A SIR epidemic model for citation dynamics

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Abstract The study of citations in the scientific literature crosses the boundaries between the traditional branches of science and stands on its own as a most profitable research field dubbed the ‘science of science.’ Although the understanding of the citation histories of individual papers involves many intangible factors, the basic assumption that citations beget citations can explain most features of the empirical citation patterns. Here, we use the SIR epidemic model as a mechanistic model for the citation dynamics of well-cited papers published in selected journals of the American Physical Society. The estimated epidemiological parameters offer insight into unknown quantities as the size of the community that could cite a paper and its ultimate impact on that community. We find a good, though imperfect, agreement between the rank of the journals obtained using the epidemiological parameters and the impact factor rank.

1 Introduction

Regardless of the controversial and widespread use of citation based measures as a quantitative proxy of a paper’s importance [1–6], the study of citations seems to have acquired a life of its own [7]. In fact, citation networks, citation distributions and citation dynamics are topics that range over most of the issues addressed by the science of complexity. In addition, the large citation datasets, which unfortunately are rarely freely accessible, make the subject very attractive since, contrary to most complex systems problems, the theories about citation patterns can readily be tested against empirical data [8–10]. Our focus here is on the study of the citation dynamics or, more precisely, on the study of a mechanistic model to describe the citation histories of well-cited papers.

A remarkable outcome of the quantitative study of the citation patterns is the realization that starkly different citation histories, such as the rare ‘sleeping beauties’ (i.e., papers that are not cited for a long while and then suddenly become popular [11,12]) or the more common ‘shooting stars’ (i.e., papers that are highly cited initially but die quickly), can be explained by tuning a few parameters of mechanistic models of the citation dynamics [13–15]. A seemingly natural mechanistic model to describe the spread of ideas in the academia is the SIR epidemic model [16], which, however, has not yet been applied to the analysis of the citation histories of individual papers.

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Accordingly, here we use the SIR epidemic model to fit the number of citations received over a period of 15 years by 300 hit papers published in 6 selected APS journals. We define hit papers as the 50 most cited papers published from 2000 to 2003 in each of those journals. The data used in our analysis are from the American Physical Society Data Sets for Research (available upon request at [17]), which include only internal citations, i.e., citations to papers published in APS journals from papers published in APS journals as well. In Sect. 2, we offer a brief overview of the APS Dataset.

The epidemiological parameters of the SIR epidemic model have a direct interpretation in terms of the citation dynamics, as we explain in great detail in Sect. 3. Following the maxim ‘citations beget citations,’ we assume that the citations of a given paper are promoted by a certain number of influential papers whose bibliographies include that paper and whose potential to influence yet-to-be-written papers to cite it is determined by the transmission parameter $\beta$. Papers cease to be influential at a rate $\gamma$. The ratio $R_0 = \beta/\gamma$ is very close to 1 for most of the hit papers considered here, so that the ‘shooting stars’ and the ‘sleeping beauties’ citation patterns are obtained for large and small values of $\beta$, respectively. An epidemiological parameter of particular interest is the potential maximum number of citations $S_0$ a hit paper can receive, which yields an estimate of the size of the community that could in principle cite that paper. The SIR model allows the ready estimate of the total number of citations a paper ever acquires $\Upsilon_\infty \leq S_0$, which can be seen as the ultimate impact of a paper [15]. The relative ultimate impact $\Upsilon_\infty/S_0$ happens to depend on the basic reproductive number $R_0$ only.

Although the SIR epidemic model is used to fit the citation history of individual papers and for each paper the fitting procedure produces specific values of the epidemiological parameters $S_0$, $\beta$ and $\gamma$, in Sect. 4 we argue that the medians of the epidemiological parameters obtained by fitting the citation histories of the 50 hit papers of each selected journal offer valuable information to characterize and rank those journals. In particular, the ranks produced by the medians of the parameters $S_0$ and $\beta$ interchange two journals only in comparison with the Impact Factor (IF) rank [18]. In general, however, the higher the IF of a journal, the less its relative ultimate impact.

2 APS Dataset

The APS Dataset comprises citing article pairs and article metadata of about 636000 papers published in 17 journals of the American Physical Society from 1893 to 2018 [17]. The first journal, Physical Review, ceased publication in 1969, and the most recent journal in the dataset, Physical Review Materials, was launched in 2017.

With more than one century of existence, the APS journals lived through the World War I and the World War II. The total number of papers published per year in the APS journals shown in the upper panel of Fig. 1 reveals the distinct impact these two major events had on the academic productivity of the physicists. Whereas WWI caused no discernible changes on the number of papers published in the Physical Review, most likely because this journal was not yet the main publication choice of the European physicists, WWII caused a sharp drop on the number of published papers, which reflects the worldwide disruption this event produced in all activities unrelated to warfare. More importantly, this panel shows that the number of published papers grows at an exponential rate [2], which probably prompted the splitting of the Physical Review Series II into Physical Review A, B, C and D in 1970. Nevertheless, the exponential growth trend continued for the offspring journals, leading to the current difficulty of physicists to keep pace with the advances of their own research subfields [19,20]. The
Fig. 1  Number of papers published in all APS journals from 1893 to 2018 (upper panel). The dashed straight line is the fitting function \( f(x) = a \exp \left[ (x - 1900)/b \right] \) with \( a = 63 \) and \( b = 18 \). The lower panel shows the number of papers published in Phys. Rev. Series II (.), Phys. Rev. Lett. (♀), Phys. Rev. A (△), B (○), C (○), D (□) and E (○).

Table 1  Number of papers published from 2000 to 2018 in the 6 APS journals used in our citation dynamics analysis

| APS Journal        | Number of papers |
|--------------------|------------------|
| Phys. Rev. A       | 5826             |
| Phys. Rev. B       | 18028            |
| Phys. Rev. C       | 3131             |
| Phys. Rev. D       | 7589             |
| Phys. Rev. E       | 8137             |
| Phys. Rev. Lett.   | 12163            |

lower panel of Fig. 1 shows the number of papers published in the APS journals we will consider in this paper. In addition to the journals already mentioned, the panel includes the Physical Review Letters that was introduced in 1958 and the Physical Review E that was launched in 1993. For completeness, we also include in the panel the Physical Review, Series II which replaced the Physical Review, Series I and was active from 1913 to 1969. Those are the 7 APS journals with the largest number of papers published since 1913.

Here, we focus on the 54874 papers published in Phys. Rev. Lett., Phys. Rev. A, B, C, D and E from 2000 to 2018. Table 1 shows the number of papers published in each of these journals in that time window. For each journal we pick the 50 papers published from 2000 to 2003 that received the highest number of citations up to 15 years (180 months) after their
publication dates. Those papers are named hit papers and next we will show how to model their citation patterns using an epidemiological model. We refer the reader to Ref. [9] for the analysis of the citation statistics of Physical Review from 1893 through 2003.

3 Epidemiological model

We characterize the citation histories of the hit papers by their cumulative number of citations received in the period of 180 months from their publication dates. Figure 2 illustrates this quantity for three representative citation histories in the time window considered. In particular, the number of citations of the paper shown in the upper panel [21] exhibits a very rapid increase followed by stabilization within about 30 months after its publication. This is the editors’ dream paper for it has the perfect timing to boost the IF of a journal. The citation record of the paper shown in the middle panel [22] exhibits a steady and consistent growth of little less than one citation per month. Perhaps the most interesting citation pattern is that of the paper exhibited in the lower panel [23], which displays a latent period followed by a steady speed up of the number of citations. This panel illustrates the ‘sleeping beauties’ citation pattern that makes the prediction of the impact of a research using short-time information (say, a 24-month window) a somewhat shortsighted enterprise [11,12].

The main assumption behind our approach to model the citation histories illustrated in Fig. 2 is that citations beget more citations, so that the citation dynamics could be modeled as the spread of an infectious disease. This means that a particular hit paper comes to the knowledge of prospective citing authors through the reading of papers that cite the hit paper. Here, we model the citation dynamics of a hit paper using the popular SIR model [24,25] where the susceptible (S), infected (I) and removed (R) classes must be properly reinterpreted within the citation dynamics context.

In particular, once a hit paper is published we assume that there are a maximum number of citations it can receive, which we denote by \( S_0 \). This is the number of papers in an abstract population of papers not yet written that are susceptible to cite the hit paper. This number can only decrease with time, and we denote by \( S(t) \leq S_0 \) the number of citations the hit paper can still receive after time \( t \) from its publication date. Of course,

\[
\Upsilon(t) = S_0 - S(t)
\]

is the measurable total number of citations the hit paper received until time \( t \), which is shown in Fig. 2 for three selected hit papers. In principle, \( S_0 \) could be estimated if we knew the size of the community that works on the subject addressed by the hit paper, the mean number of papers published per month by researchers in that community and the average number of references those papers contain.

A simple way to model the decrease of the number of susceptible papers with time is through the contact process

\[
\frac{dS}{dt} = -\beta S \frac{I}{N},
\]

where \( I = I(t) \) is the number of papers that have cited the hit paper before or at time \( t \) and that can still influence susceptible papers to cite that paper. In other words, \( I(t) \) is the number of influential (or infective) papers. Although the hit paper does not cite itself, we will assume that it contributes to \( I(0) = I_0 \). We note that the hit paper may not contribute to \( I(t) \), i.e., it may not be influential any more at time \( t > 0 \) so that its new citations are prompted by third-party papers. (Just think of the many papers citing classic books whose authors never
Fig. 2 Cumulative number of citations $\Upsilon$ of three representative hit papers as function of the time $t$, measured in months, after their publication dates. The symbols are the citation data extracted from the APS dataset, and the solid curves are the fittings with the SIR model. The epidemiological parameters $[S_0, \beta, \gamma]$ are $[42000, 9.36, 9.25]$ (upper panel), $[3150, 0.48, 0.47]$ (middle panel) and $[1050, 0.13, 0.10]$ (lower panel).

read those books.) The coefficient $\beta$ in Eq. (2) is a measure of the persuasion power of the influential papers, i.e., it is a measure of the likelihood an author will cite the hit paper because that author read a paper that cites the hit paper. Because $\beta$ is a per capita transmission rate, we have introduced the constant factor $N = S_0 + I_0$ in Eq. (2) to guarantee that its value is on the order of 1 regardless of the value of $S_0$, and that this equation is dimensionally correct. (The unit of $S$ and $I$ is papers.)
The equation for the number of influential papers
\[ \frac{dI}{dt} = \beta S \frac{I}{N} - \gamma I \] (3)
makes plain the fair assumption that influential papers cease to be influential at a rate \( \gamma \) and move into the removed class. Papers in the removed class play no role in the citation dynamics and their number is given by
\[ \frac{dR}{dt} = \gamma I. \] (4)

Since \( d(S + I + R)/dt = 0 \) we have \( S(t) + I(t) + R(t) = S_0 + I_0 = N \), because the removed class is empty at \( t = 0 \). Moreover, since the number of citations is reported on a monthly basis, we use the month as our time unit so that \( \beta \) and \( \gamma \) have unit 1/month.

We note that our epidemiological approach builds on an assumption different from the vastly popular cumulative advantage or preferential attachment assumption, in which the probability that a publication is cited is an increasing function of its current total number of citations [1,9]. In our case, this probability is a function of a (variable) fraction of the total number of citations; namely, it is a function of the number of influential papers.

Perhaps the most interesting quantity in the citation dynamics context is \( \Upsilon_\infty = \lim_{t \to \infty} [S_0 - S(t)] = S_0 - S_\infty \), which gives the total number of citations a hit paper acquires during its lifetime, i.e., its ultimate impact. Of course, \( \Upsilon_\infty \) cannot be measured but can be easily inferred using our epidemiological approach. In fact, it is given by the positive root of the transcendental equation [25]
\[ \Upsilon_\infty = S_0 \left[ 1 - \exp \left( -\Upsilon_\infty + I_0 \right) \right] \] (5)
where \( \rho = \gamma / \beta \). Hence \( \Upsilon_\infty = S_0 \) only in the limit \( \rho \to 0 \). For finite \( \rho \), a hit paper will receive only the fraction \( \nu = \Upsilon_\infty / S_0 \) of the potential citations it could receive. For instance, for the papers analyzed in Fig. 2, the estimated total number of citations they will receive is \( \Upsilon_\infty = 1060 \) (upper panel), 166 (middle panel) and 446 (lower panel).

Assuming that \( I_0 \ll N \approx S_0 \) we rewrite Eq. (5) as
\[ \nu = 1 - \exp \left( -\frac{\nu}{\rho} \right), \] (6)
which has a nonzero solution provided that \( R_0 = 1 / \rho > 1 \). Here \( R_0 \) is the basic reproductive number that ultimately determines the overall impact of a hit paper on the abstract population of susceptible papers. Since our focus is on hit papers only, we have \( R_0 > 1 \) necessarily. In fact, with very few exceptions, the values of \( R_0 \) of the hit papers were all very close to 1.

The SIR model has only three adjustable parameters, namely \( S_0, \beta \) and \( \gamma \), and our goal is to estimate these parameters by fitting Eq. (1) to the cumulative number of citations extracted from the APS dataset. The quality of the fitting can be appreciated in Fig. 2. Incidentally, the paper considered in the upper panel of this figure has the largest value of \( \beta \) among the 300 hit papers considered in our study.

4 Epidemiological journal ranking

The results of our fitting procedure are summarized in Fig. 3, which shows the epidemiological parameters \( S_0, \beta \) and \( \gamma \) that best fit the theoretical estimate of \( \Upsilon(t) \) to the empirical cumulative
number of citations. Each symbol in a panel corresponds to the estimated epidemiological parameter of a particular hit paper. Because of the considerable spread of the values of the estimates, which is particularly pronounced for $S_0$, it is convenient to summarize the parameter distributions by their medians, $\bar{S}_0$, $\bar{\beta}$ and $\bar{\gamma}$, which are shown in Table 2 together with the medians of the basic reproductive number $\bar{R}_0$ and of the ultimate fraction of the potential citations received $\bar{\upsilon}$. The order of the journals listed in this table is determined by the value of $\bar{S}_0$. 

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**Fig. 3** Epidemiological parameters $S_0$, $\beta$ and $\gamma$ that best fit the theoretical estimate of $T(t)$ to the empirical cumulative citation numbers. Each symbol corresponds to a particular hit paper published in the indicated APS journal. The unit of $\beta$ and $\gamma$ is 1/month, and the unit of $S_0$ is papers.
Table 2  Medians of the potential number of citations ($\tilde{S}_0$), the per capita transmission rate ($\tilde{\beta}$), the removal rate ($\tilde{\gamma}$), the basic reproductive number ($\tilde{R}_0$) and the fraction of the potential citations received ($\tilde{\upsilon}$) for the selected APS journals

| APS Journal   | $\tilde{S}_0$ | $\tilde{\beta}$ | $\tilde{\gamma}$ | $\tilde{R}_0$ | $\tilde{\upsilon}$ |
|--------------|--------------|----------------|----------------|-------------|----------------|
| Phys. Rev. Lett. | 19350       | 1.400          | 1.385          | 1.008       | 0.021         |
| Phys. Rev. D  | 9325        | 0.915          | 0.910          | 1.012       | 0.031         |
| Phys. Rev. B  | 4750        | 0.730          | 0.715          | 1.026       | 0.059         |
| Phys. Rev. A  | 2900        | 0.570          | 0.550          | 1.031       | 0.072         |
| Phys. Rev. E  | 1900        | 0.455          | 0.445          | 1.028       | 0.070         |
| Phys. Rev. C  | 1600        | 0.355          | 0.340          | 1.037       | 0.084         |

Fig. 4  Evolution of the Impact Factor from 2000 to 2019 of the journals Phys. Rev. Lett. (▽), Phys. Rev. A (△), B (○), C (●), D (□) and E (⋄). The hit papers considered in this paper were published between 2000 and 2003.

Remarkably, Table 2 shows that $\tilde{S}_0$, $\tilde{\beta}$ and $\tilde{\gamma}$ are good predictors of the rank of the selected APS journals according to the IF metric [18]. In fact, if we consider that the hit papers were published between 2000 and 2003, the epidemiological rank offered in this table interchanges Phys. Rev. C and Phys. Rev. E only as compared with the IF rank (see Fig. 4). The good agreement between these ranks is not very surprising in the sense that it is well known that the size of the community, which in our approach is measured by $S_0$, correlates well with the IF [26]. It is important to note, however, that $S_0$ does not correlate well with the number of papers published in a journal during the period of analysis shown in Table 1. In addition and perhaps more importantly, because the IF is measured in a 24-month window, it correlates well with the transmission rate $\beta$, since large values of this parameter result in many citations in a short time provided there are plenty of susceptible papers (see upper panel of Fig. 2). These findings validate our theoretical approach to model the citation dynamics as well as the procedure we used to estimate the epidemiological parameters.

The positive correlation between the IF metric and $\tilde{\gamma}$ is more intriguing and, perhaps, illuminating. We recall that a high value of $\gamma$ implies a quick obsolescence of the influential papers, i.e., those papers are influential for a short period of time only. This means that the epidemiological approach predicts that papers that cite hit papers published in high-impact factor journals are not likely to be very impactful themselves. This scenario is evocative of the many application papers that use a novel analysis method presented in a hit paper.

The surprising finding revealed in Table 2 is the negative correlation between $\tilde{\beta}$ (and hence the IF metric) and $\tilde{R}_0$ or $\tilde{\upsilon}$. We recall that $R_0$ and $\upsilon$ are related through Eq. (6).
Actually the true relevance of $R_0$ can be appreciated only through its link to $\nu$, which reveals that $R_0 > 1$ does not imply that an infective agent (a hit paper in our case) will take over the entire susceptible population. Interestingly, our epidemiological analysis indicates that, when the size of the susceptible community $S_0$ is taken into account, hit papers published in high-impact journals actually have a smaller (relative) number of citations than hit papers published in low-impact journals. We note that $\tilde{R}_0$ and $\tilde{\nu}$ are not related by Eq. (6): these quantities are estimated from the distributions of $R_0$ and $\nu$ of the hit papers for each journal.

5 Conclusion

The literature already offers several mechanistic models for the citation dynamics of individual papers. Some of them build on the similarity between the S-shaped curves of the cumulative number of citations and the curves that describe the diffusion of innovations to argue that the same mechanisms that drive the adoption of a new product, viz. innovation and imitation [27,28], may explain the citation process as well [13,14]. However, the likely most successful mechanistic model of citation dynamics builds on assumptions proper to this dynamics, viz. preferential attachment, fitness and aging [15]. As already pointed out, preferential attachment or cumulative advantage means that the probability that a publication is cited is an increasing function of its current number of citations [1,2,9]. Fitness expresses the notion that papers differ with respect to the perceived novelty and importance of their contents [29,30] and aging captures the fact that the perceived novelty and importance of a paper eventually fade out [31]. There are, of course, many intangible factors behind an author’s decision to cite a paper, such as the reputation of its authors and the journal where it was published, that can be identified in a citation network analysis but cannot be implemented in a mechanistic model [32].

Here, we take a different approach that is inspired by the study of the spread of Feynman diagrams through the theoretical physics communities of different countries using models of epidemics [16]. In addition to the SIR model, that seminal study considered more complex models that, for instance, take into account the incubator or exposed (E) class, which is composed of individuals that had contact with the idea but that are not yet ready to spread it. Thus, a susceptible individual does not transit immediately to the exposed class once it is exposed to the idea as in the SIR model. The exposed class is especially significant for ideas that require long periods of apprenticeship such as the Feynman diagrams. In the context of citation dynamics, the exposed class describes papers in process (still not published) that will cite the hit paper. In practice, this new class introduces a delay between exposition and infection. However, despite introducing an extra free parameter, namely the average incubation (or maturation) time of the paper process, the SEIR model does not improve significantly the quality of the fitting of the trajectories for the rise of Feynman diagram adoption as compared with simpler epidemiological models [16]. Hence, our focus on the SIR epidemic model.

As pointed out, the advantage of our approach is that the epidemiological parameters have a direct interpretation in terms of the citation dynamics. For instance, a paper’s relative long-term impact (i.e., the total number of citations a paper will ever acquire) is easily derived within the epidemiological framework [see Eq. (6)], and it is a function of the basic reproductive number $R_0 = \beta/\gamma$ only. This result is similar to the ultimate impact of a paper derived in Ref. [15], which happens to depend only on the relative fitness of the paper. In fact, recalling that in the infectious disease context $R_0$ is the average number of people infected from one person and that in the evolutionary context the fitness of an organism is
measured by the number of offspring per generation it produces, it is fair to think of $R_0$ as the fitness of the paper, so the two distinct approaches reach similar conclusions. However, the epidemiological approach does not make the preferential attachment assumption, since it assumes that the probability that a publication is cited at a certain time is a function of the number of influential papers at that time, which is a time-dependent fraction of the current number of citations.

The distributions of the values of the epidemiological parameters that describe the citation histories of the 50 hit papers for each one of the 6 APS journals considered allow us to characterize those journals and define an epidemiological rank. It turns out that there is a good, though not perfect, correlation between the rank obtained using the transmission rate $\beta$ or the potential maximum number of citations $S_0$ a paper acquires and the IF rank. Surprisingly, this rank correlates negatively with the rank obtained using the basic reproductive number $R_0$, which implies that hit papers published in high-impact factor journals have less relative long-term impact ($\nu = \gamma_\infty / S_0$) than hit papers published in low-impact factor journals, although their absolute long-term impact ($\gamma_\infty$) is much greater. The fact that the IF rank is obtained using citations from papers published in all journals indexed at the Web of Science may explain the discrepancies with the epidemiological ranks that use data of APS journals only, particularly in research areas such as Nuclear Physics where there are many traditional journals owned by other publishers.

In summary, the SIR epidemic model proved very valuable to fit the citation histories of hit papers and, in addition, offered unexpected insights into the citation dynamics. The good correlation between the IF rank and the epidemiological ranks suggests that this simple epidemic model succeeded in picking out the essential elements behind the citation dynamics.

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Data Availability Statement This manuscript has associated data in a data repository. [Authors’ comment: The citing article pairs and article metadata used to generate the citation histories of the 300 hit papers considered in the manuscript are available under request from the APS Data Sets for Research at https://journals.aps.org/dataset.]

References

1. R. Merton, The Sociology of Science (University of Chicago Press, Chicago, 1973)
2. D.J.S. Price, Science Since Babylon (Yale University Press, New Haven, 1975).
3. F. Radicchi, S. Fortunato, C. Castellano, Proc. Natl. Acad. Sci. USA 105, 17268 (2008)
4. F. Radicchi, S. Fortunato, B. Markines, A. Vespignani, Phys. Rev. E 80, 056103 (2009)
5. B. Uzzi, S. Mukherjee, M. Stringer, B. Jones, Science 342, 468 (2013)
6. J. Ioannidis, K.W. Boyack, H. Small, A.A. Sorensen, R. Klavans, Nature 514, 561 (2014)
7. J. Mingers, L. Leydesdorff, Eur. J. Oper. Res. 246, 1 (2015)
8. S. Redner, Eur. Phys. J. B 4, 131 (1988)
9. S. Redner, Phys. Today 58, 49 (2005)
10. M.L. Wallace, V. Lariviére, Y. Gingras, J. Informetr. 3, 296 (2009)
11. A.F.J. van Raan, Scienteometrics 59, 467 (2004)
12. Q. Ke, E. Ferrara, F. Radicchi, A. Flammini, Proc. Natl. Acad. Sci. USA 112, 7426 (2015)
13. J. Mingers, J. Oper. Res. Soc. 59, 1013 (2008)
14. C. Min, Y. Ding, J. Li, Y. Bu, L. Pei, J. Sun, J. Assoc. Inf. Sci. Technol. 69, 1271 (2018)
15. D. Wang, C. Song, A.-L. Barabási, Science 342, 127 (2013)
16. L.M. Bettencourt, A. Cintrón-Arias, D.I. Kaiser, C. Castillón-Chávez, Physica A 364, 513 (2006)
17. https://journals.aps.org/datasets
18. E. Garfield, JAMA 295, 90 (2006)
19. P. Larsen, M. Von Ins, Scientometrics 84, 575 (2010)
20. E. Landhuis, Nature 535, 457 (2016)
21. K. Hagiwara et al., Phys. Rev. D 66, 010001 (2002)
22. M.S. Kim, W. Son, V. Bužek, P.L. Knight, Phys. Rev. A 65, 032323 (2002)
23. I. Souza, N. Marzari, D. Vanderbilt, Phys. Rev. B 65, 035109 (2001)
24. W.O. Kermack, A.G. McKendrick, Proc. R. Soc. A 115, 700 (1927)
25. J.D. Murray, Mathematical Biology I: An Introduction (Springer, New York, 1993)
26. B.M. Althouse, J.D. West, C.T. Bergstrom, T. Bergstrom, J. Assoc. Inf. Sci. Technol. 60, 27 (2009)
27. E.M. Rogers, Diffusion of Innovations (Simon and Schuster, New York, 2010)
28. F.M. Bass, Manag. Sci. 15, 215 (1969)
29. J.G. Foster, A. Rzhetsky, J.A. Evans, Am. Sociol. Rev. 80, 875 (2015)
30. J. Li, Y. Yin, S. Fortunato, D. Wang, Nat. Rev. Phys. 1, 301 (2019)
31. Y.-H. Eom, S. Fortunato, PLoS ONE 6, e24926 (2011)
32. Y. Dong, R.A. Johnson, N.V. Chawla, IEEE Trans. Big Data 2, 18 (2016)