

Towards a new brain science: lessons from the economic collapse

Jaime Gomez-Ramirez,^{*†} and Manuel G. Bedia [‡]

Abstract

Economies are complex man-made systems where organisms and markets interact according to motivations and principles not entirely understood yet. The increasing dissatisfaction with the postulates of traditional economics i.e. perfectly rational agents, interacting through efficient markets in the search of equilibrium, has created new incentives for different approaches in economics. The science of complexity may provide the platform to cross disciplinary boundaries in seemingly disparate fields such as brain science and economics. In this paper we take an integrative stance, fostering new insights into the economic character of neural activity. The objective here is to precisely delineate common topics in both neural and economic science, within a systemic outlook grounded in empirical basis that jolts the unification across the science of complex systems. It is argued that this mainly relies on the study of the inverse problem in complex system with a truly Bayesian approach.

1 Introduction

Since the financial crash in 2008, economic science and the economic profession are under siege. Critics point fingers at ivory tower economists, devoted to the construction of unfalsifiable models based on unrealistic assumptions in purely theoretical basis. Economies are complex man-made systems where organisms and markets interact according to motivations and principles not entirely understood yet. Neo-classical economics is agnostic about the neural mechanisms that underlie the valuation of choices and decision making. The increasing dissatisfaction with the postulates of traditional economics i.e. perfectly rational agents, interacting through efficient markets in the search of equilibrium, has created new incentives for different approaches in economics. Behavioral economics [3],[25] builds

¹Universidad Politécnica de Madrid
José Gutiérrez Abascal, 2 Madrid 28006
*E-mail address:*jd.gomez@upm.es

²Biomedical Engineering Laboratory, Okayama University
700-8530 1-1-1 Tsushima-naka , Kita-ku , Okayama-shi

³Universidad de Zaragoza
María de Luna 1, 50018 Zaragoza
*E-mail address:*mgbedia@unizar.es

on cognitive and emotional models of agents, neuroeconomics addresses the neurobiological basis of valuation of choices [23],[14] or Evolutionary economics [5], [7],[6],[2],[8] which strives for a new understanding of the economy as a complex evolutionary system, composed of agents that adapt to endogenous patterns out of equilibrium regions. The science of complexity may provide the platform to cross disciplinary boundaries in seemingly disparate fields such as brain science and economics. Social science, and in particular economics, is undergoing a decisive historical moment. New mathematical models able to palliate the dissatisfaction with core tenets in classical economics, like rational agents, symmetric information and equilibrium need to be devised.

We argue that the most important problems that natural and social science are facing today are inverse problems, and that a new approach that goes beyond optimization that takes into account the subjective knowledge of the agent is necessary. The rest of the paper is organized as follows. Section 2 describes the main assumptions of orthodox economics and why they provide an ill-founded basis. Section 3 addresses the issue of predictability, and it is argued that the idea of having predicting model in non deterministic physics, entails a wrong understanding of the ill-posed nature of the inverse problem. Section 4 provides a new theoretical framework for modeling complex economic systems that emphasize the relevance of adopting an “inverse thinking” approach in solving the inverse problem. We conclude with Discussion in 5.

2 Orthodox economics

The core tenet of orthodox economics axiomatically states that agents are 1) perfectly rational 2) maximizers of a function cost and 3) interact in an equilibrium market. This triad has shown itself to be fatally flawed. Markets are instruments of extraordinary efficiency in processing information, integrating the views of a large number of agents regarding the prices of complex assets. In classical economics, it is assumed that prices fully reflect all available and relevant information, which is equally accessible for all agents. In this view, prices adjust almost instantaneously to every new piece of information or perturbation driving each price to its new equilibrium state.

There are several drawbacks to this theory. First, markets are composed of heterogeneous agents with very different models, motivation and strategies. Second, the rationale that markets are regulated by a sort of homeostatic mechanism able to drive prices to their intrinsic values, has been disproved during financial crashes. It might be emphasized that this view is also reductionist, in the sense that information is ultimately and entirely reflected in one variable, the price of the stock. Third, the idea of equilibrium is an intrinsic epistemic asset in conventional economics. Thus, an economic explanation can be seen as finding the minimum set of basic assumptions necessary for establishing the existence of equilibrium which is unique and stable [20]. Conventional economic models, in order to make their models workable i.e. get the analytical solutions, entail unrealistic assumptions such as, the existence of a global conservative law

or perfect competition between agents, which are utility maximizers that make an optimal use of information that is identically available for all the agents.

3 A new look to predictability

In several occasions, economic models have shown to be powerless in predicting bubbles and crashes that were invariably followed by important disruptions in economic activity and even social unrest. It might be remarked that modern macroeconomic theory may not possibly predict crisis, because it is built upon a corpus of theoretical assumptions in which such extreme events may not be predicted at all [1]. Yet it is worth reminding that the use of terms like predictability or deterministic behavior in systems of the extraordinary complexity of national economies is, at best, a formidable exercise of optimism. This statement is also valid for systems of very reduced dimensionality. Since Lorenz [21] and Rössler [24], it has been known that chaotic behavior may occur in systems with as few as three variables. Thus we cannot pretend to find predictability in systems which are myriad of order of magnitude larger. Clearly, we might not ask for a new science of economics with predictive powers in situations where predictability is out of place. We can only expect from social scientists to predict financial bubbles and market crashes, as much as it is expected from natural scientists to predict earthquakes, tsunamis or virus mutations.

3.1 The inverse problem

The main point that we want to make here is that all the problems in the previous section, predicting financial bubbles, tsunamis hits etc. are inverse problems. Inverse problems are ill-founded and that is the reason why we are bad at predicting those critical events. To solve an inverse problem is to infer the value of parameters of interest for a given phenomenon, based on the direct measurement of observables. This form of inference is ill-posed in the sense that solutions to the problem may not exist, be multiple, and be instable, that is, small error in the measurements lead to large differences in the solution [16]. In engineering the inverse problem is to solve the inverse of the forward model's equations, that is, given the equations that describe the system's configuration or system's internal state $m(x)$, calculate the equations of the position and momentum of the system y .

$$m(x) = y, x = m^{-1}(y) \quad (1)$$

Systems identification or inferring the model m from the accumulation of observations (x_i, y_i) is also an inverse problem, in statistics system identification is called regression problem.

There are strong limitations to this approach, not only technical issues like the unrealistic assumption of linearity in order to use frequency domain techniques, but at the phenomenological level. First, the problem is ill-posed in the sense that there are infinitum continuous time functions

f , that perfectly match the sampling data, that is, we have redundancy. Second, the problem is unstable because small errors in the output function y may be amplified, resulting in much greater errors in the estimation of the function m . Interestingly, increasing the sampling rate of the measured function does not solve this situation, it may indeed worsen it [10]. This condition needs to be conveniently recognized, specially in the current state of increasingly powerful measurement techniques. New strategies that aim to quantify the uncertainty in model and data need to be explored [9], [27]

3.2 Dealing with the bias/variance dilemma in the inverse problem

In any process of inference lies a fundamental problem, this is what Geman calls the bias and variance dilemma [13]. The error in approximating a function $f(x)$ that matches the observed data y , has two components, the variance which related to the uncertainty in the measurement of data, and the bias which is due to uncertainties in the model space, $\varepsilon = b + v$, where ε is the error, b is the bias and v is the variance. The bias and variance dilemma states that in order to minimize the error we can reduce the error of one of the components, bias or variance, but not both of them. Thus, or we bet on variance by assuming that measurement uncertainties are trivial, or we bet on bias by neglecting inaccuracies in the model, but we can not get along with both. A direct implication of this statement is that the idea of finding an optimal solution for the inverse problem must be abandoned.

The regression problem in statistics, which is a particular case of inverse problem, will help us to elaborate this point. The regression problem is to find an estimator $f(x) = y$ for the purpose of approximating the desired response y . The regression of Y on X is $E[Y|X]$, that is, the mean value of Y given X . Non parametric estimators can be arbitrarily well approximated, this property is called consistency and it is the major reason of the popularity of non parametric estimators such as neural networks or Boltzman machines. Consistency guarantees that for a sufficiently big training data set, non parametric estimators achieve the best possible performance for any learning task. It is important to note that the condition of a “a sufficiently big training data set” entails that consistency is an asymptotic property, which can be formally stated as follows:

$$\lim_{n \rightarrow \infty} E[f(x) - E[y|x]] = 0 \quad (2)$$

that means that non parametric estimators $f(x)$ are consistent for all regression problems $E[y|x]$. But there is a toll to pay here. The versatility of the estimator to optimally approximate any task is necessarily sensitive to the characteristics of the data. For example, when data samples are small or have dispersed distribution, parametric estimators may outperform non parametric ones. Indeed, non parametric estimators are optimal because they are consistent, but consistency is an asymptotic property. In real problems, the training data set can not be assumed to be arbitrarily big, therefore we have to deal with the variance. If we acknowledge

this basic fact we can see clearly that the traditional approach in the inverse problem, consisting on finding the operator or model that optimally predicts the outcomes is unrealistic because it is based on an asymptotic property i.e. consistency, and technically unsuitable due to nonlinearities in the functions to be optimized and the high dimensionality in space of candidates.

4 Cisbioeconomics

We coin the term *cisecobionomics* which refers to the study in biological basis of how economic units make decisions to adapt within a ecosystem, using an inner or subjective perspective. Here we understand economic unit as a system with an internal representation of itself, for example living organisms (and not only them) are economic units, ecosystem as the network of economic units that are modeled using an internal or first person *cis* approach. The internal perspective aims at quantifying what information the economic unit has about its world, rather than quantify the information that external observers have of the economic unit. It ought to be remarked that the rationale in using optimal functions such as utility or value in either brain and economic theories, must be found not only in mathematical tractability. This approach entails an idea of the inverse problem that is at odds with the ill-posed nature of the problem. We need to introduce a priors or bias, that is, knowledge of the model parameters such that variability can be reduced without eliminating possible solutions.

It has been proposed the the function of all nervous systems can be viewed as “decision-making” to promote future biological fitness [11]. In this respect, decision making in the brain can be seen as a process that tries to minimize its uncertainty about the world. Thus the computational goal of the brain is to anticipate the output of actions in order to minimize uncertainty about its world. This view is compliant with Helmholtz conceptualization of the brain as an inference machine that predicts sensations. The use of Bayesian probability theory has additionally suggested a complementary view in which the brain aims to optimize the probability representation of what caused its sensory inputs. The Bayesian brain hypothesis postulates the brain as an inferential machine, that makes predictions about the world based on probabilistic models, that are updated according to the sensorial information available at every moment. Friston has built a variant on the Bayesian Brain wherein the brain optimizes a free-energy function that tells the error between the brain internal representation and the true state of the world that is being represented [12], [19]. The free energy principle integrates other global brain theories that share the view of the brain as an optimizing machine. For example, in Hopfield’s approach [17], [4] neural network attractors mediate in cognitive processes like concept formation and memory, and operate according to the optimization of an overall energy function. In [22] the function of the brain is to optimize the mismatch between sensory input and the predicted inputs of the model. The free energy principle aims to unify theories like neural Darwinism, infomax principle or Bayesian brain, which

share a common assumption i.e. the brain always optimizes one quantity, called value, expectation or free-energy, depending on whether the approach relies upon economic, Bayesian or thermodynamic theory respectively.

Thus, we have identified a critical common theme that pervades in brain function modeling and in economic systems modeling: there is one quantity called by names like value, expected reward or utility that is being maximized, or minimized in which case the quantity is called surprise, cost or prediction error. In particular, the free energy is an upper bound in surprise

$$\text{surprise} = \frac{1}{\text{value}} \quad (3)$$

in such a way that organisms avoid undesirable surprising states by minimizing their free energy, in order to keep their internal physiological state values within regions that promote their survival.

However, the idea that the complex machinery of the brain may be reduced to the minimization of one single quantity seems very unlikely. This is rooted on the mistaken understanding of homeostasis as the universal physiological principle [15]. There are other forms to achieve dynamic stability different to homeostasis [28]. Friston understands the brain as an inference machine that is always optimizing its free energy by avoiding surprises, that is, the brain is constantly minimizing surprises which may be pernicious for the survival of the organism. It must result obvious that this view is reminiscent to idea of utility maximisation as a mechanism that drives economies to equilibrium. Among other things, financial crashes have very acutely showed that the conception of economic equilibrium based on the mechanical analogy of a pendulum is untenable. The benefit attained in terms of mathematical tractability by adopting the hypothesis that economic agents achieve equilibrium by maximizing utility, must not make us neglect basic facts. For example, the idea that economic agents are utility maximizers is unverifiable, it is a necessary a priori to solve the equations for a unique and stable equilibrium, that is to say, we need a priori knowledge or bias to deal with the inverse problem. The bias works as a selection mechanism that reduces the set of solutions of the inverse problem. Once we have the models that result to apply a bias, the next step is to test how well they predict. Thus, predictions allow us to discard forward models when their prediction do not match a given criterion, but not to solve the inverse problem [26]. The idea of using optimization as a solver of the inverse problem is untenable and was described in detail in section .

Economic agents, that is, human beings provided with brains, value goods and services in order to take decisions referred to those goods and actions in an attempt to forecast a favorable outcome. But they decide so in multiple ways according to ecological and historical contexts. Moreover, their actions have one direction that goes from the irreversible past to the uncertain future. With this caveat in mind, basic assumptions in the free-energy principle for the brain like “any self-organizing system that is at equilibrium with its environment must minimize its free energy [19]” must be carefully scrutinized. Moreover, to assume ergodicity in a non dissipative systems like the brain is hardly justifiable [18]. The same critic

and rationale necessarily applies to economic systems modeling.

5 Discussion

Complexity science has had a considerable success at addressing questions with a new synthetic vision and a conceptual toolkit that orthodox approaches miss. However, the answer for many of those questions remain unsolved. We sorely need to develop a theoretical framework, based on realistic scenarios in which the plurality of internal motivations of the economic agents (individuals, firms, institutions), help us to establish a systemic understanding of complex socio-economic systems. In this paper we defend the view that economics may be called to act as a natural bridge able to connect social and technological aspects. This positioning may sound extremely risky, the recent financial meltdown and the inability of the economic models to forecast these extreme events, has done nothing but reinforced the old motto “economics is the dismal science”.

The paper sets the basis of a new theoretical foundation to address the inverse problem, that is, deduce models of function from the behavioral analysis of the system, with a truly subjective or Bayesian approach. Predicting financial bubbles, the eruption of a volcano, or the formation of cognitive neural networks in the brain are inverse problems, which as we know since Hadamard’s seminal work are not well-posed problems. The paper explores the challenges that economic modeling faces and put them in perspective with recent advances in brain function theory like the free-energy principle. It provides a new perspective in tackling the inverse problem, adopting a truly Bayesian internalistic view, that does not rely on searching an unique solution to the inverse problem through maximization of functions like utility. Here we adopt an “inverse thinking”, which mainly relies on the introduction of bias or a priori knowledge that constrain the solutions of the inverse problem. The candidate models are then tested against the data, that is, those that do not predict data within an established criterion are discarded or falsified in Popperian parlance. Note that this approach is different from solving the inverse problem by calculating the optimal function that is the best match with the given data. The paper builds on this approach to provide new insights to complex system modeling that spring from a truly Bayesian approach to the inverse problem in complex system modeling.

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