Heterogeneous, satisficing scientists on the road to scientific consensus

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Abstract. *Recently, philosophers of science, sociologists and economists of science have spent considerable effort to get a better understanding of scientific processes on the micro and macro level. However, these models make rather strict assumptions in regard to the scientists' capabilities to process information. The aim of the simulation model presented in this paper is to motivate a decision process of scientists that is based on non-optimizing behavior and rather simple heuristics. Scientists are endowed with diverging preferences concerning scientific insight and scientific reputation. The aim is to show how the scientific practice of (non-)conforming behavior influences the emergence of scientific consensus. Simulation results show how decision heuristics of scientists who engage in a new scientific idea influence their scientific fellows and how their behavior promotes the emergence of a new scientific belief.*

Keywords: Agent-based modeling (ABM); conformity; Economics of Scientific Knowledge (ESK); knowledge generation; reputation; satisficing; scientific consensus

1 Introduction

The aim is to show how the scientific practice of (non-)conforming behavior influences the emergence of scientific consensus. The key feature of the simulation model is that scientists are endowed with diverging preferences concerning scientific insight and scientific reputation. The aim of the approach is twofold: It intends to contribute to the literature of simulation models of science by providing a motivational background of the agents. In addition to this, the underlying processes in the simulation model are rooted in the discussion of the literature of "Economics of Scientific Knowledge" (ESK). The mathematical approaches related to ESK seem to lack coherence in that they address epistemological and social aspects in a process of scientific consensus building, but make use of concepts of neoclassical microeconomics and Bayesian decision theory that impose very strict assumptions concerning the rationality of individual and social decisions [1–5]).

In particular, it is argued that scientists do not use elaborated probability calculus when they decide in favour or against a scientific belief [6]. Further, it is claimed that scientists only have limited knowledge of the scientific rigor of a new scientific belief and that they cannot foresee the support of the scientific community. Accordingly, scientists do not maximize utility but follow a satisficing principle [7]. Their decision is based on a simple heuristic which reflects their limited availability of information. Thirdly, the focus in the science process is put on the role of consensus-building in the emergence of a new scientific belief. An important mechanism in the process of consensus-building that has been disussed in the literature is (non-) conforming behavior. From the perspective of an individual scientist, conforming behavior can be a reputational strategy [8, 9], but at the same time non-conforming behavior can be a strategy to differentiate oneself [10]. In particular, it is the priority rule in science that induces scientists to show non-conforming behavior from time to time.

2 The Simulation Model

2.1 Overview

Scientists are assumed to have a preference for scientific insight or reputation. A uniformly distributed weighting parameter $\alpha \in [0, 1]$ is assigned to every scientist and defines her as knowledge preference type (KT) with $\alpha > .5$ or reputation preference type (RT) with $\alpha \leq .5$. The mechanism that allows scientists to achieve their particular aim is to generate additional publications. Following the lottery example borrowed from the Netlogo Library [11], the propensity to generate additional publications is higher for those scientists who already have a high cumulative productivity (i.e., a high number of publications) and who follow the prevailing scientific paradigm, i.e. who show conforming behavior. If the parameter of conformity $\in [-1, 1]$ is close to zero, there is an almost even distribution among two scientific beliefs. A conformity parameter that converges to (minus) one indicates that the distribution is very uneven, yielding a positive value for the majority and a corresponding negative value for the minority.

As explained elsewhere [12], the simulation model is driven by two core processes: The process of knowledge generation that accounts for the depreciation of accumulated knowledge and diminishing marginal returns of efforts in a particular scientific field [13], and secondly, the process of how the scientist's reputation is influenced by organisational inertia. The parameter of organisational inertia $(1 - \delta)$ points to the fact that some disciplines are "tightly knit in terms of their fundamental ideologies, their common values, their shared judgments of quality, (...) and the level of their agreement about what counts as appropriate disciplinary content" [14]. Accordingly, even though a scientist may achieve a high number of publications, this does not necessarily imply an equivalent ranking value. Table 1 summarizes the simulation.

2.2 The Decision Heuristic

Scientists calculate their aspiration level resulting from knowledge growth ($\Delta w_{i,t}$) or reputation ($ra_{i,t}$). The aspiration level *asp* of scientists who have a preference for knowledge growth over reputation ($\alpha > .5$) is calculated as the mean knowledge growth over the last m periods (decision horizon):

$$asp_{i,t}^{KT} = \sqrt[m]{\prod_{t=1}^{m} \Delta w_{i,t}} \tag{1}$$

In contrast to knowledge growth, reputation is defined as a social disposition. Thus, the aspiration level of scientists with $\alpha <= .5$ is referenced to the best rank in the scientific community. The aspiration level of RT scientists is defined as

$$asp_{i,t}^{RT} = \frac{(ra_{i,t} - 1)^2}{(n_t - 1)^2} \tag{2}$$

with n_t number of different rank classes. If the scientists' outcome is below their aspiration level, scientists are termed dissatisfied. If scientists are dissatisfied, they might accept a new scientific belief that is about to emerge, even if this means to show non-conforming behavior and to accept a lower probability to win the publication lottery in the short run. In particular, it is argued that pioneer scientists who initiate a new belief are highly committed to a new scientific belief. They stick to the new scientific belief even if it gets not adopted by the majority of other scientists. In general, the propensity to adopt a new scientific belief is higher for scientists who have a high degree of dissatisfaction *diss* and a high preference for their respective aim.

$$diss_{i,t}^{KT} = \alpha * \big(1 + \overbrace{(asp_{i,t} - \Delta w_{i,t})}^{\text{attainment discrepancy}}\ \big) \tag{3}$$

$$diss_{i,t}^{RT} = (1 - \alpha) * \big(1 + \overbrace{(asp_{i,t}^{RT} - asp_{i,t-1}^{RT})}^{\text{change of ranking}}\big) \tag{4}$$

Both types of dissatisfied agents adapt their behavior when their degree of dissatisfation exceeds a certain threshold. This threshold is defined by the parameter of conformity. Agents are assumed to use this parameter as an indicator to assess knowledge growth or reputation under a new scientific belief. Below-average KT scientists tend to adopt the idea of the innovators, since they strive for knowledge growth and are assumed to imitate deviaters, i.e. scientists who engage in a new scientific belief. For a high value of conformity (uneven distribution), adaption would imply that the agent's dissatisfaction is stronger than the risk of committing to a scientific idea that turns out to be a minority belief. Minority implies a lower chance to gain additional publications. Accordingly, below-average RT scientists tend to adopt the idea of the current majority, since they want to improve their reputation via successful publication activities. In general, when a new scientific belief starts being adopted, the conformity parameter decreases and induces even agents with a low preference for knowledge growth and reputation to adapt their strategy.

Table 1. Pseudocode of the simulation model

```
initialize parameters:
    preference types of agents
    decision horizon of agents
    prevailing scientific belief (= -1)
while simulation time < termination time
scientists
    publish
    update their knowledge stock
    update their ranks
    calculate target value from knowledge and reputation
    store target values to calculate aspiration level
if ticks = decision horizon
    scientists calculate aspiration level
    if current performance ≤ aspiration level
    adapt strategy:
    if above-average KT dissatisfied
        engage in a new scientific belief (= 1)
    if any? such deviaters
        if below-average KT dissatisfied
          adopt belief of deviaters
        if RT dissatisfied
          adopt idea of majority
update conformity, publication lottery
calculate statistics: adoption rate of scientific belief(s)
```

Note: The NetLogo sourcecode can be provided upon request.

3 Findings

The simulation experiments show that higher adoption rates strongly correlate with the existence of tipping points where a steep decline of conformity is followed by a steep increase of the parameter value. The emergence of such a tipping point is contingent on a critical mass of scientists who already adopted the new scientific belief. This result is consistent with the findings of [15], who already pointed at the importance of transition phases that strongly influence the result on the macro level. On the micro level, the findings so far show that there are regimes where conformity plays a major role in the adoption process of a new scientific belief. It is shown that the closer one gets to the tipping point, the influence of the parameter of conformity is significantly higher than the cumulative productivity with regard to the propensity to win the publication lottery. In regard to the methodological approach of the simualtion model, it is shown that the decision heuristic can be interpreted as an endogenous explanation for the rate of change in the adoption process of a new scientific belief. In particular, simulation results have shown that the median dissatisfaction of scientists is commensurable with the median absolute conformity of scientists in the following way:

$$\frac{dtanh(m_c)}{dm_c} = \gamma * \frac{(1 + median(diss))}{(1 + med(abs(conf)))} \tag{5}$$

with $\gamma \in [0, 1]$ and $dtanh(m_c)/dm_c$ displaying the rate of change of an exogenous tanh function as a function of a critical mass of adopters m_c.

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