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Homo Socialis: The Road Ahead

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ABSTRACT

When I started the publication project with Herbert Gintis on the *homo socialis* (Gintis and Helbing, 2015), the most important motive for me was to trigger a scientific debate. So, from my perspective, our joint paper on the *homo socialis* is not to be seen as an end point or eternal truth, but as the starting point of a new theory for socio-economic systems. In this comment, I will expand on my paper with Herbert Gintis, and I will use the opportunity to present some further thoughts and materials.

1 Evolution of the *Homo Socialis*

Since my PhD days, I have wondered how it was possible that psychology, sociology, and economics were all claiming to model the decision-making of people, while at the same time using (at least partly) different sets of models and assumptions. So, overcoming the divide between economics and the other social sciences seemed necessary (Eckel and Sell, 2015), and this has been part of my research agenda ever since. My collaboration project with Herbert Gintis was born out of a project with Thomas Grund and Christian Waloszek, that was part of this agenda, where we put the *homo economicus* to the test. Thomas, Christian and I simulated the evolutionary dynamics that is sometimes claimed to be the reason for the existence of the *homo economicus*. Our computer simulation model distinguished utilities from payoffs and made four assumptions, none of which directly implied other-regarding behavior (Grund *et al.*, 2013; Helbing, 2013a):

1. Agents decide according to a best-response rule that strictly maximizes their utility function, given the behaviors of their interaction partners (their neighbors).

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2. The utility function considers not only the own payoff, but gives a certain weight to the payoff of the interaction partner(s). The weight is called the "friendliness" and set to zero for everyone at the beginning of the simulation.

3. Friendliness is a trait that is inherited (either genetically or by education) to offspring. The likelihood to have an offspring increases exclusively with the own payoff, not the utility function. The payoff is assumed to be zero, when a friendly agent is exploited by all neighbors (i.e., if they all defect). Therefore, such agents will have no offspring.

4. The inherited friendliness value tends to be that of the parent. There is also a certain mutation rate, but it does not promote significant levels of friendliness.

What did our computer simulations of the biological evolution of utility maximizing agents tell us? For many parameter combinations, the outcome was indeed a *homo economicus*, as most economists would expect. Surprisingly,

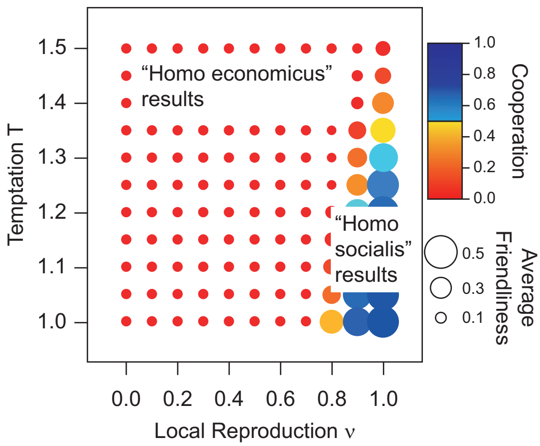

Figure 1: Outcome of an evolutionary simulation of human preferences (from Grund *et al.*, 2013). When children are raised close to their parents, we find not only other-regarding behavior (cooperation), but also the emergence of a *homo socialis* with other-regarding preferences. This provides a theory explaining experimental findings on fairness preferences, conditionally cooperative behavior, and individual utility functions (Fischbacher *et al.*, 2001). The results of the computer simulation further prove that the consideration of "externalities" (i.e., of external effects of decisions and actions) can yield a better system performance and benefit everyone, which hints towards superior organization principles for economies, as they now become possible by the Internet of Things with emergent sensor networks that will make it possible to measure externalities of all kinds (see http://papers.ssrn.com/sol3/papers.cfm?abstract_id=2583391 and http://futurict.blogspot.ch/2014/09/creating-making-planetary-nervous.html).

however, there was also an area of the parameter space, where a *homo socialis* with other-regarding preferences emerged, namely when offspring grew up next to their parents (see Figure 1) Given that most humans actually do raise their children at home, this is quite intriguing. It is also interesting that, while in the beginning of our agent-based computer simulations other-regarding preferences are disadvantageous, they can achieve higher payoffs after several dozen generations.

Remarkably, with the *homo socialis*, there exists a second reference point, besides the *homo economicus* that an analytical economic theory could be built around. So, is it possible that economic theory was developed around the wrong reference point? Indeed, many human interactions are indicative of the *homo socialis* rather than the *homo economicus*. Moreover, could it be that the difference between the behavior of the *homo economicus* and the *homo socialis* is so big that it cannot anymore be treated as a small deviation from the *homo economicus* – an approximation error, which averages out over sufficiently many decisions? If so, the average behavior would effectively deviate from mainstream economic theory, and we would need a new economic theory, and new economic institutions as well (see, for example, Helbing, 2013a – in particular the discussion of the social preference literature relating to economic laboratory experiments).

In fact, in an ever more networked world, where consumers interact and buy products through social media, the concept of separate decision-making is decreasingly plausible. If decisions become more interdependent than they used to be, theory must increasingly account for the implications of "networked minds," and representative agent theory will have to be replaced by theories of complex dynamical systems (Helbing and Kirman, 2013). As Gallegati (2015) points out: "sociality implies interaction, which produces externalities." And as Lewis (2015) underlines, Hayek noticed already early on that economic systems should be studied as complex systems. This would have to include explanations of emergent collective phenomena and novel system properties resulting from individual-level interactions as mentioned by Lewis (2015) and Nowak *et al.* (2015). The question is: are these just gradual improvements or will the implications of complex social interdependencies be as exciting as the discovery of quantum mechanics or of the theory of relativity? Is economic theory perhaps at a turning point?

One might, of course, argue that rational choice theory has already been adapted long ago to account for individual preferences. This is reflected by individual utility functions. However, it is too simple to say that economics is the study of choice under constraints with given preferences, and to leave it to sociologists to explain the individual preferences. As some of the comments to our paper have rightly pointed out (Hechter, 2015; Hodgson, 2015; Isaac, 2015), without a theory how to theoretically determine these individual preferences, ideally in advance, rational choice theory is pretty incomplete and of limited use. But, I believe that a theory describing how individual preferences and utility functions come about can actually be formulated. In fact, in the study of Grund *et al.* (2013), individual utility functions are an outcome of an evolutionary process, and they are a result of interactions in the past.

Having said this, let me respond to some of the comments to the paper of Herbert Gintis and myself, as I lay out further ideas on the evolution of human decision-making and its (as I believe) rather interesting implications. The replies to our paper contain many thoughtful comments, and I agree with many of them. They have highlighted different aspects that certainly deserve attention in the further debate about a core analytical theory for the social sciences. The great majority of these points actually turn out to have played important roles in my email exchange with Herbert Gintis, when we worked on our common paper. Apparently not all of these points made it into our paper, but this gives me an excellent opportunity to present them here.

2 Limitations of Equilibrium Theory

The question to what extent economic systems can be assumed to be in equilibrium, has been in the center of scientific debates (Ormerod, 2015; Witt, 2015). I have been questioning equilibrium approaches myself (Helbing and Balietti, 2010). In fact, they may not always be suitable to describe (decisions and learning in) quickly changing environments.

Therefore, my paper with Herbert Gintis certainly does not want to imply that equilibrium can always be assumed. Our point was to say that the analysis of stationary points can be insightful, and that the classical equilibrium concept can be extended in ways that consider social aspects. Generally, however, a system of equations of the kind $F_k(x_1, \ldots, x_i, \ldots, x_n) = 0$ with a solution $(y_1, \ldots, y_i, \ldots, y_n)$ may just reflect the stationary state of a dynamical set of equations $\mathrm{dx_k}/\mathrm{dt} = F_k(x_1, \ldots, x_i, \ldots, x_n)$. In such a case, it makes sense to determine the eigenvalues of the matrix with the elements dF_k/dx_i in the stationary point $(y_1, \ldots, y_i, \ldots, y_n)$. If all of these eigenvalues are negative (or have negative real values), deviations from the stationary point $(y_1, \ldots, y_i, \ldots, y_n)$ as they may be caused by perturbations of the system would tend to decrease over time. Consequently, the system would be driven towards the stationary point $(y_1, \ldots, y_i, \ldots, y_n)$ – at least, if there is just one stationary solution, or if the perturbation is sufficiently small. In this case, the system will be usually well described by its equilibrium $(y_1, \ldots, y_i, \ldots, y_n)$.

However, if at least one of the eigenvalues is positive (or has a positive real value), the system will eventually be driven away from the stationary solution

$(y_1, \ldots, y_i, \ldots, y_n)$, and it might end up in a different stationary solution. In systems of non-linear dynamical equations, non-stationary behaviors such as oscillatory or chaotic solutions can be possible as well, which is well-known from complexity theory (Haken, 2012; Nowak *et al.*, 2015). Moreover, even if (the real values of) all eigenvalues are negative (i.e., all variables tend to follow a damped dynamics) such that the system is expected to behave stable, it might happen that new perturbations occur before previous ones have disappeared. A nice example for this effect, which is sometimes called *convective instability*, is the "bullwhip effect" that is sometimes observed in supply chains (Helbing and Lämmer, 2005). A similar effect might be relevant for financial markets (where it may create bubbles or crashes) and for other socio-economic systems experiencing high innovation rates.

In fact, non-equilibrium behaviors of socio-economic systems are common. A socio-economic system in equilibrium cannot produce the innovations needed to adapt well to a changing world. It is the nature of many innovations that they destabilize a previously established equilibrium and promote a new structure, process or system behavior. Innovations tend to increase diversity, and diversity tends to accelerate innovation (Helbing *et al.*, 2005). Moreover, a diverse economy is related with a high gross national product (Hidalgo *et al.*, 2007; Page, 2008). Innovations are, therefore, desirable. The related process of differentiation is an important non-equilibrium feature of successful economies, and heterogeneity should therefore be a key ingredient of economic models (Gallegati, 2015).

So far, however, it is still a theoretical challenge to understand the conditions that create particular kinds of inventions, and also the conditions supporting their spreading. A model that allows one to grasp innovation as system-immanent process, considering effects of randomness, would be highly desirable. However, this is difficult because innovations may be disruptive in the sense that they do not just improve the performance of a previously existing technology or procedure, but also create entirely new quality dimensions or functionalities. As one of the comments put it, strategy spaces cannot be specified ahead of time (Wolpert, 2015). Innovation is open-ended (Lewis, 2015). It can transcend to the existing socio-economic system and may not be captured by a closed system of equations. Therefore, certain aspects related to novelty-generation and emergence, such as "radical" (Ormerod, 2015; Lewis, 2015) or "fundamental" uncertainty (Helbing, 2013b), where the probabilities and/or utilities of certain events cannot be enumerated anymore, are difficult to account for.

Nevertheless, evolutionary models (Helbing, 1992; Young, 1993; Weibull, 1997; Helbing *et al.*, 2005; Gintis, 2009) considering mutations are trying to grasp at least some of the process of novelty-generation. But certain outcomes can only be understood by co-evolutionary processes, for which correlations are essential. Then, the common factorization assumption used to derive the mean-value equations underlying many representative agent models cannot be applied (an application would eliminate relevant emergent phenomena). The entire concept of *correlated equilibria* (or *resonant correlations*, as Vernon Smith (2015) likes to call them) would obviously not work, if correlations were not relevant.

3 Role of Randomness

I fully agree that randomness may have significant effects (Smith, 2015). For example, it may lead to the emergence of cooperation between strangers (Grund *et al.*, 2013). The emergence of the *homo socialis* that I mentioned earlier would not occur without "errors" or "noise" (Smith, 2015). In fact, the transition from the *homo economicus* to the *homo socialis* needs a coincidence of random mutations of several behaviors in a certain neighborhood. Initially, such mutations are dysfunctional and do not pay off, that is, they turn out to be mistakes. But beyond a certain critical group size, friendliness pays off.

Another example for the relevance of noise has been given in a recent experimental paper (Mäs and Helbing, 2014). There, we have shown that a deterministic micro-level theory – the myopic best response rule – describes 96 percent of all individual decisions correctly, but it surprisingly fails to reproduce the outcome of the collective dynamics. This can happen when small deviations matter, that is, when the stationary (or equilibrium) solution is unstable. Then, tiny perturbations can sometimes trigger dramatic amplifications through cascade effects, which may even have system-wide impacts (Helbing, 2013b). Note that heterogeneity in a system may have similar implications as well (Gallegati and Kirman, 1999). In such cases, local interaction effects and correlations can be so relevant that they sometimes produce very different outcomes from what a representative agent model predicts (Gallegati, 2015).

Interestingly, adding noise to decision models can increase their predictive power. For example, in contrast to the above-mentioned deterministic best response model, a stochastic version corresponding to the multi-nomial logit model (McFadden, 1973), reproduces the distribution of macro-level experimental outcomes much better (Mäs and Helbing, 2014).

4 An Alternative Foundation of Decision Theory

In many cases, it is possible to model the role of noise by stochastic games (Wolpert, 2015) or by following a master equation approach (Weidlich, 2000). The latter can also be used as an alternative starting point of choice theory (Helbing, 1995). This line of thought to substantiate utility theory can be summarized as follows (Helbing, 2004): Let us assume choice options $x_1, x_2, \ldots, x_i, \ldots, x_n$, and choice probabilities $p(x_i)$ (which may change over time). Then we can define a transformation via $p(x_i) = N * \exp(ß^* v_i)$, where N is a normalization factor and $ß$ is a noise parameter. This transformation with the exponential function may be justified by the logarithmic law of psychophysics, underlying our senses or the geometric averaging that people tend to perform. There is also a relationship to the gross-canonical distribution in physics (Helbing, 1995). If the parameter $ß$ were infinity, this would correspond to a deterministic choice of the option with the highest utility, but in realistic settings, $ß$ is finite.

The values v_i, which I will call utilities, can be ordered to define a preference scale, which reflects different choice probabilities. An interesting implication as follows: Let us assume a lottery choosing x_1 with probability q and x_2 with probability $(1 - q)$. The expected utility of this new choice option x_3 would be $v_3 = q^* v_1 + (1 - q)^* v_2$. The choice probability would then be proportional to $\exp(ß^* v_3) = \exp\{ß^*[q^* v_1 + (1 - q)^* v_2]\} = \exp(ß^* q^* v_1)^* \exp[ß^*(1 - q)^* v_2] = p(x_1)^{q^*} p(x_2)^{(1-q)}$ with $p(x_1) = \exp(ß^* v_1)$ and $p(x_2) = \exp(ß^* v_2)$. This is the well-established and widely used Cobb-Douglas function.

In many cases, one needs, of course, to consider joint probabilities $p(x_i, x_j) = p(x_i|x_j)p(x_j)$. Then, the Bayesian formula follows directly from probability theory. We can also transform the conditional probabilities $p(x_i|x_j)$ of choosing x_i given x_j – without limitation of generality we may write $p(x_i|x_j) = N * \exp(ß^* u_{ij})$. Then, u_{ij} can be split up into an asymmetric and a symmetric part: $u_{ij} = s_{ij} + a_{ij}$ with $s_{ij} = (u_{ij} + u_{ji})/2 = s_{ji}$ and $a_{ij} = (u_{ij} - u_{ji})/2 = -a_{ji}$. One possible specification of the asymmetric part would be $a_{ij} = v_i v_j$, where v_i can again be called utility. s_{ij} may be interpreted as similarity between two options x_i and x_j. $d_{ij} = \exp(-ß^* s_{ij}) = d_{ji}$ can be used to define distances.

Conditional probabilities are necessary to understand not only conditional choice (which is, for example, relevant to understand social norms), but also sequences of actions, which are part of many social roles, and they are relevant for correlated equilibria as well. Turn-taking and its evolution is a nice example for this (Helbing *et al.*, 2005a).

The above foundation of utility-based decision theory has the appeal that it does not require to assume a computation or even the maximization of utility. It just assumes choice probabilities. When conditional probabilities are considered, one can also model dependencies on irrelevant alternatives and intransitive preferences scales (Isaac, 2015; Ormerod, 2015), such as different restaurant choices (Hodgson, 2015). In fact, conditional preferences are important to understand the variability of preferences over time. For example, when we have eaten, we are not hungry anymore, and other things become more preferable. I will come back to this saturation-kind of time dependence of individual preferences below.

Another nice example is a competitive game on a circle, where one gets the highest payoff, if one is a step ahead of the others (Frey and Goldstone, 2013). This produces a constant forward movement. For example, in business, one always likes to be a step ahead of the competition. This causes constant change. But after a few steps, one might end up again where one started. In fact, *fashion cycles* are a well-known phenomenon (Helbing, 1995).

5 Beyond Rational Choice

In agreement with some of the comments (Goldstone, 2015; Nowak *et al.*, 2015), I am convinced that the above decision theory needs further extensions. There is a lot of evidence that evolution has equipped humans with different incentive and reward systems, for example, sexual pleasure (to ensure reproduction), possession-related satisfaction (to survive in times of crises), appreciation of novelty (to explore opportunities and risks), or empathy-related satisfaction – sympathetic fellow-feeling, as Vernon Smith (2015) calls it. These establish different motivational factors, which I claim, should not be aggregated into a single utility function, but would be better represented by different dimensions of utility.

These different utilities cannot be perfectly traded against each other, and their relative importance may change quickly, thereby changing also our preference scales. In other words, human behavior results from different drivers, which dominate for some time and then give place to another. At each point in time, depending on the respective situational context, we prioritize a certain objective – here, the concept of *self-regulation* comes in (Lindenberg, 2015). The switching between diverse objectives might be imagined to work similarly to the self-controlled traffic lights we have developed to serve vehicle queues at intersections (Lämmer and Helbing, 2008). This self-control approach is based on the service of the most pressing local needs. Interestingly, when the externalities on neighboring intersections are taken into account, this distributed bottom-up control even outperforms classical attempts of top-down optimization (Helbing, 2013a).

Let us discuss next how the apparently incompatible decision theories based on rational choice models and on the concept of decision heuristics (Gigerenzer *et al.*, 2000; Gilovich *et al.*, 2002) may be related to each other. It is plausible to me that people try to increase their different rewards (see the “hedonic goal” mentioned in Lindenberg (2015)), and that they learn various heuristics for this, to improve their turnouts. It also makes sense to assume that a heuristic is selected depending on the situational context of a decision, such that framing matters (Lindenberg, 2015). In contrast to the utility-maximizing approach of rational choice theory, heuristics do not necessarily result in optimal choices. However, they are time- and energy-efficient, and on average, they work well, given sufficient opportunities to learn. Therefore, after a long enough learning time, the application of good heuristics would come pretty close to the maximization of a utility function. In other words, on an aggregate level, rational choice theory would be a good approximation of heuristic-based decision-making (but multiple utility dimensions for different, non-aligned reward systems and the switching between them would still have to be taken into account). In such a framework, rational decision-making may be seen as an emergent, approximate outcome, depending on the decision context (Gallegati, 2015).

In fact, I am convinced that we can understand the diverse reward systems as results of (co-)evolutionary processes, and that the decision heuristics and their application can be explained as a result of reinforcement learning, given certain cognitive abilities. The ERC MOMENTUM project, which I am currently leading, is trying to elaborate such an approach, based on agent-based computer simulations of cognitive agents with a virtual brain. These simulations distinguish processes on three different time scales: (i) decision-making, (ii) learning, and (iii) biological evolution. They involve genetic inheritance under mutations and reinforcement learning in an environment, where individuals compete for different kinds of rewards and individual success influences reproduction rates and the likelihood to be imitated. The ultimate ambition of the MOMENTUM project is to explain the emergence of the reward systems, individual and collective intelligence, social behavior, and culture from first principles.

Furthermore, to understand collective intelligence, it is important to consider the social nature of individuals. *Networked minds* (Grund *et al.*, 2013) allow for parallel information processing, knowledge sharing, etc. Then, not everyone has to evaluate all pieces of information relating to a certain problem (such as identifying the best insurance contract). It is enough if everyone evaluates some information and then compares the conclusions with others. (In fact, we don't read the details of all insurance contracts, before we choose one, but we ask some colleagues and friends we trust, and follow up some of their recommendations by further in-depth analysis. This is something not well represented by a theory of independent decision-making.) Putting it differently, collective intelligence allows individuals to process information in a distributed way, and to jointly find solutions that are better than each individual one. An important precondition for this is diversity, that is, the fact that individuals often do not decide and behave in a representative way (Page, 2008).

6 Gene-Culture Co-evolution

This brings us to the subject of gene-culture co-evolution, the understanding of which requires concepts such as cultural and multi-level selection (Lewis, 2015). Determining to what extent individual preferences result from genetic inheritance as compared to cultural transmission by learning will certainly require further scientific studies. Universal facial expressions (Ekman and Friesen, 1971) probably support the genetic inheritance of certain cultural abilities, but many other aspects such as religious values and beliefs may be just transmitted culturally. Imitation (Helbing, 1992, 1995), teaching, and learning play a similarly important role for inheriting culture, as genetic inheritance plays it for the spreading of physiological capabilities. There must be a reason why most human offspring stay with their parents for almost two decades. This actually suggests a high relevance of cultural transmission.

However, when trying to understand human behavior, the role of biology can certainly not be ignored. Evolution determines our physiological capabilities. Our brain determines our cognitive ones. Cognitive abilities influence our behavior, our social institutions, and our reproduction, hence, evolution as well. In other words, we probably have a co-evolution of physiological, cognitive and social abilities. In fact, in certain cases it is not so clear whether a behavior is genetically inherited or culturally spread. For example, is a preference for fairness and cooperation genetically or culturally inherited, or both? The capacity to speak, evolving together with language use, is an interesting example for a co-evolution between physiological and cultural abilities. I also expect that the cognitive capacity for empathy (being able to put oneself into the shoes of others, see Lindenberg (2015)) is genetically transmitted, while education determines how we use it.

7 Importance and Origin of Morality

The above considerations are also relevant for another important subject, which has been highlighted by one of the comments, namely learning to self-restrain (Smith, 2015). It has been rightly pointed out that "formal legal rules are insufficient to generate emergent coordinated actions; informal moral rules of promise-keeping and truth-telling are needed as well." (Lewis, 2015; see also Hodgson, 2015). Yes, moral judgments are not simply expressions of an individual's interests, preferences, sentiments or beliefs, but a matter of doing the right things, even if one doesn't like them. And, I agree that the ability to consider moral rules is part of what makes us human. In particular, I concur with the statements that "norms are a glue of societies," as Michael Hechter (2015) points out, and that the "moral legitimacy of the legal system in the eyes of citizens is crucial" (Hodgson, 2015; see also Lindenberg, 2015).

The theory of correlated equilibria offers a partial understanding of some of these issues. For example, it allows one to explain the emergence of social conventions (Helbing, 1992; Young, 1993), social norms (Helbing and Johansson, 2010), or turn-taking without a *choreographer* (Helbing *et al.*, 2005a; Goldstone, 2015). Generally, social conventions and social norms help to improve coordination and to reduce transaction failures (Winter *et al.*, 2012). They may change the conditional choice probabilities or even the choice set (when norms are internalized). However, the concept of correlated equilibria is certainly not giving a full picture. On the one hand, contents of moral values are hard to capture by means of theories. On the other hand, norms are often stabilized ("cemented") by institutions such as police and jurisdiction, religion and culture.

But can we at least understand the origin of morality by quantitative models? This is in fact the case. A partial answer is given by one of our agent-based computer simulations (Helbing *et al.*, 2010). It studies a social dilemma situation, in which people can choose between four different strategies: (1) cooperate and punish defectors, (2) just cooperate, while avoiding costly punishment, (3) defect, or (4) defect while punishing other defectors. One may call type (1) moral and type (4) immoral or hypocritical behavior. The simulation outcomes for this setting, when assuming the imitation of better-performing behaviors of interaction partners, is quite interesting: When everyone interacts with everybody else or with randomly chosen interaction partners, corresponding to a representative agent model, a "tragedy of the commons" results, where most individuals defect, while defection is not punished. In contrast, in a spatial setting where everyone interacts with direct neighbors, moral behavior can emerge, that is, a widespread cooperation with a punishment of defectors. (Therefore, both the first- and second-order free-rider dilemmas are solved.) This is due to homophily: "birds of a feather" (i.e., similar strategies), cluster together. As a consequence, moralists don't have to compete with cooperators, but interact with defectors, such that costly punishment can succeed and spread. Local interactions and the co-evolution of punishment and cooperation are the keys to success. But, the evolution of morality has, of course, further facets: it also involves deliberation, which requires higher-level intellectual abilities; and it also concerns the evolution of particular cultures and social institutions.

8 Role of Data and Experiments

Finally, I agree with the comment that we need better data even more than better theories (Macy, 2015). Therefore, the role of computational social science (Lazer, 2009) deserves to be stressed a lot more. I believe quick scientific progress of socio-economic theories will crucially depend on the establishment of a circular feedback between theory and empirical or experimental evidence (Eckel and Sell, 2015): data allow one to validate and calibrate or even empirically derive socio-economic models, but theories can also help one to identify interesting decision experiments (Helbing and Yu, 2010) and to set up better measurement processes.

Besides lab and web experiments, Big Data about human activities will play a much bigger role in future socio-economic research (Conte *et al.*, 2011). This ranges from the behavior of financial markets (Preis *et al.*, 2012) over mobility patterns (Song *et al.*, 2010) or daily activities (Golder and Macy, 2011) to the spreading of culture (Schich *et al.*, 2014). I also agree that we need to pay more attention to the socio-economic interaction networks (Schweitzer *et al.*, 2009; Hechter, 2015; Macy, 2015; Nowak *et al.*, 2015), as they can have dramatic influence on the system behavior (Helbing *et al.*, 2010). The activities of my research team are, in fact, trying to bring these aspects together. For this, we have developed the Open Data Search Engine, "Living Archive" (http://livingarchive.inn.ac, https://github.com/bitmorse/livingarchive), the NodeGame platform for Web experiments (http://www.nodegame.org/preview/, https://github.com/node Game), and the Virtual Journal platform to identify relevant scientific literature across disciplinary boundaries (http://vijo.inn.ac, https://github.com/bitmorese/vijo). These activities subscribe to an open source spirit enabling a community-based effort. The aim of the FuturICT initiative (http://www.futurict.eu) is to develop this on a global scale. We can do this together and thereby create a collective knowledge base that cuts across disciplinary boundaries. It would be great, if we could even establish a collective (problem-solving) intelligence, which goes beyond an additive approach. Will you be part of this?

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