How Computational Models Predict the Behavior of Complex Systems

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Abstract

In this paper, we argue for the centrality of prediction in the use of computational models in science. We focus on the consequences of the irreversibility of computational models and on the conditional or ceteris paribus, nature of the kinds of their predictions. By irreversibility, we mean the fact that computational models can generally arrive at the same state via many possible sequences of previous states. Thus, while in the natural world, it is generally assumed that physical states have a unique history, representations of those states in a computational model will usually be compatible with more than one possible history in the model. We describe some of the challenges involved in prediction and retrodiction in computational models while arguing that prediction is an essential feature of non-arbitrary decision making. Furthermore, we contend that the non-predictive virtues of computational models are dependent to a significant degree on the predictive success of the models in question

Introduction

Computational models are of interest to philosophers insofar as they promise new ways to explore scientific hypotheses and provide access to the inner workings of complex phenomena or to target phenomena that are difficult to examine by other means. Computational models are currently allowing research into topics where cognitive, ethical, political, or practical barriers would otherwise loom large. Whether in nuclear weapons testing, climate science, studies of the behavior of epidemics, or studies of the internal dynamics of stars, to take just a handful of cases, computational models are often the only viable research tool for scientists.

To date, computational models have generated two related kinds of questions for philosophers of science. First, what additional epistemic resources, if any, do such models provide us? (Humphreys 1994) Second, in what ways, if any, do the kinds of explanations derived from computational models differ from those provided by other kinds of scientific models? (Guala 2002; 2005; Morgan 2005; Parker, 2008; Winsberg 2010, Frigg et al 2008)

In this paper, we consider a third set of questions concerning the features of the predictions derived from computational models. We believe that careful consideration of prediction in computational modeling can shed light on more general concerns in the philosophical literature about the scientific status of these models. We focus on the consequences of the irreversibility of computational models and on the conditional nature of their predictions. The conditional, or *ceteris paribus*, nature of the kinds of predictions provided by computational models will be discussed in detail below. By irreversibility, we mean the fact that computational models can generally arrive at the same state via many possible sequences of previous states. Thus, while in the natural world, it is generally assumed that physical states have a unique history, representations of those states in a computational model will usually be compatible with more than one possible history in the model. This is an important feature of computational models which is directly relevant to philosophical questions concerning the status of these models and which has generally been overlooked in the philosophical literature. We believe that addressing some of the larger philosophical questions about computational models depends on specifying as precisely as possible, the manner in which computational models generate predictions.

Our analysis of prediction in computational models contributes to the existing philosophical literature on the epistemic status of models. However, our motivation in this paper is practical as well as philosophical. On our view, the primary purpose of computational modeling is to allow us to intervene in, or respond to, complex natural or social processes in a non-arbitrary manner. In addition to their increasingly significant role in scientific investigation, computational models figure centrally in policy deliberations concerning climate change and economic policy making (Meadows, 1972; Holling, 1978; Walters, 1986; de la Mare, 1996; Brunner, 1999; Pielke, 2003; Adams, 2004; Walters and Martell, 2004; Allan and Stankey, 2009a; Rockström et al., 2009; Likens, 2010). (Butterworth and Punt, 1999; Lee, 1999; Morgan and Morrison, 1999; Doak et al., 2008; Allan and Stankey, 2009b; Allan and Stankey, 2009a; Ivanović and Freer, 2009; Chapman, 2011). Thus, the problem of understanding the epistemic status of the evidence provided by computational models has direct practical significance.

Given the central place of the predictive power of computational modeling in policy decisions, and given the high stakes involved in many of these policy decisions, we are concerned that the existing literature on modeling demonstrates some misunderstanding of prediction in computational models. For example, many authors have argued that the use of computer modeling in these contexts is unwarranted because such models simply cannot provide reliable predictions of complex dynamics in the systems of interest. (Ascher, 1989; 1993; Brunner, 1999; Oreskes, 2000; 2001; Beven, 2002; Aligica, 2003; Beven, 2006) Such criticisms fall into roughly four principal types:

a) computational models have a poor track record of prediction
b) model predictions are not testable because of their conditional nature;
c) models reflect the subjective beliefs and assumptions of their creators;
d) the principal purpose of computational models is not to predict.

Critics of the predictive power of computational models generally continue to advocate for the use of such models while arguing that the benefits of computational modeling are limited to one or more of the following (Brugnach, 2010, D'Aquino et al., 2003) :

a) explanation of past events;
b) increased understanding of natural processes;
c) learning;
d) providing an avenue for communications.

These roles are presented as alternatives to what is sometimes regarded as a naïve attachment to the predictive power of models. In our view, this line of criticism risks detaching these models from their most important role in decision making. Critics seem to assume that prediction is an ideal or discretionary input, rather than a *requirement* for decision making.

Our paper describes some of the challenges involved in prediction and retrodiction in computational models while arguing that prediction is an essential feature of non-arbitrary decision making. Furthermore, we contend that the non-predictive virtues of computational models, such as the four listed above, are dependent to a significant degree on the predictive success of the models in question.

Computational models have some undeniable limitations with respect to prediction and retrodiction. However, these restrictions are not unique to computational models. We argue that all so-called special sciences are subject to the same ceteris paribus conditions. Ceteris paribus conditions, or provisos, are a ubiquitous feature of explanation and prediction in the special sciences. The predictive power of computational models, like the predictive power of the special sciences more generally, will always be conditional in nature. We will explain the role of conditional prediction in computational models in more detail here.

One counterintuitive result of our investigation is our observation that prediction in computational models is more reliable than retrodiction. On reflection, this is a straightforward result of the nature of computational models. However, recognizing this fact should cause us to think carefully about the explanatory value of the kinds of retrodictive accounts of complex systems which we derive from computational models. We will explore some of the implications of this feature of computational models below.

1. Deciding and Predicting

As discussed above, we believe that the modeling community bears an unusually high level of social responsibility. In recent years, public attention has focused primarily on the use of modeling for climate change initiatives, but perhaps even more commonly, results from modeling in economics have direct bearing on decisions in governmental and corporate institutions. Many authors (Ascher, 1989; 1993; Brunner, 1999; Oreskes, 2000; 2001; Beven, 2002; Aligica, 2003; Beven, 2006) regard this influence as unwarranted. It is useful from the outset to understand how we ought to evaluate skeptical attitudes toward model predictions. To begin with, we should examine the distinct kinds of skepticism which we might encounter: First, let's deal with the most extreme kind of skepticism with regard to prediction before tackling the more difficult practical questions concerning the evidential status of computational models.

Given complex problems, policy makers and others are forced to decide how to evaluate and interpret evidence with respect to alternate courses of action. Clearly, there are reasons to be cautious with respect to the predictive power of scientific models. However, notice that our reasons for skepticism are relative to our criteria for judging the predictive success of a model. Once we adopt higher standards, fewer models will pass our test. Perfect predictive success is clearly an unreasonable criterion to apply when judging a model. Few scientists would demand this level of predictive power. In the context of practical decision making, skepticism is an unreasonably expensive luxury.

Given the need to act in a non-arbitrary manner, the core problem is to determine what tool currently provides the most reliable predictions concerning the phenomena of interest. In this spirit, the question would shift from 'can model predictions be trusted?' to 'how do we compare models to one another and to other approaches to prediction?' Clearly this new question can be understood in information theoretic terms where predictability can be contrasted with randomness. For example, while we cannot trust weather forecasts in detail beyond a window of about 5-6 days, we can be confident that there is not an equal probability that the temperature in El Paso on an August day could be 40°C or -40°C. (Boschetti et al., 2010) While El Paso weather is difficult to predict with any precision during the short August rainy season, we can be highly confident that our pipes won't freeze in August.

While perfect precision with respect to complex natural and social processes may not be available for finite beings, we contend that the epistemic function of computational models derives from their capacity to limit the space of possible futures that we need to consider in deciding on a course of action. On our view, computational models should stand the test of experience and should be discarded or modified if they fail to improve our capacity to act in relation to the relevant complex systems under consideration.

At this point we are ready to explain the connection between decision making and the acquisition of new evidence. New evidence can allow an epistemic agent to eliminate irrelevant alternatives for action. Jaakko Hintikka noted this basic connection between knowledge and alternative possibilities in his early articulation of epistemic logic. He put the connection in modal terms which we can paraphrase straightforwardly as follows: To know *p* means to be in the position to rule out possibilities in which it is not the case that *p*. (1962) Once we begin to think about inquiry and decision making in terms of ruling out possibilities, the modal character of epistemic terms is relatively obvious. Just as a necessary truth is one which is true in all possible worlds, an agent's knowledge can be understood as the set of truths which obtain in all of the agent's *epistemically* possible worlds. In other words, for an agent to know *p* means that in all worlds compatible with the agent's knowledge, it is the case that *p*. While this is an admittedly idealized conception of knowledge the general view applies equally well to practical decision making. So, for example, in contexts where probabilistic measures are unavoidable, we can understand Hintikka's approach as a way of thinking about the level of significance we give to alternative possibilities. More practically still, we can understand the elimination of irrelevant alternatives in terms of the level of resources we devote to alternative possibilities. As we can see in the following passage, the core of Hintikka's view derives from some very ordinary considerations:

> To take a simple example, let us suppose that I am getting ready to face a new day in the morning. How does it affect my actions if I know that it will not rain today? You will not be surprised if I say that what it means is that I am entitled to behave as if it will not rain – for instance to leave my umbrella home. However, you may be surprised if I claim that most of the important features of the logical behavior of knowledge can be teased out of such simple examples. (Hintikka 2007, 11-2)

For cases where uncertainty is unavoidable, examples like this can be recast in probabilistic terms such that the threshold for the decision to take the umbrella will be crossed given our confidence that the weather forecast or some other factors rules rainy futures out or in. Modern work in epistemic logic has built upon this view of the relationship between knowledge and possibility. So, for example, the connection between epistemic and pragmatic considerations continues into the 1980s and 1990s. Many researchers in Artificial Intelligence define belief, for instance, as the set of propositions which an agent would be willing to act upon. In this paper, we identify the predictive power of computational models as their capacity to help us to exclude some range of possible future scenarios. Their epistemic power is simply their capacity to help us reduce the range of possibilities which we need to consider when we make our decisions.

We assert that (in spite of many complicating factors) computational models stand or fall by reference to their predictive power. We understand predictive power in terms of the power to permit decision makers to eliminate irrelevant future states.

Of course, models can also be used in exploratory fashion (Humphreys 1994, Boschetti, 2010), highlighting dynamical behaviors of which we may not be aware. Failing to recognize these behaviors means the inability to plan for them. A full analysis of this topic is beyond the scope of this work, but within the current discussion we notice that, even in the case of the exploration of novel system behavior, the final outcome is an enriched predictive power: we are now able to envisage behaviors which previously we did not expect. In other words, computational models enhance our predictive power by improving our ability to estimate the occurrence both of events we were previously aware of and events we became aware via the very use of models. Clearly, computational modeling allows us understand the implications of our assumptions in ways that would be difficult with unaided human intelligence. So, not only does prediction involve eliminating irrelevant alternatives, it also involves the discovery of unanticipated implications of the alternatives which remain on the table after the elimination of irrelevant alternatives.

In the absence of any predictive power all events we are aware of would be treated as though they had the the same probability of occurring and all events we are not aware would be treated as having probability 0. Modeling allows us to make this distribution more realistic.

From a commonsense perspective, this might seem obvious. However, for many modelers, there is legitimate resistance to the idea that models predict properties of the systems under consideration in any straightforward way. We will endeavor to show that while modelers are correct to approach the problem of prediction cautiously, they would be wrong to give up on predictive power as a criterion for evaluating and comparing models. Our view is that prediction is an essential component to any non-arbitrary planning and decision making.

There are a number of important complications with respect to prediction. Clearly, for example, the effectiveness of a prediction is scale-dependent (Israeli and Goldenfeld, 2004). For example, while the geophysicists do not claim to provide accurate predictions concerning the timing of large earthquakes, they are nevertheless able to predict the broad geographical areas in which such earthquakes can be expected. This kind of predictability offers little help to short-term planning (Pielke, 2003), but has considerable practical impact in deciding, for example, where expensive anti-seismic construction methods are necessary. Similarly, while we accept that we cannot predict the outcome of an individual roulette round, the gambling industry is built on predictability of its long term global behaviour. Indeed it is so predictable that a mismatch between outcomes and prediction serves to alert casinos to potential cheats.

Prediction is an integral part of any non-arbitrary decision making process. At an organisational level, prediction has a role, implicitly or explicitly, in the formulation of plans and the assessment of which avenues should be followed. Formulating a plan implies choosing among potential alternatives and predicting which one is more likely to deliver desired outcomes. The same applies to the implementation of a plan. The need to carry out a prediction of the future behaviour of our environment and the likely outcome of our interaction with it is so pervasive that it has been proposed as the defining distinction between living and non-living systems and is implied in much work on information theory and computational dynamics (Rosen, 1885; Crutchfield, 1994; Ellison et al., 2009; Poli, 2010).

2. A model of a complex problem: prediction and retrodiction

Because of the scope of the issues under consideration, in this paper, we will begin by limiting our discussion to an idealized case where we help ourselves to a number of assumptions. Let's assume, for the sake of understanding predictions in computational models that:

1) Our model represents our understanding of a complex natural process *P*
2) We already have a computational model *M* of *P*
3) The model is 'structural' in the sense that it is not a purely statistical model. Rather than modeling simple data correlation, the model represents our understanding of salient mechanisms in a computationally tractable manner (extension of the discussion to non structural models can be addressed by following the line of argument in (Suchting, 1967)).

In short, we are assuming that the model is a success and that it looks like the kinds of computational models that feature prominently in contemporary scientific investigation. Obviously, such an assumption will appear question begging from the perspective of thinkers who are skeptical of the very possibility of successful computational models. It will not be possible to answer such total skepticism in this context. Moreover, we do not concern ourselves here with how the model represents *P*, we simply assume that it does an good job doing so.

Figure 1 (below) shows the natural process *P* and our model *M* of *P*. At time t_0 we collect some data D_{t_0} about *P*. Depending on the nature of the problem we need to address, we may use *M* for two purposes. We may want to assess what may happen in the future at time t_n. Since *M* respects our perception of the 'arrow of time' (causes lead to effects), using *M* in this fashion is usually called a 'forward' model and leads to a prediction of D_{t_n}. Alternatively, we may wish to assess what may have happened in the past at time t_{-n}. Since it attempts to reverse the arrow of time, this use of modeling is often referred to as 'inverse' modeling (Parker, 1977; Tarantola, 1987) and leads to a retrodiction of $D_{t_{-n}}$.

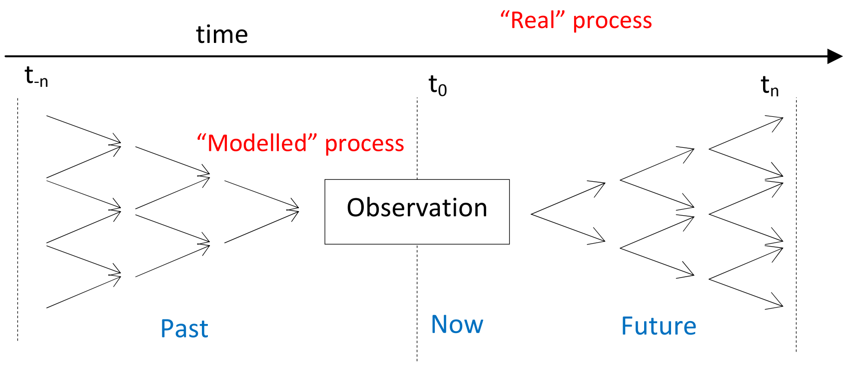

Figure 1

In an ideal case, the retrodiction would be carried out with an inverse model M^{-1} such that $M^{-1}(out)=in$, where *in* refers to the input and $out=M(in)$ to the output of M, respectively. Unfortunately, inverse models such as M^{-1} can be written explicitly for only a very small set of forward models M. This is true not only for closed-form models but also for purely numerical models. As a result, most inverse engineering and scientific problems need to be solved by iterative methods in which M is run with sets of inputs *in* until a reasonable match between $M(in)$ and the expected output, D_{t_0} in our case, is found. The procedure which allows us to recover $D_{t_{-n}}$ from M and D_{t_0} is called inversion, optimisation, or regression, depending on the discipline (Parker, 1977; Tarantola, 1987). Here we will call it inverse modeling and will call this procedure M^{Inv}.

Assessing the effectiveness of a computer model in predicting or retrodicting can thus be cast in terms of the reliability of the two processes M (prediction) and M^{Inv} (retrodiction). By 'reliable', we mean the following: given the model output of the forward process (prediction, M_{t_n}) and of the inverse process (retrodiction, $M_{t_{-n}}^{Inv}$), we ask which one is likely to be closer to the states of the 'real' process $D_{t_{-n}}$ and D_{t_n}, respectively. In other words we ask whether $|M_{t_n}, D_{t_n}| > |M_{t_{-n}}^{Inv}, D_{t_{-n}}|$, where $|x,y|$ is some kind of metric of common use and practical usefulness. For example, $|x,y|$ could be a norm (often L_1 or L_2 are used), a measure of correlation or mutual information, or even a subjective evaluation (Takagi, 2001).

Let's begin by considering deterministic models with the help of Figure 2. This figure shows an idealized representation of the state space of the model M at 3 different times $S_{t_{-n}}$, S_{t_0} and S_{t_n} (empty boxes). At time t_0 we make a set of observations D_{t_0} and we use this information to parameterize our model M. The 'real' process P proceeds and at time t_n we make a new set of observations D_{t_n}. Because the model M is not exact, the prediction of M at time t_n $M_{t_n} \neq D_{t_n}$ and we call the prediction error $E_p = |M_{t_n}, D_{t_n}|$. Figure 2 also shows other runs of M, starting with different initial conditions in S_{t_0} ($D'_{t_0} \neq D_{t_0}$) and generating different predictions in S_{t_n} (notice that the mapping of S_{t_0} into S_{t_n} generated by M does not need to be smooth).

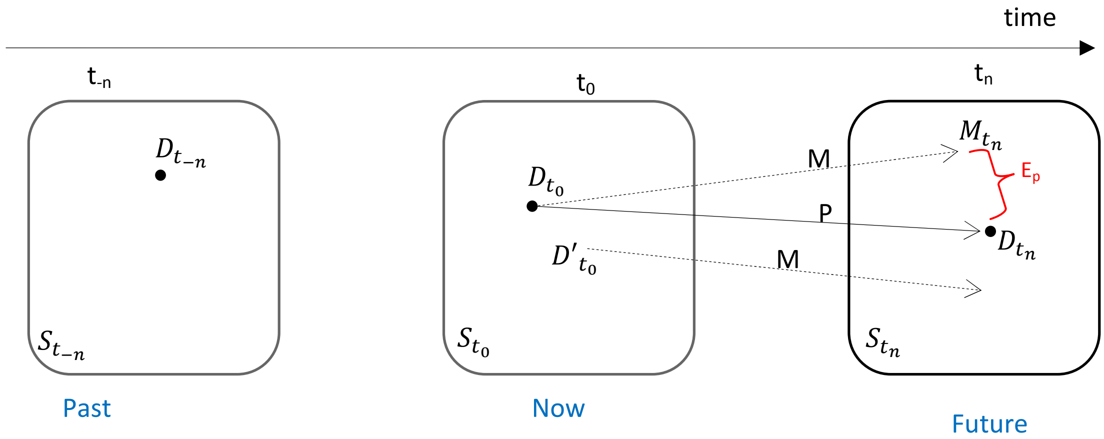

Figure 2

In Figure 3, we use the same representation to describe the inverse process M^{Inv} which allows us to retrodict from D_{t_0} in order to recover $D_{t_{-n}}$. As explained above, this is an inverse process carried out by iteratively mapping $S_{t_{-n}}$ into S_{t_0} via M, until a satisfactory match $|M_{t_0}, D_{t_0}|$ is found. Ideally, M should map $D_{t_{-n}}$ into D_{t_0} so that $E'_p = |M_{t_0}, D_{t_0}| = 0$. Of course we cannot expect this match to be exact. The same approximations (or errors) which prevent M from modeling P exactly, and which are responsible for $E_p = |M_{t_n}, D_{t_n}| \neq 0$ in Figure 2, are likely to imply $E'_p = |M_{t_0}, D_{t_0}| \neq 0$. As a consequence, it is likely that a point $D'_{t_{-n}}$ in $S_{t_{-n}}$ ($D'_{t_{-n}} \neq D_{t_{-n}}$) may generate a prediction at time t_0 for which $|M(D'_{t_{-n}}), D_{t_0}| < |M(D_{t_{-n}}), D_{t_0}|$. The point $D'_{t_{-n}}$ for which $|M(D'_{t_{-n}}), D_{t_0}|$ is minimum will be chosen as retrodiction. The error in the retrodiction will then be $E_r = |M(D'_{t_{-n}}), D_{t_0}| \neq 0$. If M is non linear and 'complex', the magnitude of E_r and E_p may vary considerably as a function of the location of the parameterization in $S_{t_{-n}}$ and S_{t_0}, but we have no a-priori reason to expect $E_r < E_p$. This is the crucial message of this work and we will address it again below. At this point, it is important to emphasize that E_r arises from the same process which generates E_p and that the relative magnitude of E_r and E_p cannot be deduced a-priori.

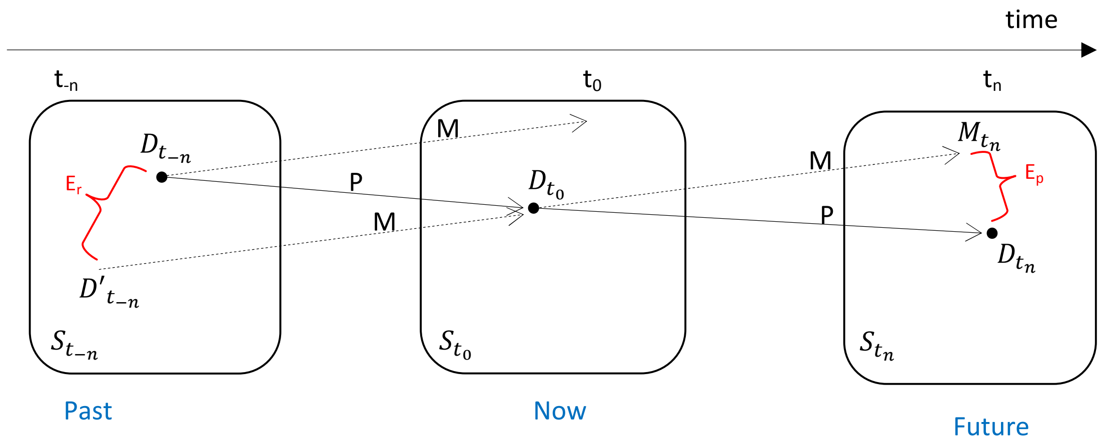

Figure 3

Two further problems, which affect any real world modeling exercise, complicate the inverse modeling M^{Inv}:

a) M^{Inv} does not necessarily have a unique answer
and
b) M^{Inv} can be computationally very expensive.

'Non uniqueness' or 'equifinality' is the property of a system wherein, under certain conditions, families of input parameters can produce the same model output. In systems which exhibit non- uniqueness, there are a variety of ways that a system can tend towards a specific state. Many studies in applied mathematics focus on measuring the level of non uniqueness or on determining the extent to which non-uniqueness is a mathematical artifact (due to over-parametrization, inappropriate parameterization or lack of information) or a genuine feature of the real process (Parker, 1977; Tarantola, 1987).

Non-uniqueness is a feature of inverse modeling but not of forward modeling, the outcome of which under ordinary circumstances is deterministic. When needed, non-deterministic elements in the solution of the forward problem can be obtained only by imposing random variations to some input parameter. This approach is commonly used to mimic non-deterministic processes (for example by using random choices to model agents' behavior under uncertainty) as well as chaotic ones, whose behavior is determined by small variations in initial conditions.

Figure 4 shows how non-uniqueness can affect retrodiction. In this case, even if an exact match $|M_{t_0}, D_{t_0}|$ =0 can be achieved (that is even if the model allows to match the current observations perfectly), we are unable to differentiate among the (potentially infinite) number of solutions D'_{t-n} which provide the match (gray shadow in Figure 4).

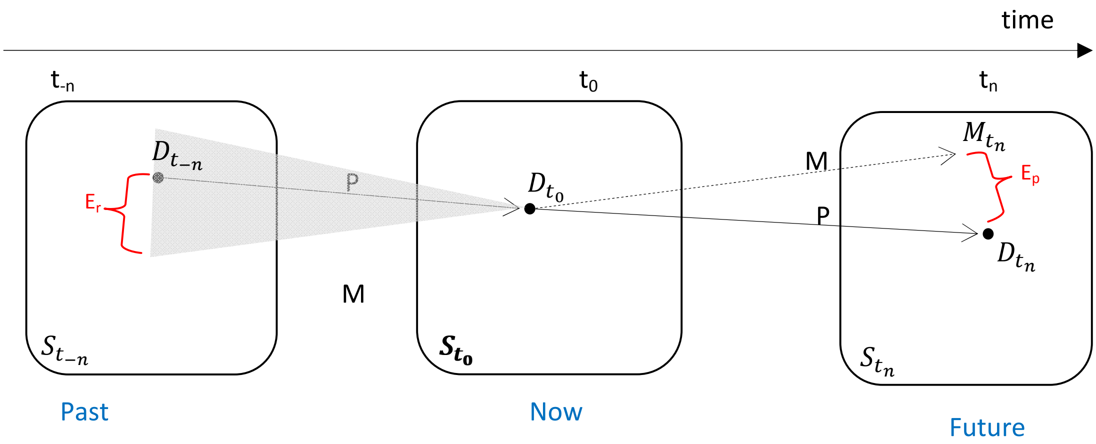

Figure 4

The previous argument can easily be extended to non-deterministic models, as summarized in Figure 5. Non-determinism in M implies that the output M_{t_n}, obtained by running M initialized with D_{t_0}, is not unique, as represented by U_p in S_{t_n} in Figure 5. As discussed above, this non-deterministic outcome is obtained by using random perturbation in the input parameters, thereby generating artificial non-uniqueness in the forward modeling. Notice that, as before, there is no reason to assume that U_p is smooth. The same reasoning applies to the output M_{t_0} obtained by running M initialized with D_{t-n}, which is necessary to carry out the iterative inverse process M^{Inv}. As a result, the set of input D'_{t-n} in

$S_{t_{-n}}$ leading to acceptable measures of $|M_{t_0}, D_{t_0}|$ adds to the uncertainty resulting from non-uniqueness in Figure 4. This is represented as U_r in Figure 5.
Finally, as we mentioned above, *M* can be computationally very expensive. In many real world applications, this implies that *M* cannot be run as many times as the iterative process M^{Inv} would require. This, in turns, adds further errors to $|M_{t_0}, D_{t_0}|$ and, as a result, potential further errors in E_r.

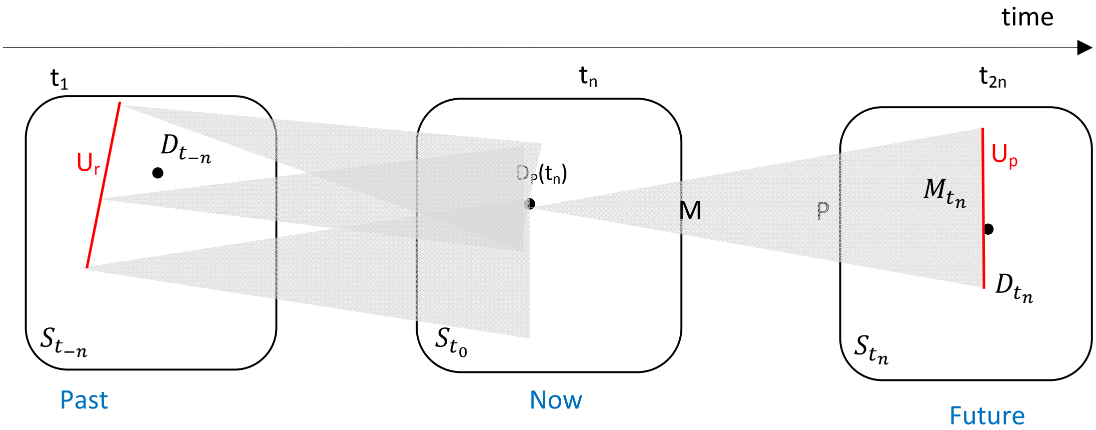

Figure 5

If we accept that E_p represents the error in prediction and E_r the error in retrodiction, the previous analysis suggests that a) E_r is inextricably related to E_p, b) there is no reason to assume that in general $E_p > E_r$ and c) in practice, it is more likely that $E_r > E_p$ as a result of non-uniqueness and the computational effort which may prevent the inverse process M^{Inv} to run to completion. This leads to the unintuitive conclusion according to which, in the absence of additional information, we should trust a model prediction more than a model retrodiction.

So, how does this apply to the explanation of past events? Some initial observations can be drawn from the previous discussion. Above, we assumed that *M* represents our understanding of a complex natural process *P* and is provided to us. In other works *M* is the basis for any explanation of the process which aims at recovering the salient history of the system. So, arguably, explanation then can be equated to deciding what model, among many, best describes the process *P*.

If we then assume that such explanation is not yet agreed upon, we can imagine that a family of models $M_i=[M_1, M_2, .. M_n]$ is available and we need to choose the most suitable model. The previous reasoning can then be applied by noticing that the mapping between state spaces at different times t_{-n}, t_0, and t_n becomes also a function of M_i.

The role of additional information in the choice of model is crucial for the development and maturation of a modeling project. Additional information may for example tell us which path among the many available, the system has taken at a time $t_{-n}<t_{-m}<t_0$. This can constrain the inversion process M^{Inv} by making it both more reliable. Similarly, that information may be used to better initialize the forward model *M*. Whether the prediction or the retrodiction will benefit more from the introduction of additional information is difficult to establish a priori.

3. Common uses of complex models

In the previous section we have shown how, in most real world applications, inverse modeling is in fact iterated forward modeling. However, in practice, forward modeling, often involves inverse modeling. There are two basic reasons for this interplay. First, even the best structural model used in predictive work requires some tuning of parameters. By tuning, we mean finding combinations of parameters which match past observations, theoretical constraints or mere expectations. In practice any principled process of adjusting parameters will involve an inverse process of the kind described in the previous section.

Many engineering and scientific problems appear to ask forward or predictive questions concerning the system of interest. So, for example, we might be interested in whether a flood will occur under some set of conditions or whether some intervention can stop the next flu pandemic. In these cases we are asking what effects some intervention will generate. However, ideally one important goal of these kinds of simulations is to provide a more general kind of understanding, such that we can answer questions like:

> "what will prevent the next flood?"
> or
> "what can stop the next pandemic?"

Any progress towards answering questions like these using computational models must involve inverse methods. Clearly, the kind of mastery we seek with respect to complex phenomena lies not so much in being able to answer a long list of forward questions. Instead, it consists in being able to generalize from lists of answers to forward questions in tackling unspecified future problems. Expert modelers achieve understanding of this kind by reflecting on mapping relations between input parameters and outputs and by carrying out a sensitivity analysis of their model based on their experience and presumably via something like an unconscious inverse exercise. While experience and expertise are important, the accuracy of a researcher's deliberations, as we have seen above, depends crucially on the reliability of the forward model.

Not all learning that results from using computer models needs be so formal. Let's take an analogy often employed to explain the role of numerical models in complex processes: the flight simulator. Complex socio-ecological models, for example, offer decision makers the same opportunity offered by flight-simulators to trainee pilots: they provide the opportunity to test policy initiatives in the safe world of virtual simulations. However, it is reasonable to expect that flight-simulators will provide effective training only in so far as the flight-simulator simulates well, that is, only in so far the flight-simulator effectively predicts how the real plane will behave under similar circumstances. We have no reason to believe that a pilot trained on an inaccurate flight simulation should learn how to handle a real plane in the real world. Similarly, there is no reason to believe that a decision maker should improve his/her ability to address a real world using a model which provides poor prediction on how the real world functions.

Some researchers have emphasized other roles for computational models most common is some relatively poorly defined notion of "understanding". However, we as we have argued here, that the use of computational models for the development of understanding, still depends on their reliability as predictors.

4. The Conditional Nature of Predictions is a General Feature of Explanation in the Special Sciences

There is clearly some relationship between the predictive and explanatory roles of computational models and the improvement in our capacity to exert control either over a natural process or relative to the natural processes in question. It might be the case that while some specific natural process is beyond our control, understanding the process permits us to adjust our behavior in advantageous ways in light of our understanding. Admittedly, this notion of understanding is not very well-defined. As a way of getting clearer on what we mean by understanding, it is useful to consider its relationship to explanation. How do we ordinarily explain events and regularities?

As a way of beginning to answer, consider how we might begin to explain some specific observation in ordinary life. One way of explaining an event is to reconcile it with a broader system of laws or regularities. So for example, if I notice that my neighbor is earnestly moving a live chicken around his head three times, I am likely to be puzzled by his actions. The mysterious quality of his action could be (partly) removed when we learn that he is a member of the Heredi community and that he is performing Kapparot, a traditional ritual where the believer attempts to transfer his sins to a chicken. This explanation takes the form of a generalization about the behavior of members of the community, adds some additional information about the beliefs and desires of the person performing the action, and thereby serves to reconcile this event with a broader unified picture of people and their behavior. The strangeness of the isolated event is eliminated (to some extent) by being told of how it fits with all of our other beliefs about people, their religious practices and their community affiliations.

Ordinarily, the purpose of explanation in everyday life is simply to reconcile some event or regularity within a broader framework of understanding. So, for example, after hearing that my neighbor is performing Kapparot, I will have an improved understanding of his actions. While we would probably still might admit to not *really* understanding what he is up to, for the practical purposes of our immediate neighborly relationship, we have a sufficient level of understanding.

Thus, most ordinary explanations are dependent for their success on meeting the needs of the audience in question. So for example, as Hilary Putnam explained, when we are interested in an explanation of something like a forest fire, there are an infinite number of facts which are irrelevant to our interests in seeking an explanation. (1982) We could imagine, visitors from outer space, observing the forest fire, and explaining to their conspecifics that the planet Earth is subject to forest fires because its atmosphere is dangerously saturated with oxygen. Human forest fire investigators on Earth would be unlikely to be applauded if their explanation of the fire was simply that the atmosphere at the time held sufficient levels of oxygen to sustain combustion. To at least some extent, our purposes, in providing explanation, shape the judgment as to whether some explanation is successful or not. We can call this the audience relativity factor of explanation.

In ordinary explanations, we attempt to reconcile some event or regularity with some accepted set of generalizations. Let's contrast this audience-relative feature of ordinary explanation with an idealized conception of scientific law. In simple terms, scientific laws serve as generalizations which take the form of conditionals:

For all x if x is an F then x is a G.

In ordinary social scientific explanation, such laws do not hold strictly. Why does Mary eat fish on Fridays? All Catholics eat fish on Friday, Mary is a Catholic, so Mary eats Fish on Fridays. The generalization that serves to explain Mary's behavior in an analogous manner as the Kapparot case above, *is not strictly true* insofar as it is not exceptionless. It is certainly nowhere near meeting the standards that one would use for measuring the success of a physical law. Nevertheless, it is a satisfying explanation for certain purposes and for certain people. Specifically, it would be satisfying to people with the right kinds of background knowledge about people, religions, food, days of the week, and the like. By contrast, idealized, maximally general physical laws hold without exception. Such laws can be said to answer "why" questions independently of agent interests and background knowledge. So, in the case of physical laws, we can say that one of the goals of physics is for audience relativity to drop out as a relevant factor in determining the legitimacy of an explanation. Some philosophers of science, notably Nancy Cartwright, have denied that such laws really can be provided by physics and claim instead that all laws are subject to what are known as *ceteris paribus* or 'all other things being equal' clauses. (Cartwright, 1983)

In the case of computational modeling, there can be no presumption of maximal generality. Instead, as we have discussed elsewhere (Boschetti et al., 2010) computational models always involve conditional prediction. As we can now see, this is not a unique feature of computational modeling. All sciences which do not claim maximal generality face the need to cope with conditions or *ceteris paribus* clauses.

The explanatory power of computational models will be judged relative to their capacity to assist us in the intervening in, or perhaps preparing for, the natural processes in question, under the conditions stipulated by the modeler. The explanatory power of these models is judged in relation to their capacity to satisfy our purposes.

This is not an anti-realist account of explanation. In fact, we assume, that the most important criterion for deciding whether or not we actually have explanation provided by computational models is the capacity of those models to provide predictions. The predictive power of these models is the sole test of their adequacy and is the sole marker of their epistemic value.

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