Levels of Granularity in Cognitive Modeling

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1. Introduction

Within each general modeling paradigm, such as connectionism or dynamical systems, any particular model also makes a choice as to the desired level of granularity. A connectionist model might attempt to capture details of individual neurons, as in a retinal model, or else it might allow the model's nodes to represent larger abstract groupings of functionally related neurons. This paper surveys several broad classes of cognitive models with respect to their stance on model granularity.

In addition to examining traditional cognitive models, this paper also discusses how we might attempt to overcome the granularity divide amongst these models. In particular, we point towards Holland's work on emergent behavior in complex adaptive systems as paving the way for understanding cognition more deeply at multiple levels of granularity. We begin by motivating the discussion by examining the goals of cognitive modeling.

2. Purpose of Modeling

The primary reason to build a model of a physical system is arguably to make prediction possible. While the best possible model of any system would be a facsimile of the system itself, such a "model" provides little predictive power. We might build a scale replica of our solar system, but Kepler's laws of planetary motion allow us to immediately make predictions far into the future that would be impossible with the replica [Holland 1998]. Of course, predictive power due to simplification of reality comes at the price of loss of predictive accuracy. Indeed, Holland claims that "the single most important factor in making an accurate prediction is the level of detail" [Holland 2002]. A key task facing a modeler is to choose the level of detail that best balances amount of detail and predictive power. Note that, in general, including more details does not necessarily lead to more accuracy, due to the complexities inherent in simulating complex systems. Effects of numerical instability or chaotic dynamics, for instance, can overwhelm models that work with too much detail for the predictive task.

Due to complexity, prediction with a high degree of accuracy may not be possible in a model uninformed by a requisite amount of *understanding*. The modeler needs to select not only the amount of detail to include in a model, but also the general types of structures that make up the model. A model of the weather, for instance, might explicitly include such high-level structures as storm fronts or the jet stream. A forecaster might either hope for these features to emerge from a lower-level model or else build these into the model up-front. The choice has important ramifications: a model based on the higher-level granularity of storm fronts might be more reliable in some situations, while a lower-level model based on features like air pressure and moisture content might perform better in other cases. Deep understanding of the system under consideration is necessary to posit higher-level features and to describe their dynamics. A secondary motivation for modeling is to gain the understanding necessary to develop richer models to aid the primary goal of prediction.

What is the goal of cognitive modeling?

As a cognitive scientist it seems reasonable that the goal of cognitive modeling is to better understand the internal mechanisms of thought, to see how thinking "really" works. The study of cognition has particular significance as it is closely related to deep philosophical questions about the nature of mind and consciousness. But we can productively sidestep the issue of philosophy of mind by recalling the secondary motivation of modelers above, and focus on understanding thought mechanisms in service of building better-informed predictive models of cognitive processes.

Marr proposes three different levels of explanation for use in understanding cognitive systems: 1) computational theory (input-output analysis), 2) representation and algorithm, and 3) implementation [Marr 1982]. Clark argues that although this division into three distinct levels may be "too neat", it points out how understanding a single level such as the neural substrate of the brain is not sufficient to understand how computation is organized at larger levels of granularity.

The word "level" is used here in different contexts, so it is important to keep the uses distinct. Marr's three levels refer to the three distinct types of analysis listed above. The level of granularity in a model refers to the relative size of the units of representation.

3. Reconciliation of levels

The need for bridge-building

As mentioned above regarding connectionism, we don't have a principled way to simplify from vast numbers of neurons down to a manageable set for use in a connectionist simulation. Such a strategy for simplification would also be useful to other cognitive approaches such as dynamical systems and physical symbol systems. Even more interesting is the possibility for building connections between different modeling strategies. We would like to see how a connectionist model would produce something like a PSS at a higher level. Hofstadter [1986] also seeks such a bridge between levels:

> The best traditional AI (and cognitive psychology) is something like classical physics: true on all scales, but in some sense "irrelevant" on a large scale. The problem is therefore to link these two vastly different levels. In physics, the "correspondence principle" says that the equations of quantum mechanics must turn into their classical counterparts in the limit of large quantum numbers. In that sense, a beautiful bridge is rigorously established between the unfamiliar micro-world and the familiar macro-world. I would like see such a bridge established between connectionism and the study of cognition itself, which includes traditional AI, cognitive psychology, linguistics, and the philosophy of mind.

In astronomy, the bridge-building problem was as simple as calculating a center of mass and discarding negligible gravitational effects. How can we find analogous cognitive centers of mass?

Emergence

In his study of complex adaptive systems, Holland [1988] provides ideas about how to study complex emergent behavior. The link between lower and higher cognitive levels, such as a link between connectionism and PSS, can be viewed as understanding how symbols can emerge from the interaction of vast numbers of neurons. Both Holland and Clark [2001] emphasize the role of *persistent patterns* in the study of emergence. Holland writes that “Only persistent patters will have a directly traceable influence on future configurations in generated systems… the persistent patterns are the only ones that lend themselves to a consistent observable ontogeny.”

In a complex system, if patterns emerge, they can be used as the basis for prediction. A model that accounts for higher-level patterns can thus escape the facsimile trap and generate predictions without simply simulating every small detail of the original system. These emergent patterns will pave the way towards bridge-building – if connectionism and a higher-level theory like PSS are to be consistent, the emergent patterns of a connectionist network will at some point match up with the higher-level symbols.

One difficulty of prediction in a complex system is the worry that emergent phenomena are “uncompressible” in terms of predictable patterns, that is, they are “those phenomena for which prediction requires simulation.” [Clark 2001] Clark counters this pessimistic attitude, however, writing that

> My intuition, by contrast is that emergent phenomena are often *precisely* those phenomena in which complex interactions yield robust, salient patterns capable of supporting prediction and explanation, i.e., that lend themselves to various forms of low-dimensional projection.

There is, then, room for optimism. However, it is worth noting that a viable, predictive theory of emergent behavior in complex systems is still a distant goal. It is imperative, however, that cognitive science embrace and support the search for such a theory, as the lack of bridges between levels will remain a serious obstacle to cognitive science for the foreseeable future.

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