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Modeling Reality

> *Why don't I have a complete plan for reforms? In order to play chess, one must know the rules ... how to move the various pieces on the board. But it is not possible to know the situation on the chessboard after the 15th or 25th move.*
> -- Vaclav Klaus, President, Czechoslovakia

Scientists, managers, executives, and government leaders are expressing increasing concern about the safety and reliability of complex computer systems. As such systems take charge of everything from phone calls to flights, we are exposed to a growing danger of man-made disasters.

Important among complex computer systems are computer models used for simulations and predictions of phenomena in areas ranging from physics to hardware engineering to socio-economic systems. Computer models have become an area of concern unto themselves. Their misuse could lead governments to adopt disastrous policies in dealing with such subjects as global warming and global economic stability. The proliferation of computer models supporting divergent points of view -- for example, computer simulations supporting conflicting theories of global warming or nuclear winter -- can easily mislead the lay public. Models whose results depend on assumptions about human behavior are the most likely to produce controversial results.

In early November 1990 the Association for Computing Machinery (ACM) brought together leading scientists, business executives, and government officials to discuss public-policy questions surrounding computer models. I will summarize the main points about modeling made by the principal speakers at that meeting.

Modeling Expertise

Knowledge-Based Systems (KBSs) are important examples of computer models. A KBS is supposed to reproduce the decisions of an expert in a domain. KBSs have come under fire because to many observers the majority of them have fallen sort of the promise of competent performance.

John Kunz attributes part of the problem to a design-and-testing process taken from software engineering, a process that begins with a formal specification and ends with an acceptance test [9]. This process cannot take into account that the standards for expert performance can shift as a field changes. Kunz argues that, to obtain reliable KBSs, continual testing and improvement must be the standard approach. The tests must do more than compare KBS decisions with real situations; they must validate that at all times the recommended actions fulfill the purpose of the system, that the reasoning procedures are valid for the domain, and that the recommended actions are consistently endorsed and assessed as competent by human experts. Kunz recommends that the tests include simple realistic cases as well as tests that apply various stresses to the KBS. He recommends that some of the tests be retrospective (comparing KBS decisions with those of experts in the past) and that some be prospective (testing the KBS against experts in real time)

KBSs are founded on the assumption that an expert works from a complete theory of the domain. Once a theory is articulated as a set of rules and stored in a database, the superior power of the computer can draw inferences much faster than the expert. That this has not been accomplished cannot be blamed on a lack of computing power, memory, research effort, or cooperation of experts. An explanation gaining credence is that experts themselves do not work from complete theories, and much of their expertise cannot be articulated in language. The advocates of neural networks claim they have found a way to overcome the inability to articulate expertise. Neural networks mimic the biological structure of the brain and therefore the expert's approach to gathering and organizing information; once the networks have been trained, their advocates say, they will be able to acquire the knowledge experts have than cannot be articulated as rules.

At the ACM meeting Jay Forrester argued that all human decisions are taken with respect to (possibly subconscious) mental models, and that computers should be used to augment human mental-modeling powers [6]. He is interested in models that make predictions about the future behavior of large organizations and societies. He maintains that human beings are notoriously inept at understanding the dynamics of systems that contain feedback control loops. Feedback loops, which are familiar features of mechanical systems and biological organisms, also permeate organizations and social systems. The modeling approach Forrester calls System Dynamics is aimed at giving us a tool to aid in understanding the operation of systems for which we have only a static description. He claims that many organizations can be successfully modeled because the members of the organization follow principles that are either explicit or are part of their habitual behavior; hence they can be stated as precise static rules that can be embodied as interacting functions in the model. Forrester has a good deal of optimism that system dynamics is a powerful general approach.

Limits of Modeling

Stuart Dreyfus, a long-time advocate of modeling and critic of expert systems, is concerned that we understand the limits of modeling so that our claims about models can be well grounded [4]. He argues that in most socio-economic domains, neither conventional mathematical modeling (including rule-based artificial intelligence) nor neural-network modeling are as trustworthy as the judgments of impartial, experienced experts. He calls the actions of expert in a domain a form of "skillful coping," about which there are extant four main theories: (1) Expert behavior is an unconscious application of a complete theory that can be articulated and computerized. This theory underlies KBSs, which he argues are unlikely to be more than minimally competent but not expert. (2) It is uninterpretable neuronal and biochemical activity that can nonetheless be reproduced after enough sensory input has been captured following the expert's approach to gathering data. This theory underlies neural network models, which he argues cannot be expert because they cannot adapt their interconnection patterns as does the brain during learning and relearning. (3) It is a process of recalling memories that match the current situation. He does not see how this can explain expert ability to cope skillfully with surprises and dilemmas. (4) It is uninterpretable brain activity evolved from a domain theory learned during an initial formal encounter with the domain through some teacher. He is most drawn to this theory because admits of both conceptual reason and experiential reasoning.

Dreyfus says that Forrester bases system dynamics on the first theory, whereas he himself finds the fourth theory much more credible and consistent with evidence about skillful coping. He concludes that computers that provide facts and suggest decisions can improve the judgment of experienced people. In the hands of inexperienced people, however, such computers may actually degrade coping skill. Education that equates expertise with models can inhibit the development of good judgment.

Steve Kline draws a sharp distinction between physical systems and systems that include human beings [8]. He uses a simple complexity index to demonstrate the qualitative differences between these two kinds of systems. His measure counts the number of variables, parameters, and feedback loops in the system being modeled. Physical systems modeled by differential equations (e.g., fluid flows) have low model complexity (on the order of 10^1) and may have high computational complexity. Hardware systems (e.g., airplanes and computer networks) have moderate model complexity (on the order of 10^6) and moderate to high computational complexity. But models for "human systems" -- brains, personalities, organizations, economies, and societies -- all have extremely high model complexity (on the order of 10^{13} and beyond).

In Kline's analysis physical systems and hardware systems have three characteristics that lead to low model complexity: they operate under invariant rules, their parts are context independent, and they are not self-observing. In contrast, human systems have changing rules and are self-observing and context dependent. Human systems are far more complex than physical because the "rules of the game" can change or evolve unpredictably. Kline ends up questioning the "science-based" approach to modeling human systems, an approach rooted in the Newtonian (mechanistic) tradition, which assumes that all the universe is governed by fixed laws.

Eleanor Wynn continues the skepticism toward computer models of human activities by questioning whether the perspective of information processing itself is sufficient to understand human systems [15]. Noting the widespread agreement that we do not know how to design complex software systems that are dependable, she observes that most of the discussion about software occurs within the paradigm of software engineering that begins with a formal specification and ends with an acceptance test. She argues that this paradigm completely misses how good designs are made because it is context-independent and cannot take into account the perspectives of users. She cites a "Scandinavian" paradigm of participatory design that consistently yields effective systems.

Description, Computation, Prediction

These authors share the conclusions that models involving human behavior are unavoidably complex, that such models may not work except in limited cases and even then they will be made to work by ongoing development rather than prior analysis. They suggest that one's trust in the reliability of such models depends on one's assumptions about how biological organisms and societies of such organisms learn and act. But the authors diverge on this claim: Models can produce greater understanding of complex human phenomena, lead us to wise decisions, and guide us to effective actions. Forrester is optimistic about this claim. Kunz implicitly accepts it in the domain of knowledge-based systems. But Dreyfus, Wynn, and Kline express serious doubts. The divergence of views on this important question is at the heart of the debate over computer modeling of human realities.

In what follows I will offer my own analysis of this claim, and I suggest ways that computers can assist us effectively in the domain of human actions.

What is a model? We usually understand a model to be a symbolic representation of a set of objects, their relationships, and their allowable motions [14]. We use models in three principal ways:

DESCRIPTION: We sometimes use a model to describe how a system works. Examples are a scale model of a railroad, the equations of motion of a planet, the scientific method, and the software design process.

COMPUTATION: We sometimes use a model to guide, to reproduce, or to calculate action in the domain. Examples are following directions from an inertial guidance system (guiding), a flight simulator (reproducing), or computing a measurement (calculatiing).

PREDICTION: We sometimes use a model to predict the future state of a system with tolerable certainty. Examples are models that predict the lift of a wing in flight, the position of a star, of the future state of the weather or the world economy. A model is useful for prediction only if the future state can be calculated much more rapidly than in real time, and only if its users agree that the assumptions about parameter values and governing laws will hold at the future time.

These three aspects are hierarchical in the sense that prediction relies on a model to compute a future state given future values of parameters, and computation relies on a precise description of the allowable motions of a system. Models are of universal interest because of our unavoidable concern to anticipate and prepare for future action, and because they make the world seem simpler and more understandable.

Maps are models that rely on all three aspects. I can use a map to achieve an understanding of the layout of a city and to discuss possible tours with others (description); or to navigate through the city (computation); or to figure how long it will take me to reach my destination (prediction).

What is reliability in modeling? A model is reliable if we find that it recurrently agrees with phenomena in the domain modeled. A model with many parameters is unlikely to be judged reliable because it is infeasible to explore the parameter space completely during testing and because the model's calculations may be sensitive to small changes in an unknown few of the parameters. A model is also unlikely to be judged reliable if we have not found a set of variables sufficient to describe the phenomenon of interest.

The more sophisticated predictive models provide indicators of the certainty of the prediction. These measures take the form of confidence intervals associated with numerical values or probabilities associated with states. If not interpreted properly, these measures can give a false sense of security about the reliability of the model -- everyone has experiences in which we were certain of an outcome that never happened.

Some modelers say that these measures allow comparisons: a model with smaller confidence intervals than another would be judged as the more powerful. It is important to ask whether a model does significantly better than random guesses. Even if it does, it need not be reliable because the uncertainty in its predictions is too high.

What is complexity? Complexity is an assessment we make about our capacity to accurately describe, compute, or predict phenomena in a domain. This assessment is related to the number of variables, parameters, and loops that exist in a system: the greater those numbers, the greater our uncertainty about how the system works and the lower our capacity to describe, simulate, or predict it accurately.

Note that chaotic behavior in the sense recently understood as "mathematical chaos" is not assessed as complex by this standard [5]. Such behavior may be described by simple equations, and its future trajectory can be calculated by iteration. These mathematical tools and powerful computers now allow us to calculate in excellent detail phenomena that we used to call complex -- examples include cloud formation, leaf structure, and turbulence. Present computers are not fast enough for prediction -- for example, recent joint studies of turbulence by researchers at Stanford and NASA-Ames took six months of accumulated Cray-YMP time for each case. On the other hand, chaotic functions do not necessarily provide reliable models because the future states can sometimes be very sensitive to the initial condition, about which there is often great uncertainty.

It is worth noting that we can make separate assessments of complexity about a model and about the domain modeled. This is because the model is itself another system that has variables, parameters, and loops. It is possible to offer a simple model for a complex domain, although we would be surprised if the model were reliable in this case. It is common to see complex models for simple domains. Our ideal is a simple model that reliably and rapidly reproduces the selected phenomena of the domain.

Meta-modeling

In an effort to understand where the complexity of models originates and how approximations arise, some modelers have modeled the modeling process itself. Subhash Agrawal's book is an example [1]. If you will permit me some light mathematics, I can show you how the modeling process itself introduces complexities that are often overlooked.

One can regard the construction of a model as a series of steps, each of which transforms a model into a simpler model by introducing a simplifying assumption. Let us focus on one of these steps. Suppose that we have a model M with parameters P and one variable x. It can be used to calculate a value of its variable by an algorithm $x = M(P)$. Suppose now we seek a faster algorithm by introducing a simplifying assumption A that maps the values of the original parameters and variable into the new parameters P' of M': $P' = A(P,x)$. The new model can now be used to calculate a value for the variable: $x = M'(P') = M'(A(P,x))$. Notice that the calculation is of the form: $x = F(x)$. The predicted value of the variable is now the fixed point of a complex function. If the value of x is initially unknown, an iteration must be employed find a convergent value, and the total computation time is not simply one application of the simpler model. Some of the fixed points of the function may be stable and others unstable, meaning that the final value may depend on the initial condition. Moreover, the time to convergence becomes an issue and there is a possibility of chaotic behavior (in the mathematical sense) in the iteration. This situation gets worse when several variables of the original model participate in the simplifying assumptions.

The conclusion is that "simplifying assumptions" can introduce rather than resolve computational complexities, a possibility that looms larger for systems with many variables and models with many simplifications. And, as Wynn points out, it is easy for us to ignore these complexities by persuading ourselves that the model is real or that the simplifying assumptions are of no consequence.

Meta-assessments

In addition to assessments of reliability and complexity, we often make a third kind of assessment -- a meta-assessment -- about whether the complexity or degree of reliability is "good" or "bad". I bring this up because in many discussions about modeling complex systems, I hear a background of frustration that the systems to be modeled, and thus the models themselves, are complex. It is "bad" that things are complex and a challenge to our ingenuity to find a reliable and computable model anyway. If we have such a meta-assessment, it will be extremely difficult to conclude that some systems are not worth an attempt at modeling. For example, many people accept that a major responsibility of government is to "plan" the economy, and thus it is necessary to have reliable models that will allow prediction of future states of the economy resulting from various policies, so that we can determine now which policies to enact. We seek a scientific approach to governance. In this context, the absence of a reliable model of the world economy is "bad" and is sufficient to motivate the expenditures of millions of dollars in pursuit of computer models of the world's economy.

We do not always judge that complexity is "bad". We live in an unimaginably complex world of 5 billion people, each engaged in a network of conversations with others. Declarations made in distant parts of this network can affect the possibilities open to us even though we are not part of the conversation leading to the decision. (The Iraqi takeover of Kuwait is a good recent example.) Most of us simply accept that the world network of human conversations is highly complex and unpredictable, that the rules of the game may be altered without warning at any time, and that the rules will surely evolve. Our strategy in this case is not to find models whose predictions can guide our actions; it is rather to create organizations and use their power to effect action. Successful organizations don't rely on computer models; they develop strategies to position themselves in the world marketplace. Entrepreneurs such as Tom Peters thrive in this environment of complexity and uncertainty -- they assess complexity as "good".

Another category of meta-assessments are those people make of the future as they carry out their work in organizations and social systems. We call these assessments "moods". Not only do individuals have moods, so do organizations and social units. Organizations with good moods (high morale) generally do better than those with bad moods, and one of the jobs of managers and executives is to generate good moods in their organizations [12]. A country can enter a depression if enough people get into a mood of pessimism in which they hoard their money. Our inability to predict moods adds to the complexities we face in making predictions about organizations and social systems.

Evolving Rules

Systems with many human participants may be so subject to changes of rules that their future trajectories cannot even be described as computable functions, much less predicted. It is often difficult or impossible to determine the variables that affect the phenomenon -- understanding human personalities or the collapse of complex societies [13] are examples.

What drives us to seek models in the face of evidence that reliable computable models may not exist? We have all been brought up in a scientific world view, conditioned by 300 years of successful physics modeling dating, from the time of Newton, which inclines us to believe that all the world's a mechanism, a clock that God created and left ticking. We tend to believe that everything, including the human brain, the human personality, and human social systems, can in principle be modeled by a set of equations. Given enough research we can find the equations, and given enough computer resources we can solve them [2,11].

Our science tradition has a darker side. It views the world, including people, as a collection of resources to be acquired, used, optimized, and discarded when no longer needed. It views situations, including those that involve the human condition, as "problems" for which technological and procedural "solutions" are to be found. We need to ask ourselves whether our drive to model human complexities might not be an overextension of science, and whether our drive to use scientific models to solve world problems might not reflect the hubris of science. We need to ask ourselves whether some of the models of complex phenomena we seek to construct would gain us anything if we could find them.

At bottom, a model is nothing more than an interpretation of the world. The invention of interpretations is a fundamentally human activity that is intimately involved with our understanding of truth. As scientists, we like to say that scientific laws and mathematical theorems already exist awaiting discovery. But if we carefully examine the processes of science, we find paradigms other than discovery. Roald Hoffmann says that creation of new substances not found in nature is the dominant activity in disciplines such as chemistry and molecular biology [7]. Bruno Latour goes further, observing that in practice a statement is accepted as true by a community if no one has been able to produce evidence that persuades others to dissent [10]. Science is a process of constructing facts, and different scientific communities can construct different systems of interpretation of the same physical phenomena. Western and Eastern medicine, for example, are two scientifically valid systems of interpretation about disease and human disorders; each recommends different interventions for the same symptoms and sees phenomena that are invisible to the other, and their interpretations are not easily reconciled.

Productive Uses of Computers

Several conclusions emerge from the discussion above:

- As part of our modeling efforts we must come to understand the domains over which a given model is reliable, partly reliable, and unreliable. We must also understand the situations in which models can be useful as a way of grounding speculations about the future dynamics of systems.

- Systems whose rules can evolve or change in unpredictable ways are unlikely to have a reliable predictive or speculative model.
- We must be careful with the output of models, being constantly skeptical that those outputs are "facts" or are accurate descriptions of the world.
- In our technological age, it is easy to accept the claim that every phenomenon can be ultimately modeled given sufficient knowledge and computational resources.
- If our mood disinclines us to accept complexity, it is easy to substitute the model for reality and to confuse our opinions as "scientific facts" supported by the model.

In spite of my questions and doubts, I accept that in limited domains we may be able to find reliable predictive models of systems in which humans participate. At this point, however, we have no consensus on where the limits are.

If we cannot model human systems, what can we do with computers? We can use them to augment human capacities, especially in those aspects where we are limited, notably in processing power and in memory. We can use KBSs as advisors that suggest actions based on analysis of past situations, and let the current decision taken by the human become another data point for future analysis. We can use the worldwide network of computers to gather information. We can use computers to help manage and track the flow of work and information. We can confine models to domains in which their predictive power can be used reliably, namely domains in which the rules are known in advance. In all cases, however, we must let the computer support the decision-maker, and not let the computer make the decisions.

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