Models and People:
an alternative view of the emergent properties of computational models

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Abstract

Computer models can help humans gain insight into the functioning of complex systems. Used for training, they can also help gain insight into the cognitive processes humans use to understand these systems. By influencing humans understanding (and consequent actions) computer models can thus generate an impact on both these actors and the very systems they are designed to simulate. When these systems also include humans, a number of self-referential relations thus emerge which can lead to very complex dynamics. This is particularly true when we explicitly acknowledge and model the existence of multiple conflicting representations of reality among different individuals.

Given the increasing availability of computational devices, the use of computer models to support individual and shared decision making could potentially have implications far wider than the ones often discussed within the ICT community in terms of computational power and network communication. We discuss some theoretical implications and describe some initial numerical simulations.

1 Introduction

Within the Complex System Science (CSS) framework, the analysis of computational models in terms of emergent properties is usually carried out in relation to a model's functioning, that is in relation to what a model *does* [1-6]. As an example, we can consider an ecological model as shown in Figure 1. This model can be analysed in terms of the ecological processes we aim to simulate or, at increasingly lower levels of analysis, in terms of the abstract mathematical concepts used to describe such processes, the numerical tools used to implement the mathematical concepts, the algorithms used to carry out the computation and so on. Then, much of the study of emergent processes focuses on how the interactions among entities and processes at a certain level generate qualitatively different processes at higher levels of analysis [3,7-10].

A similar analysis can be carried out in the 'opposite' direction, that is at levels of analysis 'above' the model itself. In this case, we focus on how a model is *used*. For example, our ecological model can be used to address scientific questions or support real-world decision making. At these higher levels of analysis the model itself interacts with other entities, structures and agents including data and other computational tools. Specifically relevant to this discussion, at this level it also interacts with people: modellers, scientists, decision makers and at times the general public.

The main proposition of this paper is that the analysis of these 'higher' levels can be carried out within the same CSS framework used to describe a model's functioning. This allows us to recognise that some processes arising from the interaction between models and people can be defined as emergent according to the very same definitions commonly used to analyse the interaction of agents and processes within a computational model.

As an example, we discuss how our ecological model may be used i) to address a scientific question and ii) how the scientific insight so gained can then be used to facilitate, guide or support decision making in an hypothetical environmental management problem (Figure 1, top) [11-16].

2 Computational models and scientific questions

Within a traditional, positivistic view of science, we can interpret the scientific endeavour as formulating and answering questions: an experiment attempts to provide a more or less definitive answer to a question formalised in the form of a hypothesis.

Increasingly, models are used in place of real-world experiments for this purpose [17-21]. Technically, models don't answer questions, they process an input and generate an output and a modeller needs to interpret input and output in relation to the question [22-24]. We like to think that models carry out conditional predictions [25-27], that is, the output of a model is a prediction of a future state of a system, given the conditioning imposed by the initial state (as represented by the model input) and the system dynamics (as coded in the model algorithm). Within this view, one aspect of the art of modelling lies in designing the model input so that it usefully describes the hypothesis. This description should be accurate but broad enough to allow the modeller to generalise the answer (implicit in the model output) beyond the precise technical details of the model implementation.

It is important to highlight that formulating the question, mapping it into the input and model dynamics, and interpreting the model output in terms of the question are actions carried out by the modeller, not the model [28]. At this level of analysis the model clearly interacts with the modeller, possibly other scientists who provide the hypothesis and the data on which a model is tested.

3 Computational models and real-world decision making

At the next level of analysis the scientific insight obtained via our model could provide knowledge or information to policy makers or the general public. Three issues[1] become particularly relevant here. First, at this level, questions are most often inverse, not direct. In addition, effectively converting modelling results into information useful for decision making is affected by barriers which have more to do with human cognition and psychology than the complexity of the problem at hand: i) different types of uncertainty besides traditional scientific uncertainty and ii) complex aspects of human cognition besides rational/scientific thinking, become particularly significant. We analyse these issues here.

The vast majority of questions of real-world significance are inverse [22,35]. Direct questions ask about the *final* state of a system given the initial state. For example, a direct question may ask, given certain physical properties, whether pillars of specific size and material can enable a bridge to sustain a certain load. In contrast, inverse questions ask about the *initial* state of a system given the final state. An inverse question asks *what* size and material properties pillars need to have to enable a bridge to sustain a certain load.

Complex inverse questions can almost never be answered via direct modelling, because rarely a model of the inverse process is available [22]. Rather, most inverse problems need to be solved by iterative methods in which a forward model is run with different sets of inputs until a reasonable match between the model output and a desired state is found. Inverse questions thus require the machinery of

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[1] We acknowledge that these issues also affect the use of model in scientific enquiry [29-34], but in general they manifest themselves more clearly and have a larger impact on the decision making phase on the process.

inverse theory [35,36], whether carried out implicitly by the modeller [37-39], or explicitly via computational routines. As a result, inverse modelling is considerably more complex than forward modelling. It requires further artistry from the modeller in the choice of the inversion procedure, the search parameter space and various trade-off between computational efficiency and target precision. Also, inverse modelling requires more challenging cognitive effort to translate its results into information useful for decision making.

Once a scientific advice based on this inverse question is provided to the decision makers, this information needs to be analysed in terms of its level of uncertainty. Modellers and decision makers can understand uncertainty quite differently, as captured graphically in Figure 2. Uncertainty to a modeller or a scientist is commonly understood in terms of data accuracy, model reliability and inherent process stochasticity (Figure 2a). Within this view, additional information can reduce uncertainty by helping develop a better model of the problem. Indeed, minimising the uncertainty of a model outcome (understood, as in Figure 2a, as the difference between current knowledge and reality), given some constraints on computational resources, can be viewed as the very definition of optimal model [1,2,4,40,41]. However, real-world decision-making is a social process, which needs to account for a very large set of constraints and requirements. Here uncertainty assumes a social connotation and the acceptance of model results becomes dependent on, among other issues, context, type of problem, implications of the model, characteristics of the audience, the reputation of the modeller, frames of reference, power relations and culture [42,43]. Within this view, additional information does not necessarily reduce uncertainty, because the information itself is processed in terms of the cognitive-social context and existing worldviews (Figure 2b). Because worldviews influence the mental representation of the problem, a unique computational model of these mental models may be very difficult to develop, if possible at all. Crucially, even if this computational model could be developed, the assessment of its suitably and quality would also not be unique, since different worldviews may embrace difference criteria according to which the accuracy of the model should be evaluated. In these situations, the challenge is less about developing good or optimal models, than about accepting, sharing and negotiating models.

It is within this social framework that the cognitive processes of each individual decision maker take place. An extensive literature describes how these cognitive processes go well beyond the traditional rational analysis usually expected from technical policy making [44-59]. People can make apparently trivial logical mistakes [49,59-67], filter scientific advice depending on whether it confirms or contradicts their expectations and desires [68-77] , and employ different levels of cognitive effort in analysing scientific advices depending on the decision making context [49,51,52,78-83].

Particularly important for our discussion, these cognitive processes are not randomly distributed within the population, rather they are highly correlated. This means that they can be modelled, at least in principle. A number of tests [84,85] can provide the modeller with a signature of the team the model needs to interact with, to help design a communication program. Importantly, this information can also be used to describe the agents our ecological model needs to simulate. We discuss this in the next section.

4 Modelling real-world decision making

It is today well understood that modelling can support the management of natural resources not only by studying the dynamics of the resource itself but also by simulating how humans regulate their interaction with and exploitation of the natural resource [15,86]. This implies that our ecological model, for example, needs to include the very decision-making process described in the previous session, including its cognitive components.

It is easy to see how this leads to a self-referential process: the model is now asked to simulate i) the way the model itself is used to make decisions, ii) how these decisions affect the ecological processes and iii) how these in turns affect the next decision-making process step, in a potentially adaptive manner.

An attempt at making these modelling relations explicit is discussed in [87]. It describes a simplified model of how the general public represents the climate change debate as the interaction between wealth generation, population dynamics and warming. This simplification is chosen purposely to study the way people represent and reason about climate change rather than the dynamics of the actual, highly complex bio-physical and socio-economic system. Among various parameters describing the basic functioning of the climate, economy and the human system, two sets of parameters were specifically designed to account for i) the different beliefs the public may hold on whether and how climate change can impact the environment and the economy and ii) the different values which underlay preferences for various climate mitigation and adaptation policies. Different sets of value and belief parameters effectively allow the numerical model to implement different climate change 'mental models' commonly found among the general public. Conditioned on its inherent simplification, the model can then be used to provide numerically and dynamically consistent projections of the system state into the future. In other words, the model allows us to assess the dynamically consistent environmental and economic consequences of different sets of mental models (beliefs and values).

We then asked members of the Australian public to implement a numerical version of *their* climate change 'mental model' by setting the belief and value parameters [88]. Also, we asked them to predict the long-term dynamical evolution of the system (that is to 'run' their mental models), which we compared to the predictions of the numerical model. The results of this experiment are particularly suggestive: the responders' chosen parameterisation is largely in line with current scientific agreement and correlates well with their stated and measured attitudes. However, the match between the responders' future state projections and the ones obtained via the numerical model (using as input the parameters chosen by the responders) was poor. This appears to be due to two factors [88]. First, while the choice of the model input parameters (describing the current system state) correlates well with the responders' political ideologies and attitudes towards the environment and the economy, the responders' future projections correlate with their aspirations and fears. Two different cognitive processes seem to be at play in *formulating* vs *evaluating* a mental model, which may prevent establishing a coherent link between model assumptions and conclusions. Second, many responders failed to account for the feedbacks inherent in the proposed model, which is in line with the well-known impact of poor appreciation of system dynamics on decision making [49,60-67,89,90]. These results suggest that decision makers (including the general public) would be able to parameterise simple numerical models in a manner which is both meaningful and consistent with their mental models. These models may then help them overcome known cognitive difficulty by bridging the gaps between assumptions and expectations and by helping them assessing the impact of dynamical processes on the likelihood of specific policies' achieving their stated goals.

This discussion highlights a role for a numerical model which is rarely discussed within a CSS framework: not only can a model help understanding the functioning of a complex system, but also it can provide an insight into the user's cognitive strategies, biases, assumptions, beliefs and aspirations, which in turns may affect the functioning of the system via the impact these insights have on the user's actions.

5 Modelling, emergence and causation

We started by analysing the role of a model in supporting decision making and this led us to discussing the role of the model as providing an insight into cognitive aspects of human decision making. Here we discuss whether these two roles can be framed within a common understanding of the relation between mental and numerical models.

Usually, numerical and mental models are understood as alternative representation of a natural process. Modellers in particular often see their models as virtual laboratories, miniature versions of the real world, in which experiments can be more easily carried out. The reliability of a model is then discussed in relation to the match between modelled results and observations (Figure 3a). This view leads some authors (and many users) to scepticism about the ability of computer models to represent and predict the behaviour of highly complex systems [91-99].

However, a numerical model necessarily needs to originate from the modeller's understanding of the modelled process, that is from a mental model. This suggests that the numerical model can also be seen as a formal implementation of the modeller's mental model. This is the view according to which Nature does not solve differential equations, but mathematicians do. A model implementing a numerical solution to a differential equation is thus simulating the action of a mathematician, not of Nature (Figure 3b).

According to this view, it is natural to use a *numerical* model to simulate or verify the conclusions of a *mental* model. Rather than underscoring the inadequacy of a numerical model in simulating reality, this view highlights the benefits inherent in carrying out a simulation via a computer rather than via our cognitive abilities: fast computation, check for consistency, circumvention of known human fallacies, explicit formalization of assumptions and unbiased presentation of the results. In the philosophy of science, this view has been defended by Paul Humphreys [100] who argued that computational models are best understood as extensions of our native cognitive capacities.

Within an emergence framework, this leads us to analyse the interaction of a computer model with reality, the mental model it originates from and the modifications to the mental model it may suggest. The CSS tradition provides a number of definitions of the concept of emergence. Here we focus on four: pattern formation, efficiency of prediction, intrinsic emergence and causal emergence [3].

Pattern formation captures the most intuitive view of emergence: the interaction of low level entities, leading to symmetry breaking, generates a coordinate behaviour which is expressed via patterns which are novel and identifiable as such by an external observer. Given that a system can be viewed and studied at different levels, and that multiple different patterns will likely appear at different levels, it is natural to ask at what level and on what patterns our analysis should focus. A reasonable answer in provided by the concept of efficiency of emergence: "the level at which it is easier or more efficient to construct a workable model" [40]. At this level, the observed patterns provide us with simpler or fewer structures on which to focus the analysis of the overall system.

The two previous definitions apply to an observer external to the system. Intrinsic emergence refers to features which are important within the system by conferring additional functionality to the system itself. These emergent features may support global coordination-computation-behaviour [1]. In the case of stock market pricing, for example, agents must take local economic decisions and would benefit from having information about other agents' behaviour. If they identify an emergent feature which provides such information, then they can use it for their own decision making. Naturally, the same feature can then be employed by all other agents. Thus this emergent feature can act as an avenue for global information processing and coordinated behaviour. Clearly, the agents' behaviour influences the emergent feature, but now this also affects the behaviour of the agents by determining their future actions. Self-referentiality becomes a fundamental ingredient for complex dynamics and intrinsic emergence.

With causal emergence we define the arising of structures on which we can exert direct control without manipulating, nor concerning ourselves with, the lower level constituents [23]. As an example, actions which manipulate stock market pricing (like interest rate changes, shared beliefs, expectations of booms and busts or fraudulent information) would affect the agents' understanding of the system and thus their behaviour, effectively carrying out an intervention on the real market. The emphasis here is not on who holds the causal power (who manipulates the stock market, possibly from outside the system), rather on the avenue used for causal intervention. The identification of a structure able to influence the majority of the agents provides an efficient instrument for intervention on the overall system.

These definitions of emergence find an analogue in the dynamics of the interaction between reality, mental models and computer models. They also differ depending on the nature of the process we model. Figure 4a shows the hypothetical use of a computer model to understand planetary dynamics. The detection of regularities in such dynamics allows us to identify patterns with high efficiency of prediction. We can exploit these regularities in the development of mental models and then formalise these mental models in the form of numerical models. These numerical models may in turn help further refine our mental models and possibly affect our behaviour. However, because we are unable (at least with current technology) to intervene in planetary dynamics, developments in mental and computer models do not provide causal power on the system under analysis.

Figure 4b shows the use of our ecological model to understand a hypothetical ecological system. Again, the computer model codifies our understanding as represented by the mental model. The mental model however may be so complex that very few individuals are able to reason about it, let alone being able to infer its dynamics. The numerical model then becomes an effective way to communicate such understanding. When different numerical routines/modules are provided by different researchers, combining them into a single numerical model becomes an effective avenue for communication among researchers. The numerical model then represents the current *shared* understanding of the system functioning and can thus be seen as an intrinsic emergent feature in the process which leads a community of individual to reach a common understanding of a system of interest.

Finally, Figure 4c shows the use of our ecological model for decision making. The same analysis as discussed for the planetary dynamics applies. However, now our understanding of the problem, as guided by the interaction between mental and numerical models, may lead us to acting on the ecological system. The numerical model now provides an avenue for causation: by manipulating the model we could change our system understanding, which in turns can lead to different decision-making and thus different interventions on the real-world system. This is the very role that computer model is designed to have in supporting decision making.

6 Modelling the model's emergence properties

In a number of previous works [23,24,101,102], we have argued that the arising of genuinely novel, causal emergent properties cannot be modelled within a purely numerical framework. A simpler task is to model the impact of these properties once they are indentified in a system. In [103] we describe one such attempt. Agents need to make decisions on an issue and are characterised by two cognitive features. One cognitive feature defines their need for consistency [104]. Agents in high need for consistency tend to give a similar answer when facing the same decision problem. As a result, once a decision is made, the probability of the agent making the same decision in the future increases.

In order to make a decision, an agent needs a representation (a mental model) of the issue. The agents' second cognitive feature (individualism vs conformism) refers to preferences for different mental models. Very individualist agents may develop their own representation, while conformist agents may be more willing to adopt a representation shared with their social peers (we call these 'socially agreed mental models') [105].

Referring to the discussion in the previous section, a crucial question is what defines a socially agreed mental model. In [103] we define this as the set of views which are shared among all agents which identify themselves with that social group (notice the self-referentiality implied in the definition). Numerically, this is achieved by simply clustering agents according to their views and taking the set of cluster centres as socially agreed mental models.

The self-referentiality in the definition of the socially agreed mental models leads naturally to a two-way dynamics between two levels of analysis: the level of the individual agents' decision making and the level of the socially agreed mental models; i) each agent's decision is affected by its own cognitive style (individualist vs conformist and need for consistency) as well as by the socially agreed mental models and ii) the socially agreed mental models depend on the agents' decisions, which, via their need for consistency, influences their current and future views.

Numerical analysis of this dynamics is discussed in [103]. Two features of these results are particularly relevant to this discussion. First, socially agreed mental models are stable features of the distribution of the agents' views of the problem. They quickly polarise the agents' views into a number of clusters which are stable in the sense that, once they are formed, a re-initialisation of the agents' opinions does not change the socially agreed mental models. In this sense, the socially agreed mental models can be seen as intrinsic emergent structures, providing agents information on the distribution of beliefs in the community with no need for communication between agents. Second, by externally manipulating one of the socially agreed mental models we can affect the overall dynamics of the system. The intervention leads to a cascade: the agents belonging to the externally manipulated socially agreed mental model are affected and so are the other agents, which in turns affects their own socially agreed mental models. As a result, the socially agreed mental models provide an avenue for causal intervention and thus display causally emergent properties.

7 Summary and Discussion

The previous discussion lays at the intersection of three well established fields of research and attempts to integrate and complement them. First, a large body of work in the social sciences, social cognition, political sciences and network theory has focussed on how ideas, norms and memes spread among communities and how they can affect their behaviour. Second, the Complex System Science community has placed a considerable effort in modelling emergent phenomena. In principle, a model capable of integrating mental and computer models dynamics into the modelling process itself and capable of adapting to the emergent properties arising from this dynamics, could encompass the overall framework we describe in this paper. A *very* simple version of such an attempt is described in Section 6 . When it comes to much more complex processes, we are sceptical that the full complexity of genuinely novel, causal emergent properties can be modelled within a purely numerical framework [23,24,101,102]. Even if this was possible, such a model would still play a role equivalent to the one of the ecological model described in Figure 1. This is crucial; besides science-fictional views of networked computer models completely by-passing human concerns and interaction, such a model would still interact with humans, who could analyse the model outcome, say, and thus change and adapt their behaviour in response. As long as human-decision making is at the core of human action, the framework described in Figure 1 cannot be replaced by a pure numerical computation.

Third, in the last few decades, the explosion in Information and Communication Technologies (ICT) has had a dramatic impact on our lives and the way we communicate, we carry out our science and we interact with the world. It is likely that ICT capabilities will continue expanding. This leads to expectations for further developments, ranging from speculations about the occurrence of singularities [106-108] to less abrupt trends in communication capabilities, virtual reality, 'big data' processing and distributed autonomous agents. This is likely to provide more information, faster communication, further scientific knowledge and more and better tools for real world intervention. As discussed in [109], this can help, but not necessarily qualitatively improve, complex decision making and the management of human, economic and natural resources. In particular, it is unlikely that these developments will affect the cognitive limitations and fallacies we discussed in Section 3 , and the impact they can have on decision making.

In the previous sections we have shown how computer models can help understanding, decision making, communications between scientists and decision makers and the detection of avenues for causal intervention. of course, more traditional ITC tools also facilitate these processes. Anyone can use online resources or fast communication to seek information which can help understanding a problem or making a decision. This understanding can then be shared with others. Social media facilitate the generation of novel ideas, concepts and understanding. Some people use social media to help their own decision making. These processes are also an avenue for shared decision making with causal implications, since they can affect and coordinate human action. In doing so, they also display their intrinsic emergent properties. Our main claim, however, is that the interaction between computational and mental models extends the potential for future ICT developments. It provides a vision in which the emphasis is on human cognitive abilities as much as on the computational tools.

We describe this vision with an example. In a now popular experiment, Sterman [63] showed that a lack of understanding of the relation between CO_2 emissions and sequestration can lead even well educated people to potentially supporting policies which do not matching their preferences. Similar conclusions are supported by Moxnes and Saysel [62]. This is one instance in which the logical fallacies discussed in Section 3 can have considerable undesired real-world implications. In principle, a person at risk of falling into this fallacy could seek information and understanding online, from peers or via social media. However, in order to do so, this person i) would need to be aware of this problem, ii) would need to be able to find information related to that specific question or iii) would need to be able to abstract out the general problem (in this case stock flows and accumulation), find a solution to the general problem and then apply that solution to the specific instance under analysis (CO_2 accumulation). In contrast, our vision would entail the possibility of quickly developing a simple model of the problem or to import this model from the internet (possibly provided by the very proponents or opponents of the policy) and use such model to better understand the problem's implications[2].

Our discussion suggests that computation models are unique among computational tools in the sense that they can i) encapsulate understanding, ii) which can be shared, iii) is less subjected to logical fallacies and iv) can help humans become aware of their own cognitive processes. While it is common to think of ICT as delivering information, knowledge and capabilities, this analysis focuses on delivering shared understanding as well as insights into cognitive processes at both an individual and social level; in other words, cognitive self-awareness. The dream, or utopia, is that this may lead to better shared, complex decision making.

8 Figures

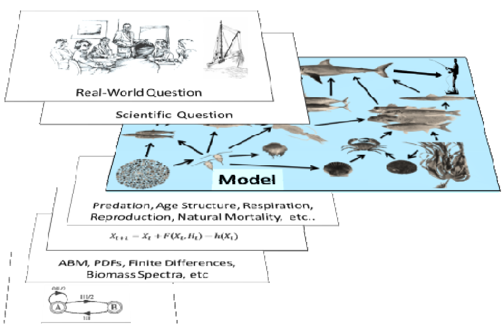

Figure 1. Levels of analysis as traditionally employed in Complex System Science highlight the interaction of processes at different resolution/scope. Starting from our ecological model (coloured

[2] Obviously, models can be developed to deceive, but so can discursive arguments. We refer to [110], for a masterful description of how models, more than discursive arguments, can be open to transparent analysis and verification.

layer), lower levels of analysis pertain to the model inner functioning. Similarly, higher levels of analysis refer to model use.

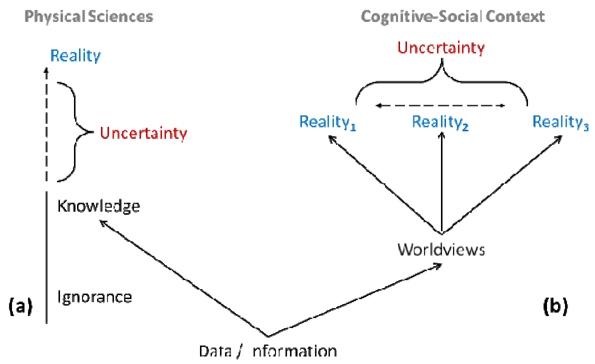

Figure 2. Alternative understanding of uncertainty. For a modeller/physical scientist, there exists an external 'reality' we aim to describe. Perfect knowledge of this reality is unachievable and represents an abstract goal. Uncertainty is then understood as the gap between our current knowledge and this ideal perfect knowledge (a). Within a cognitive-social context, reality is the result of how humans understand, represent, communicate and come to agree on a certain process. Here uncertainty is understood as the difference between alternative views of reality (b). While on the left additional information can reduce uncertainty, on the right this is not necessarily so because information itself is processed in terms of the cognitive-social context. While on the left model improvement may reduce uncertainty, on the right a better understanding of reality can be achieved only via multiple alternative models.

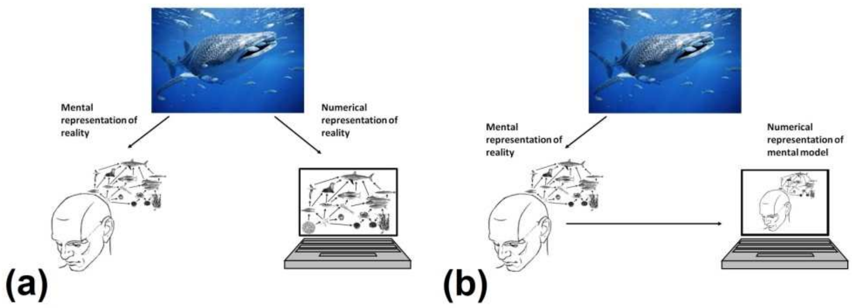

Figure 3. Alternative views of the relation between reality, mental models and computer models. (a) Mental models and computer models are alternative representation of reality. (b) Computer models are a formalisation of mental models, which represent our understanding of reality.

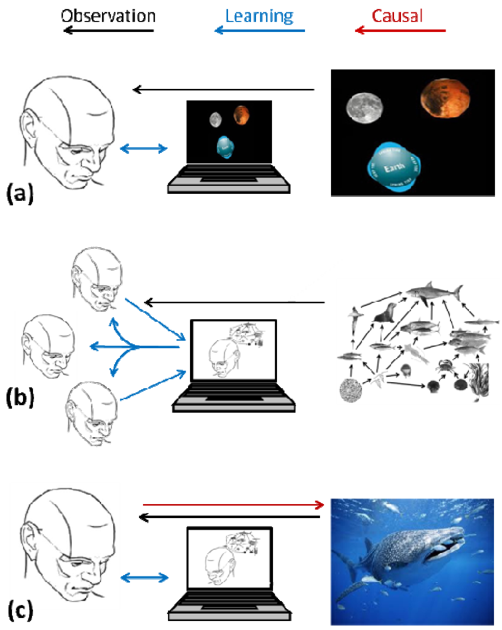

Figure 4. Different types of emergence in the interaction between reality, computer models and mental models. Efficiency of prediction (a), intrinsic emergence (b) and causal emergence (c).

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