

A HIPPOCAMPAL-LIKE NEURAL NETWORK MODEL SOLVES THE TRANSITIVE INFERENCE PROBLEM

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INTRODUCTION

Both rats and humans can solve configural learning problems. Based on lesion experiments in rats, configural learning is regarded as a hippocampally dependent function¹ when reconfigurability is critical. We have previously shown that a hippocampal-like neural network model^{2,3} solves the configural problem of transitive inference (TI)⁴. Here we confirm this result and investigate the robustness of this demonstration as a function of network activity levels.

THE PROBLEM OF TRANSITIVE INFERENCE

Figure 1a describes the TI problem which is regarded as a logical problem in cognitive psychology (see references in Siemann and Delius,⁵). TI is based on a relationship such as "greater than". TI is said to develop if subjects can infer from A is greater than B and B is greater than C, that A is greater than C. In psychological experiments, at least 4 pairs of 5 atomic items as shown in Figure 1a are used. After learning which atomic stimulus (A, B, C, D) is the correct choice in each of these four pairs (A>B, B>C, C>D, and D>E), the subject gets the novel BD combination in which B should be the correct choice. Here the BD test is critical, but one can also test on the AE pair. However, combinations involving an end element (A or E) are quite easy because A has always been the right answer and E has always been the wrong answer.

Figure 1b suggests a control example for TI which is called non-transitive inference. Note that the atomic stimulus E is discarded, and in the fourth stimulus pair, this E is replaced by the atomic stimulus, A. One example of non-transitive inference is the game 'paper, rock, scissor', where paper defeats (covers) rock, rock defeats (breaks) scissor, and scissor defeats (cuts) paper.

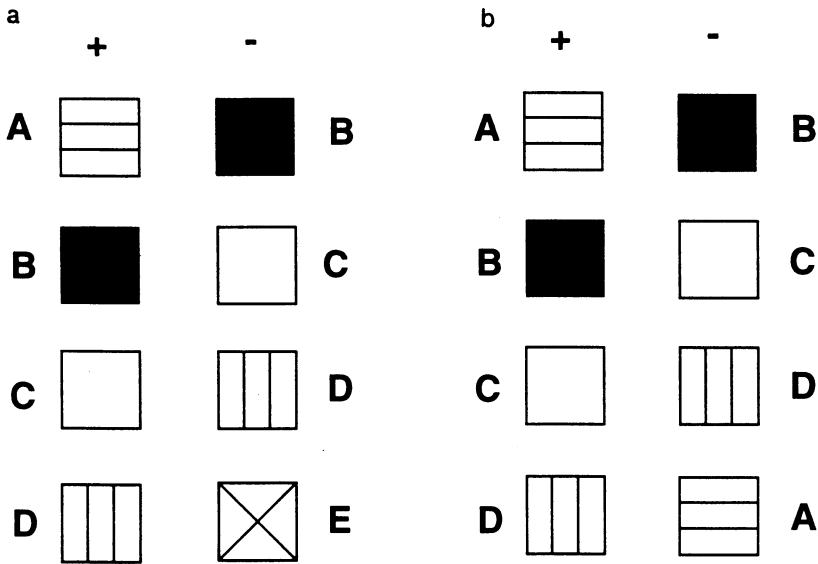


Figure 1: The two problem sets showing the input pairs (e.g., A+B-). Correct and incorrect stimuli are represented as + and - respectively. In both transitive inference (a.) and non-transitive inference (b.), the test input is the novel pair BD. For transitive inference B is the right answer, but there is no logically correct answer for the BD pair in the non-transitive inference situation.

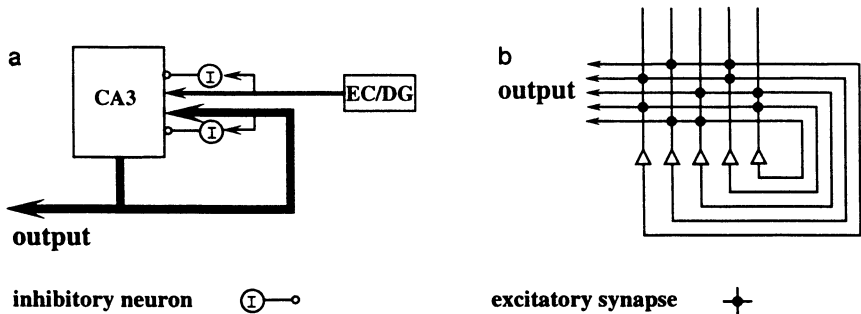


Figure 2: The Model. a. In the model the input layer is a combination of the entorhinal cortex and dentate gyrus. Accompanying this feedforward excitation is a proportional feedforward inhibition. The strong excitation of the network results from the recurrent connections, which is also accompanied by a feedback inhibition. The output of the network is the state of the excitatory CA3 cells themselves, and this is decoded by a simple cosine comparison. b. The recurrent excitatory synapses are sparse and randomly placed.

THE NETWORK

The hippocampal model is essentially a model of region CA3 (Figure 2). The input layer corresponds to a combination of the entorhinal cortex and dentate gyrus. To make the system's operation as transparent as possible, decoding is performed by similarity comparisons rather than a CA1-subiculum-entorhinal decoding system. The CA3 model is a sparsely (10%) interconnected feedback network of 512 neurons where all direct connections are excitatory and the network elements are McCulloch-Pitts neurons. There is an interneuron mediating feedforward inhibition, and one mediating feedback inhibition. Inhibition is of the divisive form, but the system is not purely competitive because of a slight delay. Synaptic modification develops over training. The process controlling synaptic modification is a local, self-adaptive postsynaptic rule that includes both potentiation and depression aspects^{6,7}. The network computations are all local and are contained in three equations: spatial summation adjusted by inhibition; threshold to fire or not; and local Hebbian synaptic modification (see Levy and Wu,⁸ Wu et al.,⁹ Levy et al.,¹⁰ for details).

In the simulations activity levels are varied by adjusting the inhibition constants K_r prior to learning. The range of activity level we tested goes from 10% to 15%, corresponding K_r from 0.054 to 0.047.

ENCODING TRANSITIVE INFERENCE

To study transitive inference, the same hippocampal-like network (but with different settings of parameters) that learned transverse patterning¹¹ is employed, and a similar set of input codings is constructed. That is, the inputs are sequences of stimulus, response, and reinforcement (e.g. (AB)(AB)(AB)aaa+++), where each pattern is repeated three times. A staged learning paradigm is followed as in the experiments of Dusek and Eichenbaum¹. In this paradigm, there are five phases of training. Phase 1 consisted of the presentation of 10 trials of each pair in serial (i.e., ten trials of A+B- followed by ten trials of B+C-, then ten trials of C+D- and ten trials of D+E-). While in Phases 2, 3 and 4, trials were presented in blocks of 5, 3 and 1 trial respectively. The last phase of training is a random pair presentation of the four premise pairs.

RESULTS

Figure 3 is a comparison of experimental data of Dusek and Eichenbaum¹ and our results of network simulation. As noted, the BD test rather than the AE test is critical here because the AE comparison is not affected by the hippocampally inactivating lesions¹. From Figure 3, one can see that B is the typically chosen answer (percent correct about 80%) when the BD pair is tested (which is not presented during learning). Likewise, A is the typical answer for the AE probe pair.

For the non-transitive inference problem (Figure 1b), where the novel test pair is essentially totally ambiguous, it turns out that the network failed to make consistent responses on the BD comparison. In fact, the networks randomly choose B or D without any noticeable preferences (percent correct about 50%, see Figure 4) when the BD pair is tested. In addition, their selection between A and C is random (Figure 4).

In the transitive inference problem, whether or not the network will succeed or fail is determined by the cell firing patterns the network constructs. That is, when BD

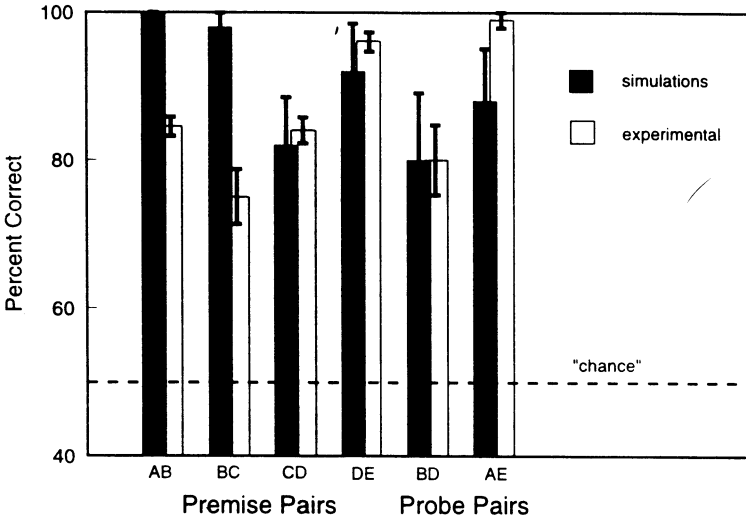


Figure 3: A comparison of experimental data and network simulations of the transitive inference problem. The open rectangles are the experimental results of Dusek and Eichenbaum¹. The filled rectangles are the simulation results. Note that, as in the rat experiment, the model performs significantly above chance on the BD comparison. Error bars represent the standard error of the mean over 15 simulations. Dashed lines represent chance performance level. The activity level used here is 13% and K_r is 0.049.

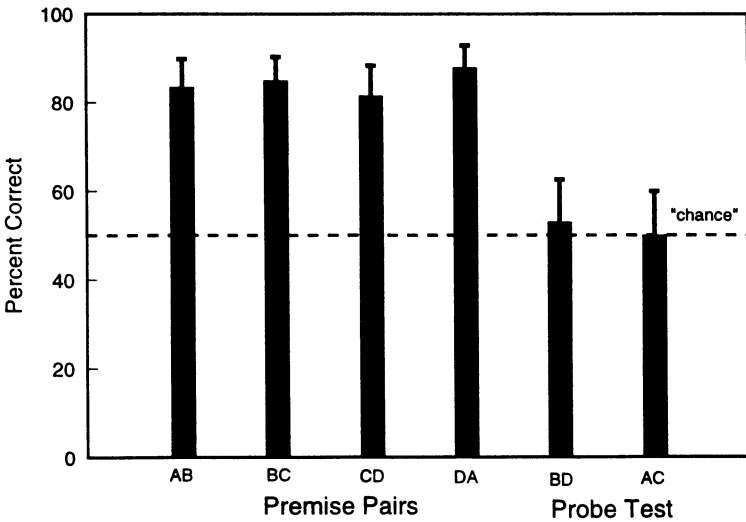


Figure 4: Network simulations of the non-transitive inference problem. Note that, the network randomly chooses B or D without noticeable preference on the BD comparison. Error bars represent the standard error of the mean over 20 simulations. Dashed lines represent chance performance level.

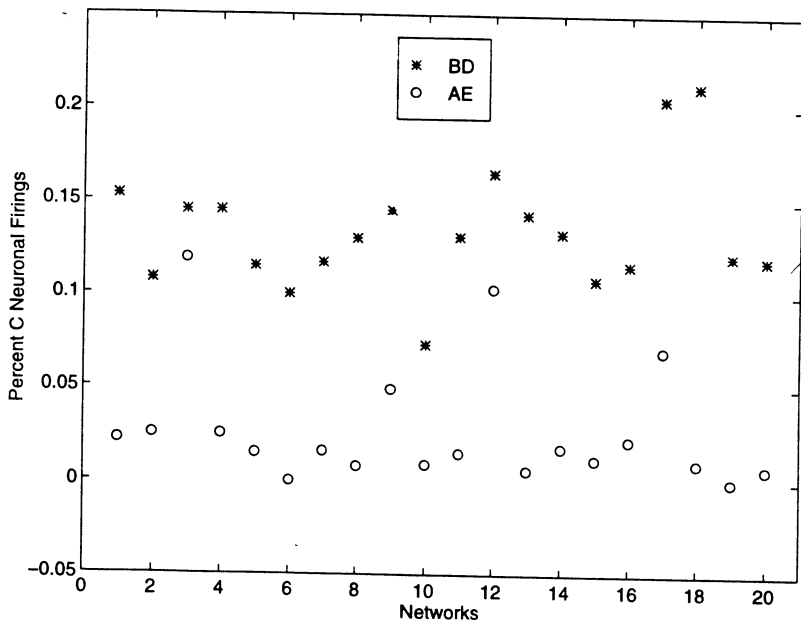


Figure 5: Percent C neuronal firings evoked by BD (*) and AE (o) for 20 different simulations. Note that BD fires many more C neurons than AE does. Moreover, when AE has relatively high C firings, the networks (4 out of 20) fail in performing either on BD or CD tests.

activates enough ($\sim 13\%$, see Figure 5, asterisks) C neuronal firings, which are defined by testing of C alone, the B answer is chosen over the D answer. This activation of so many C neurons by BD rarely occurs when the non-transitive inference problem is learned (Figure 5, open circles).

DISCUSSION

Configural learning problems, studied experimentally by psychologists, require a hippocampus for successful learning. In this report, we have again shown that a hippocampal-like network can solve a particular configural learning problem. Such results together with the network's ability to perform successful sequence prediction/goal finding^{10,12}, strengthen the qualifications of this hippocampal model.

However, not every simulation will succeed on the TI problem. A network's activity level plays an important role because it affects the learned patterns of neural firing. To test the robustness of the model, we have tried several activity levels. For example, the activity level used here (13%), gives a better network performance than the one used elsewhere (e.g. 15% in Levy and Wu⁴). However, if the activity level is too high (e.g. 25%) or too low (e.g. 4%), the network fails to produce good performance on the TI problem, although such statements are dependent on network size with lower activities working in larger networks.

ACKNOWLEDGMENTS

This work was supported by NIH MH48161 and MH00622, by Pittsburgh Supercomputing Center Grant BNS950001 to WBL, and by the Department of Neurosurgery, Dr. John A. Jane, Chairman.

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