Modeling and Simulating Crowdsourcing as a Complex Biological System: Human Crowds Manifesting Collective Intelligence on the Internet

Thierry Buecheler[1], Rocky Lonigro[1], Rudolf M. Füchslin[2] and Rolf Pfeifer[1]

[1]Artificial Intelligence Laboratory, Department of Informatics, University of Zurich
[2]Center for Applied Mathematics and Physics, School of Engineering, Zurich University of Applied Sciences
buecheler@ifi.uzh.ch

Abstract

Crowdsourcing, a real-life instance of human collective intelligence, is a phenomenon that changes the way organizations use the Internet to collect ideas, solve complex cognitive problems, and build high-quality repositories (e.g., Wikipedia) by self-organizing agents around data and knowledge. Many recent studies have highlighted the factors and the small sets of parameters that play a role when a large crowd interacts with an organization. However, no comprehensive simulation has yet been developed to incorporate all these parameters, investigate Artificial Life phenomena such as emergence and self-organization and potentially generate predictive power. Based on a presentation at ALIFE XII, this paper describes the development of a simulator for human crowds performing collective problem solving in a Crowdsourcing scenario. It details the mechanics of a multi-agent system (MAS) by building on insights from empirical science in several disciplines. The simulator allows running sensitivity analyses of multiple parameters as well as simulation of intractable interactions of complex networks of irrational agents. In addition, the paper provides a review of Crowdsourcing and human collective intelligence literature structured from an Alife point-of-view.

Introduction

Many researchers in the Artificial Life community are researching self-organizing, decentralized systems (e.g., large groups of ants or vertebrates such as bisons [*collective animal intelligence*]) that show, in their interactions, a high degree of (self-)stability and flexibility. Social scientists are transferring these insights to social networks and other interactions between humans.

A Crowdsourcing scenario provides an excellent setting for investigating *human collective intelligence*, generated through networks of interactions among individuals and between individuals and the environment. "Crowdsourcing" (Howe 2008), an instance of collective intelligence (Buecheler et al. 2010, Robu et al. 2009) emerging from de-centralized actions of a community of users, is a phenomenon currently occurring all over the world, strongly benefiting from new technologies and the development of Web 2.0: In essence, a "seeking" entity (e.g., a company or university) seeks the support of an *apriori* unknown and potentially very large group of intelligent agents (i.e., humans) by posting its unsolved problems on the internet. A simple and famous example is the Wiki Foundation (seeker) using internet users (crowd of solvers) to produce the world's largest encyclopedia (Wikipedia) with high-quality results (Giles 2005). This can either happen directly, as with Wikipedia, or through "information brokers", such as Innocentive.com or NineSigma.com that connect seekers and solvers through a platform. Small start-up companies as well as large established institutions (such as Fortune 500 companies and universities or other large organizations like NASA) are currently using Crowdsourcing for a variety of purposes.

The underlying complex dynamics are being intensively investigated by researchers from several disciplines, sometimes using different names like "Open Innovation" (Chesbrough 2003) or "Swarm Intelligence" (Dorigo and Stützle 2004) for slight variations of the phenomenon of interest. Recent studies investigate single parameters or specific settings of Crowdsourcing (e.g., Sieg et al. 2011, Leimeister et al. 2009, Alonso et al. 2008). However, so far there has been no comprehensive simulation of the complex interactions between agents involved in this scenario. This paper and the simulator presented attempt to move the research forward by combining the majority of parameters from the publications mentioned above and many more from empirical studies.

Phenomena relevant in an Artificial Life context such as self-organization, stigmergy and especially emergence, are very relevant when trying to understand complex dynamics between humans in real-life organizational scenarios (Bandte 2007). The emerging phenomena in organizations are created through interpersonal, analytically irreducible factors such as spontaneity, informal structures and interactions, ad hoc processes and groups as well as informal conventions such as norms and similar social patterns. This paper describes the underlying dynamics of a complex Crowdsourcing system and an implementation in our simulator, based on a framework for multi-agent systems (MAS). The simulator uses parameters based on empirical studies and integrates a set of essential factors and rules of interactions between members of the "crowd" and the seeking entities. Hence, this paper also provides a structured literature review of Crowdsourcing parameters. Due to its modular set-up, the simulator allows for the addition of more factors, once understood by scholars, to increase the accuracy of simulation runs and, potentially, its predictive power. The large set of rules and unpredictable outcomes, such as negotiation results between agents

(modeled in the MAS), allow the observation and statistical evaluation of emergent phenomena.

In what follows we review the state of the art in Crowdsourcing and Open Innovation research and relevant multi-agent simulation topics, then explain which parameters we are modeling and further dive into the details of the simulator before discussing first insights, use cases, and potential next steps.

State of the Art

We discuss three sections of prior literature particularly important to our context: First, we discuss the application of swarm behavior and problem solving insights from biology to Crowdsourcing, then relevant insights from management and organization science, often published in the context of "Open Innovation". In the third part, we look at theoretical and empirical evidence from other contexts that are also important for the creation of this simulator.

Crowdsourcing, Communities and Group Behavior

(Krause et al. 2010) describes the advantages and challenges of transferring insights from biological studies to human social interactions (using the term "Swarm Intelligence"). Similar to swarms, flocks, and herds, humans follow certain local rules of interaction in large groups. In a Crowdsourcing context, these local rules are evolving over time. Initially, chaotic behavior converges into social patterns and the crowd members use their local knowledge (similar to birds in a flock or fish in a school) to interact with other agents and contribute to Crowdsourcing. In most cases, the crowd self-organizes without a central body of control. Self-organization, as defined by (Camazine et al. 2003), states that "the rules specifying interactions among the system's components are executed using only local information, without reference to the global pattern", emerging from lower-level components of the system.

The crowd is especially good at solving coordination or cooperation problems (Surowiecki 2004). Schelling (Schelling 1960) investigated the reasons for this and found a possible explanation in focal points ("Schelling points"), towards which human expectations converge, leading to an eventual convergence of actions, comparable to John Dewey's "cooperative intelligence". They usually don't act for the good of the whole crowd, but act according to what's best for themselves (see Surowiecki 2004). This includes behavior that is judged highly irrational or short-sighted from an outside perspective (see e.g., Simon 1996). Nevertheless, humans can coordinate their actions and achieve complex goals that would not be achievable by individuals (like writing a high-quality encyclopedia or finding a relevant piece of information from billions of web-sites[1]).

From a collective intelligence point of view, cognitive problems (as often appear in a Crowdsourcing context) are even harder to solve than coordination or cooperation problems, because they are often difficult or perhaps impossible to centrally organize for a group approach. The

---

[1] Google's pagerank algorithm crowdsources a great deal of collective human intelligence to rate the importance of pages by linking to them.

solution approach to such problems is usually emergent and contains almost no formal structuring (see, e.g., *ultimatum* or *common good* games).

Organizations and Open Innovation

We will use an organizational (more precisely, Open Innovation) context for the basis of the simulation to define more clearly the environment within which our agents are interacting. In this context, Crowdsourcing is often seen in as innovation-seeking: Organizations create, acquire, and integrate diverse knowledge and skills required to develop complex innovative technologies. Since knowledge is available from the outside (see, e.g., Chesbrough 2003) the organizations may benefit from leveraging external knowledge. Crowdsourcing is an increasingly popular approach to doing that. Not only are seekers and solvers involved, but also a wide variety of other, intermediate organizations. The acquired capabilities are combined and re-combined without centralized, detailed managerial guidance – again showing a high degree of self-organization. Joel West, one of the first researchers to address "Open Innovation", defined it as "using the market rather than internal hierarchies to source and commercialize innovations."

Other Important Insights

Two important underlying concepts in Crowdsourcing are *private information* and *tacit knowledge*, both emphasizing the "stickiness" of information (information used in technical problem solving is often costly to acquire, transfer, and use in a new location, see von Hippel 1994). An important prerequisite for the success of Crowdsourcing is to maintain the *diversity* of the crowd members' knowledge and skills throughout the process and to avoid *groupthink*.

Private information. The economist F.A. von Hayek ((von Hayek 1945) observed that humans possess a special type of local information that is hard to aggregate. Due to such "private information", nearly every individual "has some advantage over all others because he possesses unique information of which beneficial use might be made." Crowdsourcing brings together and motivates individuals to collaborate and produce innovation or solve problems based on this private information.

Tacit knowledge. Michael Polanyi coined the term in the 1950s using "riding a bicycle" as an example of something humans are able to do "without quite knowing how". In a Crowdsourcing context, three phenomena can be observed: Communication between different experts may lead to new developments, which implies that each expert's knowledge is not "tacit". What Crowdsourcing does is establish new correlations between pieces of knowledge acquired by individuals. A second phenomenon is knowledge that is not "owned" by an individual, or *collective tacit knowledge*. It is neither clear how it can be described nor how it is acquired as a "good of the group". An example of such collective tacit knowledge under constant change is human natural language, which is constantly changing. Crowdsourcing not only generates, but potentially also maintains collective tacit knowledge.

The third phenomenon derives from the observation that an individual may have knowledge but not be able to communicate it in a formalized way ("riding a bicycle"). Several studies suggest that especially such tacit knowledge and knowledge of technique are best conveyed through collaboration (Lee and Bozeman 2005), as happens in Crowdsourcing. In summary, Crowdsourcing helps to locate and productively use these different types of tacit knowledge that cannot be found by the most sophisticated search engines due to its "tacitness".

The combination of private information and tacit knowledge explains why "irrational" individuals can produce rational outputs: "Rationality" requires some basic assumptions plus logic. In order to apply logic, the assumptions need to be stated in one or the other form of a proposition. Tacit knowledge can be rational and logical, but cannot be stated or codified. Therefore, individual behavior may appear irrational to outsiders. Due to the collective intelligence unearthed during a Crowdsourcing interaction, combining private information (tacit or not) to a solution for a complex problem, the seemingly irrational becomes rational and productive. This implies, however, that optimal group outcomes are hard to achieve because the barrier of perceived individual irrationality needs to be overcome.

Expertise, diversity, independence and groupthink.
Scott Page (Page 2008) found evidence for the advantage of diversity in groups performing complex tasks by running agent-based simulations. His surprising insight was that groups with diverse agents almost always performed better than groups consisting only of expert agents. Herbert Simon (1996) used the term "docile" for individuals who tend to accept information and advice from the social groups to which they belong. He theorized that these individuals have great advantage in fitness over those who are not docile. And it is not easy to stay independent of a social environment since learning is a social process. One can therefore say that although the members of a crowd should show a certain level of docility by e.g., building on previous solutions (if public), the group as a whole should maintain a high diversity of skills and private information. On the other hand, the crowd should avoid groupthink. Irving Janis, defined the term "groupthink" in the 1970s as follows, based on William H. Whyte's original 1952 definition: "A mode of thinking that people engage in when they are deeply involved in a cohesive in-group, when the members' strivings for unanimity override their motivation to realistically appraise alternative courses of action.". On a closed Crowdsourcing platform, where solvers cannot see other solvers' solutions (which is often the case when monetary premiums are involved) the likelihood of groupthink is clearly much smaller. (Surowiecki 2004) identifies stock bubbles and crashes as famous examples where all of the factors that make crowds smart, disappear: independence, diversity, and personal opinion.

Synthesizing the above sections, once a problem has been formalized and established (and it is well understood what a solution is), methodologies exist for its solution, a group of experts may obtain the "correct" solution. However, as long as these methodologies do not exist, no "objective" formulation of the problem and/or evaluation criteria for solutions are not completely formalized, diversity may beat expertise (see

discussion and further references in Buecheler et al. 2010). Restricting the group of problem solvers to experts overlooks the fact that this happens at the price of groupthink (acquiring expertise usually includes a certain level of docility). Maintaining diversity therefore inhibits the very occurrence of groupthink.

Crowdsourcing in a Nutshell

This section briefly describes the Crowdsourcing process used for our simulator and introduces nomenclature in *italics*. (Muhdi et al. 2010) gives a more detailed description of the activities involved.

1. Deliberation: A *seeker* (an organization[2] or individual) decides to use external sources to generate ideas or solve a specific problem.
2. Preparation: The seeker chooses an intermediary (information broker), i.e. a website that brings together the seeker and the *crowd* (group of *solvers*) and usually enters into a contract with this information broker.
3. Execution: The seeker posts a *problem* on the Internet. The solvers self-organize and self-select which of all posted problems they would like to work on. The seeker might or might not interact with the solvers during this phase.
4. Assessment: After the execution phase (or perhaps in parallel), the submitted ideas are clustered, rated, and the best idea is rewarded. In our simulator, one to five ideas (the *winning solutions*) receive the *prize premium* (if any).
5. Post-processing: The collected ideas are incorporated into the seeking organization and "side effects" (e.g., creative spillovers useful elsewhere) are managed (if any).

Complexity and Focus Trade-off in MAS

This simulator attempts to optimize the balance between complexity and focus.

Many simulators for understanding social behavior are based on mathematical models using partial differential equations (PDEs). Multi-agent system simulations have been shown to have certain advantages over these models when simulating large groups of agents. This is also true for a Crowdsourcing model: PDEs cannot handle diverse populations efficiently. Diversity requires particle or agent based models for two reasons: PDEs are increasingly difficult to solve if the number of variables increases and they cannot handle discretization (you either have at least one individual knowing about XY in a group, or this knowledge is not there at all. There is never half of an expert) or stochastic fluctuations as appear in Crowdsourcing.

Our simulator is built on modules that incorporate empirically shown parameters in a Crowdsourcing scenario. Thus, it intrinsically simplifies and omits certain properties. (Couzin and Krause 2003) states that

---

[2] We use "seeker" for any kind of individual or organization (including companies and universities). Science is, in many cases, trying to find inventions or seek evidence for observed/hypothesized phenomena. The processes and paradigms, however, are similar to a large extent.

modeling often does not attempt to include all the known properties of a system, but rather to capture the essence of the biological organizing principles. […] to gain insight into the dynamics of a collective phenomenon not all of the complex details are necessary or relevant.

However, too much simplification can make a model unnecessarily unrealistic and uninteresting. The simulator includes an adequate level of complexity by incorporating several parameters, while focusing on the parameters that give the "simplest explanation" for the emerging phenomena.

Parameters Used for the Simulator

In this section, we show parameters allocated to "seekers", to the "problem" and finally to "solvers". In addition, we list some important global parameters used. See Figure 1 for an overview of the most important parameters and their interdependencies.

Seeker Parameters

The seeker parameters model environmental and internal variables for the seeking organization (e.g., a company or university).

Degree of revealing and Intellectual Property (IP) regime. Depending on the strictness of the IP (or "appropriability") regime (Teece 1986) organizations, especially firms, adopt different formal and informal methods (patents, trademarks, copyright, time-to-market, trade secrets) to adjust their degree of openness. This influences the potential success of the problem in Crowdsourcing: the trade-off between openness to provide maximum information to the solvers while protecting own intellectual property needs to be found. (Henkel 2006; von Hippel and von Krogh 2003) show that openness is not automatically a disadvantage. IBM (according to Kazman and Chen 2009 the most patent-productive company in the world) began making more money from crowdsourced services than from all its patent-protected intellectual property (Benkler 2006). (Dahlander and Gann 2010) has further elaborated on this trade-off in an excellent literature review on Open Innovation while (Lakhani et al. 2006) has shown the importance of openness in a Crowdsourcing context. The difficulties of protecting IP in Crowdsourcing have not yet been resolved.

University researchers tend to be more open (see, e.g., David 2003) but since the introduction of the Bayh-Dole Act in the US in 1980 and similar legislation in other countries, there has been a trend towards more "closed" research. In this context, (Heller and Eisenberg 1998) popularized and discussed the phrase "tragedy of the anticommons".

Level of NIH. (Katz and Allen 2007) described the effect of the "Not-Invented-Here" (NIH) syndrome, the "tendency of a project group of stable composition to believe it possesses a monopoly of knowledge of its field, which leads it to reject new ideas from outsiders to the likely detriment of its performance", on R&D project groups. This syndrome is clearly relevant in a Crowdsourcing context and it has been shown that a lower level of NIH supports successful internal and external solution development (Brown and Eisenhardt 1995).

Absorptive capacity. The term defined in (Cohen and Levinthal 1990) refers to the ability of a seeker to recognize the value of new, external information, assimilate it, and apply it to commercial ends. This parameter is assigned to the seeking agents and will rise over time, when the seeker climbs the Crowdsourcing learning curve and accumulates prior related knowledge (see also Brown and Eisenhardt 1995 for a discussion). The basic assumption for both NIH and absorptive capacity is that the individuals at the seekers' interfaces and the crowd co-evolve by exogenous influences and endogenous self-organization (Mitleton-Kelly 2003).

Historical success rate. This parameter is used to modify the "Level of NIH" and "Absorptive Capacity" parameters over time. In essence, it shows how far the seeker is on the Crowdsourcing learning curve.

Crowdsourcing success. This parameter can only be set as a dependent/output variable. It estimates the success of the product or patent based on the solution/idea gained in the Crowdsourcing process (not incorporating side effects). (Howe 2008) found that an InnoCentive.com company's average earnings from a successful solution are twenty times the fee paid to a solver. The parameter is influenced by the solution quality, the level of NIH and the absorptive capacity of the seeker. A side remark: The measurement of Crowdsourcing success varies widely between different types of organizations or businesses. Examples are business measures related to finances, employees' motivation, new product revenue, spending in R&D, number of patents, time to market, and combinations thereof. The build-up of absorptive capacity could in fact already be a goal and measure of success for an organization.

Problem Parameters

Problem value – intrinsic. Several Crowdsourcing interactions do not only target crowds looking for additional income, but also solvers working for intrinsic motivation. Open source developers, for example, show very different motivating factors (see intrinsic motivation factors, below).

Problem value – monetary. Most Crowdsourcing platforms assign a prize premium to a problem. Although on many platforms there is no limit, the seeker may divide the premium from zero up to five "winning" solutions in our simulator, in order to constrain simulation complexity (typical is 0 to 10).

Problem field. Every posted problem is assigned a primary and (optional) secondary field (or scientific discipline). Examples are "molecular biology" or "organization science". For our simulator, we used the fields selectable at Innocentive.com (currently the largest Crowdsourcing platform). Solvers do not only work successfully on problems from their respective fields: (Lakhani et al. 2006) found the odds of a solver's success increased in fields in which they had no formal expertise, confirming a network theory insight from (Granovetter 1973): The most efficient networks are those that link to the broadest range of information,
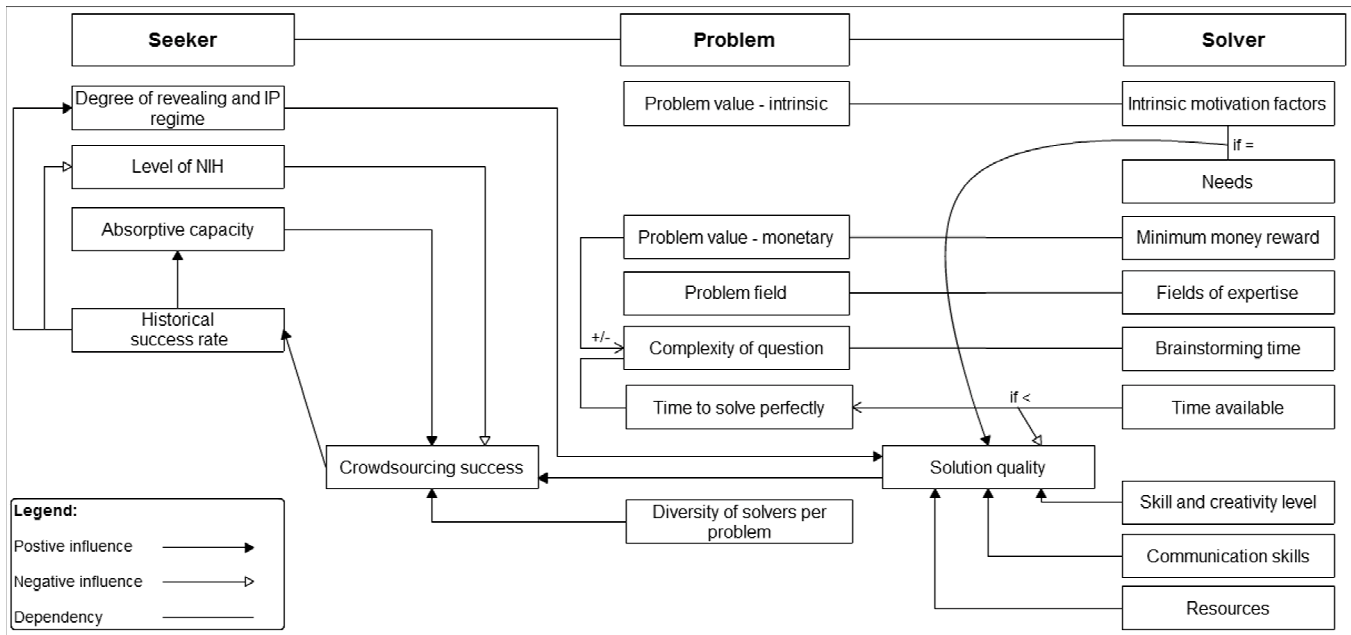
Figure 1 - Overview of simulation parameters described in this paper and their interactions

knowledge, and experience. (Howe 2008) summarizes another important insight from Lakhani's paper:

> A full 75 percent of successful solvers already knew the solution to the problem. The solutions to the problems in the study – many of which […] had stumped the best corporate scientists in the world after years of effort – didn't require a breakthrough, or additional brainpower, or a more talented scientist's attention; they just needed a diverse enough set of minds to have a go at them.

Complexity of question. This parameter indicates how complex a question is and the time investment needed by a solver. It also influences how well a solver can understand the question and how much time the solver needs to brainstorm a potential solution. (Benkler 2006) defines the benefits of dividing a problem to decrease its complexity as the "property of a project that describes the extent to which it can be broken down into smaller [...] modules that can be independently produced before they are assembled into a whole. […] While creative capacity and judgment are universally distributed in a population, available time and attention are not." (Schenk and Guittard 2009) differentiates between routine tasks Crowdsourcing and complex tasks Crowdsourcing: "Routine tasks Crowdsourcing seeks a number of complementary contributions necessary for the construction of data and information bases. Complex tasks Crowdsourcing follows a diametrically opposed pattern […]."

Time to solve perfectly. This parameter is used in the simulation to determine the time a solver would need to solve a problem perfectly. However, it is not known to seekers or solvers, but only to the simulator.

Diversity of solvers per problem. This parameter combines the diversity of solvers (backgrounds, age, etc.) that worked

on the solved problem. A higher diversity grade will generate a better winning solution (see "State of the art").

Solver Parameters

The solver parameters include parameters for the members of the crowd and the submitted solutions (if any).

In a Crowdsourcing scenario, pedigree, race, gender, age, level of expertise and similar are not relevant (on most platforms, the participants are anonymous to others). Such typical moderating variables in team and sociological studies are not relevant to Crowdsourcing success.

Intrinsic motivation factors.
Successful Crowdsourcing involves satisfying very basic needs. (Bartl 2010) writes:

> Drawing on a rich body of motivation research relevant motives are curiosity, self efficacy, skill development, information seeking, intrinsic playful task, recognition, altruism and community support, make friends, personal need/dissatisfaction or compensation and monetary rewards.

Solution quality. In the simulator, solution quality is influenced by the solver's skill level, communication skills, resources (e.g., laboratory supplies), time available and the seeker's degree of revealing (accuracy and background information in problem description). Examples of quality are, e.g., enhanced technical performance, lower cost, good reliability, contribution to the research question or uniqueness. Seekers judging the solutions are regarded as "satisficers" (Simon 1996).

Fields of expertise. Every agent has a set of skills in one or more fields of expertise, influencing both problem selection and solution success potential. However, the solver does not

necessarily need to have a field of expertise that matches the problem field exactly (see explanation of problem field, above). A solver with high general skill and creativity levels is able to pick problems outside his or her fields of expertise. The "skills" parameter includes the solvers' private information, as defined by von Hayek.

Brainstorming time. Indicates the total time a potential solver takes to understand and respond to a posted problem.

Time available. Analogous to computer programs like SETI@home that use collective CPU spare cycles for supercomputing and hence leverage the power of the network, crowd members generally contribute to posted problems during their "spare cycles", their downtime and energy not claimed by work or family obligations (Howe 2008), hence every simulator agent has a defined time available.

Skill and creativity level. This parameter shows a solver's ability to solve a problem well. With a skill and creativity level above a certain threshold, the solver is also able to select and work on problems outside the field of expertise.

Communication skills. A solver with a higher (written) communication skill will have a greater chance of winning since she or he is better able to describe the idea/solution. In addition, this parameter positively affects the communication with other crowd members (if enabled).

Resources. Comprises all relevant resources (infrastructure, tools etc.) except for time and money that an agent has at hand and that are relevant for the chosen problem.

Needs. An agent with a need related to a field or type of problem more likely picks that problem and, if working on the problem successfully (resources, skills, time etc.), has a higher likelihood of delivering a superior solution. (Putnam 2000) and several others found that social innovation often occurs in response to social needs and that market pull (identifying and understanding users' needs) is substantially more important to product success than technology push.

Global Parameters and Further Comments

For this simulator version, we assume a "closed" Crowdsourcing system, i.e., members of the crowd cannot see solutions already submitted by other members.

Acquaintances. The set of agents (seekers and solvers) starts with a set of agents the agent in question knows from "earlier times". With every Crowdsourcing interaction, the set grows. "Old acquaintances" might be forgotten over time.

Goal. Every agent has a "goal". For seekers, this is usually "maximization of Crowdsourcing success". Solvers have all kinds of goals, including maximizing an intrinsic motivation factor or monetary income.

Direct communication. A global parameter that toggles whether seekers and solvers can directly communicate after the solver has picked a problem. The parameter simulates anonymity that is ensured on many Crowdsourcing platforms.

A solution delivered by a solver communicating with the seeker increases the chance of winning (better understanding of the problem and its circumstances and hence higher quality solution). Communication with other crowd members decreases the solution quality due to reduced independence and diversity.

Whenever a relation is needed between parameters and there is no empirical evidence available, we use a "power law" according to (Mandelbrot and Hudson 2008) including the special case of the "1:10:89" rule: for every 100 people on a given site, 1 will create something, 10 will vote on what he or she created; the remaining 89 will consume the creation. "Super contributors", usually between 1% and 2.5% of all solvers, depending on the platform, are usually responsible for a large share of crowdsourced data and knowledge collections.

Simulator Set-up

(Wooldridge 2008) writes: "the steady move away from machine-oriented views of programming toward concepts and metaphors that more closely reflect the way in which we ourselves understand the world" is an ongoing trend. Further, he says agent-based solutions are appropriate when "the environment is open, or at least highly dynamic, uncertain or complex" and "agents are a natural metaphor". Our highly scalable simulator conforms to these prerequisites.

The Jade Framework Used for the Simulator

Jade ("Java Agent DEvelopment Framework") was developed in 2000 as "an enabling technology, a middleware for the development and run-time execution of peer-to-peer applications which are based on the agents paradigm" (Bellifemine et al. 2003).

Agents, as defined for this kind of multi-agent programming, are autonomous, proactive and social peers that are provided interoperation capabilities by the framework. Jade provides the programmer with the capabilities to create agents that are loosely coupled and come with a fully enabled asynchronous messaging system between all actors.

Further points for selecting Jade over other frameworks were its interoperability by being compliant with the FIPA ("Foundation for Intelligent Physical Agents,") specifications, its open source license, the large programmer community, the amount of documentation available and the great scalability.

Design

The simulator models both seekers and solvers involved in a typical Crowdsourcing context. The current version does not include the potential intermediary as an additional type of agent: The Jade Framework provides a "Yellow Pages" agent is used as a "broker" and matches solvers with problems.

Solvers are able to search the yellow pages as a directory for problems matching their given skills. The seeker and solver can then start communicating with each other directly, if allowed.

After toggling global conditions, users of the simulation software define value ranges for the active parameters and choose which variable is the dependent variable for this simulation cycle. Figure 2 shows a screenshot. The output
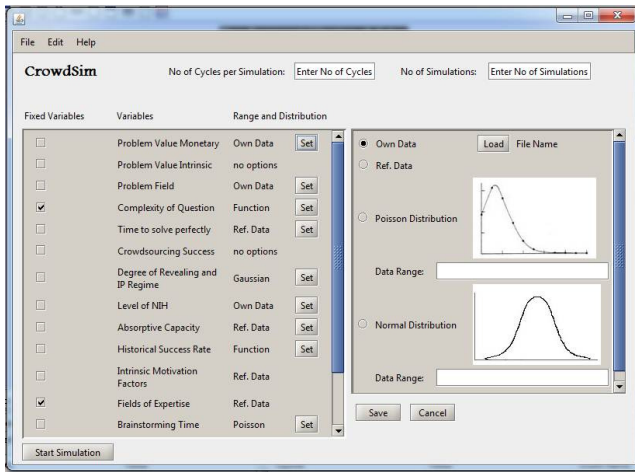
Figure 2 - Screenshot of parameter selection and data initialization screen

variables can be aggregated over several cycles and used for sensitivity analyses and other (e.g., statistical) evaluations.

Discussion and use cases

We present three use cases where the simulator can be used and further refined. The simulator's robustness is currently being increased by incorporating data from Crowdsourcing in two domains: Corporate R&D and basic science as conducted at research universities. To this end, we will use data collected in the studies presented in (Lakhani et al. 2006) and (Buecheler et al. 2010).

Use Case 1: Scientific Inquiry: Analogies to Biology

Scientists may (and will) use the simulator for confirming observations from biology in a complex network of irrational human agents. E.g., we hypothesize that solution development in open Crowdsourcing systems (as observed, e.g., in Mathwork's Matlab programming contests: Gulley 2004) resemble the developments of evolution in the sense that phases of regular, gradual evolution alternate with more punctuated sequences and stasis. (For a critical discussion see e.g., Smith 1988). In addition to these varying speeds, we expect to observe other phenomena like mass extinctions, co-evolution, and growing complexity of the behavior patterns and strategies that survive. (Emmeche 1994), (Lindgren 1992).

Use Case 2: Scientific Inquiry: Crowdsourcing Dynamics

The simulator helps achieve three goals that (Axelrod 1997) has compiled: 1. Explore/describe: find basic dynamics and interdependencies and correlations between (Crowdsourcing) parameters. For example, we hypothesize that the functions for resources, needs and fields of expertise need to be correlated to best approximate empirical outcomes and communication skills need to be correlated with acquaintances. 2. Confirm/explain: use the simulator to explain agents' complex behavior and verify or falsify assumptions while constantly ameliorating the simulator

through empirical data. 3. Forecast/predict: consider complicated input variables and influencing factors to generate predictions, heuristics or narrower solution spaces.

Use Case 3: Practical Use

Practitioners from the private sector (as well as scientists wishing to use Crowdsourcing as a tool, see Buecheler et al. 2010) may use the simulator for testing Crowdsourcing scenarios, parameter sensitivities and the optimal setting for their Crowdsourcing plans before setting up a real (costly) platform and interface. Crowdsourcing consultancies, which are currently being founded all over the world, can use the simulator to test real-life settings. This not only helps increase effectiveness, but also perhaps communicates the value of Crowdsourcing and supports increasing the openness of the seeking organization.

Conclusions

In contrast to simple existing models, the simulator allows the user to predict what is needed to achieve optimal Crowdsourcing results with the given resources, incorporating a large set of potential influences. In addition, the modular and extensible way the simulator is built enables the user to increase the accuracy and predictive power when scientists gain new empirical insights.

Contributions by Authors

Most of the theoretical contributions were written by the first, third and fourth authors. The simulator design and details are mainly contributed by the second author.

References

Alonso, O., D. E. Rose, B. Stewart. 2008. Crowdsourcing for relevance evaluation. *Newsletter ACM SIGIR Forum* 42(2) 9–15.

Axelrod, R. M. 1997. Advancing the art of simulation in the social science. *Complexity* 3 193–199.

Bandte, H. 2007. *Komplexität in Organisationen. Organisationstheoretische Betrachtungen und agentenbasierte Simulation.* Deutscher Universitäts-Verlag / GWV Fachverlage GmbH Wiesbaden, Wiesbaden.

Bartl, M. 2010. The Making-of Innovation » The Morphology of Co-Creation, http://www.michaelbartl.com/co-creation/article/the-morphology-of-co-creation/ (July 12, 2010).

Bellifemine, F., G. Caire, A. Poggi, G. Rimassa. 2003. Jade - A white paper. *exp* 3(3) 6–19.

Benkler, Y. 2006. *The wealth of networks. How social production transforms markets and freedom.* Yale Univ. Press, New Haven, Conn.

Brown, S. L., K. M. Eisenhardt. 1995. Product Development: Past Research, Present Findings, and Future Directions. *The Academy of Management Review* 20(2) 343–378.

Buecheler, T., J. H. Sieg, R. M. Füchslin, R. Pfeifer. 2010. Crowdsourcing, Open Innovation and Collective Intelligence in the Scientific Method: A Research Agenda and Operational Framework. H. Fellermann, M. Dörr, M. M. Hanczyc, L.

Ladegaard Laursen, S. Maurer, D. Merkle, P.-A. Monnard, K. Stoy, S. Rasmussen, eds. *Artificial Life XII. Proceedings of the Twelfth International Conference on the Synthesis and Simulation of Living Systems*. MIT Press, Cambridge, Mass., 679–686.

Camazine, S., J.-L. Deneubourg, N. R. Franks, J. Sneyd, G. Theraulaz, E. Bonabeau. 2003. *Self-organization in biological systems.* Princeton University Press, Princeton, N.J.

Chesbrough, H. W. 2003. *Open innovation. The new imperative for creating and profiting from technology.* Harvard Business School Press, Boston, Mass.

Cohen, W. M., D. A. Levinthal. 1990. Absorptive Capacity: A New Perspective on Learning and Innovation. *Administrative Science Quarterly* 35(1, Special Issue: Technology) 128–152.

Couzin, I. D., J. Krause. 2003. Self-Organization and Collective Behavior in Vertebrates. *Advances in the Study of Behavior* 32 1–75.

Dahlander, L., D. Gann. 2010. How open is Innovation? *Research Policy*(IN PRESS).

David, P. A. 2003. The Economic Logic of "Open Science" and the Balance between Private Property Rights and the Public Domain in Scientific Data and Information: A Primer. *Stanford Institute For Economic Policy Research* SIEPR Discussion Paper No. 02-30.

Dorigo, M., T. Stützle. 2004. *Ant colony optimization.* MIT Press, Cambridge, Mass. ; London.

Emmeche, C. 1994. *The garden in the machine. The emerging science of artificial life.* Princeton Univ. Press, Princeton, N.J.

Giles, J. 2005. Internet encyclopaedias go head to head. *Nature* 438 900–901.

Granovetter, M. S. 1973. The Strength of Weak Ties. *The American Journal of Sociology* 78(6) 1360–1380.

Gulley, N. 2004. In praise of tweaking: a wiki-like programming contest. *ACM Interactions* 11 18–23.

Heller, M. A., R. S. Eisenberg. 1998. Can Patents Deter Innovation: the Anticommons in Biomedical Research. *Science* 280 698–701.

Henkel, J. 2006. Selective Revealing in Open Innovation Processes: The Case of Embedded Linux. *Research Policy* 35(7) 953–969.

Howe, J. 2008. *Crowdsourcing: Why the Power of the Crowd is Driving the Future of Business.* Crown Publishing, New York.

Katz, R., T. J. Allen. 2007. Investigating the Not Invented Here (NIH) syndrome: A look at the performance, tenure, and communication patterns of 50 R & D Project Groups. *R&D Management* 12(1) 7–20.

Kazman, R., H.-M. Chen. 2009. The Metropolis Model: A New Logic for Development of Crowdsourced Systems, http://cacm.acm.org/magazines/2009/7/32094-the-metropolis-model-a-new-logic-for-development-of-crowdsourced-systems/fulltext (April 5, 2010).

Krause, J., G. D. Ruxton, S. Krause. 2010. Swarm intelligence in animals and humans. *Trends in Ecology & Evolution* 25(1) 28–34.

Lakhani, K. R., L. B. Jeppesen, P. A. Lohse, J. A. Panetta. 2006. The Value of Openness in Scientific Problem Solving. *Harvard Business School*(HBS Working Paper Number: 07-050).

Lee, S., B. Bozeman. 2005. The Impact of Research Collaboration on Scientific Productivity. *Social Studies of Science* 35(5) 673–702.

Leimeister, J., M. Huber, U. Bretschneider, H. Krcmar. 2009. Leveraging Crowdsourcing: Activation-Supporting Components for IT-Based Ideas Competition. *Journal of Management Information Systems* 26(1) 197–224.

Lindgren, K. 1992. Evolutionary phenomena in simple dynamics. C. G. Langton, C. Taylor, J. D. Farmer, S. Rasmussen, eds. *Artificial life II. Proceedings of the Workshop on Artificial Life, held February, 1990 in Santa Fé, New Mexico*. Addison-Wesley, Redwood City, Calif., 295–312.

Mandelbrot, B. B., R. L. Hudson. 2008. *The (mis)behavior of markets. A fractal view of risk, ruin, and reward,* 1st ed. Profile Books, London.

Mitleton-Kelly, E. 2003. Ten principles of complexity and enabling infrastructure. E. Mitleton-Kelly, ed. *Complex systems and evolutionary perspectives on organisations. The application of complexity theory to organisations*. Pergamon, Oxford, 23–50.

Muhdi, L., M. Daiber, S. Friesike, R. Boutellier. 2010. Crowdsourcing: an alternative idea generation approach in the early innovation process. *The proceedings of the XXI ISPIM Conference. The dynamics of Innovation*, [14 pages].

Page, S. E. 2008. *The difference. How the power of diversity creates better groups, firms, schools, and societies,* 3rd ed. Princeton Univ. Press, Princeton, NJ.

Putnam, R. D. 2000. *Bowling alone. The collapse and revival of American community.* Simon & Schuster, New York, NY.

Robu, V., H. Halpin, H. Shepherd. 2009. Emergence of consensus and shared vocabularies in collaborative tagging systems. *ACM Transactions on the Web (TWEB)* 3(4) Article 14.

Schelling, T. C. 1960. *The strategy of conflict.* Harvard Univ. Press, Cambridge, Mass.

Schenk, E., C. Guittard. 2009. Crowdsourcing: What can be Outsourced to the Crowd, and Why? HAL: Sciences de l'Homme et de la Société. *archives-ouvertes.fr.*

Sieg, J. H., M. W. Wallin, G. von Krogh. 2011. Managerial challenges in open innovation: A study of innovation intermediation in the chemical industry. *R&D Management*(IN PRESS).

Simon, H. A. 1996. *The sciences of the artificial,* 3rd ed. MIT Press, Cambridge, Mass.

Smith, J. M. 1988. Punctuation in Perspective. *Nature*(332) 311–312.

Surowiecki, J. 2004. *The wisdom of crowds. Why the many are smarter than the few and how collective wisdom shapes business, economies, societies, and nations,* 1st ed. Doubleday, New York, NY.

Teece, D. J. 1986. Profiting from technological innovation: Implications for integration, collaboration, licensing and public policy. *Research Policy* 15(6) 285–305.

von Hayek, F. A. 1945. The Use of Knowledge in Society. *American Economic Review* 519–530.

von Hippel, E. 1994. "Sticky Information" and the Locus of Problem Solving: Implications for Innovation. *Management Science* 40(4) 429–439.

von Hippel, E., G. von Krogh. 2003. Open Source Software and the "Private-Collective" Innovation Model: Issues for Organization Science. *Organization Science* 14(2) 209–223.

Wooldridge, M. J. 2008. *An introduction to multiagent systems.* Wiley, Chichester.