of experimental conditions. One can apply statistical inference and computational learning theory to infer the model structure and eventually formalize the dynamics rules governing biological processes.

Finally, the non-trivial topology of complex networks brings an intrinsic layer of complexity to the control problem. From the advances towards understanding complex networks accumulated in the last decade, we know that network topology fundamentally affects many dynamical processes on it, from epidemic spreading to synchronization phenomenon. We also know that even in the case of linear control, the topological characteristics of the networks have a big impact on their controllability [1].

In sum, our ultimate goal is to develop the mathematical underpinning behind the control of complex networks, unifying under a single theoretical foundational framework. This is a problem that given its complexity and depth of applications will probably engage network science and control community for the next decade.

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doi: 10.1093/nsr/nwu025
Advance access publication 12 July 2014

Measuring science is based on comparing articles to similar others. However, keyword-based groups of thematically similar articles are dominantly small. These small sizes keep the statistical errors of comparisons high. With the growing availability of bibliographic data, such statistical errors can be reduced by merging methods of thematic grouping, citation networks and keyword co-usage.

Pieces of our collective human scientific knowledge are constantly defined and modified through our global scientific communication. The most common units of this process are publications, also called articles or papers. These units (i) provide ‘road signs’ for newcomers to a field and (ii) allow the scientific community to steer its work toward consensus-based goals given the available resources. Due to the size of science automated measurements are necessary to achieve these two goals. In particular, the steering aspect involves decisions about manuscript acceptance and science funding, which includes even jobs of scientists. Thus, it seems reasonable to move to the public domain not only scientometric algorithms but also bibliographic data [1]. With more data in the public domain, our current assumptions about the data itself may be challenged.

To measure science, one needs to measure the scientific communication process, which is a network of articles (nodes) connected by citations (directed links) and tagged with article keywords. Most current scientific metrics are built on article-level metrics (ALMs) and the most common ALM is the (total) citation number. The citation number—similarly to other mention-counting ALMs—has the following major properties. First, there are more publications every year (Fig. 1a) and the number of references per publication is growing too (Fig. 1b). Second, papers with an earlier publication date have had until now more time to receive citations. Third, the citation count by itself blanks out citation context [2], which includes citing paper quality. In summary, the citation number tends to favor papers that appeared close (in time and topic) to the origins of large and still active research areas. Improvements
Figure 1. Scientific publication statistics by year from the ACM Digital Library, the American Physical Society (APS), the arXiv, MathSciNet, PubMed, Scopus, the Social Science Research Network (SSRN) and the Web of Science (WoS). Scopus data assign January 1 to previous year. WoS data licensed by EU ERC COLLMOT.

Both major applications of measuring science (i.e. learning and decisions) compare papers, individuals, groups or institutions to similar others. Note that these comparisons are mainly built on comparing papers (articles). A comparison of articles assumes that we can assign each to one or more article sets that are characterized by averages (medians) taken over the given set. In fact, the existence of such homogeneous article groups is an unspoken axiom in scientometrics: it is widely assumed that all scientific articles can be assigned to thematically homogeneous groups of articles. To keep statistical errors low, these groups need to be large.

With keywords the least and most stringent conditions of thematic similarity in a group of papers are that (a) all papers share at least one keyword and (b) all papers have the exact same keyword list. Fig. 2a and b shows that the distribution of the sizes of such article groups decreases (at medium and large group sizes) faster than a power law with slope $-1$. With simple math this means that the probability for a paper to belong to a group drops with the group’s size faster than a power law with exponent 0, which is a constant. So, a paper is more likely to belong to a small group than to a large group. Moreover, if only papers with similar publication dates are allowed in a thematic group, then group sizes are further reduced. In summary, the above unspoken axiom implies that instead of homogeneous large groups of papers, science is dominated by homogeneous small groups of papers.

Two consequences of the dominance of small article groups are that (i) a keyword-based comparison of articles with thematically similar others keeps statistical errors high (with all analyzed keyword schemes) and (ii) these errors propagate from ALMs to all other metrics. The growing availability of bibliographic data may reduce this type of statistical error. It allows now the integration of content-based keyword assignment schemes with citation networks [13] and the network of keywords as defined by their joint usage on publications (Fig. 2b). We point out that in Fig. 2 keywords provided by authors (e.g. APS PACS terms or arXiv categories) and keywords assigned by databases (e.g. PubMed MeSH terms or WoS KeyWord-Plus terms) show similar distributions. This and other universal properties [5] of large-scale bibliographic data may provide more precise standards for quantifying scientific contributions.

**FUNDING**

This work was supported by Hungarian National Scientific Research Fund (OTKA K105447), EU ESF FuturICT.hu (TÁMOP-4.2.2.C-11/1/KONV-2012-0013), EU ERC FP7 (COLLMOT 227878).
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doi: 10.1093/nsr/nwu027
Advance access publication 24 July 2014