THE CHAOSTRON: AN IMPORTANT ADVANCE IN LEARNING MACHINES

Chaostron is a learning machine which incoporates several radically new design features. These are described, and some results of experiments on Chaostron are given.

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The concept of the Chaostron developed from reporting observations of animal learning behavior in stress-inducing situations. Two examples are especially worth citing.

Boosie in 1948 studied the behavior of cats in an aqueous environment. Typically, a cat which is confined to a cage totally immersed in water exhibits an initial period of disorganized, apparently random action, involving great muscular activity. This pattern of behavior ceases, often quite abruptly, when the animal discovers that a state of reduced energy expenditure permits cessation of respiratory activity. The learning, in fact, takes place is unquestionable, since presentation of further stimuli does not cause the animal to return to its initial active (and ill-adapted) condition.

J. C. Gottesohn has reported strikingly similar findings in his monumental work on the religious beliefs of chimpanzees. We differ from Gottesohn in the interpretation of some of his results, but the main points are clear; in a stressful situation, a period of random trial and error precedes the solution of the problem, and the solution is usually found quite suddenly, in its complete and final form.

This, then, provides the basis for Chaostron. The authors feel strongly that the key to successful automation of learning tasks lies in randomization of the response pattern of the machine. The failure of various previous attempts in this direction, we feel, has been due to two problems; first, the difficulty of getting a sufficient degree of randomness built into the structure of the machine, and second, the expense of creating a device large enough to exhibit behaviour not significantly influenced by the operation of any one of its components. We are deeply indebted to Dr. R. Morgan for a suggestion which showed us the way out of these difficulties; design for the Chaostron was done by taking 14,000 Western Electric wiring charts, cutting them into two-inch squares, and having them thoroughly shaken up in a large sack, then glued into sheets of appropriate size by a blindfolded worker. Careful checks were made during this process, and statistical tests were made on its output to insure against the propagation of unsuspected regularities.

Unfortunately, we have not, as yet, been able to complete the wiring of Chaostron. We felt, however, that it should be possible to estimate the effectiveness of Chaostron even before its completion by simulating it on a high speed digital computer. This procedure had the further advantage of attracting the interest of representatives of the Bureau of Supplies and Accounts of the United States Navy, who found in Chaostron an excellent aid to control of the Navy's spare parts inventory. The Navy, as a result, was generous enough to offer time on a BuShips computer for the simulation of Chaostron.

The computer of choice for the simulation runs was the IBM STRETCH machine, which not only operates at very high speed, but is also able to accept input programs coded in YAWN language, which closely resembles colloquial English. We felt it very important to use a source language for the simulation programs which would contain as much ambiguity as ordinary speech, since undue preciseness in specification of the simulation programs might accidentally "tip off" the machine to the nature of the desired solutions.

In the event, it was not possible to obtain a STRETCH computer for the project, and so the simulation was done by simulating STRETCH simulating Chaostron on an IBM 704. All simulation runs were conducted in essentially similar universes of environments; the computer was presented with a sequence of circles, squares and crosses represented by punched cards, and was required to print, after examining each stimulus, one of the words "circle," "square" or "cross." No reinforcement from the experimenter was provided, since it was feared that such reinforcement would bias the learning process, and thus vitiate the validity of any conclusions we might wish to draw from the results.

The first trials were run with the input stimuli represented on the punched cards as geometric patterns of punching in the appropriate shapes. As a control, one run was made with no stored program initially in the machine, to check that the learning rate of the untutored machine was not so great as to interfere with further studies. For this run, the machine memory was cleared, the cards containing patterns were placed in the card reader, and the load cards button was pressed. After three hours the machine had not printed its response to the first input pattern; evidently the rate of learning under these conditions is very low (we judge it to be on the order of 10^{-6} concepts for megayear).

Therefore, we proceeded with the main series of experiments, in which a random program was loaded into the computer ahead of each batch of data cards. A total of 133 random programs were tried in random sequence. Even in this series of experiments the machine took a surprisingly long time to respond to the stimuli; in most cases the run had to be terminated before the first response occured. However, on run number 73, the computer responded

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to the first stimulus card (which was a square!); on run 114, the computer responded.

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to every stimulus; and on run 131 the computer ejected the printer paper twice.

Unfortunately, budget difficulties forced us to abandon this approach after 133 trials, in spite of the promising appearance of the early results. Thus, our conclusions are perforce based on a smaller data sample than we would like. Nonetheless, certain points are clear.

1) The correlative reinforcement model of learning advanced by Dewlap, et al., is untenable in view of our results. No triphasic system could function without a degree of organization exceeding that which we have used in the simulation studies. Even this degree of structure, however, resulted in extremely slow response to comparatively simple stimuli.
2) It seems evident that further understanding of machine learning requires resynthesis in operational terms of the conceptual framework provided by the Liebwald-Schurstein-Higgins suggestion that memory traces are renewed by associative stochastic increments to ideometric pathways shared by stimulus-coupled functional elements.
3) Not only is machine learning possible, but in fact it occurs under conditions of considerable difficulty. Indeed, it appears that even the simplest machines have a great amount of innate "curiosity" (where by "curiosity," of course, we do not mean to imply that anthropomorphic categories or judgements should be applied to machines, but merely that the machines have a desire to learn).

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