Editorial

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Science and technology (S&T) underpin and pervade the knowledge-based economy—their importance is undisputed. During the last few decades, science policy has embraced scientometrics to gain insights into the structure and evolution of S&T and devised diverse metrics and indicators. However, without a deep understanding about the S&T system, new metrics might result in undesirable behavior, e.g., authors might publish the least publishable unit (also called salami slicing) to increase publication counts (see also discussion of key problems in the *Leiden Manifesto* (Hicks et al., 2015)). Note also that the social actors in the S&T system adapt their behavior; changes in metrics and indicators can lead to complex system dynamics (Leydesdorff, 2015).

Ideally, policy makers would be able run computational models of policy interventions and use the predictions to "fly the future," before the interventions are implemented (Rouse, 2014, 2015). Computational models of science, technology, and innovation can represent and simulate the complicated interaction of processes, make possible their rigorous validation and comparison with empirical data, and enable a community of researchers to share, critique, and improve the models (Edmonds, 2010). Models support and make more rigorous crucial scientific tasks, such as establishing explanations and making predictions (Cartwright, 1990). They support data-driven, informed decision-making by experts (Börner, 2016).

A number of recent books and special journal issues (Börner et al., 2011; Scharnhorst et al., 2012; Watts & Gilbert, 2014; Ahrweiler et al, 2015) review existing formal models of STI. This special issue features exemplary works that model S&T dynamics and the interplay between individual behavior and institutional boundary conditions. It aims to bridge the gap between research on computational models and their application to studying, understanding, and governing the S&T system. Although it is impossible to predict the nature and essence of the next scientific or technological innovation, it is often possible to predict the circumstances leading to it, e.g., where innovation is most likely to happen and under which conditions. For example, recent studies quantify the impact of professional networks on successful career paths (Petersen, 2015), estimate when technologies can be expected to emerge depending on changes in patent network topology (Erdi et al., 2013), or predict which institutions might be most productive over the coming years (Bland et al., 2005).

This issue opens with a paper by **Ahrweiler** (2016, this issue) on the usage and utility of agent-based models that empower policy makers to arrive at better policy solutions. The paper starts with the simple statement: "Policymaking implies planning, and planning requires prediction." It then showcases how agent-based simulation models can be employed to support scenario analysis, experimentation, policy modeling, and testing prior to any policy implementation in the real world.

Brunswicker et al. (2016, this issue) apply a spatial autocorrelative model to study the impact of open-source programming efforts on scholarly impact measured via citations. Using data of the nanoHUB development community, in which 477 nanotechnology tool developers have contributed more than 715 million lines of code, they show that a scientist's contributions to digital innovations such as code has positive effects on authorship capital. However, the digital practice structures create negative dependency effects—the probability that work by an individual programmer is cited declines if another topically proximate programmer is more highly cited.

Alstott et al. (2016, this issue) use patenting histories of 2.8 million inventors extracted from more than 3.9 million USPTO patents for the period between 1976 and 2010 to study inventor trajectories and success. They extract and layout normalized patent-based technology networks and use the resulting maps in technology development planning and management. Individual inventors and firms can locate themselves and their knowledge on the map, and observe what technology domains are nearby in the technology space, making it possible to identify easy targets for new inventions.

Chavalarias (2016, this issue) introduces the 'Nobel Game,' a model that investigates the mechanism of scientific conjectures and refutations, and their consequences. Within the framework of evolutionary game theory, this model aims to capture the impact of science policies on the trade-off between research speed and research quality. Specifically, high pressure on scholars to publish rapidly translates into higher speed of discovery but much lower result quality.

De Langhe (2016, this issue) applies an agent-based model of Kuhn's paradigms and their dynamics. The model is intended to serve as a foundation for further work on tracking scientific revolutions.

Bollen et al. (2016, this issue) propose a novel way of allocating research funds that replaces the traditional peer review of projects by crowdsourced funding of people. The proposed 'FundRank' model was validated using citations as a proxy of how researchers might distribute funding; funding distributions are shown to be similar to those by NSF and NIH.

In order to arrive at a more holistic and systematic understanding of the processes that shape the structure and dynamics of science, technology, and innovation, future modeling efforts should focus on

- the comparison of different model types, and
- the combination of models across different levels—from the individual (micro) to the population (macro) level.

- standardized model descriptions,
- model registries and inventories in support of study replication and model reuse,

Teams of modelers that include producers (researchers, industry, and government) and users (science policy makers and other decision makers) of models are likely to be most successful when identifying challenges and proposing solutions in modelling research, model application, associates education, and outreach.

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