

“Critical Transitions” and “Avalanches” in Journal-Journal Citation Relations

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Introduction

Using the complete *Journal Citation Reports* (*Science Citation Index*, SCI, and *Social Sciences Citation Index*, SSCI) during the period 1994-2016 as data, we address the question of change and stability in the sciences at the level of the (n^2) aggregated citation links between (n) journals. Information theory enables us to study longitudinal developments first at the level of cells and then to aggregate, since the Shannon-formulae are based on using Σ s. Micro-developments in the data can thus be related to theorizing about the sciences in terms of distributed change (Price, 1976; cf. Kuhn, 1962).

Our results suggest that the dynamics can be explained by considering Bak *et al.*'s (1987) model of “self-organized criticality”: the knowledge base can be considered as a pile of meta-stable constructs which are continuously disturbed by new knowledge claims bringing also new citation relations. “Avalanches” of variable size can then be expected. The effects, however, are local; the meta-stable regions operate in parallel. The overall system remains tending towards meta-stability—at “the edge of chaos” —because of the ongoing fluxes of new manuscripts creating and rewriting relations in terms of citations at different scales (Zitt *et al.*, 2005).

The “journal literature” can be considered as the core of scientific literature (Price, 1965); new disciplinary developments can be expected to lead to new journals (Price, 1961). However, the internet revolution may have changed this landscape. Google Scholar (since 2004) collects articles on a case-by-case basis by crawling the web. Consequently, Google Scholar does not delineate the universe of scholarly documents. Furthermore, with the introduction of *PLOS ONE* in 2006, new journals have emerged that deliberately abstain from disciplinary criteria in the peer-review process in favor of a focus on novelty in terms of methods and data.

As a consequence, journals may have lost some of their exclusiveness and perhaps precision in maintaining borders among disciplines (Harzing & Alakangas, 2016). Boyack & Klavans (2011; Klavans & Boyack, 2017), for example, argue that “direct citation” at the article level (Waltman & van Eck, 2012) has become an organizer of the literature more strongly than

journals or other possible groupings of citations. However, articles are one-time events, whereas citation relations among journals can be assessed in terms of structural developments over time.

In this study, we use aggregated journal-journal citation *relations* as units of analysis. The journal-journal citation relation is a link in the networks of which journals are the nodes. Each relation specifically combines *two* journals. The citation relations among the 10,000+ journals contained in the *Journal Citation Reports (JCR)* of the SCI and SSCI can be organized as a matrix of $(10,000+)^2$ cells, each representing a valued relation between a citing and a cited journal.

Data

For each year, we construct a matrix of N journals in the columns citing the same N journals in the rows. The number of journals N grows from 5,765 journals in 1994 to 11,487 in 2016. Each *JCR* (in both databases) contains a file with name changes, mergers, and splitting of journals. We use the latest name abbreviation and backtrack from the most recent year of change adding this name to all previous years.

The 23 matrices (1994-2006) were transformed into 21 matrices (1996-2016) with three-year moving averages in order to dampen fluctuations. Since the dynamic evaluation requires also three years (t as the *a posteriori* year, $t-1$ for the revision of the prediction, and at $t-2$ as the *a priori* distribution), we have 19 observations for each cell (1998-2006). In the final step, we incorporate only values larger than ten (as the aggregate for three years) in order to suppress the possible noise effects of small values.

Methods

There are both theoretical and methodological reasons for *not* using the differences between maps of consecutive years as indicators of change. Cluster analysis and mapping techniques (e.g., community finding) are static analyses. Furthermore, community-finding algorithms begin with a random seed, so that it may even be difficult to reproduce the cluster structure in the same year. When one compares the results of static analyses year-on-year by subtraction, one loses control of whether substantive change is measured or the choice of another sub-optimum by the clustering algorithm (e.g., Figure 1).

The dynamic extension of Shannon's (1948) definition of the information content of a distribution [$H = - \sum_i p_i \log_2 p_i$] is provided by Kullback & Leibler's (1951) divergence measure $I = \sum_i q_i \log_2 (q_i / p_i)$, where I measures the expected information of the message that the *prior* distribution ($\sum_i p_i$) has turned into the *posterior* distribution ($\sum_i q_i$). The *prior* distribution can also be considered as a prediction of the *posterior* one.

In the case of a perfect prediction, $I = 0$ and the two distributions are similar. If the prediction is imperfect, it can be improved by a distribution at an in-between moment of time (Figure 2). This improvement of the prediction of the *a posteriori* probability distribution ($\sum_i q_i$) on the basis of an in-between probability distribution ($\sum_i p_i'$) compared with the original prediction ($\sum_i p_i$) can be formulated as follows (Theil, 1972, at p. 77):

$$\begin{aligned} I(q : p) - I(q : p') &= \sum_i q_i \log_2 (q_i / p_i) - \sum_i q_i \log_2 (q_i / p_i') \\ &= \sum_i q_i \log_2 (p_i' / p_i) \end{aligned} \quad (1)$$

Figure 1: Alluvial diagram of three-year moving averages of journal-journal citation relations in 2005, 2011, 2016, using (Rosvall & Bergstrom, 2010)'s *Mapequation* at <http://www.mapequation.org/>.

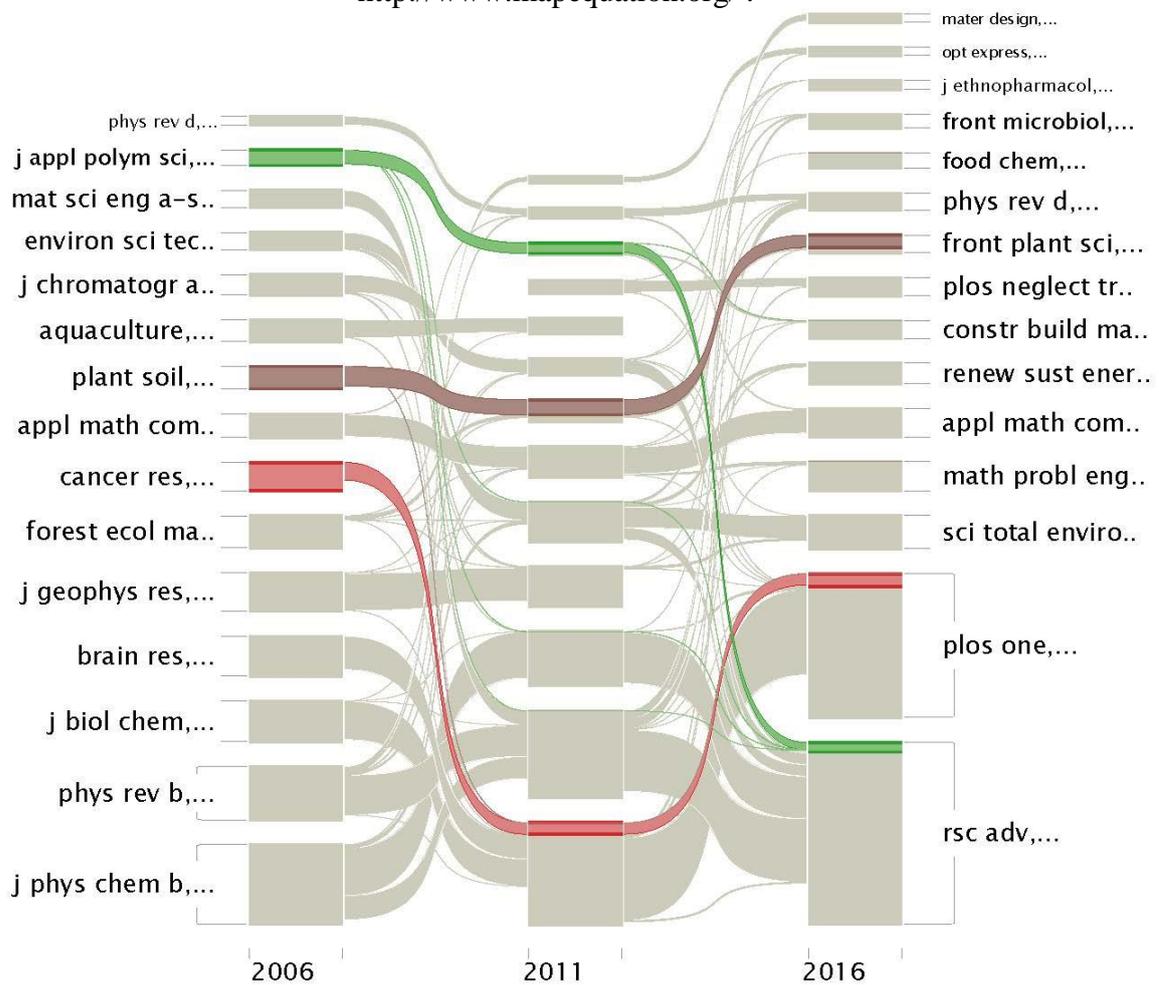
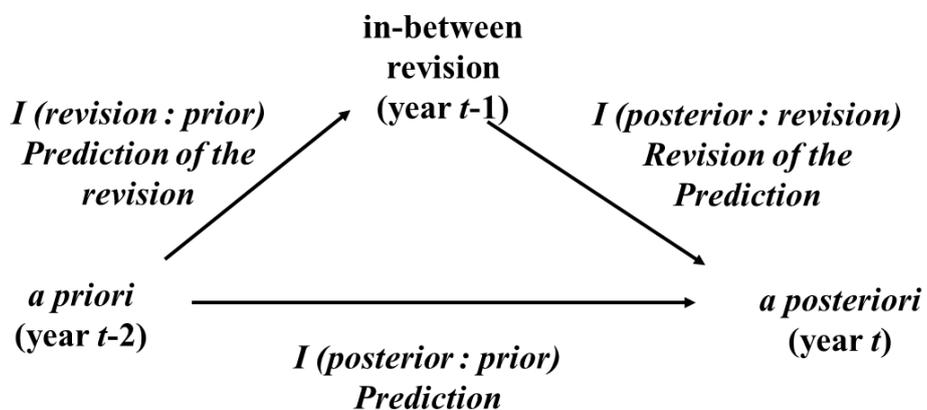


Figure 2. Prediction and possible revision of the prediction among three distributions.



The in-between year can also be considered as an auxiliary station in the signal transmission from the sender to the receiver. If the auxiliary station boosts the signal from the sender to the receiver, the system loses its history because what happened before the rewrite at the auxiliary station no longer matters. Contrary to the geometry of Figure 2, the sum of the information distances via the intermediate station is then shorter than the direct information path between the sender and the receiver. In other words, the generation of a negative entropy indicates a discontinuity. The Kullback-Leibler divergences can thus be combined to analyze critical or path-dependent transitions in a set of sequential events (Frenken & Leydesdorff, 2000; Leydesdorff, 1991; 1995, at p. 341).

In summary, one can define an indicator

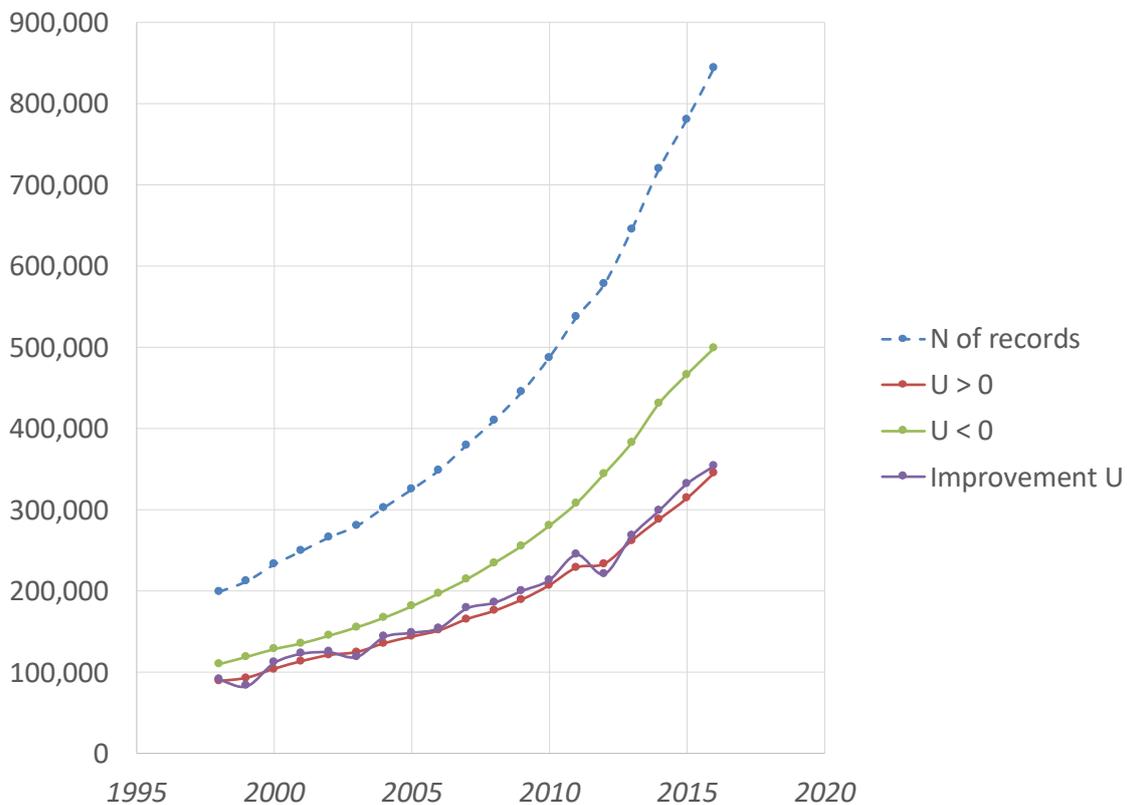
$$U = I(q:p') + I(p':p) - I(q:p) \tag{2}$$

in which q indicates posterior, p prior, and p' revision of the prediction. If $U < 0$, the transition is critical. In other words, negative entropy is generated along the arrow of time.

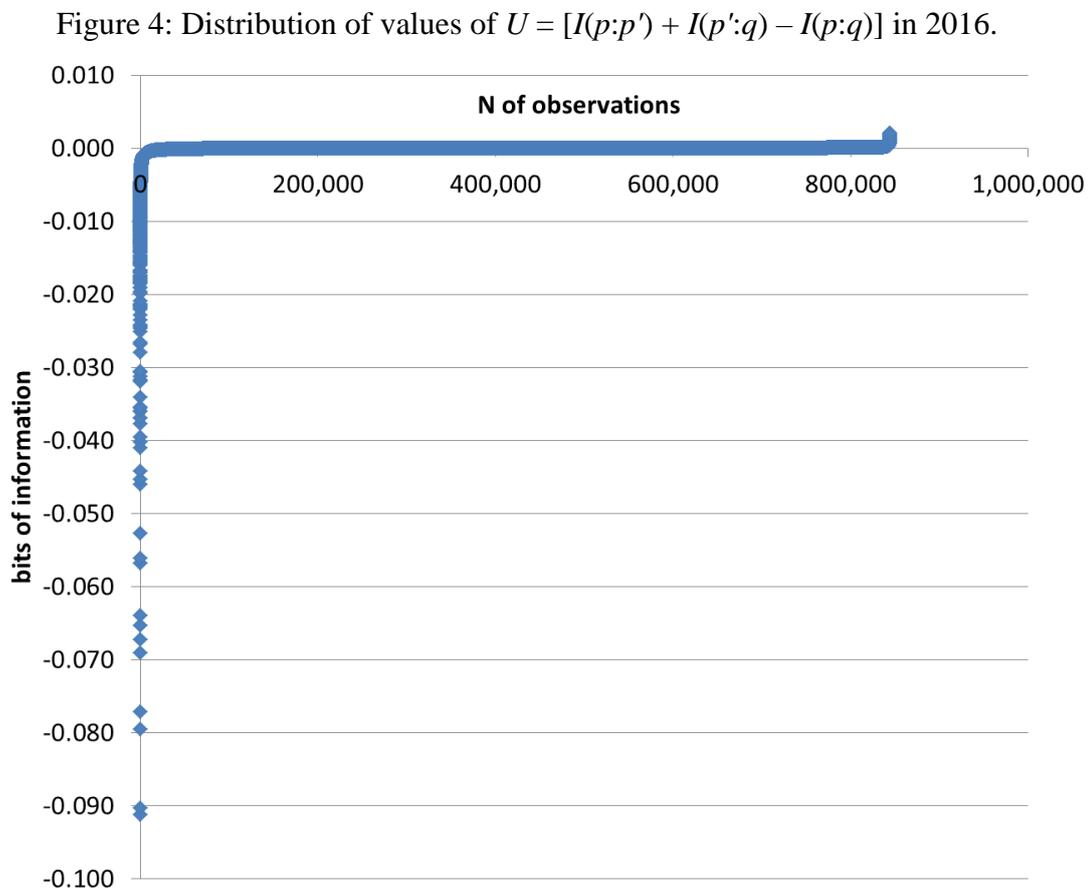
Results

Figure 3 shows the longitudinal development of the numbers of observations for which the predictions are improved and path-dependencies are generated during the period 1998-2016. The lines for the improvement of the prediction virtually coincides with the *absence* of a path-dependency ($U > 0$). Improvement is the case in on average 43.0% of the observations (st. dev. = 1.8%). We had not expected this coincidence; but one can derive why this is the case for analytical reasons (Leydesdorff *et al.*, forthcoming: Annex).

Figure 3: Numbers of observations, 1998-2016



The patterns are repeated from year to year. Note that critical transitions are the rule (57%) more than the exception. The values of the critical transitions (in bits), however, vary widely within each year (Figure 4).



In 2016 for example, 770,170 of the 844,476 observations (91.2%) have values between -0.1 and +0.1 millibits. This large segment is represented in Figure 4 as a flat line along the x -coordinate. At both ends, however, the critical transitions can have much larger absolute values. Plotting these values log-log for the top 10,000 on either end provides two power-law-type distributions (Figure 5) with an excellent fit ($r^2 > .99$).

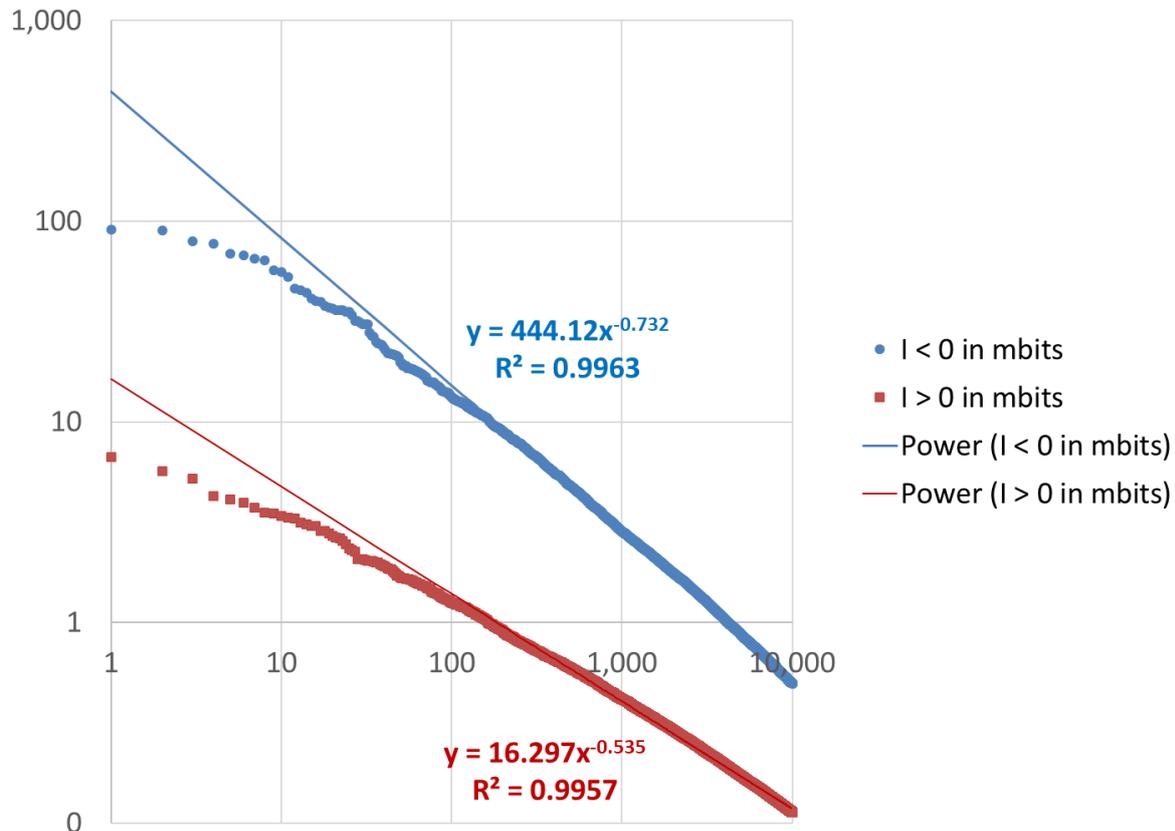
We added the equations to the figures to show the exponents, which are on the order of 0.65. For a scale-free network, this exponent has to be larger than one (e.g., Broido & Clauset, 2018). The distribution also fits more than .99 to a non-scale-free distribution such as the log-normal or Weibull distributions. The interpretation of this finding is therefore not trivial (Clauset *et al.*, 2009).

Self-organized Criticality

One possible interpretation of the curves might be that the fit marks the signature of self-organized criticality or $1/f$ -noise. For explaining self-organized criticality, Bak & Chen (1991, at pp. 26f.) used the example of a pile of sand on which one grain of sand is dropped regularly: “Now and then, when the slope becomes too steep somewhere on the pile, the grains slide down, causing a small avalanche. [...] When a grain of sand is added to a pile in the critical state, it can start an avalanche of any size, including a ‘catastrophic’ event. But most of the time, the grain will fall so that no avalanche occurs.” Even the largest avalanches

involve only a small proportion of the grains in the pile, and therefore even catastrophic avalanches cannot cause the slope of the pile to deviate significantly from the critical slope.

Figure 7: The 10,000 most important path-dependent transitions (in blue) versus the 10,000 highest positive values (in brown)



In other words, the effects of an avalanche are local and do not affect the overall structure of the pile. The system remains in a critical state so that one can expect avalanches to remain equally possible. “Even though sand is added to the pile at a uniform rate, the amount of sand flowing off the pile varies greatly over time.” In contrast to white noise, $1/f$ noise suggests that the dynamics of the system are strongly influenced by past events. The pile has a history of construction and reorganizations over time.

This model of self-organized criticality differs from the Kuhnian model of normal science versus revolutionary science as phases in paradigm transitions (Kuhn, 1962). The flux of manuscripts with knowledge claims contain references to other journals which can be compared with the grains of sand that hit the sand pile or, in this case, the knowledge base as a construct. The effect can be an avalanche of any size depending on the state of the system at that specific place and time. The selection environments determine the size of the avalanches more than the intrinsic qualities of the knowledge claims providing the variation.

Unlike grains of sand, however, one expects knowledge claims to be related. Bak and his colleagues (Bak & Chen, 1991; Bak, Tang, & Wiesenfeld, 1987) worked in their physical experiments with sand grains of uniform granularity. Our “grains” are dropped on a sand pile, but they are of different granularity in that they may be impure, containing, for example, lumps of clay. Golyk (*s. d.*) compared Bak’s model with Zipf’s Law, which states that in

literary texts, the frequency of a word is inversely proportional to its rank in the frequency table, given a large sample of words used. As against sand grains, such texts have complicated non-local correlations such as syntax and cognitive structures (e.g. references), yet the accumulation leads similarly to log-log lines (Price, 1976).

For self-organized criticality (SOC) to occur, a large number of unrelated meta-stable configurations is needed. Golyk concluded that both “models with local interactions (such as BTW) as well as models with non-local (literary texts) correlations may lead to power-law distributions” (at p. 4). However, the theory of self-organized criticality has hitherto been rather phenomenological. There is no strict criterion for the value of the exponent, such as one finds in the case of preferential attachment leading to power-law distributions where one uses $2 < \alpha < 3$ as a criterion for scale-freeness. Bak *et al.* (1987, at p. 383) report values of the exponent as low as .42 in studies of SOC.

SOC can be simulated using a cellular automaton as a grid. The exponent is also determined by the dimensionality of the model, and perhaps by the different objects of study such as earthquakes, water droplets on surfaces, human brains, etc. (Jensen, 1998). The original claim that SOC would be scale-free (Bak *et al.*, 1987, p. 381) is not needed for SOC as a phenomenon. Scale-free networks are rare (Broido & Clauset, 2018), whereas SOC is abundantly the case in very different systems.

Summary and conclusions

Using dynamic entropy measures such as Kullback-Leibler’s (1951) divergence, Theil’s (1972) improvement of the prediction, and Leydesdorff’s (1991) test for critical transitions as indicators of change over time, we found “self-organized criticality” in the 10,000+ most pronounced cases of evolutionary change. It seems to us that the model of self-organized criticality makes it possible to show regularities that help us to understand the evolutionary development of the sciences where disciplines are both enabled and constrained by what is past—or conventional—and what is possible or can be sustained by the system. While it is impossible to say where change will occur, the fact that it will occur is expected. Smaller, local events may be fractals of what occurs elsewhere on a larger scale. However, we do not expect the system to be scale-free. The scaling coefficients may vary among disciplines.

The sciences can be understood as developing in terms of interdependent continuities and discontinuities. The continuities are needed for the accumulation of the “sand pile” into a knowledge base, with the inertia of institutionalized relations maintaining the relevant structures. The discontinuities provide options for a rewrite (Fujigaki, 1998) or a reorganization. These may happen as lightning (“grains of sand”) striking the ground—in an unpredictable way—but the effect can be a local “avalanche” of any size and accordingly a reorganization.

Unlike a sand pile, the knowledge base is a construct comprising specific structures. Whereas some multidisciplinary journals participate in this reorganization of the knowledge base every year—because of their multidisciplinary character—large numbers of journal links are unresponsive to changes in the environment, so that the transitions remain close to zero in terms of bits of information. The system is both dynamic by chance and structurally “frozen,” but in different parts of the structure. Kauffman & Johnson (1991) described this as a co-evolution to the edge of chaos; the constructed knowledge base is at many places meta-stable, while at other places, the systems may be temporarily locked and therefore unable to change.

In addition to this unexpected result, the use of critical transitions enables us to show how research fronts can be expected to shift rapidly. In the full paper, we focus on research about renewable energy: in 2010, journals which focused on “biomass” were most dynamic. This shifted to an orientation towards themes like electrical power, construction, and clean production in 2016. The same journals were present in 2004, but this research area was at the time not yet involved in the dynamics of discontinuity.

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