Modeling animal brains with evolutive cognitive schemas

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Abstract. Very specifically, functional behavior assessment is a domain in developmental psychology looking at the reasons behind a child's observed behavior. More generally, it can be considered as the search for the explanation of human and non-human actions. Towards this goal, computational cognitive neuroscience offers a new range of possibilities that contrast with the usual statistical approaches. An attempt to assess brain functionalities in learning is illustrated here through the simulation of analogical inferences. As a main result of this paper, the mapping of evolutive cognitive schemas onto neural connection structures involving two types of cognitive transfer points out to a possible discontinuity between human and non-human minds.

Keywords: hebbian learning, neural process, cognitive schema, analogical infehrence, simulation.

1 Introduction

As early as in 1936, Piaget considered, and later defined [1], a cognitive schema as being "*a cohesive, repeatable action sequence possessing component actions that are tightly interconnected and governed by a core meaning*". According to this theory, cognitive schemas constitute the building blocks for knowledge acquisition. This concept has been first found incompatible (see e.g., [2]) with the then dominant paradigm of behaviorism, essentially because at that time the corresponding internal processes could not be observed nor measured. Since then, the statistical analysis of sophisticated experimental results and/or simulations [3] has led to the discovery of patterns of neuronal activations that could be identified with building blocks of perception [4]. Acquired memory and skills could thus rely on combining these elementary assemblies into higher-order constructs. These results, however, do not identify the processes relating perception and behavior. In other words, as pointed out by many commentators (see e.g., [5][6]), they do not allow for describing *algorithms* and underlying *circuits.* What is then needed, they conclude, is a ''*middle-out*'' approach that can identify plausible structures linking biology and cognition.

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This need can be related to the general "*what*" and "*how*" questions of cognitive science as addressed by the historical Marr's "tri-level" hypothesis [7] that distinguishes *computational*, *algorithmic* and *implementation* levels. Adding on this, Poggio [8] argues that, in order to discover the representations used by the brain, one needs to understand "*how* an individual organism learns and evolves them from experience of the natural world", and that "learning algorithms and their a priori assumptions are deeper and more useful than a description of the details of *what* is actually learned". As a consequence, *evolution* and *learning* should be added to the levels in cognitive studies.

Towards this goal, a different approach to brain modeling has been proposed [9]. Defined by a logic program of about 300 lines, an experimental platform for this new type of modeling can be run on any PC. The corresponding formal framework stands out of the usual methods by focusing on *processes*. It relies for this on three concepts of computer science and mathematical logic i.e., the formal notions of:

- an *object in context* represented by expressions in a logical language
- *communicating processes* between *concurrent threads* that can be used to model the interaction of objects obeying various communication protocols
- a *virtual machine* interpreting virtual code that differs from a processor's native code.

In software engineering, a virtual machine constitutes the key mechanism that allows for interfacing high level objects i.e., software, with their low level physical support i.e., hardware. In a multi-level model of brain structures and processes, such a machine does function as an interface between the neural and cognitive levels, therefore allowing for grounded models of cognition to be formulated by relating perception and behavior at a *symbolic* level. This does not mean however that abstracting away physiological details detaches cognitive models from their supporting neural substrate: *quite to the contrary, as we shall briefly review below, communication protocols representing synaptic plasticity actually drive the hebbian learning of cognitive structures*.

2 Material and methods.

Our overall methodology can be described by the following sequence:

a) *micro scale* virtual circuits implementing synaptic plasticity through asynchronous communicating processes are first defined

b) *meso scale* virtual circuits corresponding to basic cognitive processes are then composed out of these micro scale circuits

c) both types of virtual circuits are finally compiled into *virtual code* to be interpreted by a virtual machine.

Communication protocols for *micro scale* circuits as well as the specifications of our virtual machine are given in open access in [9]. Examples of mesoscale circuits corresponding to cognitive software running on top of a simulated biological substrate are presented below for illustrative purposes. At the same time, they do constitute the building blocks of the developments to be presented in our Results section.

2.1 A case of classical conditioning

As a general evolution principle, organisms tend to devise and use “tricks” for their survival. The ability to evaluate a threat by learning predictive relationships e.g., by associating a noise and the presence of a predator, is an example of such tricks realized by *classical conditioning.*

Let us consider the classical conditioning in the defensive siphon and gill withdrawal reflex of *aplysia californica* [10]. In this experiment, a light tactile conditioned stimulus `cs` elicits a weak defensive reflex, and a strong noxious unconditioned stimulus `us` (usually an electric shock) produces a massive withdrawal reflex. After a few pairings of stimuli `cs` and `us,` where `cs` slightly precedes `us`, a stimulus `cs` alone triggers a significantly enhanced withdrawal reflex i.e., the organism has learned a new behavior. This can be represented by a wiring diagram, or *virtual circuit* (see Figure 1), adapted from [11] to allow for a one to one correspondence with symbolic expressions.

```
sense(cs)-*->=>-motor(cs)
           /|\
           ltp
            |
sense(us)-+->=>-motor(us)
```

Fig. 1. A virtual circuit implementing classical conditioning.

In Figure 1, the components `sense(us)` and `sense(cs)` are coupled with sensors (not shown here) capturing external stimuli `us` and `cs` and correspond to sensory neurons. The components `motor(us)` and `motor(cs)` are coupled with action effectors (also not shown) and correspond to motor neurons. Finally, the component `ltp` embodies the mechanism of long term potentiation and acts as a facilitatory interneuron reinforcing the pathway (i.e. augmenting its *weight*) between `sense(cs)` and `motor(cs)`. The interaction of these components are represented by the iconic symbols `->=>-` and `/|\` that correspond to a synaptic transmission (i.e., `->=>-` represents a *synapse*) and to the modulation of a synapse, respectively. The symbols `*` and `+` stand for conjunctive and disjunctive operators (i.e., they are used to represent the convergence of incoming signals and the dissemination of an outgoing signal, respectively). Classical conditioning then follows from the application of hebbian learning [12] i.e., “neurons that fire together wire together”. Though it is admitted today that classical conditioning in aplysia is mediated by multiple neuronal mechanisms [13] including a postsynaptic retroaction on a presynaptic site, the important issue is that the learning of a new behavior requires a conjoint activity of multiple neurons. This activity in turn depends critically on the temporal pairing of the conditioned and unconditioned stimuli `cs` and `us`, which in conclusion leads to implement the `ltp` component as a *detector of coincidence.*

2.2 A simple case of operant conditioning

The ability to assess and to remember the consequences of one's own actions is another example of associative learning providing survival advantages. In this case, *operant conditioning* [14] associates an action and its result, which can be *positive* or *negative*. Toward this goal, the organism will first receive either an *excite* or an *inhibit* feedback stimulus, corresponding for instance to a reward or punishment, respectively; it will then associate this feedback with an appropriate action.

Let us consider a simple thought experiment where a *pigeon* is learning to discriminate between grains and pebbles corresponding to two possible vectors **`I`** of external visual stimuli **`[mat,smooth]`** and **`[shiny,smooth]`**. The *circuit* given in Figure 2, represents the wiring of four components **`sense(I)`**, **`learn(accept(I))`**, **`accept(I)`** and **`reject(I)`**, together with two **`ltp`** and two opposite **`ltd`** (for long term depression) components. In addition to the external stimuli captured by component **`sense(I)`**, this circuit incorporates the two internal stimuli **`excite(accept(I))`** and **`inhibit(accept(I))`** that correspond to feedbacks from probing the food according to a set of *accepted* elements.

```
          ---*->=>-accept(I)
         |  /|\
         |  LTP
         |   |
         |   +------------------------------------------
         |   |                                          |
         |  LTD                                         |
         |  \|/                    |excite(accept(I))--
sense(I)-+---*->=>-learn(accept(I))|
         |  /|\                    |inhibit(accept(I))-
         |  LTD                                         |
         |   |                                          |
         |   +------------------------------------------
         |   |
         |  LTP
         |  \|/
          ---*->=>-reject(I)
```

Fig. 2. A generic virtual circuit implementing simple operant conditioning

At the beginning of the simulation, the pathways from **`sense(I)`** to **`learn(accept(I))`** is open, while the pathways to both **`accept(I)`** and **`reject(I)`** are closed. After a few trials, the pigeon will have learned to close **`learn(accept(I))`** and to open either **`accept(I)`** or **`reject(I)`**. This process matches a fundamental principle in circuit neuroscience according to which *inhibition* in neuronal networks during baseline conditions allows in turn for *disinhibition*, which then stands as a key mechanism for circuit plasticity, learning, and memory retrieval [15]; this gives rise in turn to two populations of neurons that have opposing spiking patterns in anticipation of movement [16] as well as two eligibility traces with different temporal profiles, one corresponding to the induction of **`ltp`**, and the other to the induction of **`ltd`** [17][18].

3 Results

Following our previous results [9] on modeling the first three levels of animal awareness according to Pepperberg & Lynn (2000 [19]), the mapping of analogical inference schemas onto neural connection structures involving two types of cognitive transfer points out to a possible discontinuity between human and non-human minds.

3.1 Learning a simple analogical inference schema

Let us first consider a simple analogical inference schema involving two predicates **`p`** and **`q`** applied to objects **`X1`** and **`X2`**, i.e.

```
{p(X1)}                   {big(dog)}
{p(X2)}        e.g.,      {big(bear)}
 q(X1)                     strong(dog)
 ------                    -----------
 q(X2)                     strong(bear)
```

where {**`F`**} represents a fact **`F`**, or proposition, that has been previously memorized. This schema can be viewed as first inducing an implication i.e., **`p(X) -> q(X),`** where **`X`** is a variable, and then applying modus ponens i.e.,

```
 p(X) -> q(X)
 p(X)
 ----
 q(X)
```

The corresponding circuits (where **`A`**, **`B`** are parameters defining a context e.g., **`left`**, **`right`**, and **`I`**,**`J`** vectors of percepts representing **`p`**,**`q`**) are given below. In Fig. 3, each half circuit implements the operant conditioning for building a storage memory trace relying on a *long term storage* (**`lts`**) process [9]. In Fig. 4, a structure relying on a *long term retrieval* (**`ltr`**) process and representing an implication is build in the upper half and then applied in the lower half through iterated hebbian learning.

```
                       p(X1)                  {p(X1)}
                     --*>=>-see(A(X1(I)))-+---*--{see(A(X1(I)))}
                    | /|\                 |  /|\
                    | ltp                 |  lts
                    |  |                  |   |
                    |  |                   ---
                    |  +-----------------------------------------
                    |  |                                         |
                    | ltd                                        |
 p(X1)              | \|/                                        |
 sense(A(X1(I)))-+--*->=>-learn(see(A(X1(I))))|excite(see(A(I)))-

 sense(B(X2(I)))-+--*->=>-learn(see(B(X2(I))))|excite(see(B(I)))-
 p(X2)              | /|\                                        |
                    | ltd                                        |
                    |  |                                         |
                    |  +-----------------------------------------
                    |  |                   ---
                    |  |                  |   |
                    | ltp                 |  lts
                    | \|/                 |  \|/
                     --*>=>-see(B(X2(I)))-+---*--{see(B(X2(I)))}
                       p(X2)                  {p(X2)}
```

Fig. 3. Virtual circuit for memorizing perceptions

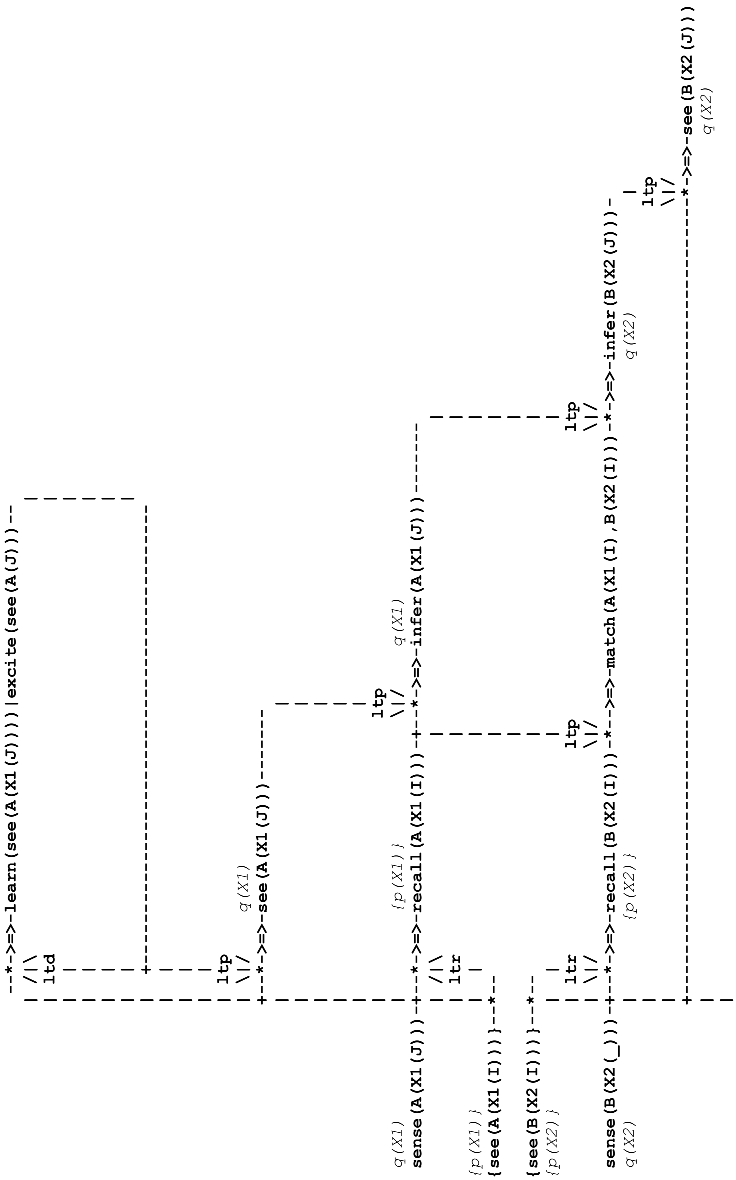

Fig. 4. Virtual circuit for implementing a simple case of analogical inference

3.2 Learning an analogical inference schema implementing transitive relations

Let us now consider a case of relational inference based on transitive relations i.e.,

```
{p(X1,Y1),p(Y1,Z1)}        {smaller(mouse,cat),smaller(cat,dog)}
{q(X2,Y2),q(Y2,Z2)}  e.g., {higher(tree,house),higher(house,car)}
 p(X1,Z1)                   smaller(mouse,dog)
 q(X2,Z2)                   higher(tree,car)
```

This inference consists in first inducing a second order implication representing a generic transitive relation, where `P,X,Y,Z` are variables

```
 P(X,Y), P(Y,Z) -> P(X,Z)
```

and then applying modus ponens

```
{P(X,Y), P(Y,Z) -> P(X,Z)}
 P(X,Y)
 P(Y,Z)
 P(X,Z)
```

Let us extend the definition of the perceptual context by adding two parameters `C`, `D` e.g., `front`, `rear`. The circuit implementing this inference schema is given in Fig. 5. As a distinctive difference from the previous circuit, where remembered facts `{p(X1)}` and `{p(X2)}` need to be matched to ensure that they involve the same property `p` (see the center of Fig.4), the circuit in Fig. 5 relies on remembered facts `{p(X1,Y1),p(Y1,Z1)}` and `{q(X2,Y2),q(Y2,Z2)}` that possibly call for different properties `p` and `q`, and thus cannot be matched. As a result, whereas the analogical inference implemented in Fig. 4 allows for the cognitive transfer of a property `q`, the circuit of Fig. 5 allows for the cognitive transfer of structural analogies between any two transitive relations. Consequently, the learning step leading to `infer(D(_(K),Z2(L)))` in Fig.5 still carries a non instantiated argument, thus highlighting the fact that these brain inferences are partial processes inscribed in a context D relating a perception to an action, in this case `see(D(X2(K),Z2(L)))`.

Without entering into the details of these virtual circuits (see [9]), let us just mention the role played by the parameters defining context i.e. , `A`, `B`, `C`, `D` (e.g., `left`, `right`, `front`, `rear`), which allow for representing perceived invariant structures and their memorization for later reuse, as just discussed above.

3.2 Characterizing the differences between human and non-human minds

Let us finally turn to an example of relational inference of the following type

```
{p(X1,Y1),q(Y1,Z1)}        {father(bill,mary),mother(mary,sam)}
{p(X2,Y2),q(Y2,Z2)}  e.g., {father(tom,cathy),mother(cathy,jack)}
 r(X1,Z1)                   grandfather(bill,sam)
 r(X2,Z2)                   grandfather(tom,jack)
```

This extension involves the two types of cognitive transfers just considered. A combination of the two corresponding circuits is however far from being straightforward, the difficulty being here the parallel matching of multiple interleaved properties. Whereas behaviors relying on simple analogical reasoning and transitive inference, as modeled by the circuits of Fig. 4 and 5, have been observed in non-humans animals, this more complex example is unarguably out of their reach. It is interesting to note that previous modeling approaches relying on substitutions [20] have led to similar conclusions [21]. On the other hand, further results [22] pertaining to a simple form of meta-cognition observed in animals, namely memory awareness, have been obtained

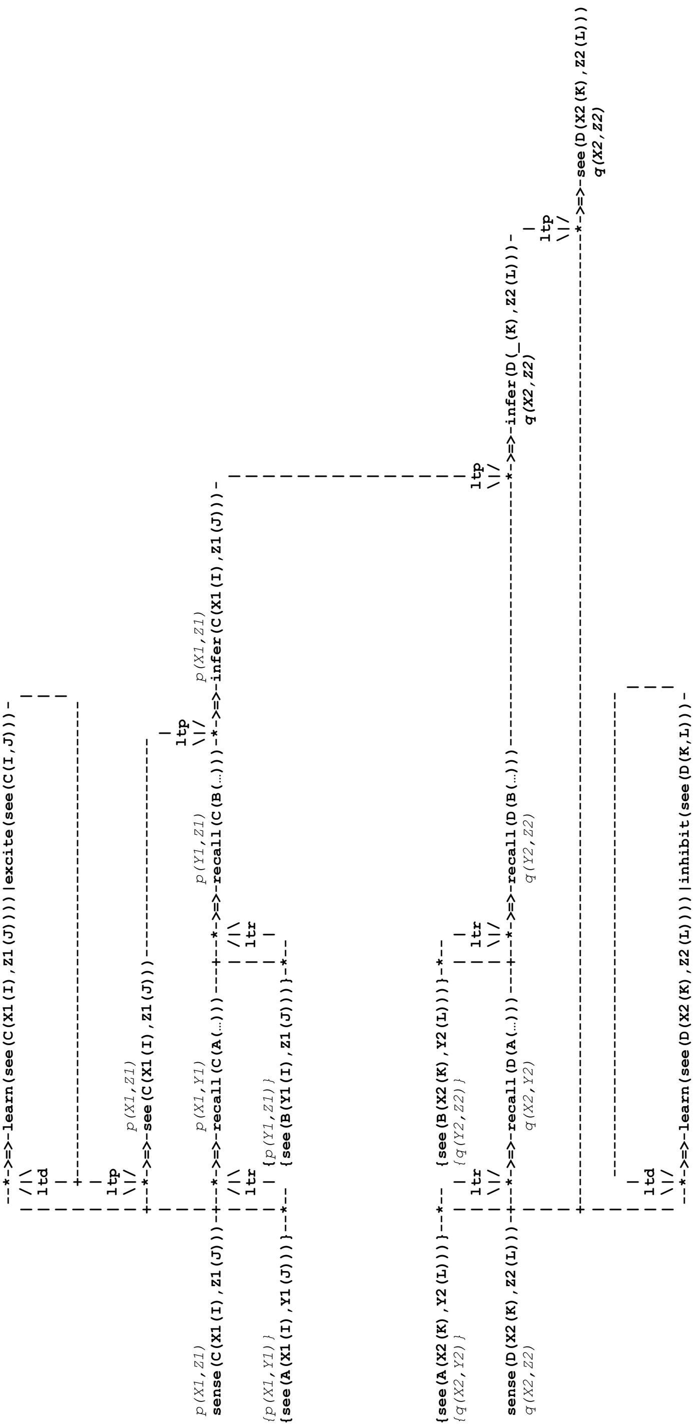

Fig. 5. Virtual circuit implementing transitive inferences

by combining elementary circuits (more precisely, this higher-order functionality can be reduced to successive layers of associative memories implementing *retrospective revaluation* as defined in [23]). If, as argued in [21], one of the challenges confronting cognitive scientists today is to explain the functional discontinuity between human and nonhuman minds, then an approach towards answering this question might be to study the various types of cognitive transfers that need to be embedded in evolutive cognitive schemas of the kind presented here.

4 Discussion

A common way of characterizing cognitive models is given by the two competing paradigms of artificial cognitive architectures i.e., the traditional "*sense-think-act*" cycle of cognitivist systems, on one side, and the simplified "*sense-act*" cycle of *embodied* and/or *emergent* cognition, on the other. Our proposed model falls into the second category, but it does so by resorting to a kind of symbolic computational framework generally associated with the first approach.

Various proposals have been made to close the gap between the level of individual neurons and symbolic levels supporting behavior. A possible solution is to consider group of neurons, or *neural assemblies*. It is proposed here to model neural assemblies in a simulation framework driven by a virtual machine acting as an interface between neural dynamics and symbolic information defining perceptions and behaviors. While the usual approach to simulating neural dynamics starts with current flows represented by differential equations, we opted for a conceptual abstraction of synaptic plasticity represented by communicating processes between concurrent *threads*. Whereas in some simulations threads are equated with individual neurons, in others they do represent multiple interconnected neurons whose coordinated activity converges into an aggregated result. Threads thus constitute a general and versatile tool for simulating various levels of structures and/or processes e.g., Hebbian cell assemblies. As a consequence, there is no reference to any specific neural network model. In order to try and discover learning processes, and thus in sharp contrast with the usual models of interactive brain areas obtained by quantitatively fitting data (i.e., where latent estimated parameters are being correlated with neural measures), the goal here is to construct a generative model of how behaviors can be interfaced with neural dynamics.

As forcefully argued by Cooper and Peebles [24], models in Cognitive Science cannot proceed at either level (i.e., computational or implementational in Marr's sense) without tight coupling to the algorithmic and representation level. The most important part of their argumentation (which reflects our own views) is summarized in the following statement: "*Integrated cognitive architectures that permit abstract specification of the functions of components and that make contact with the neural level provide a powerful bridge for linking the algorithmic and representational level to both the computational level and the implementational level*".

The successful application of this methodology could lead to a reconsideration of the whole concept of a "neural code" allowing for relating perception and behavior. Such a neural code may well reside in the spatial arrangement of mesoscale circuit patterns (i.e., a kind of population or sparse coding, as opposed to the more traditional rate or temporal coding associated with spike trains). More precisely, perception might be related to behaviors through the paths found by evolution via iterated hebbian learning.

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