The economic agent's Meta-Brain: a biological-economic complex agent-based model

Daniela Cialfi[1,2,*,†]

[1]Institute for Complex Systems (Council of National Research of Italy) UoS La Sapienza University, 00185 Rome, Italy
[2]Enrico Fermi Research Center, 00184 Rome, Italy

Abstract

During last decade, agent-based models show even more challenges regarding economic agent's behaviour: while agent-based models could produce behavioural complexity without a complex brain, some models that simulate economic behaviour assumed to do that with a brain. At the same time, artificial intelligence presents a similar challenges involving representation complexity: while minimal representation could produce behavioural outputs like economic decision-making processes, elaborate internal representations might offer a variety of behaviours. For this reason, the consequences of complex economic behavioural repertoires and flexible internal models has involved the implementation of more realistic and informative agent-based models. In this research paper, it is highlighted a different way to address the above-mentioned issues via the use of computational approach called meta-brain model. More specifically, rather than taking a standard deep learning approach, the layers' implementation is instead inspired by biological neuroanatomy trying to mimic the neocortical-thalamic system relations. To conclude, it is proposed an economic meta-brained agent architecture able to modelling a specific cognitive-economic process: the acquisition of an external knowledge by an economic agent. Then, the application of this economic meta-brain model might be used to build the heterogeneous representations specific for particular environmental context.

Keywords

Complex agent-based model, Economic meta-brain, Variational free energy principle, Uncertainty

1. Introduction

Nowadays, according to Donald J.Former, what emerges is the necessity to treat economy as a complex system. This consideration allows researcher to analyse the behaviour of non-linear systems and in particular, what emerges from the interaction of low-level buildings blocks [1]. Within this new framework, the attention of scholars is focused on the role that technology could have in the economic growth: key instrument which favours the development of more efficient goods and service production. From this consideration what emerges is the existence of deep relationship between knowledge, technology and economic growth: it could be seen as

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*Corresponding author.
danielacialfi@gmail.com (D. Cialfi)
0000-0001-8953-062X (D. Cialfi)

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[1]From a methodological point of view, this was possible thanks to the adoption of physics and neuroscience concepts, such as Bayesian Brain, statistical mechanics and active inference.

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the result of an increase in the flow of knowledge and, on the other side, the rise of new ways of cooperation between the various actors of the economic system. Consequently, the principal purpose of this paper is to present a new architecture able to master action, optimisation and choice assumptions when applied to economic theory. By describing the concept known as the variational free energy principle, this paper draws its attention to how this methodological architecture could be used to mitigate the rational choice theory trying to re-formulate the way how an economic agent optimises [2]. The present approach will result in an economic agent Meta-Brain which implements a specific process: the acquisition of external knowledge and how the economic agent transform it internally [3].
To conclude, the present paper is structured as follows: Section 2 attempts to discern the way how economy could be seen as a complex system and Section 3 presents the methodological configuration used in the present paper. Next, Section 4 gives an empirical application of the variational free energy principle developing at the first instance an Economic Meta-Brain and, in the second part of the section, a cognitive model of a specific economic system. Finally, Section 5 provides final remarks and discusses the future challenges presented by this avenue of economic research.

2. Economy seen as a complex systems

As emerged in the Introduction, related to the concept of technology as a complex phenomenon, scholars are directing their energy toward the analysis of knowledge as a complex phenomenon as well. This is possible thanks to the presence of a methodological shift: from a macro-type level of analysis, in which the relationships between different actors of the network are studied exclusively in a specific time interval, to a micro level where the object becomes the agent behaviour. Just the rising of this shift led to the following question:

How does an economic agent combine internally the different knowledge bases?

A possible answer derives from considering the economy seen as a complex system. According to [2], the use of the second law of thermodynamics, necessary to contextualize the relationship between evolution and complexity, can be used also to describe an economic system. More specifically, this approach could allow the formalisation of a new notion of economic evolution: the development of complexity structure within the economic system generated, for example, by the continuous acquisition of the energy available from the surrounding environment. This, according to the hypothesis formulated by [3], leads to affirm that economic systems could be seen as an inevitable consequence of the reformulation of entropy law [4]. Continuing along

[2]In the theory of optimal control learning, the major purpose is to select an action that maximises some value function such that the preferred state of the world will evidence the action itself. From the mathematical point of view we have

$$u_t^* = \arg maxV(s_{t+1}|u_t) = \pi(s_t) \quad (1)$$

where u represents the action, s the state of the world and π the optimised action.

[3]Making this assumption is important since it could be useful for the economist to operational and transform immaterial process, e.g. the acquisition of external knowledge, into material one, such as the objective explanation of the economic utility.

[4]To be precise, according to the author, the economic system could be considered evolutionary stable due to their efficiency in expanding both the process of acquiring knowledge and structural complexity of the economic system

this line, according to [2], it is possible to state that *"[...] as economic systems grow and develop, they should increase their total dissipation, develop more complex structures with more energy flow, increase their cycling activity, develop greater diversity and generate more hierarchical levels, al to abet energy degradation. Rules which survive in economic systems are those that funnel energy into their own production and reproduction and contribute to autocatalytic processes which increase the total dissipation of the system. [...]"*([2], p.356) [5]. Drawing the attention to this point, the rise of these interactions means that the evolution of the economic system can also take place via experimental mechanisms. For that reason, in the subsequent Section 4, a complex agent-based biological-economic is modelled in the form of a Meta Brain.

3. Why the Variational Free energy setting

As stated in the Introduction, in this research paper it is used the variational free energy principle to provide a first attempt to take into consideration how an economic agent should behave given a very high degree of complexity.In more deep, the aim is to minimise the variational free energy ([4]) providing a first formal description of the Simon' *bounded rationality* via the application of the evidence bounds. By minimizing variational free energy means:

- Application of variational mathematics to Bayesian optimality;
- Highlight the existence of bound between a recognition density and a generative density, also referred to as a Kullback-Leibler.

Consequently, this implies the minimization of an entropy system. Consequently, according to [5], as a result of the previous proposition The approximation of the Bayesian inference could be defined as a method the estimates the posterior distribution or density since the presence of computational complexity associated with the likelihood functions present in complex problems. Furthermore, this method could be used to formalize the concept of bounded rationality, as conceptualize by Simon [6]. From the previous two prepositions, derives the following lemma According to [7] and [8], action will be proceed in reference to a functional of probability distributions over preferred states where the current beliefs give the conditions for optimal behaviour taking into consideration the prior preferences [7]. As a consequence, it is possible to affirm that in the free energy principle The goal is not to maximise the expected utility but to optimise beliefs about the word states represented by $u_t^* = \arg minF(Q(s_{t+1})|u_t)$ via the subsequent actions $\pi^* = \arg min \int_\tau F(Q(s_t)|\pi)$ where $u_\tau = \pi(\tau)$. As it is possible to stress out from the above theorem, in the free energy formulation, we can not associate to an economic agent with a specific objectives or values but only states which are functions controlled by

itself. Moving on, The authors stated that the production of new knowledge and structural complexity is the result of a energy degradation.

[5]So, the immediate implication concerns the evolution of the economic system. In particular, this evolution is seen as the result of the co-evolution of knowledge and the structural energy transformation of the economic system itself.

[6]It is possible since, according to [6], Simon's notion of bounded rationality could be associated with a limitation of a cognitive process.

[7]This lemma has introduced the notion of duality (o reciprocity) between loss functions and priors. In other words: For any observed choice or decision, there are some priors that render this decision Bayes optimal.

beliefs. [8].
To sum up, the empirical application of the theorem 3 will be seen in the second part of the next section where it implements the cognitive model of a specific economic process.

4. The economic agent's Meta-Brain model: a biological-economic complex agent-based model

Nowadays agent-based models have always presented a more sophisticated and complex challenge when they come to modelling behaviour, as in this case, of an economic agent. All this is caused by more preponderant role of representational complexity: while the minimal representations can produce behavioural outputs in the form of decision-making processes, the most elaborate internal representations they have to cope with a greater variety of behaviours. All this setting is proposed with the intention of developing, under computational framework, the internal mechanisms that regulate the economic agent's capacity to acquire external information, in this case knowledge, and to transform it internally. Instead of use the standard deep learning approach, in the present research paper it was preferred an setting inspired by the biological neuroanatomy, and more specifically, by the Bayesian Brain. The choice of using this latter approach is to be found in the attitude of the brain to encode a generative model about causes of sensation able to predict sensory input ([10] and [11])[9]. For this reason, in this paper it was used the variational inference schema by the utilisation of *Kullback-Leibler-divergence* (KL-divergence hereafter) which measures the closeness of two distributions.

4.1. The economic agent's Meta-Brain model

From a strictly mathematical point of view, it is not possible to minimise the *Kullback-Leibler divergence* (KL-divergence hereafter) exactly, but it could be minimised by a function that is equal to it up to a constant. According to [7], the following result function is called *variational free energy* or *Evidence Lower Bound* (ELBO hereafter) [10]:

[8]The reader might have note that here it is not just a matter of next best action optimisation but to optimise the best sequences of actions in line with a time average equals to $\sum_{\tau}$. Thereby, according to [9], this means to apply the Hamilton's principle of least action (i.e. accumulated cost) when it is referred to good or bad behaviour.

[9]This perspective abstracts away from any particular algorithmic or neural claims. Consequently, all algorithms (and similarly any neural implementation) that compute exactly the posterior give equivalent predictions with respect to the central claims of the Bayesian brain hypothesis. Lying on this approach, generally speaking, deterministic methods are considerably faster since they turn inference into an optimisation problem over the objective function. In fact, for most of the generative models it is impossible to implement exact Bayesian inference due to the fact that there might be no analytic formula for computing the posterior densities. In this sense, there are two dominant approaches:

- Sampling (e.g. Monte Carlo methods) or;
- Deterministic approximation (e.g. variational inference) methods (e.g. [12], [13]).

[10]It is interesting to note that different bounds might potentially might lead to distinct *modes of preferences* despite the same underlying generative model. Lying on this research line, this hypothesis implies that behavioural differences might be explained by changes to the variational inference objective.This gives to the reader a family of hypothesis to test different variational objectives and their impact in explaining behavioural differences between

$$L = H[q(s)] - \ll logp(s,o) \gg_{q(s)} \tag{2}$$

For this reason, in this part of the section is implemented the economic agent's Meta-Brain through the explicit derivation of the ELBO [11].

Simple system. Let's introduce two random variables, $s \in S$ (state of world) and $o \in O$ (outcomes), with a joint density $p(o,s)$ such that

$$p(o,s) = p(s)p(o|s) \tag{3}$$

where $p(s)$ is the prior density and $p(o|s)$ is the likelihood. Now, the inference problem is to compute $p(s|o)$ such that

$$p(s|o) = \frac{p(o,s)}{p(o)} \tag{4}$$

where $p(o)$ contains the marginal density of the outcomes (the so called *evidence*). From the above equation 4, the further step is to calculate the evidence by marginalising out the states from the joint density:

$$p(o) = \int_s p(o,s)ds = \int_s p(o|s)p(s)ds \tag{5}$$

The reader might notice that the evidence integral not being available in closed form, it requires the application of the variational inference notion to make the ELBO and KL-divergence explicitly as follows [12]. If it is assumed that $p(s|o) \neq 0$ and $q(s) \neq 0$, the previous equation 5 is transformed as follows

$$\begin{aligned} logp(o) &= logp(o) + \int log\frac{p(s|o)}{p(s|o)}ds \\ &= \int q(s)logp(o)ds + \int q(s)log\frac{p(s|o)}{p(s|o)}ds \\ &= \int q(s)log\frac{p(s|o)p(o)}{p(s|o)}ds = \int q(s)log\frac{p(s,o)}{p(s|o)}ds \\ &= \int q(s)log\frac{1}{q(s)}ds + \int q(s)logp(s,o)ds + \int q(s)log\frac{q(s)}{p()s|0}ds \end{aligned} \tag{7}$$

where the left term of above equation represents the ELBO while the right term describes the KL-divergence. Making both terms explicit will allow us to use them internally of the subsequent cognitive process as this setting will lead to the presence of a great flexibility of the computational structure within the model specification.

economic agents.

[11] This implementation represents the key element for the further development of the acquisition of external knowledge and consequently how the economic agent transform it internally.

[12] In this regard, it is necessary to introduce a variational density q that can be integrated in the following way

$$q(s) \approx p(s|o) \tag{6}$$

This adjustment allows the reader to make a move from $p(o) \rightarrow \log p(o)$ to make the computations easier.

4.2. A first attempt to implement a cognitive model of a specific economic process

As stated above, in the present second sub-session it is implemented the cognitive model of a specific economic process with the use of the Meta-Brain concept described previously.
Under mathematical point of view, the goal is not to maximize the expected utility attributed to a specific state of the world (= the acquisition of a new technology), but optimise the beliefs about the states of possible worlds

$$u_t^* = \arg minF(Q(s_{t+1})|u_t) \tag{8}$$

by the application of the successive action principle

$$\pi^* = \arg min \sum_{\tau} F(Q(s_\tau)|\pi) \tag{9}$$

To apply this mechanism to the cognitive model, it is necessary to minimize the KL-divergence possessed by the agent economic, or in other words, to minimize the previous Meta-Brain [13]. By performing this minimization, the KL-divergence will become equal to zero and the agent's behaviour can be described through the following equation [14]

$$\ln P(\pi) = -G \tag{10}$$

where $\ln P$ is the probability distribution of the policy π and G the *expected free energy* which assigns the goodness to any expected policies τ. Consequently, if G could be viewed as the agent action scheme, it is possible to model a economic cognitive process based on the variational free principle as follows:

$$G = \sum_{\tau} E_G(O_\tau, S_\tau|\pi)[\ln P(O_\pi, S_\tau)|\pi) - \ln Q(S_\tau|\pi)] \tag{11}$$

where

- $\ln P(O_\pi, S_\tau)|\pi$ represents the energy term describing that the hidden states of the world S_τ (=the pre-existing condition within the context where economic agent acts) which causes
- the observable outcomes O_τ (=the behaviour of the agent given the knowledge transferred) given a particular policy τ (e.g. the development of a particular technology followed by the knowledge exchange) [15].

This implies that the specific economic process could be summarize as follows

- The first step is to look for the information it can provide a prediction on what will be the best policy (= search for the right agent to transfer your knowledge to);

[13] More specifically, this mechanism generates an intensity measurement which describes an approximate posterior distribution given the policy π.

[14] What emerges is the existence of a cognition cost: since the selection policy has a cost which is equal to the expected free energy G.

[15] Here the $\ln Q(S_\tau|\pi)$ describes the economic agent beliefs after the consequence of the policy τ.

- Subsequently, based on the information available within context (= given the initial conditions in which the economic agent is immersed), the next steps are motivated by sub-strategies that aim to align the desired events to the real ones (= for example this is right transfer my knowledge to this specific agent?);
- Through this measurement made by the agent, any future app-proximity (= to arrive at an increase in productivity) will be aimed at solving the problem of uncertainty through progressive revelation of the hidden states of the world.

Further implications. According to [14], this principle, under determinate and restricted conditions (e.g. where the perfect information is equal to $\ln Q(S_\tau|O_\tau,\pi)$), could be assimilated with the KL-control or *risk sensitivity* in the following way:

$$E_G(O_\tau, S_\tau|\pi)[\ln P(O_\tau|m) - \ln Q(S_\tau|\pi)] \tag{12}$$

indicating the existing difference between what agent will believe happen given a specific policy ($\ln Q(S_\tau|\pi)$) and what the agent want to have happen ($\ln P(O_\tau|m)$). Therefore, by this measure, in each further step the agent's goal is trying to reduce the presence of the uncertainty about the next course of action by revealing the hidden states of the world [16].

5. Conclusions

From what emerged throughout the present paper, the creation of knowledge,seen as a process of increasing the structural complexity of a economic system, it can be considered as the result of the second law of thermodynamics. In particular, it has been used a new setting, the variational free energy principle, in order to describe a specific economic process: determining what role the knowledge plays in the economic growth. This process has been possible through the implementation of a economic agent's Meta Brain first and a unified framework subsequently centred on the beliefs optimization rather than the utility maximization.From this first implementation emerges the necessity to continue along this line of research to build a more organic representation of the economic theory: describe how complex systems, like economics, could be able to balance the expected utility axioms violation and the optimization of an economic agent beliefs which follows the Hamiltonian principle of least action. This new investigation line unfolds in the following advances: i) assuming that the economic agents actually carry out optimization procedures, it is necessary not only that inside the decision making process heuristics and strategies can be used but build a procedures capable of selecting them and of adopt an appropriate representation of the same; ii) build an economic-cognitive representation of the future related to the temporal discounting behaviour of the agent, where this function should depend on real-time adaptions; and iii) introduce the pre-commitment notion into the economic theory, indicating with the previous term the strategy or method of self-checking

[16] According to [15], if there is uncertainty about volatility or how will be the further state of the world, the expected utility of specific outcome will decrease as it approaches the future. Then, according to [16], the previous statement could be considered as the natural consequence of the uncertainty accumulation phenomenon since time, according to [?], could be associated with the precision of beliefs regarding the way the economic dynamics change.

that an economic agent might use to narrow down the number of the choices available in a future time.
In conclusion, the present research paper represents only a first starting point for putting into effect the previous lines of investigation by the creation of an specific observation universe capable to verifying them.

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