. How one can quantify the corresponding contribution to fitness?

Suppose that at year  $t_0$  there appeared one or several breakthrough papers which were followed by a flurry of subsequent developments. This means that a new field (hot topic) has been born. The number of publications in this new field starts to grow explosively and then saturates. As we have shown before [21], the authors are conservative in their citing habits, and the length and the age composition of their reference lists remains more or less the same. In particular, the papers that were published in the same year constitute  $\sim 2-3\%$  of all references, the papers published an year before constitute  $\sim 8-10\%$  of all references, the papers that were published two years before also constitute  $\sim 8-10\%$  of all references, etc. Thus, the papers that were published long after the onset of a new topic have big choice in choosing their references, while the papers published soon after the onset of a new topic have a very limited choice for filling their reference list and all choose the papers that were published close to the onset. Thus, the papers that were published soon after the birth of a new field, namely, timely papers, shall have enhanced number of citations (enhanced fitness).

To put these considerations into quantitative terms, we consider a new field that appeared at time  $t_0$ . We denote the annual number of publications in this field by  $N(t_0+t)$ . Equation 2 yields the average number of direct citations that the paper in this field, which was published in year  $t_0 + t$ , garners during three subsequent years,

$$K^{dir}(t_0 + t, t_0 + t + 3) = \overline{\eta}(t_0 + t)R_0(t_0 + t)\sum_{1}^{3} \tilde{A}(\tau)N(t_0 + t + \tau).$$
(3)

where  $\overline{\eta}$  is the average fitness of the papers in the new field which were published in year  $t_0 + t$ ,  $R_0$  is the average reference list length of the papers published in year  $t_0$ ,  $\tilde{A}(\tau)$  is

the aging function for citations. Note also,  $\tilde{A}(\tau) = A(\tau)e^{(\alpha+\beta)\tau}$  where  $A(\tau)$  is the aging function for references. While the aging function for citations is specific for each discipline and publication year, the aging function for references turns out surprisingly universal and almost independent of the publication year [21]. The reference-citation duality [21] yields average fitness for the papers published in year  $t_0 + t$ ,

$$\overline{\eta}(t_0 + t) = \frac{\sum_{1}^{3} A(\tau) \frac{N(t_0 + t + \tau)}{N(t_0 + t)} e^{\beta \tau}}{\sum_{1}^{3} A(\tau) e^{(\alpha + \beta)\tau}}.$$
(4)

If the new field grows with the same rate as the whole discipline, namely,  $\frac{N(t_0+t+\tau)}{N(t_0+t)} = e^{\alpha\tau}$ , then  $\overline{\eta}$  does not depend on t. However, if this new field grows faster than the whole discipline, then  $\overline{\eta}$  is enhanced.

Figure 4 illustrates these considerations. We know that a hot topic usually appears abruptly and can be identified through a burst of citations and publications [33]. We choose several such research areas in Physics with well-defined onset  $t_0$ , with some of these areas the author of this book has had personal experience. Using Web of Science, we found all papers belonging to each of these topics, that were published in year  $t_0 + t$ . For each t, we measured annual number of papers and statistical distribution of the number of citations garnered by them during first three years after publication. Then we determined the mean and the width of these distributions. Using Eq. 4 and Fig. 3, we found the average fitness of the papers in each topic published in year  $t_0 + t$ , basing on the mean of the distribution. On another hand, we estimated this fitness using Eq. 4. Figure 4 shows that the model prediction based on Eq. 4 captures our measurements perfectly well.

Figure 4 implies that any paper published soon after the new topic appeared, has a good head start and this quantifies the "first mover advantage" introduced by Newman [35]. However, this does not mean that the papers published long after the onset of a hot topic doomed to be undercited. In fact, Fig. 4 shows only the mean of the fitness distribution for each year. The actual fitness distribution is very wide and its width is comparable to the mean. Hence, at each moment after the onset of a hot topic there are many papers whose fitness considerably exceeds the average one.

### VI. DISCUSSION

We showed here that our stochastic model of citation dynamics can be a basis for predicting citation trajectory of papers. This model shall be compared to the physics-inspired predictive model developed by Wang, Song, and Barabasi [16]. Pham, Sheridan, and Shimodaira [36, 37] developed a software package based on this model and demonstrated that it is a valid predictive tool. This model includes three paper-specific parameters: fitness  $\eta$ , immediacy  $\mu$ , and  $\sigma$ . To determine these parameters, one needs to measure initial citation trajectory of a paper, 2-3 years are not enough. As a predictive tool, this model works best for the highly-cited papers. Although this deterministic model predicts citation trajectory of a paper, it cannot specify probabilistic margins of the prediction. On the contrary, our probabilistic model includes only one paper-specific parameter- fitness, it does provide probabilistic margins of the future citation count. However, our model works better with ordinary papers and does not predict well citation trajectories of the highly-cited papers. Thus, our model is complementary to that of Ref. [16].

What are its possible applications? We believe that our model can be used for forecasting the five-year journal impact factor. The papers published in one year in one journal represent more or less homogeneous set of papers, hence predicting the mean number of citations for this set is more reliable than predicting citation trajectory of a single paper. On another hand, our model can give probabilistic margins of such prediction.

Another application can be the early identification of the breakthrough papers. So far, this was done by analyzing diversity and age structure of the reference list of papers [12, 38], diversity and interdisciplinarity of paper's content [39], or through identification of the atypical citation trajectory, corresponding to sleeping beauties [25]. An important question is how soon can we identify such rising star? Obviously, if the paper (or patent) gets more citations than what is expected from the ordinary paper published in the same year and in the same journal, then this is a candidate to be a breakthrough paper [40]. On another hand, the deviation from the ordinary citation trajectory may be accidental. Our model can make an estimate of the probability of the enhanced citation count in order to judge whether it occurred by chance or not.

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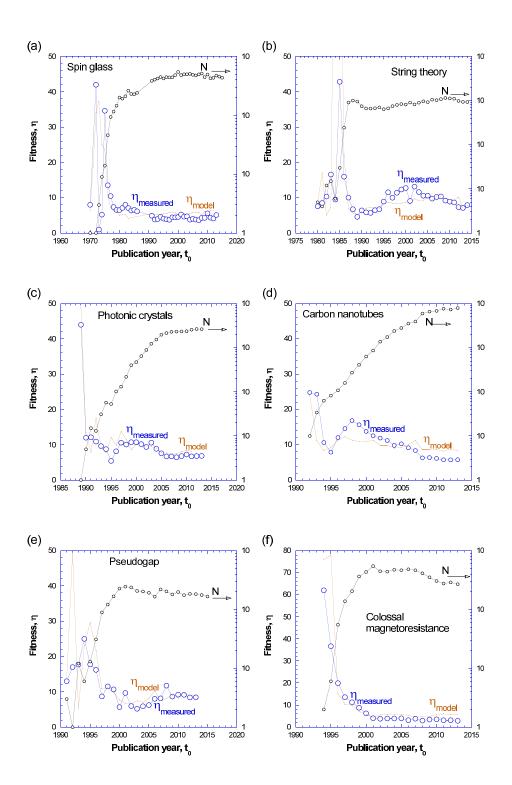


FIG. 4. Paper's fitness for several Physics research topics. Open black circles show number of research articles for each topic. Filled circles show our measurements of fitness based on the number of citation garnered during first three years after publication. Blue continuous lines show model prediction based on Eq. 4. (a) Spin glass. (b) String theory. (c) Photonic crystals [34]. (d) Carbon nanotubes. (e) Pseudogap. (f) Colossal magnetoresistance.