

# Towards Measures of Intelligence Based on Semiotic Control \*

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## Abstract

We address the question of how to identify and measure the degree of intelligence in systems. We define the presence of intelligence as equivalent to the presence of a control relation. We contrast the distinct atomic semiotic definitions of models and controls, and discuss hierarchical and anticipatory control. We conclude with a suggestion about moving towards quantitative measures of the degree of such control in systems.

## 1 Introduction: A Control Theory Framework for Intelligence

We consider some of the challenges presented in the white paper designed to prepare for this conference [13]. I take the fundamental question to be "How can we as external observers measure the degree of intelligence in a target system?"

One approach is to invoke the typical lists which can characterize intelligent behavior, including adaptability, complexity of internal models, problem solving ability, etc. But what is fundamental to each of these? For example, adaptability is the ability to adjust responses to make them appropriate under variable conditions. Problem solving is the ability to come to

a correct choice about actions to achieve a particular goal, hereby solving the problem. And finally, complexity of internal models must always be considered as relative to their ability to predict the outcome of future behaviors.

Thus can see that fundamental to all of these is the idea that intelligence requires the ability of a system to make *appropriate decisions given the current set of circumstances* [1, 2, 3]. On analyzing this a bit further, we can identify the following necessary components:

**Measurement:** The ability to know the current set of circumstances.

**Decision:** The freedom to choose between one of many possibilities.

**Goal:** The possibility that the choice made will be either appropriate or inappropriate relative to a goal state.

**Action:** The ability for the decision to affect external and future events, in order for them to be either closer to or further away from the goal.

## 2 Intelligence as Semiotic Control

We note the similarity to the scheme of an intelligent system as outlined in the conference White

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Paper [13]. This requires a “loop of closure” consisting of six modules: a world interface, sensors, perception, a world model, behavior generation, and actuation. We understand this situation as the existence of a *semiotic control* system. We know briefly outline the theory of semiotic systems.

## 2.1 Semiotic Models and Controls

There is a rich literature (eg. [5, 15, 17, 18, 19]), traceable back to the founders of systems theory and cybernetics in the post-war period [4], which has tried to construct a coherent philosophy of science based on two fundamental concepts:

- **Models** as the basis not only for a consistent epistemology of systems, but also as an explanation of the special properties of living and cognitive systems.
- **Control systems** as the canonical form of organization involving purpose or function.

While controls and models are distinct kinds of organization, what they share is a common basis in semiotic processes, in particular the use of a measurement function to relate states of the world to internal representations. Perhaps for this reason there has been some ambiguity in the literature about the specific nature of controls and models, and more importantly how they interact. This has led to confusion, for example, about the role of feedback vs. feedforward control, and endo-models *within* systems vs. exo-models *of* systems.

Consider first a classical control system as shown in Fig. 1. In the world (the system’s environment) the dynamical processes of “reality” proceed outside the knowledge of the system. Rather, all knowledge of the environment by the system is mediated through the measurement (perception) process, which provides a (partial) representation of the environment to the system. Based on this representation, the system then chooses a particular action to take in the world, which has consequences for the change in state

of the world and thereby states measured in the future.

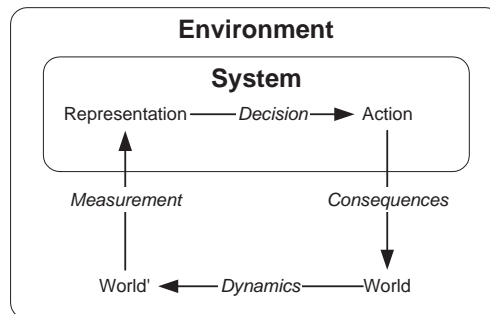


Figure 1: Functional view of a control system.

To be in good control, the overall system must form a negative feedback loop, so that disturbances and other external forces from “reality” (for example noise or the actions of other external control systems) are counteracted by compensating actions so as to make the measured state (the representation) as close as possible to some desired state, or at least stable within some region of its state space. If rather a positive feedback relation holds, then such fluctuations will be amplified, ultimately bringing some critical internal parameters beyond tolerable limits, or otherwise exhausting some critical system resource, and thus leading to the destruction of the system as a viable entity.

Now consider the canonical modeling relation as shown in Fig. 2. As with the control relation, the processes of the world are still represented to the system only in virtue of measurement processes. But now the decision relation is replaced by a prediction relation, whose responsibility is to produce a new representation which is hypothesized to be equivalent (in some sense) to some future observed state of the world. To be a good model, the overall diagram must commute, so that this equivalence is maintained.

As outlined here, models and controls are distinct and atomic kinds of organization. We have argued [8] that this capability begins with living systems, and perhaps defined the necessary and sufficient conditions for living systems.

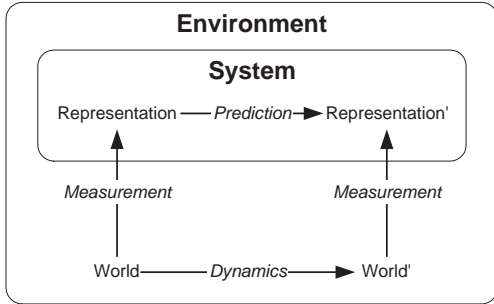


Figure 2: Functional view of the modeling relation.

## 2.2 Hierarchical Control

Of course, all of the relations described here are a great deal more complex in real intelligent systems. In particular, usually controls and models are considered together. This concept is fully developed elsewhere [7, 9]. We now summarize the primary results of these considerations.

First, the classical view of linear control systems theory [14] is recovered by introduced a “computational” step which plays the role of cognition, information processing, or knowledge development. Typically, extra or external knowledge about the state of the world or the desired state of affairs is brought to bear, and provided to the agent in some processed form, for example as an error condition or distance from optimal state. So now measured states are manipulated and compared to a goal state.

In particular, we are impressed by Bill Powers system for hierarchical control [15, 16, 6], which he has successfully generalized to explain the architecture of neural organisms. As shown in Fig. 3, he views the computer as a comparator between the measured state and a hypothetical set point or reference level (goal). This then sends the second representation of an error signal to the agent. He also explicitly includes reference to the noise or disturbances always present in the environment, against which the control system is acting to maintain good control. For us, these are bundled into the dynamics of the world.

Another great virtue of Powers’ control theory

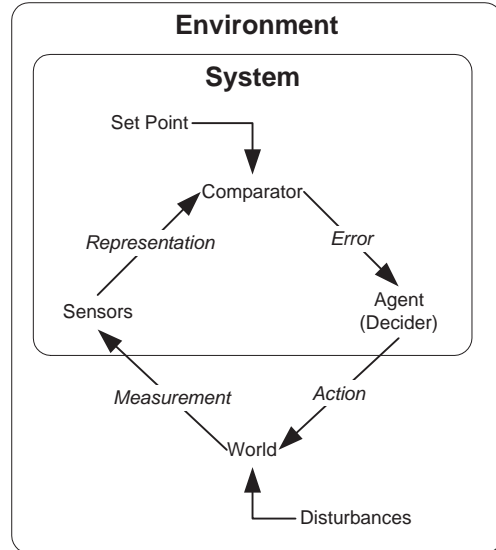


Figure 3: A Powers’ control system.

model is its hierarchical scalability. Fig. 4 shows such a hierarchical control system, containing an inner level 1 and the outer level 2. The first key move here is to allow representations to be combined to form higher level representations. In the figure  $S_1$  and  $S_2$  are low distinct level sensors providing low level representations  $R_1$  and  $R_2$  to the inner and outer levels respectively. But  $R_1$  is also sent to the higher level  $S_3$ , and together they form a new high level representation  $R_3$ .

The second step is the ability for the action of one control system to be the determination of the set-point of another, thus allowing goals to decomposed as a hierarchy of sub-goals. In the figure, the outer level uses  $R_3$  to generate the action of fixing the set point of the lower level. Note how this recovers Meystel *et al*’s “Feature 10” of multiscale knowledge representation where the action of a lower level system is actually the goal of an upper level system [13].

Notice also that the overall topology of the control loop is maintained. While ultimately the lower level is responsible for taking action in the world, it is doing so under the control of the comparison of a high-level goals against a high-level representation. Neural organisms especially are

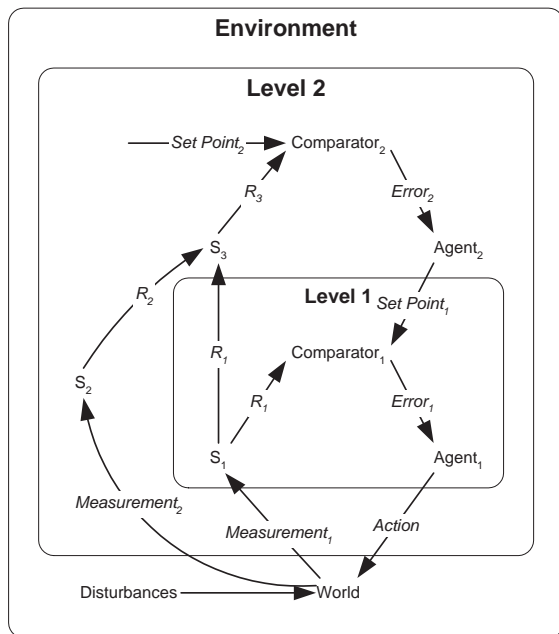


Figure 4: Hierarchical nesting of Powers' control systems.

systems of this type, low-level motor and perceptual systems combining to accomplish very high-level tasks. And of course, determination of the outermost goal is not included within Powers' formal model.

### 2.3 Anticipatory Control

While familiar to us as a standard engineering discipline, a number of researchers are pursuing the applicability of this kinds of semiotic control [12]. It is also being generalized to a number of other engineering [2] and scientific domains.

However, our normal sense of control combines it with models, which are used to aid in decision-making by predicting future states of anticipated actions, using prediction of future events to guide actions. This is what Ashby refers to as “cause control” [4], or Rosen as “anticipatory” [17], or Klir as feedforward [10]. In this architecture an endo-model embedded *within* a control system is used to make a decision as to which action to take, and thus acts in the role of the agent. It is

this view which most dominates our conception of the nature of control in general.

However, this architecture is actually highly complex and special. It is shown in Fig. 5, where now the agent is replaced by an inner system which is *both* a model and a control system (the arrows have been reflected diagonally to make the graph planar and ease the drawing). This inner system is a control system in the sense that there are states of its “world”, its “dynamics”, and an “agent” making decisions.

However, it is also a model in that the states of its “world” are in fact representations, and its “dynamics” is actually a prediction function. The inner system is totally contained within the outer system, and runs at a much faster time scale in a kind of modeling “imagination”. The representation  $R$  from the sensors is used to instantiate this model, which takes imaginary actions resulting in imaginary stability within the model. Once this stability is achieved, then that action is exported to the real world.

Note that the outer control loop here is simple, lacking computation. In Powers' terms, there is no set point which the state of the internal model is being compared to. But this could be present in a slight elaboration where an imaginary measurement is taken from “world” and compared to some set point. The outer error signal would then be fed to change the imagined actions inside the model until stability is achieved.

## 3 Tests for the Presence of Control

Thus we have now transformed the original question of “how do we measure intelligence?” to “How can we as external observers determine whether a target system manifests control relations with its environment?” and “How can we then measure the degree and modalities of that relation?” I would then offer some ideas based on the work of Powers and his colleague Rick Marken [11, 15, 16].

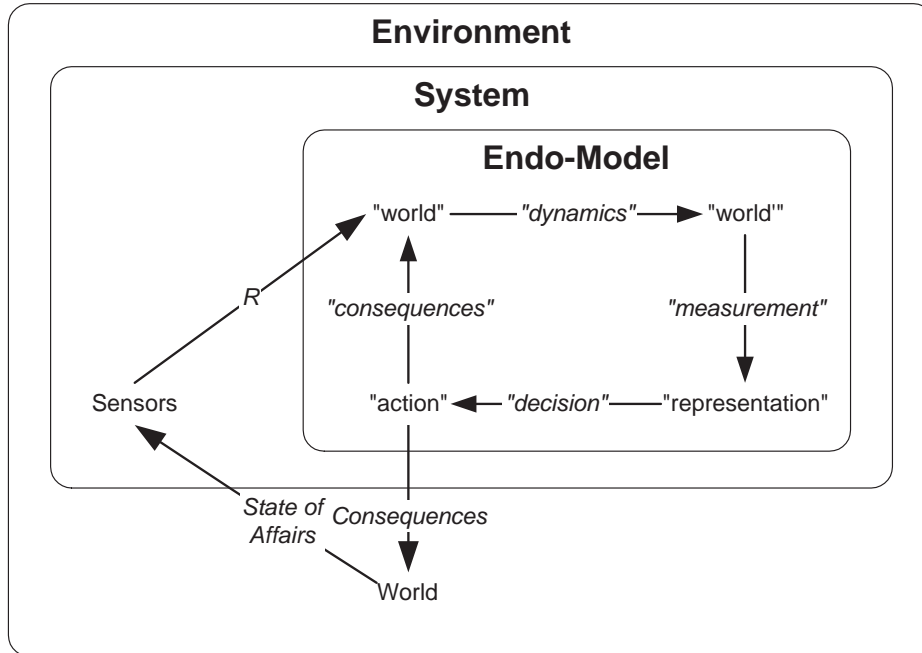


Figure 5: Anticipatory control.

They address the question from the following perspective. Control relations, in virtue of the stability of the controlled variables in the environment, have many of the characteristics of other equilibrium phenomena. Both the thermostat and the ball rolling to a stop at the bottom of a hill evidence this kind of stability behavior. In the first case, the ball does not *want* to roll down the hill, but in a very real sense, the thermostat *does* want to regulate its “perception” of the state of the room temperature.

So how can we distinguish a complex dynamic equilibrium from a control relation? Powers and Marken do this distinguishing on the basis of what they call The Test. It involves the system acting in a way which is counter to physical law: if the ball *failed* to roll down the hill, we’d be surprised, thus we hypothesize that such a ball is manifesting a control relation. Similarly, we would normally expect a room to come to equilibrium with its environment. When it does not, and we believe our dynamical model, then we would hypothesize the presence of a control

device, and we might investigate and discover a thermostat. The “intelligence” of such systems is based on their manifesting a semiotic relation which has been selected by evolution or by designers, allowing the system to “choose” to act counter to physical law.

Now the rub is that this Test thereby requires the prior presence of a model of what the system *should* be doing, so that we can be surprised when it fails to do so. Thus our recognition of a control relation in an exogenous system requires of us an *exogenous* model of reality, whether or not the system has any *endogenous* model itself.

## 4 Towards a Measure of Control-Based Intelligence

So now, given this semiotic control-based view of intelligence, we wish to go on and attempt to quantify and characterize the degree and kind of control relations present. Thus the problem of measuring intelligence revolves around our ability to measure:

- The amount of phenomena under control;
- The number of environmental distinctions measured by the system;
- The complexity of modalities of measurement and control;
- The complexity of the environmental variety available to the measurement and control of the system;
- If hierarchical control is present, what is the depth of the hierarchy of control; and
- If anticipatory control is present, what is the complexity of the internal, endogenous models?

No doubt in both real and designed systems these are all related to each other in complex ways. However, each of these quantitative terms is effectively a statistical information measure, a measure of variety or freedom. Thus they are amenable to information-theoretical measures like entropies, based on quantities of variety, distinctions, and constraints which a control system can recognize in its environment and then act on in appropriate ways.

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