The Case for Empirically Calibrated Agent-Based Models

Idealized agent-based models provide good general arguments in favour of different hypothesis. For instance, Zollman's famous models (Zollman 2007, 2010) started a whole discussion about optimal communication among scientists, e.g. (Rosenstock et al. 2017, Borg et al. 2017). Also, they can be used to detect new group phenomena, e.g. Hartmann & Rafiee Rad (2018) discovered a group dependent anchoring effect using agent-based models for deliberation. Finally, Frey & Šešelja (2018*b*,*a*) argue that abstract agent-based models have explanatory values if they can pass a robustness test under parameter and assumption changes.

On the other hand, when one wants to answer specific optimization questions, such as what is the optimal team structure in a scientific laboratory, or what is the epistemic saturation point for scientific projects, data come into play. With the goal of answering optimization questions with philosophical flavour, data-driven analyses employing statistical and machine learning techniques are conducted (Martin 1984,b, Perović et al. 2016). The benefit of a data-driven approach is a clear reach and applicability in science policy. Still data-mining methods cannot test hypothetical scenarios. We argue in favour of empirically calibrated agent-based models because of their ability to abstract from certain parameters and test hypothetical scenarios.

There are different ways to acquire data for empirical calibrations: qualitative interviews, quantitative surveys, analysis of citation patterns, laboratory investigations, analysis of the data about structures in science, etc. Moreover, empirically calibrated models can be used to show robustness of data-mining results. As an illustration we present two empirically calibrated agent-based models. The first one demonstrates robustness of the results by Perović et al. (2016). These results show that projects in high energy physics which comprise of a small number of teams –usually two with fewer members per team, outperform big ones. The second one tests the performance of realistically structured communication patterns in groups of experimental biologists.

Examples of empirically calibrated agent-based models

Simulations of scientific inquiry are largely based on idealized communication structures. Agent networks structured as a wheel in comparison to completely connected graphs dominate the literature, e.g. (Zollman 2007, 2010, Grim 2009). These structures do not necessarily resemble the typical communication between scientists in different fields. The data on team structures, from the high energy physics laboratory Fermilab, show that scientists are organized in several groups. Furthermore, the work on project efficiencies by Perović et al. (2016) allows us to identify the group structures which are usually more efficient than others. Therefore, we developed models resembling the team structures in high energy physics analyzed by Perović et al. (2016) and tested whether efficiency results coincide.

These models have very interesting properties. First, they show how beliefs can be strongly self-enforced in subgroups, even when the majority of scientists have opposite views. This is particularly evident when we consider that scientists in the subgroups interact more with each other than with other groups. Our model agrees with the empirical results from (Perović et al. 2016). From the data about projects performed in Fermilab we found that groups separated in as few small teams as possible outperform the groups separated in a higher number of bigger teams (Figure 1). The same as in Perović et al. (2016), by team members we considered only scientists without helping staff employed on the projects. Choices for the team sizes have been extracted from the data about Fermilab projects available on the repository INSPIRE-HEP (https://inspirehep.net/).

Team structures in science are field-dependent. In biology, laboratories are typically structured hierarchically and can involve several layers. We developed models simulating different management styles: from groups with one leader controlling everybody to groups with levels of hierarchy (Figure 2).[1] The first structure represents a group in which only professor commu-

[1]The inspiration for these structures came from qualitative interviews and laboratory

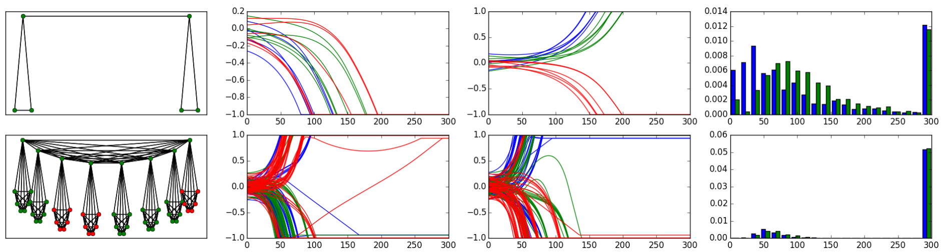

Figure 1: Empirically calibrated model. Left: structure of the group. Middle: development of the beliefs over 300 rounds for every agent in three different simulations. Two different modelling conditions are shown: without and with threshold of belief change. Histogram shows how frequent the scientists reach consensus in the indicated structure. The results are robust under both modeling conditions.

nicates with the junior group members. The second structure represent a professor communicating with several postdoctoral researchers who in turn supervise several PhD students. The last network takes into account that group leaders within the same laboratory are loosely connected. We also included time constrains: strongly connected nodes communicate less with every single node than less connected ones. E.g. a professor might be connected with 20 PhD students, but will not be able to talk to every single one all the time. When we consider this effect we can see that groups with additional levels of hierarchy perform much better than the centralized one.

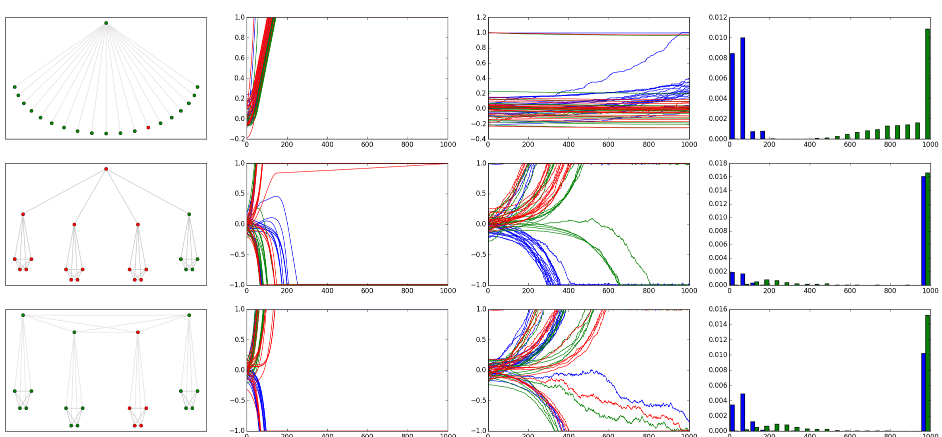

Figure 2: Models evaluating group structures in biology. Left: the group structures in biology are typically hierarchical. Middle: development of the beliefs of individual agents of the first 3 simulations in a standard model (left) and when strongly connected nodes are communicating less with every single node than weakly connected ones (right). Right: Histogram showing how fast beliefs converge in the standard model (blue) and the model considering time constrains (green).

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investigations.

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