Learning by doing
using a system-level approach to the brain

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Abstract. We show how to extend our system-level brain model to achieve learning by doing.

Our model is implemented as a set of intercommunicating brain modules that run in parallel. We extended this using an episodic memory module and a context module. The first receives event information from the cortex and constructs event representations and aggregates them into the current episode. The second uses abstractions of prior episodes to establish competitively a current context which is used by the planning module to attempt the current problem.

The resulting model implements an episodic memory which accords with current psychological thinking. In addition, it has limited working memory which is distributed over cortical modules.

Keywords: learning by doing, episodic memory, event representation, problem solving, context

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1 The extension of our model

We have previously described a system-level model of the primate cortex [4] [3] [6] [5]. Our approach uses an abstract logical representation, from which a neural representation can be derived. Figure 1 diagrams the model.

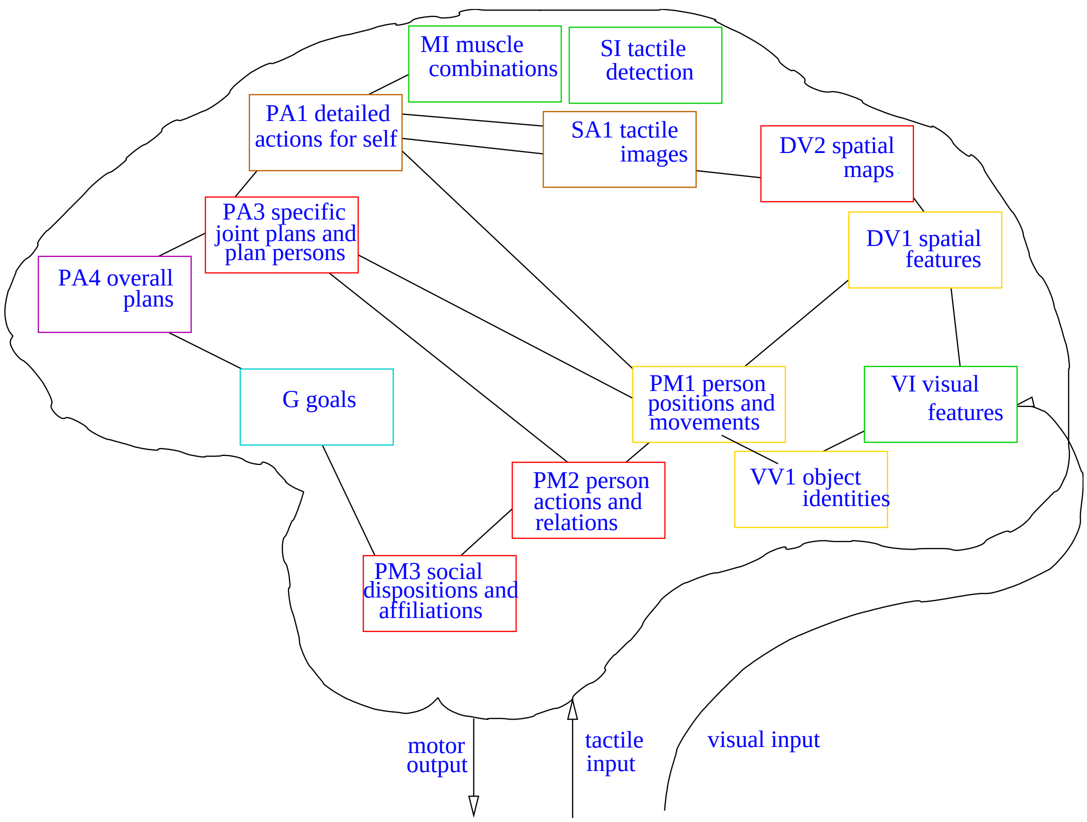

Figure 1: Our system-level model of the primate neocortex

Our original model used rules in each module which were manually programmed by us. In order to extend this model to learn new rules and to use a store of learned rules, we have developed a new model which we call a *dynamic model*. We had previously shown how to program the model to solve problems, and the Tower of Hanoi in particular [6]. We have now focussed on a learning by doing, using Tower of Hanoi as the example, and using the classic work of Anzai and Simon [1] in which a human subject learned to solve the Tower of Hanoi problem, de novo. They published a verbalization protocol obtained from a subject repeatedly attempting the problem and developing a series of strategies for solving it.

The essential problem is to develop enough apparatus so that the model can remember and observe its own behavior so that it can recognize experiences and evoke applicable existing knowledge.

Our model is implemented as a set of intercommunicating brain modules that run in parallel.

Our solution to the extension of our model has involved:

(i) adding a module corresponding to the hippocampal complex, and which receives data from cortical areas and constructs a representation of the current mental event

(ii) adding a module which stores and represents generalizations of events which form frame-like representations which we call contexts

(iii) generalizing our planning module to use the currently dominant context as a guide to its action

(iv) generalizing the action of modules so that learned information is represented as data items, and rules competitively reconstruct data items in response to their current situation.

Figure 2 summarizes the additional modules which have added to our model.

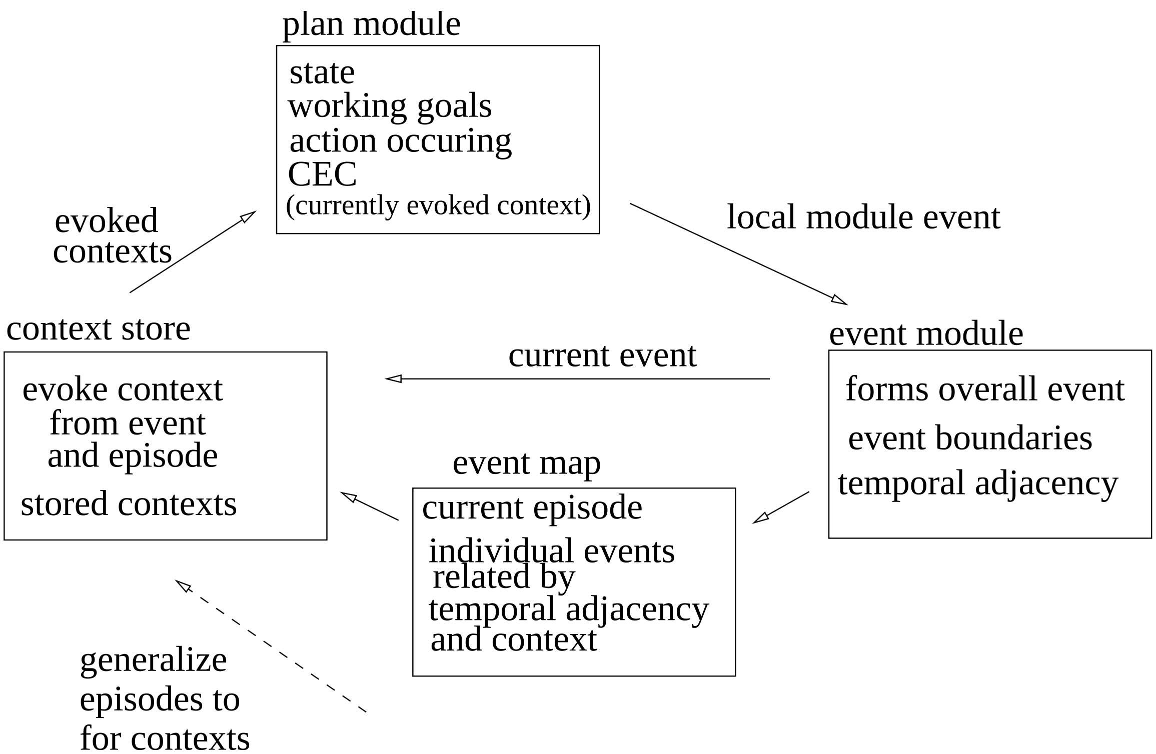

Figure 2: The basic action of the system

2 Events and episodes

Friedman [10] has reviewed the many psychological theories of episodic and autobiographical memory. These fall into nine classes, but the overall consensus is that episodic memory is not memory laid down continously in time, but rather is formed as a sequence of discrete events. Further, the relations among events are a result of quite general associative links, although temporal adjacency is often one of these.

We will take memory to be divided into (1) short term stores which can be in several different cortical modules with corresponding modalities, (2) episodic memory which is the memory of the last few minutes of mental activity, up to 15 minutes or so, (3) long term memory which is divided into autobiographical and semantic, and (4) procedural memory which uses mainly subcortical mechanisms.

We will thus take working memory to include episodic memory and also some short term stores in planning modules.

Even the accumulation of events to form episodes seems to be limited. According to Wickelgren [9], the size of sequences is limited to 3 or 4 events, and this occurs by continuous rapid chunking of events into a hierarchy of larger events.

We are thus lead to a psychological view of the action of episodic memory, that it forms and maintains the current episode which is a representation of the action of the brain during the last few minutes, and that this representation is comprised of a hierarchically chunked structure of representations of events.

3 Events and the hippocampus

The anatomical connections of the hippocampal complex for the rhesus monkey have been described by Kobayashi and Amarel [8], hippocampal complex defined to include the parahippocampal cortex, the perirhinal cortec, and the entorhinal cortex, as well as the hippocampus proper. The cortical ones are summarized in Figure 3, taken from their paper.

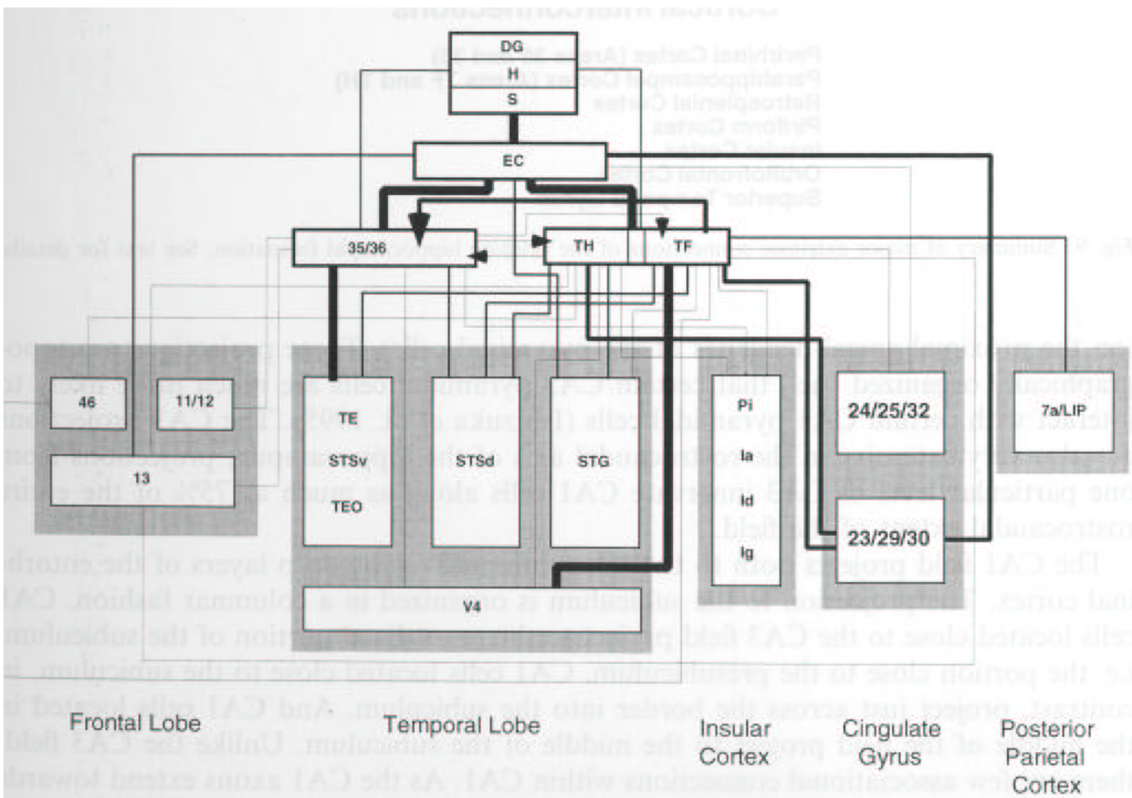

Figure 3: Cortical connections to hippocampal complex, for rhesus monkey, from Kobayashi and Amarel

There are many interesting properties of this diagram. First, many cortical areas are connected to the hippocampus. Second, connections in the main go via either the parahippocampal cortex or the perirhinal cortex, although there are some direct connections to the entorhinal cortex.

According to most analysts, for example Cohen and Eigenbaum [7], there are both input and output streams into and out of the hippocampus and they use different layers of the entorhinal cortex.

The next interesting thing is that there are only inputs from the perceptual hierarchy of the cortex and not from the action hierarchy. Also the largest input comes from V4, probably because episodic memories use images represented at this level, i.e. 2.5 - 3D surfaces. The size of input may reflect the amount of information but not necessarily its necessity or importance.

Thus, the structure of a single event is based on information received by the hippocampal complex from a range of perceptual cortical areas.

In addition, we note that there is input from areas associated with goals in our model. These are anterior cingulate areas 24/25/32 and also areas 9 and 46 where we were storing working goals.

The issue of time granularity is one we have not yet had time to explore. We imagine that different cortical modules may chunk locally and then pass these chunks to the hippocampus. This in turn will chunk further depending on the current overall event sequence, repetition, familiarity, and depending on observed context-dependent cues for the event boundaries.

4 The learning by doing task

Figure 4 summarizes the sequence of strategies learned by Anzai and Simon's subject [1].

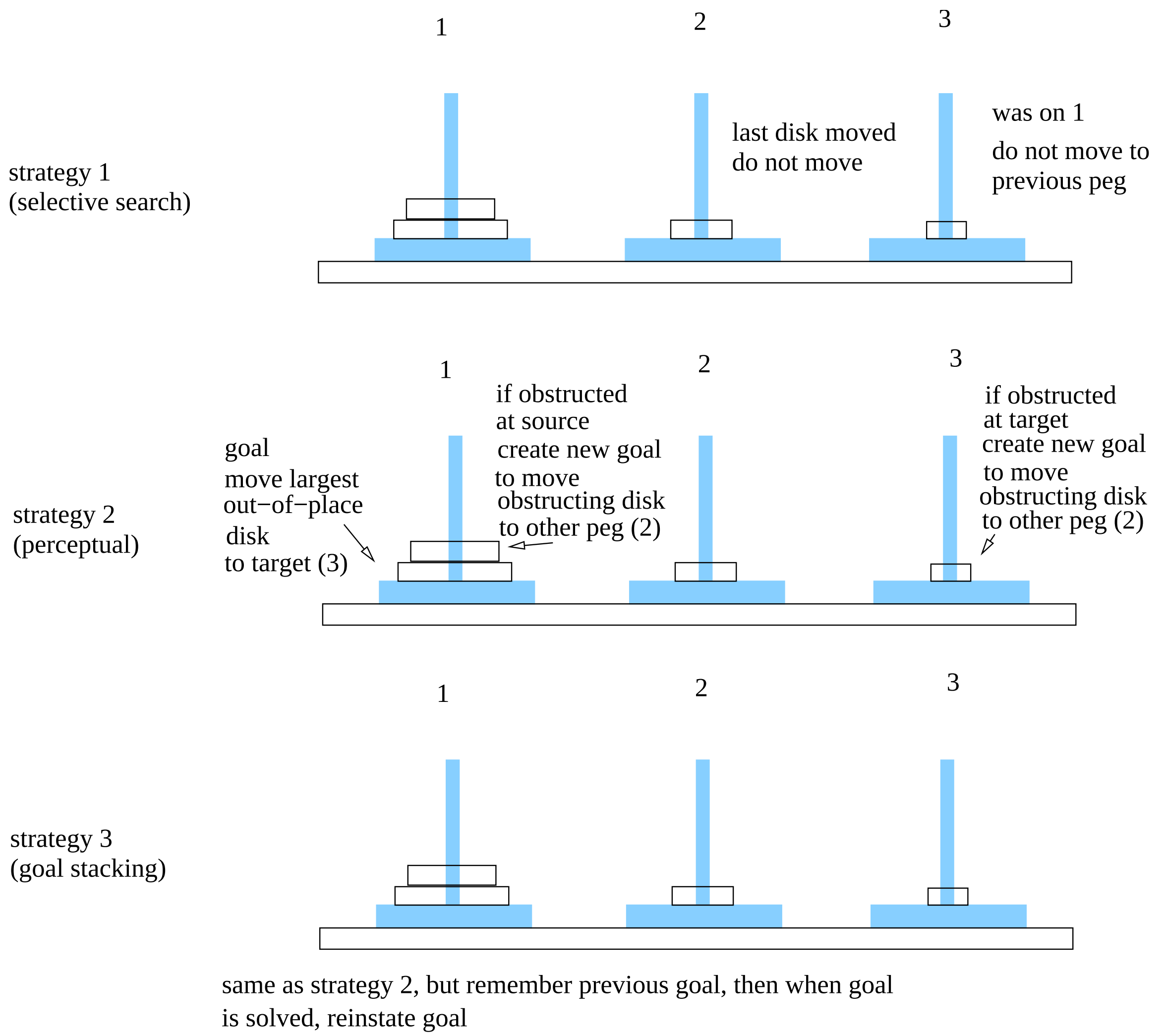

Figure 4: Anzai and Simon strategy sequence

To give a rough idea of the data we are using, the first 23 steps of the 224 step published Anzai and Simon protocol are as follows:

1. I'm not sure, but first I'll take 1 from A and place it on B.

2. And I'll take 2 from A and place it on C.

3. And then, I take 1 from B and place it on C.

(If you can, tell me why you placed it there)

4. Because there was no place else to go, I had to place 1 from B to C.

5. Then, next, I placed 3 from A to B.

6. Well . . . , first I had to place 1 to B, because I had to move all disks to C. I wasn't too sure though.

7. I thought that it would be a problem if I placed 1 on C rather than B.

8. Now I want to place 2 on top of 3, so I'll place 1 on A.

9. Then I'll take 2 from C, and place it on B.

10. And I'll take 1 and . . . place it from A to B.

11. So then, 4 will go from A to C.

12. And then . ., um . . ., oh . . ., um . . .,

13. I should have placed 5 on C. But that will take time. I'll take 1 . .

(If you want to, you can start over again. If you are going to do that, tell me why.)

14. But I'll stay with this a little more . . .

15. I'll take 1 from B and place it on A.

16. Then I'll take 2 from B to C.

17. Oh, this won't do . . .

18. I'll take 2 and place it from C to B again.

19. And then, I'll take 1, from A . . .

20. Oh no! If I do it this way, it won't work!

21. I'll return it.

22. OK?

23. I'll start over.

(Go ahead)

This subject thus was presented with the Tower of Hanoi problem which was novel to them. They began by using a very general search principle which is strategy one. This produced a sequence of positions, and from this on a second attempt at solution they applied the idea of a goal to move a particular disk to a particular peg, which they solved by a straightforward obstacle removal method, however this perceptual method erased parent goals. In a third attempt, they developed a goal ordering and then goal stacking approach which lead to simpler solution process.

We have developed mechanisms which allow our model to learn by doing in the same manner. This assumes that the subject already has the stored methods for a concept of goal, for simple obstacle removal and for goal stacking. Thus what is learned is how to select from and apply existing methods, and to produce and represent a new strategy which is the resulting combination of applications of the old.

The representation of the new strategy is obtained from the representation of the episode at the end of the process.

5 The learning by doing sequence

The sequence of stages occurs as follows:

1. Initial problem is perceived

2. This evokes a context, which is ss - selective search

3. The context sends plan and moves etc to the planning module

4. The system follows this ss strategy, generating a sequence of moves

5. An event sequence is formed in the hippocampal system

6. This evokes the obstacle context

7. An episode is recognized as an obstacle episode

8. The evoked obstacle context sends descriptions of working goals, plan and moves to planning

9. Thus planning now has a composite of both kinds of plans and moves, this constitutes ps - the perceptual strategy

10. The new plan is executed giving a new event sequence, which matches the evoked contexts to form episodes.

11. The new episode has a sequence of working goals

12. This goal sequence evokes the subgoal context

13. The sequence is perceived as a subgoal context

14. New plan, goals and moves are added to the planning module giving stack - the stacking strategy.

6 Conclusion

We have shown how to extend our system-level brain model to become dynamic, to have an epsiodic memory and to learn by doing.

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Biography. Alan H. Bond was born in England and received a Ph.D. degree in theoretical physics in 1966 from Imperial College of Science and Technology, University of London. From 1966 to 1969, he was on the faculty of the Computer Science Department at Carnegie-Mellon University, Pittsburgh. During the period 1969 to 1984, he was on the faculty of the Computer Science Department at Queen Mary College, London University, where he founded and directed the Artificial Intelligence and Robotics Laboratory. From 1985 to 1992, he lead research in applied artificial intelligence at the University of California, Los Angeles. He has published research in autonomous robotics, multiagent systems and parallel computer architectures. Since 1996, he has been a Senior Scientist and Lecturer at California Institute of Technology. His main research interest concerns the system modeling of the primate brain.