Computational Constructivist Model as an Anticipatory Learning Mechanism for Coupled Agent–Environment Systems

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> Context • The advent of a general artificial intelligence mechanism that learns like humans do would represent the realization of an old and major dream of science. It could be achieved by an artifact able to develop its own cognitive structures following constructivist principles. However, there is a large distance between the descriptions of the intelligence made by constructivist theories and the mechanisms that currently exist. > Problem • The constructivist conception of intelligence is very powerful for explaining how cognitive development takes place. However, until now, no computational model has successfully demonstrated the underlying mechanisms necessary to realize it. In other words, the artificial intelligence (AI) community has not been able to give rise to a system that convincingly implements the principles of intelligence as postulated by constructivism, and that is also capable of dealing with complex environments. > Results • This paper presents the constructivist anticipatory learning mechanism (CALM), an agent learning mechanism based on the constructivist approach of AI. It is designed to deal dynamically and interactively with environments that are at the same time partially deterministic and partially observable. CALM can model the regularities experienced in the interaction with the environment, on the sensorimotor level as well, as by constructing abstract or high-level representational concepts. The created model provides the knowledge necessary to generate the agent behavior. The paper also presents the coupled agent environment system (CAES) meta-architecture, which defines a conception of an autonomous agent, situated in the environment, embodied and intrinsically motivated. > Implications • The paper can be seen as a step towards a computational implementation of constructivist principles, on the one hand suggesting a further perspective of this refreshing movement on the AI field (which is still too steeped in a behaviorist influence and dominated by probabilistic models and narrow applied approaches), and on the other hand bringing some abstract descriptions of the cognitive process into a more concrete dimension, in the form of algorithms. > Constructivist content • The connection of this paper with constructivism is the proposal of a computational and formally described mechanism that implements important aspects of the subjective process of knowledge construction based on key ideas proposed by constructivist theories. > Key words • Factored partially observable Markov decision process (FPOMDP), computational constructivist learning mechanisms, anticipatory learning, model-based learning.

Introduction

> 1 • The constructivist approach to artificial intelligence can be defined as the set of works on this science directly or indirectly inspired by ideas coming from the constructivist conception of intelligence. This conception was essentially defined by Jean Piaget (1954) and gave rise to an important school of thought that influenced many scientific fields from the second half of the twentieth century onward. The first important AI system based on constructivist concepts appeared much later, presented by Gary Drescher (1991), but even if his model had some theoretical impact on the field of AI, it could never be used to solve significant applied problems. Since then, year after year, new papers have been published that attempt to point out a way to implement such a strong mechanism (Guerin 2011). However, the constructivist approach has never thrilled most researchers in the AI community, staying in that uncomfortable position between the promise of true intelligence and the lack of impressive results. > 2 • In this article, we present the constructivist anticipatory learning mechanism (CALM), an agent learning mechanism based on the constructivist approach of AI. CALM is designed to discover regularities in partially deterministic environments: it identifies the deterministic transformations present in non-deterministic situations. The mechanism operates incrementally: the agent learns at the same time as it needs to interact with the environment. CALM can also deal with partially observable environments: it is able to infer the existence of hidden or abstract properties, integrating them in its anticipatory cycle.
be a model necessarily based on regularities extracted from subjective sequences of observations and actions, and not from the structure of that reality, which remains unknown in its essence.

Moreover, in complex environments, special “macroscopic” properties emerge from the functional interactions of “microscopic” elements, and such emergent characteristics are not defined in any of the sub-parts that generate them (Goldstein 1999). The salient phenomena in this kind of environment tend to be related to high-level objects and processes (Thornton 2003). In this case, if we suppose the existence of a complex universe out there, it is plainly inadequate to represent the experience only in terms of primitive sensorimotor elements (Drescher 1991).

Considering these conditions, an intelligent agent (human or artificial) must have the capacity to overcome the limits of pure sensorial perceptions, organizing the universe in terms of more abstract concepts. The agent needs to be able to detect high-level regularities in the dynamics of the environment, but this is not possible if the agent is stuck in a rigid representational vocabulary.1 In a constructivist approach, cognitive development must be a process of gradual complexification of the intelligence, where more abstract structures (symbolic) are built from simpler sensorimotor interactions, in a way that harmonizes the lived experiences with the constructed model.

From the flat, unstructured, continuous flow of perceptions resulting from the situation of the agent in a complex universe, intelligence needs to build some organization. While the constructed internal knowledge might reflect an external reality to some degree, from the agent’s perspective this remains undecidable. Importantly, though, intelligence progressively organizes knowledge in increasingly abstract structures, enriching the agent’s understanding of its own experiences.

1 The agent’s representational vocabulary is the set of elements it can manipulate to create knowledge.
Coupled agent–environment system

1. **Column A**

   "14" CAES is a meta-architecture proposed in this article to define a coupled agent-environment system, respecting the notions described in the precedent section.

   The universe \(U\) is represented as a global system \(U = (A, E)\), where an agent \(A\) interacts with an environment \(E\). The agent \(A = [B, M]\) is formed by two subsystems: body \(B\) and mind \(M\). The body is the intermediate between mind and environment.

   Mind, body and environment can be each described by an abstract state space and an evolution function:
   \[ E = \{X_P, f_E\}, B = \{X_P, f_B\}, \]
   \[ M = \{X_M, f_M\}. \]

   "15" These entities are interrelated in dynamical systems. The environment continuously imposes a situation \(s\) on the agent, which responds through an actuation \(a\). The situation is given in function of the state \(x_E\) of the environment, \(s = f(x_E)\), and the actuation is defined according to the state of the body, \(a = f_B(x_B)\). In the same way, the mind is continually receiving a perception signal \(c\) coming from the body in function of its state \(x_M\), \(c = f_M(x_M)\), and sending to the body a control signal \(a\), decided in function of the mind’s own internal state, \(c = f_M(x_M)\). Part of the situation can be perceived by the mind through external sensors present in the body, while the mind can also control part of the actuation over the environment through external effectors also present in the body. The interaction of the mind with the body takes place through internal sensors and effectors.

   The mind does not know a priori what sensors and effectors are internal or external. From the point of view of the mind, both body and environment are in some way external, being part of an exteriority \(W = \{B, E\}\), the world outside the mind. The complete CAES meta-architecture is presented in Figure 1.

   "16" This configuration generates a kind of circularity, and defines each entity as a partially open dynamical system. The environment evolves in function of its own current state, but influenced also by the actuation coming from the agent, \(x_E' = f_E(x_E, a)\). Similarly, the next body state is defined in function of the actual body state, but is influenced by both the situation coming from the environment and the control signal coming from the mind, \(x_M' = f_M(x_B, s, c)\). It is the same for the mind, which continually changes its internal state (whatever that means) influenced by its perceptions, \(x_M' = f_M(x_M, p)\).

   "17" CAES is a meta-architecture because it does not define of what or how each system is made. Moreover, it does not constraint these systems as stationary. The environment as well as the body can change its respective set of rules and variables over time. The same applies for the mind, which needs to be non-stationary if we want to have some kind of learning or mental development. Such learning ability can be defined as a function \(M' = f_M(M, x_M, p)\) that changes the mind’s own space of states (creating new concepts or representational signs) and rules (changing the policy of actions that is responsible for determining the control signal based on the experience (memories and immediate perceptions).

   **Representing ontological and experiential reality**

   "18" In our understanding, a constructivist machine learning mechanism must be made using *model-based* methods. The agent constructs knowledge in order to understand its experience of interaction with the environment. Computationally, the learning problem can be divided into two parts: (a) the construction of the model, and, based on it, (b) the definition of a policy of actions, which defines the agent’s subsequent behavior.

   "19" When, for simplicity, we say that the agent constructs a *model of the world*, we need to specify that in fact it is the agent’s mind that constructs a model of an exteriority (the world outside the mind) to which the mind has access only through a limited sensorial interface. A model of the world is not a reproduction of the structure of an ontological reality, but is a model of the agent’s *experiential history*. It is a model (and not a 27 memory) because it does more than remember the past interactions: the model aims to generalize a complete system to represent the whole external world based on the finite set of experiences.

   "20" Frequently in the machine learning literature, the relation between agent and environment is not clearly defined. Traditionally, computer scientists do not make an explicit difference between the world as it is ontologically and the world represented by the agent at the limits of its sensorial interface and history of interactions. They conceive the agent as acting and perceiving directly on the “real world,” and this can give rise to confusing architectures, where situational problems disappear by omission.

   "21" We define the learning problem in the following terms: we cannot know what any “external reality” (the world outside the mind) consists of, but we suppose that it can be represented (for analytical purposes) as a *factored and partially observable Markovian decision process* (FPOMDP), where actions

   3| A dynamical system is stationary if the rules that define its evolution do not change over time.

   4| In opposition to *model-free* methods, where an agent can dynamically optimize its behavior only based on the immediate experience.

   5| The experiential history is the sequence of interactions (perceptions and actions) realized by the mind.
1 and observations correspond to the control
2 and perception signals in the CAES archi-
3 tecture. The world model constructed by
4 the mind can be represented by a factored
5 Markovian decision process (MDP) that
6 constitutes a kind of morphism of the first
7 one, constrained by the sensory interface
8 limitations, as well as by the incompleteness
9 of the experience, but possibly enriched
10 with abstract variables created in order to
11 make the system more structured and intel-
12 ligible.

« 22 » In simulated systems, where both
13 agent and environment are programs run-
14 ning in a computer, an observer can have
15 access to the whole structure (mind, body,
16 environment and their interfaces of interac-
17 tion). In this particular case, it is possible
18 to analyze the factors that characterize the
19 experiential relation with that given reality.
20 The specificities of that relation, combined
21 with the intellectual and cognitive capaci-
22 ties of the agent, will determine the difficul-
23 ty of learning a successful model,* and con-
24 sequently the agent’s possibility to become
25 adapted to the environment.

MDP framework

« 23 » Markovian decision processes
(MDPs) and their extensions constitute
widely-used representations for modeling
decision-making and planning problems
(Feinberg & Shwartz 2002). An MDP is
typically represented as a discrete stochastic
finite state machine (Puterman 1994; Rivest
& Schapire 1994): at each step of the ma-
chine is in some state s; the agent interacts
with the process by choosing some action a
to carry out; then the machine changes into
a new state s’ and gives the agent a corre-
sponding reward r; a given transition func-
tion δ defines the probabilities of the state
change according to s and a. The flow of an
MDP (the transition between states) de-
pends only on the system’s current state and
on the action taken by the agent at the time.
After acting, the agent receives an evalu-
ative reward signal (positive or negative), ac-
tording to the chosen actions or the realized
state transition.

« 24 » Solving an MDP means find-
ing the optimal (or near-optimal) policy of
actions in order to maximize the rewards
received by the agent over time. When the
MDP parameters are completely known, in-
cluding the reward and the transition func-
tions, it can be mathematically solved by dy-
namic programming methods. When these
functions are unknown, the MDP can be
solved by reinforcement learning methods,
designed to learn a policy of actions on-line,
i.e., at the same time that the agent interacts
with the system, by incrementally estimat-
ing the utility of state-action pairs and then
mapping situations to actions (Sutton &
Barto 1998).

« 25 » However, the MDP supposes that
the agent has complete information about
the state of the environment. A partially ob-
servable MDP (POMDP) (Singh et al. 2003;
Cassandra, Kaelbling & Litman 1998) is an
extension of the model that includes a set of
observations that is different from the set of
states. The underlying system state s cannot
be directly perceived by the agent, which has
access only to an observation o given by an
observation function γ. We can represent a
larger set of problems using POMDPs rather
than MDPs, but the methods for solving
them are computationally even more expen-
sive (Hauskrecht 2000).

« 26 » For a situated agent, this kind of
representation becomes inadequate because
it requires the complete enumeration of the
states, and the number of states increases
exponentially according to the number of
agent sensors (Bellman 1957). This is the
main bottleneck in the use of MDPs or
POMDPs: representing complex universes
entails an exponential increase in the state
space, and the problem quickly becomes in-
tractable.

Factoring the MDP states

« 27 » When a large MDP has a signifi-
cant internal structure, it can be modeled
compactly; the factorization of states is an
approach to exploit this characteristic (Bou-
tillier, Dearden & Goldszmidt 2000; Jonsson
& Barto 2005; Degris, Sigaud & Wullem
2006; Shani et al. 2008). In the factored rep-
resentation, a state is implicitly described
by an assignment to some set of state vari-
ables. Thus, a complete explicit state space
e numeration is avoided, and the system can
be described referring directly to its vari-
ables. The factorization of states enables
the system to be represented in a generalized
and compact way, even if the correspond-
 ing MDP is exponentially large (Guestrin et
al. 2003). When the structure of the MDP
is completely known, it is possible to find
good policies in an efficient way (Guestrin
et al. 2003). However, the research con-
cerning the discovery of the structure of an
underlying system from incomplete ob-
servation is still incipient (Degris & Sigaud
2010).

« 28 » An FPOMDP is an FMDP that
can represent partial observation (Guestrin,
Koller & Parr 2001; Hansen & Feng 2000;
Poulart & Boutillier 2004; Shani, Brafman
& Shimony 2005; Sim et al. 2008). An FPOM-
DP can be formally defined as a 4-tuple \(X, C, R, T\). The state space is factored and rep-
resented by a finite non-empty set of system
properties or variables \(X = \{X_{1}, X_{2}, \ldots, X_{n}\}\),
which is divided into two subsets, \(X = P \cup H\),
where the subset \(P\) contains the observ-
able properties (those that can be accessed
through the agent’s sensory perception), \(C\)
and the subset \(H\) contains the hidden or
non-observable properties. Each property
\(X_{i}\) is associated to a specified domain, which
defines the values the property can assume;
\(C = \{C_{1}, C_{2}, \ldots, C_{m}\}\) represents the controlla-
ble variables, composing the agent actions;
\(R = \{R_{1}, R_{2}, \ldots, R_{i}\}\) is a set of (factored) re-
ward functions, in the form \(R_{i}: P \rightarrow \mathbb{R}\); and
\(T = \{T_{1}, T_{2}, \ldots, T_{n}\}\) is a set of transformation
functions, such as \(T_{i}: X \times C \rightarrow X\), defining
the system dynamics. Each transformation
can be represented by a dynamic
Bayesian network, which is an acyclic, ori-
ented, two-layer graph. The first layer nodes
group represent the environment state at time
\(t\), and the second layer nodes represent the
next state, at \(t+1\) (Boutilier, Dearden &
Goldszmidt 2000). A policy \(\pi\) is a mapping
\(X \rightarrow C\) where \(\pi(x)\) defines the action to be
taken in \(x\). The agent must learn a policy that
optimizes the average rewards received over
that time, but it never sees the ontological state \(x\),
only a perceptive situation \(p\).

« 29 » When the agent is immersed in
a system represented as an FPOMDP, the
complete task for its anticipatory learning
mechanism is both to create a predictive model of the world dynamics (i.e., inducing the underlying transformation function of the system) and to define an optimal (or sufficiently good) policy of actions in order to establish a behavioral strategy. A good overview of the use of this representation in AI, referring to algorithms designed to learn and solve FMDPs and FPOMDPs, can be found in (Sigaud et al. 2009; Degris & Sigaud 2010).

Relation between ontological and experiential reality

30 We distinguish four main factors that shape the relation between the agent’s mind and the external world: observability, complexity, determinism and controllability.

31 The observability factor (ω) indicates the degree of access that the agent has to the environment state through its sensory perception. We can imagine this measure as being equivalent to the proportion of observable variables in the whole system in relation to the total number of variables. If the state of the environment can be represented by n bits of information and the state of the sensors affected by that world state can be represented by m bits, the observability factor ω is the proportion of m over n, where 0 ≤ ω ≤ 1. Considering an FPOMDP composed of binary variables, \( m = |P| \) and \( n = |X| \).

32 If ω = 1, the environment is said to be completely observable, which means that the agent has sensors to observe directly all the properties of the environment. In this case there is no perceptual confusion, and the agent always knows the current state. When ω < 1, the environment is said partially observable. The lower ω is, the higher the proportion of hidden dimensions of the environment is in relation to the agent’s perception. When ω is close to 0, the agent is no longer able to identify the current situation only in terms of its perception.

33 The complexity factor (q) is related to the rules that define the world dynamics, indicating how intelligible the environment transformations can be for the agent. The complexity can be measured as the average amount of information needed to define the evolution of one bit in the world state. In a highly structured world, it is possible to model precise causes for each transformation; in other words, the evolution of one variable of the system depends on only a few other relevant variables. In contrast, in an unstructured world there is too much interdependence between the variables to determine the evolution of the system.

34 The difficulty for the agent in constructing a model is related to the complexity of the world dynamics. A less complex world can be more easily structured by intelligence. A low level of complexity means that the information about the dynamics of the environment is concentrated in the variables. It indicates the average amount of relevant variables necessary to describe each transformation. When q is small, the rules that govern the dynamics of the whole system have few parameters. It is a kind of thermometer indicating how easy it is to model causality between events. In contrast, a higher level of complexity (rising to n) indicates that the information about the dynamics is sparsely distributed over all the set of variables, and in this case the agent needs to describe the transformations in function of almost all the variables.

35 The determinism factor (δ) is equivalent to the proportion of deterministic transformations in relation to the total number of transformations. In the completely non-deterministic case (δ = 0), all 2⁴ transformation functions (of every property) need to be represented in terms of 2⁴ probabilities. On the other hand, in the 25 completely deterministic case (δ = 1), every transformation is deterministic. An environment is said partially deterministic if it is situated between these two extremities (0 < δ < 1) presenting both deterministic and stochastic transformations.

36 Observability and determinism are dependent factors. Partially observable environments can present some determinant variables to a good world model that cannot be directly perceived by the agent’s sensors. Such environments can appear arbitrarily complex and non-deterministic on the surface, but they can actually be deterministic and predictable with respect to observable underlying elements (Holmes & Isbell 2006). In other words, an ontological- and deterministically world can be experienced as non-deterministic. The more an agent has sensors to perceive complex elements and phenomena, the more the environment will appear deterministic to it.

37 Finally, the controllability factor (k) represents the proportion of variables whose dynamics are influenced by the agent’s actions, within the total number of variables in the system. The controllability factor affects the difficulty of learning because it determines the capacity of the agent to experiment actively.

http://www.univie.ac.at/constructivism/journal/9/v/301.perotto
The task becomes harder because the environment is only partially observable and partially deterministic, from the point of view of the agent, constituting an FPOMDP. In this case, the agent has perceptive information from a subset of sensory variables, but the system dynamics also depends on another subset of hidden variables. To be able to create a consistent world model, the agent needs, beyond discovering the regularities of the phenomena, also to create abstract variables in order to take into account non-observable conditions that are necessary to understand the system's evolution. In other words, learning a model of the world is more than describing the environment dynamics (the rules that can explain and anticipate the observed transformations), it is also discovering the existence of hidden properties (once they influence the evolution of the observable ones) and, finally, finding a way to deduce the values of these hidden properties.

The system as a whole is in fact an FPOMDP, but CALM is designed to discover the existence of non-observable properties, integrating them in its anticipatory model. In this way CALM can infer a structure to represent the dynamics of the system in the form of an FMDP (if the agent can successfully discover and describe the hidden properties of the FPOMDP that it is dealing with, then the world becomes treatable as an FMDP because the hidden variables become known). There are some algorithms able to calculate efficiently the optimal (or near-optimal) policy, when the FMDP is given (Guestrin et al. 2003). The algorithm to calculate the policy of actions used by CALM is similar to that presented by Degris, Sigaud & Wuillemin (2006). However, the main challenge is to discover the structure of the problem based on the on-line observation. CALM does it using representations and strategies inspired by Drescher (1991).

Representing predictive knowledge by schemas

CALM tries to reconstruct, by experience, each system transformation function $T$, representing it by an anticipatory tree. The anticipatory tree is composed of pieces of predictive knowledge called schemas; each schema represents some perceived regularity occurring in the environment by associating context (sensory and abstract), actions and expected results (anticipations).

One important strategy for dealing with complexity is finding what is important to anticipate. At the beginning, the only interesting variables are those associated to positive or negative affective values. Staying focused on these variables avoids wasting energy by creating models that anticipate other non-important variables. Gradually, the variables needed to anticipate the evolution of some important variable (relation of causality) are also considered important, and the mechanism will seek to model their transformation function too.

A schema is composed of three vectors, in the form:

$$\mathbb{E}=\{\text{context} \times \text{action} \rightarrow \text{result}\}$$

denoting a kind of predictive rule. The context vector has its elements linked both with the agent sensors and with the abstract variables. These abstract variables are represented by (mentally created) "synthetic elements" not linked to any sensor but referring to non-sensory properties of the universe, the existence of which is inferred by the mechanism. The action vector is linked with the agent effectors. Context and action vectors can represent sets of equivalent situations or actions, by generalization. The result vector represents the value expected for some variable in the next time, after executing the given action in the given context. Each element vector can assume any value in a discrete interval defined by the respective variable domain.

Some elements in these vectors can take an "undefined value." For example, an element linked with a binary sensor must have one of three values: true, false or undefined (represented, respectively, by "1", "0", and "#"). The undefined value generalizes the schema because it allows some properties to be ignored in order to represent a set of situations. The learning process happens through the refinement of the set of schemas. After each experienced situation, CALM updates a generalized episodic memory, then checks whether the result (context perceived at the instant following the action) conforms to the expected result of the activated schema. If the anticipation fails, the error between the result and the expectation serves as parameter to correct the model. The context and action vectors are gradually specialized by differentiation, adding each time a new relevant event feature to identify the situation class more precisely.

The use of undefined values makes it possible to construct an anticipatory tree. Each node in that tree is a schema, and the relations of generalization and specialization guide its topology (quite similar to decision trees or discrimination trees). The root node represents the most generalized situation, in which the context and action vectors are completely undefined. Each level added to the tree represents the specialization of an element, where each branch replaces the undefined (generalized) value with one different possible defined value. This specialization occurs either in the context vector or in the action vector. In this way, CALM divides the state space according to the different expected results, grouping contexts and actions with their respective transformations.

The tree evolves during the agent's life, and is used by the agent, even if the tree is still under construction, to take its decisions, and in consequence, to define its behavior. The structure of a schema (the elementary piece of knowledge of an anticipatory tree) is presented in Figure 2.


The learning process happens through the refinement of the set of schemas. At each given moment in time, the set of schemas of our agent, gradually constructed by the mechanism, is assumed to be coherent with all the past experience, describing in an organized way the regular phenomena observed during the interaction with the universe. To do so, the mechanism must have a memory of the past situations, but this memory can be neither too precise nor too simple (because remembering all the experienced episodes would require a nonviable amount of space) nor too simple (because the lack of information would make it impossible to revise the model if there was contradiction with new disequilibrating observations).

The implementation of a feasible episodic memory is not evident; it can be very expensive if we try to stock too much information coming from the sensory flow. However, using some strong but well-chosen restrictions (such as limiting the dependency analysis between variables), and using a generalized and structured representation of the past experience, it becomes computationally viable.

CALM actualizes the generalized episodic memory and checks whether the result (context perceived at the instant following the action) is in conformity to the expectation of the activated schema in the anticipatory tree. If the anticipation fails, the error being a parameter for correcting the model. In the anticipatory tree topology, the context and action vectors are taken together. This concatenated vector identifies the node in the tree. It can be expanded following a top-down strategy: the initial tree contains a unique schema, with completely generalized context and action, and it is gradually specialized by differentiation, adding new relevant features to identify more precisely the category of equivalent situations, which entails the creation of new branches in the tree where the context and action vectors are each time more defined. In well-structured universes, the shorter way is starting with an empty vector and searching for the probably small set of features relevant to distinguish the important situations, rather than starting with a full vector and having to waste energy eliminating a lot of useless elements. Selecting the right set of relevant features to represent some given concept is a well-known problem in AI, and the solution is not easy, even using approximated approaches. To do this, CALM adopts a forward greedy selection (Blum & Langley 1997), using the data registered in the generalized episodic memory.

The expected result vector can be seen as a label in each decision schema, anticipating how the world changes when the schema is activated. Initially, all different expectations are considered as different classes, and they are gradually generalized and integrated with others. The agent has two alternatives when the expectation fails. In a way that makes the knowledge compatible with the experience, the first alternative is to try to divide the scope of the schema, creating new schemas with more specialized contexts. Sometimes this is not possible and then the schema’s expectation is reduced. In the expected result vector, “#” means that the element is not deterministically predictable. Another symbol can be used to represent some special situations, in order to reduce the number of schemas; this is the symbol “@”, used to indicate that the value of the expected element will not be changed.

### Anticipatory tree construction

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### Three basic methods

- Three basic methods compose the CALM learning function, namely: differentiation, adjustment, and integration. Differentiation is a necessary mechanism because a schema responsible for too many general contexts cannot often make precise anticipations. If a general schema does not work well, the mechanism divides it into new schemas, differentiating them by one element of the context or action vector. In fact, the differentiation method takes an unstable decision and changes it into a two-level sub-tree. The parent schema in this sub-tree preserves the context of the original schema. The children, which are the new decision schemas, have context vectors that are a little more specialized than those of their parent. They attribute a value to a undefined element, dividing the scope of the original schema. Each one of these new decision schemas engages itself in a part of the domain. In this way, the previous correct knowledge remains preserved, distributed in new schemas, and the discordant situations are isolated and treated only in its specific context. Differentiation is the method responsible for making the anticipatory tree expand. Each level of the tree represents the introduction of some new constraint. The algorithm needs to choose what will be the differentiator element, which could be from either the context vector or the action vector.

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**Figure 2**: The anticipatory tree. Each node is a schema composed of three vectors: context, action and expected result; the leaf nodes are decision schemas.
Figure 3: Differentiation method example: (a) a real experimented situation (with five variables) and executed action (one variable); (b) activated schema (with compatible context, action, and expectation); (c) associated episodic memory (representation of real situations where the scheme has been activated, in this case representing no interdependencies between variables); (d) real observed result, after the execution of the action; (e) sub-tree generated by differentiation in order to compensate the divergence observed between expectation and result.

Figure 4: Adjustment method example: (a) a real experimented situation and action; (b) activated schema; (c) associated episodic memory; (d) real observed result; (e) schema expectation - the undefined value ("#"). The adjustment method changes the schema's expectation after the application of the schema, setting the real result perceived by the agent and the real result perceived by the agent and executed action (one variable); (b) activated schema (with compatible context, action, and expectation); (c) associated episodic memory (representation of real situations where the situation represented by the schema), (d) real observed result, after the execution of the action; (e) sub-tree generated by differentiation in order to compensate the divergence observed between expectation and result.

Figure 5: Integration method: (a) sub-tree after an adjustment; (b) an integrated schema substitutes the sub-tree.

Figure 6: Synthetic element creation method: (e) incremented context and expectation vectors, and differentiation using a synthetic element.

Dealing with the unobservable

When CALM finds a group of schemas with similar expectations for approaching different contexts, the integration method comes into action, trying to join these schemas by searching for some unnecessary common differentiator element and eliminating it. The method operates as shown in Figure 5.

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1 a new term in the context and expectation vectors of the schemas. The use of synthetic elements assumes the existence of some-thing beyond the sensory perception, which can be useful to explain non-equilibrated situations. They have the function of amplifying the differentiation possibilities.

« 54 » In this way, when dealing with partially observable environments, CALM has two additional challenges: (a) inferring the existence of unobservable properties, which it will represent by synthetic elements, and (b) including these new elements into its predictive model. A good strategy for doing this is to look at the historical information.

« 55 » CALM introduces a method called abstract differentiation. When a schema fails in its prediction, and when it is not possible to differentiate it by the current set of considered properties, then a new Boolean synthetic element is created, enlarging the context and expectation vectors. Immediately, this element is used to differentiate the incoherent situation from the others. The method attributes arbitrary values to this element in each differentiated schema. These values represent the presence or absence of some non-observable condition, necessary to determine the correct prediction in the given situation. The method is illustrated in Figure 6, where the new elements are represented by card suits.

« 56 » Once a synthetic element is created, it can be used in subsequent differentiations. A new synthetic element will be created only if the existing ones are already saturated. To avoid the problem of creating infinite new synthetic elements, CALM can do this only up to a determined limit, after which it considers that the problematic anticipation is not deterministically predictable, undefining the expectation in the related schemas by adjustment. Figure 7 illustrates the idea behind synthetic element creation.

« 57 » The synthetic element is not associated to any sensory perception. Consequently, its value cannot be observed. This fact can place the agent in ambiguous situations, where it does not know whether some relevant but non-observable condition (represented by this element) is present or absent. Initially, the value of a synthetic element is verified a posteriori (i.e., after the execution of the action in an ambiguous situation). Once the action is executed and the following result is verified, then the agent can rewind and deduce the situation really faced in the past instant (disambiguated).

Discovering the existence of non-observable properties in: (a) a real experienced sequence; (b) what CALM does not do (the attribution of a probability); (c) the creation of a synthetic element in order to explain the observed difference.

Figure 7: Discovering the existence of non-observable properties in: (a) a real experienced sequence; (b) what CALM does not do (the attribution of a probability); (c) the creation of a synthetic element in order to explain the observed difference.

Figure 8: Predicting the dynamics of a non-observable property in: (a) a real experienced sequence; (b) the use of a synthetic element to explain the logic behind the observed transformations.

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ARTIFICIAL INTELLIGENCE SYNTHESIS IN CONSTRUCTIVISM

The hyper-flip problem.

Figure 9: The hyper-flip problem.

The ontological structure of the problem (a model (with its 3 variables) is not a copy of the constructed world. It consists of an agent who lives in a two-state universe. It has 3 actions (l, r, u) and 2 perceptions (0, 1). The agent does not have any direct perception of the underlying current state. It sees “1” when the state changes horizontally, and “0” otherwise. Action “u” changes the state vertically, action “l” causes the deterministic transition to the left state, and action “r” causes the deterministic transition to the right state. The flip problem is showed as a state machine in Figure 9.

« 60 » CALM is able to solve this problem. First, the mechanism tries to predict the next observation in function of its action and current observation. However, it quickly discovers that the perceptive observation is not useful to the model, and that there is insufficient information to make correct anticipations. So, it creates a new synthetic element that will be able to represent the underlying left (♦) and right (♦) states. Figure 10 shows the final solution. It is interesting to note that the constructed world model (with its 3 variables) is not a copy of the ontological structure of the problem (a machine with 4 states).

« 61 » In order to test the robustness of the mechanism, a hundred new observable variables have been inserted in the hyper-flip problem for a second scenario. These new variables present random transformation functions and do not influence the evolution of the original observation. The result is that the mechanism is not affected in its capacity to solve the problem (it finds the same solution as that previously indicated). The time of learning increases in a linear order with the addition of irrelevant variables.

Experimental results

« 59 » To exemplify the functioning of the proposed method, we will use the hyper-flip problem, and extension of the problem used by Satinder Singh et al. (2003) and Michael Holmes & Charles Isbell (2006).

It consists of an agent who lives in a two-state universe. It has 3 actions (l, r, u) and 2 perceptions (0, 1). The agent does not have any direct perception of the underlying current state. It sees “1” when the state changes horizontally, and “0” otherwise. Action “u” changes the state vertically, action “l” causes the deterministic transition to the left state, and action “r” causes the deterministic transition to the right state. The flip problem is showed as a state machine in Figure 9.

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Related work

« 62 » CALM is an original mechanism that enables an agent to create incrementally a model of an experience during the course of its interaction with the universe. The pioneer work on constructivist AI was presented by Drescher (1991). He proposed the first constructivist agent architecture, which learns a world model by an exhaustive statistical analysis of the correlation between all the context elements observed before each action, combined with all resulting transformations. Drescher has also suggested the need to discover hidden properties by creating "synthetic items."

« 63 » The schema mechanism represents a strongly coherent model. However, there are no theoretical guarantees of convergence. Another restriction is the computational cost of the kind of operations used in the algorithm. The need for space and time resources increases exponentially with the problem size. Nevertheless, some other researchers have presented alternative models inspired by Drescher, such as Yavuz & Davenport (1997), Morrison, Oates & King (2001), Chaput (2004), and Holmes & Isbell (2005), always based on the search for statistically observed regularities.

« 64 » CALM differs from these previous works because we limit the problem to the discovery of deterministic regularities (even in partially deterministic environments). In this way, we can implement direct induction methods in the agent learning mechanism. This approach presents a low computational cost, and it allows the agent to learn incrementally and find high-level regularities. For that, we have been inspired by Holmes & Isbell (2006), who used the notion of the state signature as a historical identifier of the states to develop the idea of learning anticipations through the analysis of relevant pieces of history.

« 65 » With the emergence of the factored MDP model, some important works have been realized to create algorithms designed to discover the structure of the system (Degris, Sigaud & Wuillemin 2006; Degris & Sigaud 2010; Strehl, Diuk & Littman 2007; Jonsson & Barto 2005). However, CALM, as far as we know, is the only one to merge the induction of synthetic elements to represent the non-observable variables in an FPOMDP.

« 66 » Another originality of CALM is the use, in such learning problems, of a generalized episodic memory associated to the search for important variables (related to affective values or relevant to anticipate the evolution of other important variables).
Open Peer Commentaries
on Filipo Studzinski Perotto’s “Computational Constructivist Model”

To Bridge the Gap between Sensorimotor and Higher Levels, AI Will Need Help from Psychology
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1 The formulation of the problem as it appears in the abstract of Filipo Perotto’s article packs in a lot of information that merits discussion:

"The constructivist conception of intelligence is very powerful for explaining how cognitive development takes place. However, until now, no computational model has successfully demonstrated the underlying mechanisms necessary to realize it. In other words, the artificial intelligence (AI) community has not been able to give rise to a system that convincingly implements the principles of intelligence as postulated by constructivism, and that is also capable of dealing with complex environments."

2 This suggests that the psychologists have succeeded in explaining how cognitive development takes place and that the AI community has failed in its job to implement these “principles of intelligence.”

47 > Upshot: Constructivist theory gives a nice high-level account of how knowledge can be autonomously developed by an agent interacting with an environment, but it fails to detail the mechanisms needed to bridge the gap between low levels of sensorimotor data and higher levels of cognition. AI workers are trying to bridge this gap, using task-specific engineering approaches, without any principled theory to guide them; they could use help from psychologists.

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1. Until that time, one could argue that
the "principles of intelligence as postulated
by constructivism" are implemented very
well by existing AI systems. Gary Drescher,
for example, did implement the basic princi-
ples of constructivism, but "it could never be
used to solve significant applied problems,"
because the techniques do not scale up to
9 systems with large numbers of inputs and
degrees of freedom. However, Piaget did not
give us any idea of how to deal with these
12 issues, so one could lay the blame on him.

3. To quote from the abstract again,
"there is a large distance between the de-
scriptions of the intelligence made by con-
structivist theories and the mechanisms
17 that currently exist." If we consider Piaget's
18 theory, and Drescher's system or the CALM
19 system, I am not sure that there is such a
20 large distance. Piaget's descriptions of as-
simulation and accommodation are so all
22 encompassing and so lacking in detail that
23 it seems to me that Drescher's system or the
24 CALM system constitute perfectly good
25 implementations. Psychology tends to leave
26 mechanisms very underspecified.

4. To quote again from the article's
abstract: "...and that is also capable of deal-
ing with complex environments." Here is
perhaps the essence of the problem. When
you start building an actual AI system that
has to interact with the world, you face a
daunting task of dealing with a complex en-
vironment. It seems that AI is being saddled
with the burden of not only implementing
the high-level theory, but also making sure
it can deal with complex environments. The
"complex environments" problem needs to
be thrown back at the psychologists. The
history of AI has shown that a theory of
cognition that works at a high abstract level
but cannot account for the interface to the
sensorimotor level is not much of a theory
of cognition at all. The devil is in the detail.
There are many writers who convincingly
show how high-level cognition is very much
grounded in our sensorimotor intelligence
(e.g., Barsalou 2008; Byrne 2005; Bril, Roux
& Dietrich 2005). Psychological theories
tend to overlook the need for complex
mechanisms to bridge the gap between the
sensorimotor level and high-level cognition.
Psychologists may need to become com-
puter scientists to some extent, so that they
have an appreciation of the computational
problems involved and the need for them
to describe mechanisms to account for how
humans successfully solve these.

5. On the positive side, there are
some works in cognitive science that are
beginning to attempt to address the issue
of providing some theoretical framework
to account for how a sensorimotor level can
connect with higher levels of cognition: for
example, the multi-layered cognitive system
of Bipin Indurkhya (1992, Chapter 5).

6. For the CALM system itself, I feel
the article has all the correct ideas from a
philosophical and psychological point of view,
e.g., about the agent constructing its own
symbolic structures and not having access
to the "ontological reality." However, if we are
to evaluate it as a candidate for a "general artificial intelligence mechanism
that learns like humans do" (first sentence of
abstract), then it might suffer the same
shortcomings as Drescher's work, i.e., "it
could never be used to solve significant ap-
plicated problems." For example, if the context
were to be the visual input from two stereo
cameras delivering a few million pixels in 24
bit colour at thirty frames per second and the
system is trying to predict the consequences
of actions, in the complexity of an everyday
setting, in this visual stream, it might not be
feasible to use each bit of input as a CALM
variable. One could, of course, propose
to hook the CALM system up to a higher-
level abstracted version of the visual input,
but then one runs into the issues of where
to make the cut-off between what the core
CALM system sees and what is the respon-
sibility of other abstraction mechanisms. If
the cut-off is at the wrong place, then one
runs into classical AI problems of (a) having
a core cognition that makes unreasonable as-
sumptions about how accurately it can inter-
face with the world or (b) having a prespec-
ified worldview imposed by the provided
abstractions (see Brooks 1991 or Stoytchev
2009 for problems with this). There does not
seem to be any clear theory from psychol-
ogy to guide us on how to connect the sen-
sorimotor level with some higher levels. AI
does have various different applied systems
that successfully make a connection from
high-level symbols to perception and action
in complex settings: for example, robots that
perform everyday tasks (Beetz et al. 2010).
However, each applied AI system tends to be
specialised and optimised for one particular
task. None could claim to be a reasonable
model of general human cognition, nor do
they attempt to be. This is really a job for the
psychologists.

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College, London, in 2002. Since August 2003, he has
been a Lecturer in Computing Science at the University
of Aberdeen. He is interested in understanding the core
cognition in computational terms. He has focused
on understanding infant cognitive development,
as a first step to understanding later cognition.

Environments Are Typically Continuous and Noisy

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> Upshot: The schema system present-
ed in the target article suffers from prob-
lems that had been acknowledged more
than ten years ago. The main point is that
our world is neither deterministic nor
symbolic. Sensory as well as motor noise
is ubiquitous in our environment. Sym-
bol s do not exist a priori but need to be
grounded within our continuous world.
In conclusion, I suggest that research on
schema-learning systems should tackle
small but real-world, continuous, and
noisy problem domains.

Heuristic learning principles are not enough

"About 15 years ago, I began work-
ing together with Wolfgang Stolzmann and
Joachim Hoffmann on the development of
anticipatory classifier systems (Stolzmann
2000). We attempted to tackle the funda-
mental problems of learning a cognitive
model in well-structured environments, 50
implementing contextual rule differen-
tiation, rule adjustment, and rule integration
mechanisms. With iterative improvements
and additions, the ACS2 system was devel-
oped. ACS2 combines a heuristic rule differ-

Entiation and specialization mechanism that is based on Hoffmann's cognitive learning principle, termed “anticipatory behavioral control” (Hoffmann 2003), with a generalization mechanism that is implemented by a steady-state evolutionary algorithm in ACS2. In my book on Anticipatory Learning Classifier Systems (Butz 2002), I summarized the capabilities of the developed system as well as the fundamental challenges.

While the fundamental challenges included the problem of partially observable Markov decision processes (POMDPs), I had also acknowledged that “essentially any characteristic in an environment that causes the deterministic perceptual causality to become probabilistic or noisy causes difficulties” (Butz 2002: 127). I fear that the algorithm presented in the target article suffers similar difficulties. That is, while it may be able to solve the tackled, small POMDP problem, it is very doubtful that the heuristic learning mechanism put forward is able to produce similarly good solutions in noisy, continuous environments.

Is this a concern for the constructivist community? In the following I will argue that it is indeed a severe concern and propose that the community should focus on the question of how symbolic processing capabilities can develop in noisy, continuous environments. Schema learning systems up until now have stuck to symbol manipulation problems, such as the admittedly tricky hyper-Flip problem. But are these problems constructive? Can they lead to a system that may convincingly develop a constructivist system that becomes cognitive? I doubt it.

Most schema-oriented learning systems, such as the one proposed in the target article, have not managed to develop symbol systems in a noisy, continuous realm. Schema learning systems up until now have stuck to symbol manipulation problems, such as the admittedly tricky hyper-Flip problem. But are these problems constructive? Can they lead to a system that may convincingly develop a constructivist system that becomes cognitive? I doubt it.

Natural environments

What can be done about it? I believe that the constructivist community should focus on the question of how symbolic processing capabilities can develop in noisy, continuous environments – where experiences are grounded and embodied in an actual bodily perception-action system. Evidence has been accumulating over recent years that this is not an insurmountable endeavor. The theory of event coding (Hommel et al. 2001) postulates that events may be a highly important cognitive concept for structuring experiences and thus for perceiving the environment in chunks that may be symbolizable. Also, in the cognitive robotics literature, the registration of events – such as when touching an object – has been acknowledged as a key mechanism for segmenting the environment into meaningful interaction components (Wörgötter et al. 2013). Bodily interactions with the environment were structured into a natural action grammar with properties that are strongly related to Noam Chomsky’s universal grammar (Pastra & Aloimonos 2012). Research from my own group suggests that goal-oriented representations should be separated from representations of spatial interaction for setting the stage to develop compositional concept structures, which are necessary for language development (Butz 2013).

In conclusion, I agree with the authors that schema learning approaches should be re-considered and revived. Starting with a symbolic world and facing one particular, partially-observable toy problem, however, will not advance schema learning mechanisms. Rather, these mechanisms need to be implemented in environments within which interactions are continuous, state transitions are stochastic to a certain degree, and perceptions are noisy. Tools and mechanisms are currently being developed that can segregate these continuous realms into meaningful and purposeful symbol systems. Key components of such mechanisms are anticipations, modularizations, and event-based separations. Measures of valence and resulting purposeful, goal-oriented interactions are most likely additional key concepts. A learning system that builds schemas based on these principles may in fact be the way forward towards scalable cognitive systems that develop in complex environments, effectively implementing constructivist theories of cognition.
The Power of Constructivist Ideas in Artificial Intelligence

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> Upshot • Mainstream AI research largely addresses cognitive features as separate and unconnected. Instead of addressing cognitive growth in this same way – modeling it simply as one more such isolated feature and continuing to uphold a wrong-headed divide-and-conquer tradition – a constructivist approach should help unify many key phenomena such as anticipation, self-modeling, life-long learning, and recursive self-improvement. Since this is likely to result in complex systems with unanticipated properties, all cognitive architecture researchers should aim to implement their ideas in full as running systems to be verified by experiment. Perotto’s paper falls short on both these points.

« 1 » Cognitive growth, self-inspection, anticipation (prediction based on partial observation), self-organization – what do these have in common? They are all part of a growing set of concepts from biology, cognitive science, artificial intelligence, and psychology that must be related to one another if we are ever to produce a coherent theory of intelligence, whether in machines, animals, or humans. And if our aim is to build working systems – if our stance is a software engineering one with an end-goal of building deployable systems that can operate in real-world environments, whether it be space probes, housecleaning robots, deep-sea explorers, or stock-market investment programs – then our methodological approach must embody principles that are useful for steering our efforts when designing, architected, implementing, and testing our systems.

« 2 » Filippo Perotto presents in his paper a model of an anticipatory learning mechanism, CALM, which is based on constructivist principles. His high-level model of agent-environment coupling, CAES, seems a reasonable one. Both models are based on the fundamental assumptions, which I agree with, that: (a) to understand intelligent behavior we must include in our analysis the context in which it operates; and (b) most environments of any interest to intelligent beings contain a mixture of deterministic and non-deterministic causal connections, with many of the former remaining invisible. In my view, and it would seem Perotto’s as well, an environment with complex causal relationships (e.g., our everyday world) gives rise to a vast number of potentially observable phenomena, many of which do not clearly or readily convey their underlying causes; this set of potential observable and inspectable phenomena is nevertheless the only information that an intelligent system has access to, via their sensory apparatuses, for anticipating how their external environment behaves so as to efficiently and effectively achieve its goals within it.

« 3 » Before continuing with direct commentary, some points are in order so as to elucidate the context in which I look at systems engineering, architecture, and constructivism. Due to the high number of combinatorics that a complex environment will produce, through countless interactions between its numerous elements, an agent must create models that isolate and capture some essence of underlying causes (invariants or partial invariants) in this environment (Conant & Ashby 1970). Such models must be capable of capturing abstract levels of detail that can be used to steer the operations of a system towards efficient expenditure of computational resources – any thought spent on details completely unrelated to goals (future and present) would be a waste of the agent’s time. Thus, the partial models of the environment that an intelligent agent creates will likely form some sort of a cognitive “random-access” abstraction hierarchy. Depending on the type of current goal and situation, the agent can then choose models at a particular level of abstraction at any time to help it exclude irrelevant issues from consideration when decisions are being made about how to achieve the goal in that situation. A coherent, unifying model of cognition following constructivist principles must explain how this works, in particular how goals, models, experiences, and iterative knowledge acquisition and improvement operate in concert to achieve cognitive growth in an agent. An engineering methodology for how to build artificial systems implementing such functions must go further, by helping with defining specifications for an implementable architecture, and providing guidelines on how to implement them in a way that allows experimental evaluation.

« 4 » An artificial system built to achieve general intelligence must be able to deal with novel situations – situations not foreseen by its programmers. Instead of being given pre-programmed algorithms by its designers, known to be applicable to particular and specific problems, tasks, situations, or environments, the AI itself must be imbued with the ability to generate algorithms (or, compute a control function – I do not distinguish between the two here). For this to be possible, the system must further be able to do so, the system must be reflective – that is, the system’s architecture and operational semantics must be captured in a way that enables it to read and interpret its own structure and operation. This is what I consider the essence of a constructivist AI methodology: specifications for how to imbue machines with the capability to make informed changes (whether slowly or quickly) to their own operation, via the runtime principles embodied in their architecture. I do not believe constructivist AI can be done without some form of self-programming on the part of the machine, which in turn cannot be achieved without transparency of its operational semantics. In fact, even more radically, I suspect artificial general intelligence cannot be achieved at all without such capabilities; higher levels of cognitive operation in the context of novel or unanticipated tasks, situations, and environments must require some sort of cognitive growth – namely, some form of re-programming of the cognitive system’s operation. Conversely, constructivist views on cognition are so different and incompatible with standard software engineering methodologies, especially with its tradition of manual software creation, that they cannot be used at all for engineering such systems. To address constructivist principles head on in a computational
The Power of Constructivist Ideas in Artificial Intelligence  Kristinn R. Thórisson

« 6 » The aim of AI is not just to speculate late but to build working, implemented systems. In AI, any theoretical construct aimed at advancing our understanding of how to implement cognitive functions should ultimately be judged on whether actual implementation can conclusively, or partially, allow us to conclude through reliable means (i.e., scientific experimentation), that the ideas, when operating in a relatively complete AI architecture situated in a complex world (Perotto’s target environments), are capable of scaling up. By "scaling up" I mean the ability of a system to grow in a way that supports recursive self-improvement in complex environments (e.g., the physical world), with respect to its top-level goals.

This question is of course difficult to answer, whether experimentally or analytically. A quick walk down memory lane reminds us, however, that the history of AI is replete with examples of proposals that looked great on paper but completely failed such scaling up when implemented in a running system, or when attempts were made to expand the models the ideas embodied to include more of the many functional characteristics that they originally left untouched. Unfortunately, experimental evaluation of Perotto’s proposed ideas is touched on only briefly in the paper, and the support provided to answer this question is inconclusive at best. On this count, therefore, not much can be said about the scalability of Perotto’s ideas. This is disappointing because a fundamental feature of known constructivist systems in nature is their capability to grow cognitively with experience – itself a form of scaling-up. Other phenomena, such as the power of the CALM schema formalism to produce new knowledge of complex environments, to support models of self (required for any system capable of self-directed cognitive growth), and their ability to support self-inspection, are also not addressed to any sufficient extent in the work. Since these issues are briefly touched on or left unmentioned, we can only assume that they remain unaccounted for by the present work.

« 7 » My second question regards the “size of the intelligence puzzle” addressed. An artificial cognitive system must, to have a chance at becoming a comprehensive theory of the major facets of intelligence, include a large number of functions that allow the system to operate relatively autonomously in complex environments. This theoretical scalability of an isolated mechanism is its perseverance and robustness when included in a better (larger, more comprehensive) model/theory, which can in turn serve as the foundation for building systems with increased operating power, including an increased capacity for cognitive growth and architectural complexity. If Perotto’s work turns out to be correct, if it indeed offers, as Perotto claims in the abstract, “a step towards computational implementation of constructivist principles,” how much of the phenomenon in question – cognitive growth – remains to be explained? The lack of a clear connection between his CALM and CAES models is already a sign that some amount of work remains to be done in this direction. My own list of candidate principles and features (cf. some already mentioned above) that should be accounted for in any reasonable theory of cognitive growth is, unfortunately, quite a bit longer than that addressed in Perotto’s paper. Firstly, as described above, cognitive growth requires some kind of automatic, recursive self-improvement. Although my team has made some progress on this front recently (Nivel & Thórisson 2013, Nivel et al. 2013), research on the topic is still in its infancy, with a host of unanswered practical and theoretical questions. Such questions include: What kind of representations are amenable to automatic self-programming for cognitive growth (existing programming languages and paradigms created for humans require human-level intelligence to be used – which calls for the very phenomenon we are striving to understand how to implement); how can the transparent operational semantics needed for automatic programming be achieved? Related to that are the 13 questions: How can a system’s operational semantics be measured; what kind of meta-level control structures can be used to steer cognitive growth; what kinds of control architectures can serve as host architectures for the proposed (or any other) constructivist principles? Questions regarding theoretical scalability issues loom large.

« 8 » These are, of course, not simple topics. Quite the contrary, they are deep and challenging. But they are central to two constructivist approaches, developmental robotics, and principles of cognitive growth, and it is precisely for that reason that they must not be left unaddressed, lest our efforts become victims to the same oversimplification and incorrect application of divide-and-conquer methodology that has plagued much of AI research in the past half century (cf. Thórisson 2013). Unlike so many other phenomena in AI, e.g., planning, vision, reasoning, and learning, that have been largely addressed by calling them “computational” and studying them in isolation through the same strictly allonomic methodologies as used for banking systems, word processors, and Web page construction, a constructivist methodology holds a promise – a potential – to unify a host of complex cognitive mechanisms, most of which have eluded scientific explanation so far. A holistic stance is by far the most likely to lead to an understanding of the phenomenon of intelligence, and anyone with a constructivist mindset has already taken an important step in that direction. But for this to pave the way towards a bet-

1 My use of “representations” implies a larger scope than models, capturing virtually anything that might be needed to be encoded in a particular runtime medium for a running (“live”) intelligent system.
of this constructivist AI, in which despite all the promises made, there has been a "lack of concrete results." The critique is justified if the expected concrete result was to build an artifact that would exhibit the behavior of a three-year-old infant. We are certainly not there yet. On the other hand, the constructivist AI approach certainly made huge theoretical advances by demonstrating the inappropriateness of the traditional software methodology to deal with the design of self-constructive autonomous intelligent agents (e.g., Thörisson 2012), or shifting the research focus to issues neglected in traditional AI: sensorimotor interaction, intrinsic motivation, complete cognitive architectures (e.g., Stojanov, Kulakov & Clauzel 2006; Stojanov & Kulakov 2011).

"2" In §2 and §3, Perotto introduces the conceptual structure of a schema: context action expectation, which he also calls an "elementary piece of knowledge." The "context" vector represents the readings of all external and internal sensors, and when some "action" is executed, the agent anticipates the outcome in terms of the "expectation" vector. Thus, throughout its lifetime, the agent put in particular environment should learn to predict the outcomes of its actions ("to adapt itself"), even if the environment is partially observable. Many researchers have used this "context action expectation" construct (Drescher 1991; Schachner 1996; Schachner, Real del Sarte & León 1999; Tani 1996; Stojanov, Bozínovski & Trajkovski 1997; Chaput 2004; see Stojanov & Kulakov 2009 for an overview of computational models of Piagetian schemas) in the task of learning forward-models (or anticipative models) of the environment. The simulated environment is represented via a POMDP. The states of the environment are represented with a set of properties X, and among those properties there are some that cannot be perceived by the agent's perceptual apparatus. This leads to perceptual aliasing and makes the problem of learning effects of actions in given contexts much more difficult. CALM (§38) is the learning mechanism designed to learn the dynamics of the underlying POMDP through execution of agent's actions (which, from the point of view of the POMDP are controllable variables) and construction of reliable predictive schemas, described above. §50, §51 and §52 describe the three basic methods for schema construction in CALM: differentiation, adjustment, and integration. As there are unobservable properties of the environment, sometimes CALM will fail to predict accurately the effect of some action, and in some cases, the situation can be remedied by abstract differentiation (§52). Essentially, this means that the context and expectation vectors are arbitrary values that are enlarged and attributed in a way to make them distinct from existing schemas. The new schemas are called synthetic elements as they cannot be directly perceived. The method of propagation of the value of the synthetic elements is called abductive anticipation (§57). Once (if the complexity/observability ratio allows) the agent using CALM learns the environment model perfectly, it can always predict the effect of its action in a given context.

"3" My condensed (and, I hope, not too simplistic) description of CALM in the previous paragraph is to show that although an original and efficient solution it is constructivist only in a trivial way: it learns a model of its environment incrementally. Perotto appears to be like many developmental psychologists in the 1970s: 29 - 30 What they [developmental psychologists] called construction seemed to refer to the fact that children acquire adult knowledge not all at once, but in small pieces. I did not think that this was a revelation and therefore called their approach 'trivial constructivism.' (Glasserfeld 2005: 10).

The monolithic single-thread algorithm is completely deterministic and will eventually come up with the same result, given the same learnable environment. There is no learning-to-learn (i.e., change of the learning trajectory) nor ability for reconceptualization of a given situation, or evolution of more sophisticated intrinsic motivations (more about motivations below). Moreover, 46 as Perotto notes in §9, "The agent needs to be able to detect high-level regularities in the dynamics of the environment, but this is not possible if the agent is stuck in a rigid representational vocabulary." The representational vocabulary of a CALM-driven agent is rigid: all of the possible different schemas. Synthetic items definitely enlarge it, but only up to a certain predefined limit. There is no

Anticipatory? Yes. Constructivist? Maybe

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Upshot: The CALM cognitive agent with its learning mechanism, as presented by the author, can be described as "trivially constructivist." Probably, at best, it can be seen as a model of the empirical abstraction but not of the reflective abstraction. The "intrinsically motivations" in the simulated agent presented as "evaluative signals" sent from the agent's "body" to its "mind" can be seen as low-level physiological drives. They cannot account for far more sophisticated intrinsic motivations such as curiosity.
column A

1 way in which (in a genuinely constructivist spirit) the agent can impose some organization on the sensed environment. In continuation of Sp we can read

2 **In a constructivist approach, cognitive development must be a process of gradual complexity, not a process of simultaneity of the intelligence, where more abstract
3 structures (symbolic) are built from simpler
4 sensorimotor interactions, in a way that harmonizes the lived experiences with the constructed
5 model.**

6 CALM does not provide a way to build
7 more abstract structures... from simpler
8 sensorimotor interactions.” At best, there
9 are the synthetic elements that contain ab-
10 stract properties in the sense that they do
11 not correspond to any sensory inputs. Given
12 that those abstract properties are added to
13 schemas whose context and action vectors
14 are equal, it is impossible to understand
15 them as abstract/symbolic structures in the
16 sense given in Sp. In Piagetian parlance, the
17 learning exhibited by CALM could be seen
18 as model of the empirical abstraction but not
19 of the reflective abstraction that is crucial for
20 cognitive development and creative behavior.
21 Briefly, via empirical abstraction, some
22 quality (e.g., weight or color or contingency
23 among actions and qualities) is abstracted
24 from an object/situation. On the other hand,
25 reflective abstraction is about reorganization
26 of existing schemas and their projection
27 onto a higher plane. (See Kitchener 1986: 36–65 for an informative discussion of em-
28 pirical and reflective abstraction, as well as
29 the discussion in Campbell & Bickhard 1993
30 on the knowing levels).

31 **« 4 »** In Sp, one can read that the
32 agent’s body with its “internal states and me-
33 tabolisms, elements that belong neither to
34 the mind nor the environment... allow the
35 agent to have intrinsic motivations...” I be-
36 lieve that the decision to introduce the two
37 entities (“body” and “mind”) is somewhat
38 arbitrary, given that it is barely mentioned in
39 the rest of the paper. It appears that the body
40 is introduced only to have the above-men-
41 tioned possibility to have “intrinsic motiva-
42 tions.” If this is the case, then the intrinsic
43 motivations can be related to low-level phys-
44 iological drives (hunger, pain-avoidance)
45 with no possibility for development of more
46 sophisticated forms of motivations such as
47 curiosity. If, on the other hand, the intrinsic
48 motivations can be placed in the “mind” of
49 the agent, I see no reason to draw the arbi-
50 trary body-mind distinction.

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Action, Anticipation, and Construction: The Cognitive Core

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>Upshot - Interaction-based models of cognition force anticipatory and constructivist models. The CALM model offers significant development of such models within a machine learning framework. It is suggested that moving to an entirely interactive-based model offers still further advantages.

1 Charles Sanders Peirce introduced action and interaction as the proper loci for understanding the mind well over a century ago (Joas 1993). An interaction-based model of cognition, in turn, is intrinsically anticipatory – i.e., anticipations of potential actions and interactions (Bickhard 2009b; Buij森 2004; Piaget 1954). And an action and interaction-based model of cognition forces a constructivism: it is not feasible for the world to impress competent interactive system organization into a passive mind; it must be constructed. For yet another step,

given that prescience does not exist, such a constructivism must be a variation and 2 selection constructivism, an evolutionary 3 epistemology (Campbell 1974). These char-
4 acteristics, thus, form a coherent framework
5 for understanding cognition, and, more gen-
6 erally, mind (Bickhard 2009b).

7 > « 2 » Classic passive mind models, how-
8 ever, descending from the ancient Greeks, 9 still dominate the scene, currently in their 10 “recent” incarnations of symbolic compu-
11 tationalism and connectionism. Machine 12 learning is an interesting combination of 13 perspectives: learning about the environ-
14 ment requires checking what is tentatively 15 learned against that environment, which 16 requires action and anticipation and con-
17 struction of what is checked. Most cleanly, 18 what is checked are those anticipations per 19 se. But there is still also a reliance on passive 20 models of perception (generally based on 21 sensations) and restricted models of action 22 and construction.

23 > « 5 » Filippo Perotto’s CALM is a signifi-
24 cant advance within this framework, espe-
25 cially in its ability to extract anticipatory in-
26 formation from an only partially observable 27 and not fully deterministic world, and to use 28 synthetic elements in doing so. It is impor-
29 tant to demonstrate that these more realis-
30 tic framework assumptions can be handled, 31 and to show how they can be handled.

24 > « 4 » But CALM, too, is built on sensa-
33 tion models of perceiving and on singleton 34 actions. One of the current foci for devel-
35 opment of the CALM model is to develop 36 possibilities of chaining schemas – again, 37 I would agree that this is exactly the right 38 direction. I would like to comment, how-
39 ever, on even more general approach that 40 might be considered – a fully interactive ap-
41 proach.

25 > « 3 » Consider that passive sensations, 43 insofar as they exist at all, functionally serve 44 to detect properties of the environment, and 45 that such detection – as a strictly factual 46 matter – is all that is functionally relevant 47 to the system. In particular, such detections 48 need not be understood to represent that 49 which is detected in order to account for 50 their influences on system processing. Still 51 further, such detections can also be real-
52 ized by fully interactive processes, not just 53 by passive receptive processes (Bickhard & 54 Richie 1983). On the other hand, anticipa-
55

http://www.univie.ac.at/constructivism/journal/9/1/301.perotto
Representing Knowledge in a Computational Constructivist Agent

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>Upshot - The aim of this commentary is to relate the target article to recent work about how to represent knowledge acquired from experience by a constructivist agent.

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1) Constructivist agents acquire new knowledge and maintain existing knowledge by experimenting with their environment. A key question is then how to represent knowledge for such an agent. In the target paper, knowledge that can be created and updated from data is emphasized, but a different mathematical framework and a different architecture, namely the Horde architecture (Sutton et al. 2011), is used. This commentary presents the similarities and differences between the target paper and the Horde architecture.

2) Both papers focus on a situated agent embedded in its environment. The agent does not have access to the full state of the environment. To be able to understand better its interaction with the environment, the agent needs to construct abstract representations and perceptions interpreted as detection functions, rather than sensations or false, and cognitive representation more generally can be built from organizations of anticipations (Piaget 1954; Bickhard 2009b), and offers direct approaches to modeling phenomena that are difficult to approach within standard frameworks (e.g., re-organizing the topology of representational spaces in response to understanding an analogy; Bickhard & Campbell 1996).

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Horde architecture asks its own set of questions: What are the criteria to create or delete demons based on data and experience? What should be the behavior of an agent in its environment to optimize learning in demons (intrinsic motivations)? The path to a constructivist agent for a general artificial intelligence remains uncertain.

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Some Comments on the Relationship Between Artificial Intelligence and Human Cognition

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> Upshot • In making a contribution to artificial intelligence research, Perotto has taken note of work on human cognition. However, there are certain aspects of human cognition that are not taken into account by the author’s model and that, generally, are overlooked or ignored by the artificial intelligence research community at large.

1 In his paper, Filipo Perotto has taken note of work on human cognition. In particular, he references Jean Piaget (56) and Ernst von Glasersfeld (57). The former developed his “genetic epistemology” by studying the development of human children. The latter, using Piaget as one of his main sources, developed “radical constructivism,” a philosophical treatise about how humans come to know. Rather than attempt to position the author’s work in the broad field of artificial intelligence research, something I do not feel confident to do without further reading, I wish to note aspects of human cognition that the author’s model does not take into account and that, generally, are overlooked or ignored by the artificial intelligence research community.

55

« 2 » First, I note that humans, like other biological organisms, are dynamical systems (§11), far from equilibrium, whose structures are continually being formed and reformed by the dissipation of energy. The author does state that humans are dynamical systems; however, his account is limited to the statement (in footnote 3) that “A dynamical system consists of an abstract state space evolving in time according to a rule that specifies the immediate future state given the current state.” Far richer concepts of what dynamical systems are and the challenges of modeling them are to be found, for example, in the writings of Heinz von Foerster (2003: chapter 1) and Ilya Prigogine (1981) on self-organisation. Humans are also organisationally closed, autopoietic systems, endowed with an operationally closed nervous system. Using these foundational ideas, Humberto Maturana and Francisco Varela (1980) developed a “biology of cognition.” This work adds considerably to our understanding of constructive cognitive processes. Related ideas are to be found in chapters 10 and 11 of von Foerster (2003), where there is discussion of how sensorimotor activity leads to the computation of “objects” as an invariant of an organism’s constructed reality. These works are seminal accounts of what is referred to in later literature as “enactive cognition.”

51

« 3 » The author uses the term “symbolic” in §9. The author’s model is presented as a general mechanism for learning. It, like much other work in artificial intelligence research, ignores or takes for granted that which is, with few exceptions, peculiarly human in human cognition: the ability to communicate and compute using what George Herbert Mead refers to as “significant symbols” – gestures, icons and utterances that call forth in the sender similar responses to those elicited in the receiver. Humans converse with each other and converse with themselves. This truth falsifies the claim made by many in the artificial intelligence community that brains and computers are both “physical symbol systems.”
The constructivist approach, even if those AGI has incorporated several concepts from the symbolic approach, nor with any other form of AI. Searle (1980) has challenged this claim. Scott & Shurville (2011) provide an extended discussion of the topic and propose its falsification based on their analysis that a “symbol” is a second-order “object” that two or more interacting organizations closely systems compute as standing for a given first-order “object” and compute that they are both doing so.

In his model, the author of the target paper refers to his simulated agent as having a “mind” (§11). If we take “mind” to refer to the conceptual processes that constitute humans as individual selves, then it is possible find in the literature more elaborated understandings of “mind” as an embodied, organizationally closed, self-reproducing system of concepts that arises as a consequence not only of ongoing cognitive constructions but also of social interaction (Pask, Scott & Kallikourdis 1975; Pask 1981; Scott 2007).

The commentators have touched on particular those related to the scalability and robustness of the mechanism CALM, to its relation with the CAES architecture, and to the transition from sensorimotor embodied, organizationally closed, self-reproducing to its relation with the CAES architecture, and to the transition from sensorimotor to symbolic.

**General claims**

1. “The commentators have touched important points in the ideas presented in the article. Some of the criticisms made might appear heavy, but this is due to the nature of this research, not limited to technical applied AI questions, which aims to address challenging philosophical and scientific problems.

2. “Since I declared in the beginning of the paper that until now, Constructivist AI has not been able to present impressive results,” I led the readers to expect some spectacular results. However, the stated experimental outcomes (with the hyper-flip problem) can rather disappoint such expectations. The assertion might also give the wrong impression that I considered Constructivist AI stagnant until the arrival of this article. I am in complete agreement with Georgi Stojanov when he says that constructivist AI “certainly made huge theoretical advances” (§11), and I would add that AGI has incorporated several concepts from the constructivist approach, even if those researchers do not necessarily call themselves constructivists.

3. In the long road towards constructivist artificial general intelligence, my article aims to be just a step forward, but it is still far from the finishing line. The ideas presented make up just a further brick for constructing the bridge, and not a complete definitive answer. As Stojanov says, this is already “a formidable challenge.”

4. “As is often the case with most of these ambitious investigations, the work done until now left more open hypotheses, unanswered questions, ideas and promises, than actually determined conclusions or remarkable results. Nevertheless, thanks to that ambition, it is possible to believe that the work done, albeit quite modest, points in the right direction.

5. Despite all the efforts, we still find ourselves stuck between two steep challenges. On the one hand, there is the complexity of the sensorimotor problems, which require computationally viable models capable of treating large continuous domains and realizing cybernetic adaptation, interactive processing of imprecision, refinement of skills, etc. On the other hand, there is the problem of constructing symbols to represent abstract entities and processes, which could lead the agent to a kind of higher level of thought in which the experience is organized in terms of intelligible concepts. The ideas presented in my article do not solve either of these challenges but could eventually help AI to get a foothold in both.

**Scalability and robustness**

6. The first important question cited many times in the commentaries can be summarized like this: can the mechanism scale up well to complex, continuous, large-order, real-time, noisy, non-deterministic environments? In other words: can the viability of the model be convincingly demonstrated in an experimental way? As claimed in the introduction to my article, so far nobody has been able to do this in constructivist general artificial intelligence.

7. CALM, too, suffers from scalability difficulties. It can scale up well on highly structured environments, where the agent deals with a large number of variables but where causal links are very precise, where relevant variables in function of the agent's goals are easy to identify, and where non-observable variables exist on a very small scale. I agree that it is easy to be robust in such environments. Since CALM was designed to work in discrete symbolic environments, it is not adapted to be directly applicable to large sensorimotor problems.

8. Frank Guerin (§6) suggests the example where two stereo cameras deliver a few million pixels in 24 bit color at thirty frames per second and CALM tries to predict the consequences of actions in the complexity of an everyday setting. He wonders whether each bit of input could be used as...
From continuous signals to discrete representations

One of the main limitations of CALM is the need for a predefined discrete representation of both the signals received and those transmitted by the agent. Also, time is considered as a discrete succession of cycles. However, many problems in complex environments can only be properly addressed through continuous representations, which enable an agent to face problems on the sensorimotor level.

It seems more natural to start with continuous signals and gradually construct discrete states as a sort of abstraction. This is the first step to going beyond sensorimotor primitivism and arriving in a symbolic dimension. It also applies to temporal abstraction because intelligence needs to slice the continuous flow into relevant pieces of time in order to recognize events or cycles.

In any case, schema learning mechanisms are not necessarily incompatible with continuous environments. An extension of the schema used by CALM can be used to represent changes in continuous variables. Very basically, we can represent the anticipation of an increase or decrease in the value of a certain variable, or the tendency to converge towards some specific value, given some action. In this way, each schema realizes a kind of simplified regression, where in function of some conditions (context and action), the schema can anticipate a continuous variation of some variable.

Noise and non-determinism

The definition and exploration of environments that I called “partially deterministic” (e.g., §2) should be considered worthwhile. The methods behind CALM were defined to focus on the discovery of deterministic regularities in an environment composed of deterministic and non-deterministic phenomena.

For an agent, a complex environment can appear non-deterministic because its perception, control and understanding are limited in some way (partial observability, noisy sensors, imprecise effectors, other entities acting in the same environment, etc.). Apparent non-determinism can be modeled either by creating stochastic rules, or by continuing to search for causes.

Every roboticist knows the importance of taking the noise and imprecision inherent in sensory and motor apparatus seriously. So far, CALM has not been equipped with any mechanism to treat noise explicitly. Even so, the presence or absence of noise could be represented as a cause of some perturbed anticipations, as in: aA→~noise→b.

That said, the possibility of representing certain situations as stochastic regularities could be incorporated into CALM, working as a complementary method for situations where deterministic assumptions are not possible. Such a method can allow the mechanism to search for probabilities in order to anticipate which is most likely to happen. Nevertheless, that kind of search for statistical regularities should not interfere with the search for causal relations.

Robustness and parallelization

Thomas Degris says that for “an agent to take complex decisions or to understand a complex environment, perhaps it is unavoidable to consider a large number of variables or signals” (§3). This is certainly correct, especially when the problem is close to the sensorimotor level.

As Stojanov claims, CALM resembles a completely deterministic “monolithic single-thread algorithm” (§2). In nature,
The whole system.

modules, under the baton of some principle could be imagined as the engine inside some

construction of modules, each one working in a specific level and domain, but in constant interaction with other mod-

ules. Once within this conjuncture, CALM could be imagined as the engine inside some

modules, under the baton of some principle responsible for coordinating the modules in

the whole system.

Moreover, concerning robustness, parallelization is a very powerful

means to break complexity and to deal with

cmplex environments. The neural organi-

zation and functioning of the brain is highly

parallelized. Although it was not mentioned

in my article, CALM can implement a kind

of parallelization, since the construction of
each anticipatory tree (that models the dy-
namics of one single variable) can be real-
ized independently from the other trees, i.e.,
in different separated threads.

Another way to be robust is to
 pay attention to what is important (Foner & Maes 1994). The problem of indistinctly

correlating actions with changes in sensor
data is computationally unfeasible for any

non-trivial application. This problem be-
comes more manageable by restricting the
set of sensor data the agent attends to, or the
set of internal structures that is updated, at
particular instants. In the same vein, CALM
implements a focus of attention related to
the affectively important variables.

Degris writes that "while trees

in, in principle, take advantage of specific
structures in the data, they also have issues
that can make them impractical to use as
a life-long constructivist agent in the ac-
tual world" (32) and that "even when some
of the system dynamic may be factorable,
there is no guarantee that other represen-
tations, such as value functions or policies,
will be factorable" (ibid).

Some technical choices with regard to CALM’s methods should be revised, especially with regard
to the management of episodic memory and anticipatory trees. It is evident that a
robust algorithm for such general purposes must be carefully studied. In other words, the algorithms in CALM will probably need

certain improvements.

Degris cites the “Horde” archi-
tecture, suggesting that it can “represent
knowledge similar to schemas but also
more general knowledge” (32). Horde can construct ‘demons’, which are generalized
value-functions for given partial policies.

These demons can be learned in parallel by an efficient extended reinforcement learning
method during the actuation of the agent.
However, I think that the knowledge represented by Horde is not that similar to what is
represented by CALM.

Space does not allow for a more detailed comparison between CALM and Horde. However, it is evident that architec-
tures like Horde will be a precious source of
good strategies for dealing with large real-
time sensorimotor problems, translating them, when necessary, into symbolic terms.
I believe that, the crucial problem of using efficient forms of representation aside, the most important challenge is to find a way to connect consistently the sensorimotor
(continuous, noisy, real-time, large scale)
domains to basic symbolic domains, and the latter to more abstract ones.

From lower to higher levels

Another major question repeatedly
ed in the commentaries is the passage from lower levels of interaction, based on sensorimotor primitives, to higher
levels, based on abstract concepts. The ques-

tion can be formulated like this: Is CALM able gradually to construct successive lay-
ers of abstraction in order to represent its
knowledge?

According to Jean Piaget (1957),
from a fragmented sensorimotor universe, intelligence builds elementary notions, de-
defines relations, finds regularities and even-
tually constructs an objective, substantial, spatial, temporal, regular and external uni-

verse, independent of the subject itself. A
subjective “reality” will emerge from the in-
creasing coherence between schemas in the
course of these adaptions.

In Stojanov claims that CALM does not provide a way to build more ab-
tract structures from simpler sensorimotor
interactions. At least he recognizes that CALM is able to create synthetic elements that
enlarge the sensorial context with something that is beyond perception. Even if this is simple, the synthetic elements are
certainly a form of abstraction since they do not correspond to any sensory input. How-
ever, once CALM places the synthetic ele-
ments side by side with the sensorial ones, it
does not create layers. The context is repre-
sented as a single flattened array. Evidently, we cannot go too far without some kind of robust structuring mechanism in order to
organize knowledge into different levels.

In human beings, cognition is in some way the construction of several lay-
ers of abstraction in order to understand and interpret experiences. If this process is compared with flying from the Earth to the
Moon, the inference of synthetic elements would correspond to the takeoff. It does not
give us too much altitude but it is crucial to
start the voyage.

Building synthetic elements does not constitute a form of abstract or sym-
bolistic thought by itself, but such a process contains the basic insight of what we could call “concept invention.” Synthetic elements allow the designation of entities that cannot be represented from combinations of direct sensory perceptions. Thus, the possibility of representing unobservable conditions is a breakthrough along the road from mere direct perception to more abstract forms of understanding.

Grounding symbolic concepts on sensorimotor flows

Guerin correctly claims that high-
level cognition is very much grounded in sensorimotor intelligence (34). I believe that extracting significant symbolic con-
cepts from interactive sensorimotor flows is one of the key challenges for AI today. The robotics community and the symbolic AI community can be seen as digging tunnels on the opposite sides of a mountain. Despite a lot of progress, a consistent integration of contributions from the two sides is still in

Cpietent. The same metaphor can be used to...
CALM and CAES

« 39 » Órðursson points to the lack of a clear connection between CALM and CAES models. Stoianov claims that the decision to introduce the two entities (body and mind) was somewhat arbitrary. Furthermore, Bernard Scott expressed his disappointment with the way the term “mind” was employed in my article. I agree that the relation between CALM and CAES was not developed in the paper, and that the hyperflip experiment does not illustrate that relation. So let me try to make up for this omission.

« 40 » CAES is an architecture that connects concepts from cybernetics, the theory of autopoiesis, dynamical systems, and affective AI. It is based on the definition of three entities: environment, body, and mind. CALM is the engine that plays the role of the cognitive system in the mind. Besides a cognitive system, the mind includes an affective system (responsible for evaluating the perceived situations), an emotional system (directed to the internal body states), and a reactive system (directed to the body effectors).

« 41 » Ross Ashby (1952) defined the organism (or the agent) as a system composed of a set of essential variables that must stay within a certain physiological normality (limits of viability) in order to preserve the system's integrity and, consequently, the organism's survival. A given behavior contributes to the agent's adaptation if it ensures the persistence of these essential variables within its viable limits. The presence of essential variables assumes that the agent has something like an internal environment. That is the body (Parisi 2004).

« 42 » In nature, organism and environment can exert opposing forces with respect to the global system's flow. However, only the organism is at risk of disintegration, of disappearing as unity. A non-destructive dynamical coupling is reached in the relation between the two systems when the organism interacts with the environment in order to ensure its self-preservation.

« 43 » Randall Beer (1995) integrated the cybernetic concept of organism and autopoiesis using dynamical systems. The adaption criterion is abstractly represented as a zone in the space where the flow of the system must remain. The limits of adaption are the frontiers of that region within the 2 global system space (composed by agent and environment), and the agent is considered adapted to the environment if its activity drives the global system's trajectory in such a way that it never escapes from those frontiers.

« 44 » I agree with Scott when he says that “humans, like other biological organisms, are dynamical systems, far from an equilibrium.” Even if my article does not address this issue, CAES architecture was imagined to correspond to a definition of an agent as a system far from equilibrium, in the sense proposed by Bickhard (2009a) or Xabier Barandiaran and Alvaro Moreno (2008).

Intrinsic motivations and curiosity

« 45 » Stoianov observes that the intrinsic motivations exhibited by CALM “can be related to low-level physiological drives (hunger, pain-avoidance) with no possibility for development of more sophisticated forms of motivations such as curiosity” (§4). I agree that the motivation system of my model is still far too utilitarian, even though some effort has been made to build an intrinsically motivated agent, which is consistent from the perspective of an embodied AI. It is evident that motivation is also linked to the subject's activity itself. Drinking water because we are thirsty is a kind of behavior that can be easily anchored in a biologically-driven explanation. Other behaviors, such as playing checkers, listening to music, or writing scientific papers, can hardly be explained by simply referring to physiological needs.

« 46 » Nevertheless, CALM implements the notion of curiosity for exploratory behavior. In naïve AI approaches, curiosity usually means doing random actions from time to time. In CALM, there is a measure of exploratory utility that allows the agent to plan actions that may lead to new discoveries, or new knowledge that would enhance its world model. The mechanism follows two behavioral policies: one to optimize the affective signals, and another to optimize the gain of knowledge related to relevant variables. The choice of what action to do depends on the weighting of these two policies.
Language and reflectivity

It is evident that those capacities are the notable characteristics of high-level intelligence. But to stay in accordance with constructivist principles, I believe that those abilities emerge as a result of the process of learning and interpreting the experiences on abstract levels. Piaget (1953) suggested that the basic principles regulating intellectual functioning remain unchanged over a lifetime, and that increasingly refined skills and knowledge result from the gradual complexification of the underlying constructed knowledge structures.

Conclusion

The theorems pointed out many aspects of my model that can be improved, such as the lack of sensorimotor grounding of the symbolic elements manipulated by CALM and the impossibility to create more abstract levels of knowledge to represent the agent’s experience. I am confident that improved versions of my model will be able to deal with these problems, in particular extending it to be modular. In this way, the agent will be equipped with more refined sensorimotor apparatus, capable of realizing some pre-processing of signals, coupled with other modules capable of doing some preliminary computing in order to solve some basic sensorimotor problems at a low level, filtering the data that must be sent to the first symbolic modules. Finally, a more sophisticated form of abstraction needs to be incorporated into the algorithm in order to allow the construction of an organized system of anticipatory modules, acting at different levels of abstraction.

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References


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