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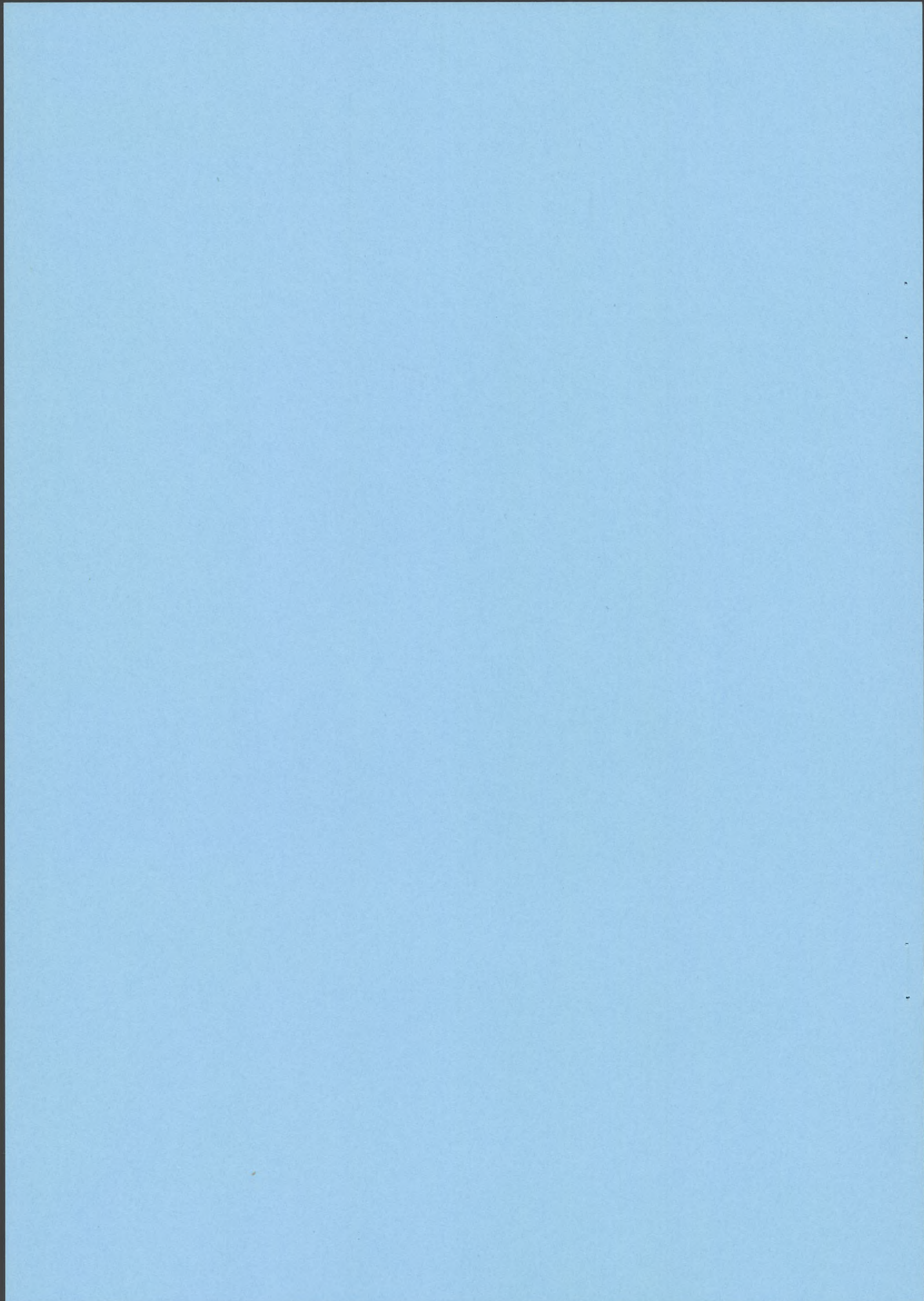
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HABITUATION AND ASSOCIATIVE LEARNING IN RANDOM MIXTURES OF
DETERMINISTIC AUTOMATA

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Malmgren, H. Habituation and associative learning in random mixtures of deterministic automata. **Göteborg Psychological Reports**, 1984, 14, No. 2. - Random systems, in the sense of random mixtures of finite deterministic automata, are non-Markov stochastic processes which may be involved in non-associative and associative learning. Random systems might be approximately realized in the form of collections of randomly structured nerve cell modules. It is shown that, given a suitable mechanism for registering and summation of state changes, such a system will show habituation to repeated stimuli. Simulation evidence is also presented to the effect that random systems learn associatively when exposed to a stimulus pattern which is related to the paradigm of classical conditioning. The results point towards the possibility that one might explain several kinds of learning phenomena solely by reference to such a random composition of parts of the nervous system, without presupposing either a built-in specific plasticity on the unit level or a pre-formed reinforcement mechanism.

Key words: Automata, conditioning, habituation, learning, stochastic processes

In this paper, the author outlines some basic properties of **random mixtures of finite deterministic automata**, and investigates certain aspects of such systems in relation to learning processes such as adaptation, habituation and associative learning. The idea that a major part of the brain should be regarded as composed of a large number of subunits which are similar in structure, but which show a certain inherent variability, has often been evoked in attempts to explain the phenomenon of associative learning (cf. e.g. Edelman 1979, Skinner 1981). Of course, if the central nervous system contains a separate selection device which "reinforces" those units which respond appropriately to a certain

stimulus, the need for a specific plastic mechanism on the intraunit level disappears. However, it can be shown that a "multi-unit" brain will exhibit learning without such preformed reinforcement mechanisms and without specific unit plasticity. The multiunit model, as such, offers a simple explanation of the phenomenon of habituation. After having discussed some very general properties of randomly composed systems, I will outline such an explanation. In the final part of the paper I discuss whether such systems can learn associatively without having to rely on specific unit plasticity or on a preformed reinforcing (selective) mechanism. Evidence for an affirmative answer to this question is presented.

Definitions

By an "automaton" is here meant a finite-state deterministic automaton with input, i.e. any device which can occupy only a finite number of states and receive a finite number of inputs, which has a discrete time and which is such that its state $a(t)$ at any moment (except the first) is completely determined by the immediately previous state $a(t-1)$ plus the previous input $b(t-1)$ (see e.g. Ashby 1956). An automaton with n states a_1, \dots, a_n and m inputs b_1, \dots, b_m is representable by an $n \times m$ matrix where a_{ij} is the state which results from state a_i with input b_j . One of the a_i 's is selected as $a(0)$. The abstract automaton which is given by such a matrix can be realized in many different ways. It should be noted that in most applications, the finite-state model is an approximation. I do not intend to discuss here the limits of the model as applied to the brain. It should, however, be noted that the results given below could be generalized to much larger classes of automata; the present limitation is dictated by computational and pedagogical convenience.

By a "random system" (R.S.) is here meant the stochastic entity which results if the numbers in the matrix for an $n \times m$ automaton ($n \geq 2$) are chosen randomly, such that the probability that $a_{ij} = a_k$ is $= 1/n$ for $k = 1, \dots, n$; all choices are made independently of each other. If not otherwise stated, the initial state is chosen in the same way. Think of the random $n \times m$ system as a collection of all possible specific $n \times m$ automata (uniformly mixed). There are of course other possible kinds of "random" systems in which, for example, not all transitions are equally probable; but again the present construction is chosen for the sake of simplicity.

In the following, we will study the behaviour of the R.S. and some similar entities under a number of different input conditions for the deterministic automata from which they are constructed. We will limit ourselves to such input conditions as are assigned to the different automata independently of the process of constructing their transition matrices and independently of their states. One important such condition is defined stochastically: by a "random system with random input" (R.S.R.I.) is here meant a random system where for each sub-automaton, and for any moment t , the probability that $b(t) = b_k$ is $= 1/m$ for $k = 1, \dots, m$; all choices independent. Think of the R.S.R.I. as the uniform supermixture of all possible automata given all possible input sequences.

Basic memory properties

The R.S., given any specified kind of input, is formally a discrete stochastic process. The state probabilities (for a moment t) of this process are the frequencies of those specific automata in the mixture which, at t , are in the different possible states; the transition probability $a_i(t) \rightarrow a_j(t+1)$ is the proportion of the automata being in a_i at t which go to a_j at $t+1$.

It is important to note that the R.S. is not under any (independently assigned) input condition a Markov process, because its transition probabilities are not independent of earlier states. Certainly, because of the symmetrical initial distribution, all state probabilities always remain $= 1/n$. It is also true that the R.S. behaves like a symmetrical Markov chain (with all transition probabilities $= 1/n$) for a finite number k of first steps, presupposed that for each specific automaton the first k inputs are all **different** from each other. However, choose any determinate input sequence, give it to all automata in the mixture and look at the behaviour of the R.S. under this condition. At some point of time T the random system (i.e., all specific automata in the mixture) will experience the first recurrence of an earlier input b . Let us denote the time of b 's previous occurrence T' . Suppose first that $T'+1 \neq T$.

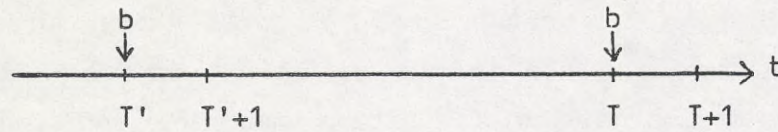


Figure 1. First recurrent stimulus.

Now exactly 1 out of n of the automata in the collection will be in the **same** state at T as at T' , i.e. for the whole stochastic entity, $P(a(T) = a(T')) = 1/n$. All specific automata for which $a(T) = a(T')$ will - because they are deterministic - go to the **same** state at $T+1$ as at $T'+1$. Consider the rest (i.e. $n-1$ out of n in the collection). Since the choice of state to which they will go is not bound by previous choices, the probability that they will go to the same state at $T+1$ as at $T'+1$ is $1/n$. For the whole collection, then, $P(a(T+1) = a(T'+1)) = 1/n \times 1 + (n-1)/n \times 1/n = (2n-1)/n^2$. The case of $T'+1 = T$ is similar; here $P(a(T+1) = a(T')) = (2n-1)/n^2$. This means that although the probability of the system's being in any given state a_k at $T+1$ is $= 1/n$, this probability is raised to $(2n-1)/n^2$ by our knowledge that it was in a_k at $T'+1$ (or at T' , respectively). This property is evidently incompatible with the supposition that the system still behaves as a Markov chain with transition probabilities $= 1/n$ all over.

In the same way one can show that the probability of a_k at $T+1$, given a_k at T , depends on whether the automaton was in a_k at $T'+1$. (If $T = T'+1$, it will depend on the state at T' .) Suppose $T \neq T'+1$. Then $P(a(T+1) = a_k | a(T) = a_k, a(T'+1) = a_k) = 1/n \times 1$ [if $a(T') = a_k$] + $(n-1)/n \times 1/n$ [if $a(T') \neq a_k$] = $(2n-1)/n^2$, while $P(a(T+1) = a_k | a(T) = a_k, a(T'+1) \neq a_k) = (n-1)/n \times 1/n$. The case of $T = T'+1$ is similar. Hence, the system is not Markov at all under the chosen input sequence.

The same result holds for every possible random system with independently assigned input, e.g., for the random system with random input, since for each such construction there will be a first moment at which the probability of recurrent input is > 0 . For all such constructions it will be true that the transition probabilities from this moment on will be influenced by suppositions about earlier states. The influence will be in the direction of **conservation of past states**. In a sense, then, the random system under any independently assigned input condition remembers more than the immediately previous state, although this does not hold for the deterministic automata which form the basis of our constructions.

Constant input sequences

Let us study the R.S. under the same input condition of repetitive stimuli for all component automata, e.g. "11111..." (we use this abbreviation to stand for b_1, b_1, b_1, \dots). The asymptotic behaviour under this condition is, for every specific automaton, that it goes into a stationary behaviour $a_k a_k a_k \dots$ or into a circular behaviour $(a_{i_1} a_{i_2} \dots a_{i_p} a_{i_1} a_{i_2} \dots)$. A set of states to which

an automaton is finally confined, given a certain input, is called a "basin" under this input. Let us first ask, what is the probability that the initial state $a(0)$ will be contained in the final basin under constant input? One can visualize the "basin-forming" process like this:

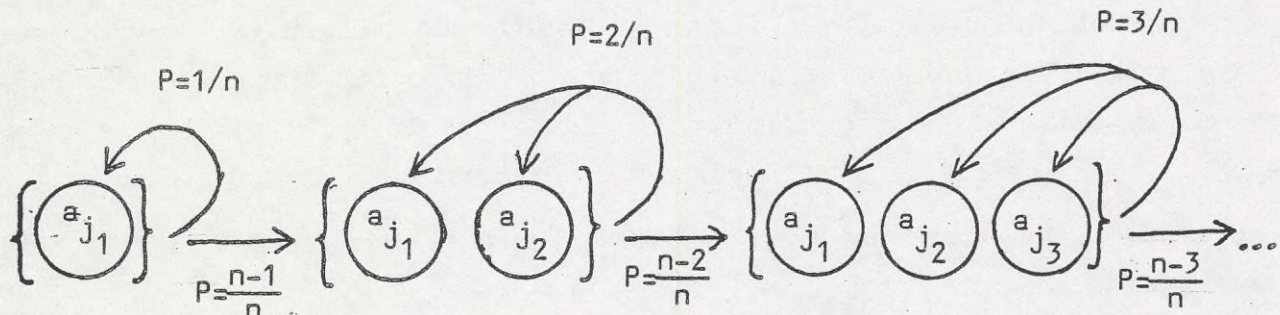


Figure 2. The basin-forming process.

In step k , the probability that process will come to an end (i.e. that the automaton will for the first time return to a previous state) is k/n , presupposed that it has not come to an end before; the probability that it will continue is $(n-k)/n$. The conditional probability that $a(0)$ will be "hit" in step k is $1/n$. So the total probability of $a(0)$ being included is

$$\frac{1}{n} \cdot \sum_{1 \leq k \leq n} \frac{n!}{(n-k)! n^k} \quad (1)$$

The probability that $a(0)$ will be included in a basin of length k is given by the k :th term in this sum. In this case $a(0)$ will recur at every k :th step ad infinitum. Hence, for any moment of time t ($t > n$), the probability of the system's state being $a(0)$ at T is

$$P(a(t) = a(0)) = \frac{1}{n} \cdot \sum_{\substack{k|t \\ 1 \leq k \leq n}} \frac{n!}{(n-k)! n^k} \quad (2)$$

For t prime, this probability will be $= 1/n$, else it will be $> 1/n$. From this it can be seen that there is no proper asymptotic probability distribution of states relative to the supposition that one starts in a certain state a_p . However, one can define a "long run" distribution as

$$P^\infty(a(0)) = \frac{1}{n} \cdot \sum_{1 \leq k \leq n} \frac{n!}{(n-k)! k^n} \quad (3)$$

Let us now instead look the distribution of basin sizes, and especially at the question, what is the probability of basin size $= 1$? It is intuitively clear (cf fig. 2 above) that smaller basins have more opportunities than longer basins to get formed in the process. The probability that a randomly chosen automaton will be caught in a stationary state can be seen to be the same as the probability of $a(0)$ belonging to the final basin, since the only difference is that the process depicted in fig. 2 has to "hit" the last element reached (a_{j_k}) instead of the first. As the process goes on, the probability that a stationary state has been reached in step t or earlier will therefore grow stepwise according to Eq. (4):

$$P(a(t) = a(t-1)) = \frac{1}{n} \cdot \sum_{1 \leq i \leq t} \frac{n!}{(n-i)! n^i} \quad (4)$$

In the following table, we have represented this process for $n = 2, 3$ and 5 ; however, we have inverted the figures so that they now show the proportion of automata which **change** their state in step t :

Table 1

Probability of state change under constant input.

	t=1	2	3	4	5
n=2	.500	.250	.250	.250	.250
n=3	.667	.444	.370	.370	.370
n=5	.800	.640	.544	.501	.498

Suppose that the random system is approximatively realized as a collection of determinate automata. Suppose also that for every single automaton there is a device which compares the state of any moment with the immediately previous state, with a "yes" answer for a detected difference, and that the "yes" responses of all these comparators are summed. Evidently this sum response will show a gradual **adaptation** to sequences of identical stimuli, similar to that represented in Table 1. Note that the adaptation will be rapid for $n=2$ and more gradual for larger n .

This explanation of adaptation in complex system makes use of the assumption of a comparator mechanism. This might seem to prejudge the issue since such a comparator does involve a kind of memory. It is, however, important to note that this memory does not reach beyond the immediately past moment. By means of the theory of random systems one can also explain why the early parts of the sequence of identical stimuli can continue to influence the degree of adaptation. (Note also that a kind of comparator may be built into our ordinary measures of "overall activity".)

Habituation proper

The proposed model holds only for a close sequence of identical inputs, while habituation proper is a phenomenon which occurs if a certain stimulus is presented several times separated by other (preferably constant) stimuli. However, there are reasons to believe that random systems will adapt in a similar way to such conditions. Suppose that (each specific automaton in) the R.S. is given a stimulus sequence:

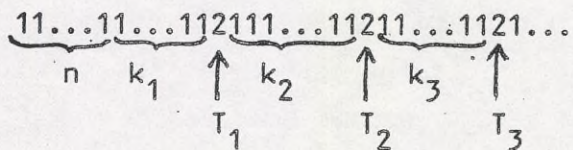


Figure 3. Stimulus sequence in habituation experiment.

where k_i is each time determined as a random number uniformly distributed on an interval (n_1, n_2) . This is similar to the situation when an organism, familiar with environment "1", suddenly begins to experience "2" with random intervals. The probability that a certain automaton will stay in the same state when given "2" for the first time is $1/n$. If it does, then in a certain proportion p of cases this very state will recur at the end of next "1" period. A lower limit of p is set by Eq. (4) (p. 6) (with $i=n$), since all automata which were already

in a stationary state when "2" occurred for the first time will of course continue in this condition under 111... in case it is not disrupted by "2". However, also these automata which happen to have a basin length (relative to 111...) which is a factor in k_2 will benefit from such a non-disruption, to the effect that the same state will recur again at the end of next "1" period (cf Eq. (2), p.5). This means that non-disruption tends to **reinforce** itself, since it will raise the probability that there is no disruption next time "2" occurs. Remains to consider the cases of disruption. If the first "2" changes the state of the automaton, the probability q that the state which the automaton came from will recur at the end of next "1" period is evidently less than p , since we have now missed, among other things, the possibility to keep any previous steady state going. Hence, disruption will not reinforce itself to the same degree as nondisruption. Since the case of recurrence is the only one which makes a difference, we can describe the situation by means of a matrix of transition probabilities from "ND" (non-disruption) to "D" (disruption) at the first and second occurrences of "2", respectively:

Table 2

Reinforcement matrix for non-disruption and disruption.

	ND	D
ND	p'	$1-p'$
D	$1-q'$	q'

where $p' > q'$. A transition according to such a matrix raises the probability of ND if this probability initially is $\leq \frac{1}{2}$, which is the case here. The total result will be that there is less disruption at the second occurrence of "2" than at the first. For $n > 2$, a similar argument can surely be made concerning later occurrences of "2". For example, among those automata that did not enter a steady state at the second "2", a certain proportion will do so for the first time at the third "2" (cf the simpler process in fig. 2). So, we can expect a steadily growing proportion of automata **not** changing their state at the "2" stimuli.

The process described above was simulated for $n = 2, 3$ and 5 with $n_1 = 6, N_2 = 17^1$). The estimated probabilities of state change at the successive occurrences of "2" are presented in the following table. Again the effect is more gradual for larger n .

Table 3

Result of habituation experiment: estimated probabilities of state change.

	T=1	2	3	4	5	6-10 (mean)
n=2 N=20.000	.507	.442	.442	.442	.444	.445
n=3 N=30.000	.669	.617	.616	.609	.608	.609
n=5 N=50.000	.800	.764	.756	.754	.754	.753

The magnitude of the observed effects certainly suggests that some kind of general amplifying mechanism is needed if one wants to account for real habituation in terms of random systems. However, I do not think that this detracts much from the value of such an account.

It should also be noted that the process described above cannot directly represent (even approximately) what happens when one organism - i.e. one collection of deterministic automata - receives a single sequence of inputs constructed according to Fig. 3. In the latter case, the different automata in the collection are given the **same** input sequence which, of course, does not correctly "represent" the whole spectrum of possible input sequences. Since, in this single input sequence, it may well happen that periods with a length favourable for non-disruption alternate with periods with an unfavourable length (e.g. large prime numbers), the probabilities of state change in the single collection will tend to fluctuate. Table 3 can, that is, only represent the sum of a number of experiments with organisms given different input sequences.

To estimate the size of the fluctuations, another simulation was performed as follows: 100 collections of N "randomly" chosen deterministic automata (for the values of N, see below) were constructed; 100 input sequences of the proper form were constructed and presented to the collections of automata (one sequence to each collection); for each collection the probability of state change at the different presentations of "2" was estimated, and for each

presentation it was noted whether this probability was **less** than at the previous presentation of "2" for the same collection. The number of collections in which this was the case were counted for each presentation of "2". These numbers are given in Table 4. (If a collection had the same frequency of state change at two successive presentations, the value $\frac{1}{2}$ was assigned.)

Table 4

Habituation in collections: percentage of collections showing response decrement.

	T=2	3	4	5	6-10. (mean)
n=2 N=800	70	54	48	53	49.0
n=3 N=1200	79	62	58.5	56	54.2
n=5 N=2000	77.5	62	53	60	53.1

It can be seen that, according to the model, single habituation sequences will be smoother for $n = 3$ or 5 than for $n = 2$.

Associative behaviour

From the collection which forms the random system, select that subset of machines for which the input b_1 carries state a_1 into itself. This is the **random system with an unconditioned response a_1 to input b_1 (R.S.U.R.)**. The condition mentioned guarantees that the system, if given a long sequence of b_1 's, will tend to go to the steady state a_1 with a probability p such that $1/n < p < 1$. (We could have chosen the latter condition as a more general definition of the concept of an unconditioned response, but the definition given is simpler.) If the output of a collection which realizes an R.S.U.R. is organized so that the **most common** state determines the final outcome, then the whole collection will have a characteristic gross unconditioned response on b_1 -sequences. For theoretical purposes, this response can be identified with a_1 in an "effector" state space. The response will be more and more specific the longer the sequence of b_1 's given, since the automata are then given more and more chances to converge on the basin a_1 . (Cf. temporal summation and the "microgenesis" of percepts.)

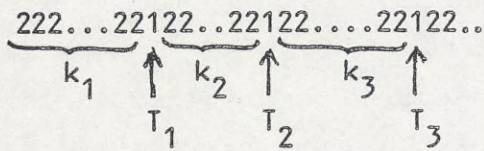


Figure 4. Stimulus sequence in conditioning experiment.

This input condition corresponds to classical (Pavlovian) conditioning, except that the inter-trial interval is itself taken as the conditioned stimulus. Will the R.S.U.R. show a conditioned response? By means of an argument similar to that given for habituation proper, I will try to make such a supposition plausible.

The R.S.U.R. is uniformly random except for the response a_1 on b_1 . This means that there is an initial probability $1/n$ that the automaton will go to a_1 on the last b_2 in the first sequence (T_1). If it does, then it will remain in a_1 at T_1+1 , and there will be a probability p , considerable higher than $1/n$, that a_1 will recur at the end of next b_2 -sequence (T_2) since its first occurrence proves that there was a basin (relative to 222...) containing a_1 in the automaton in question. If, on the other hand, an automaton does not go to a_1 at T_1 but to a_k , $k \neq 1$, then this behaviour is not **reinforced**, i.e. the state a_k is not automatically conserved at time T_1+1 . Therefore the transition probability q from response a_k at T_1 to response a_k at T_2 will be lower than p . For $n > 2$, a similar argument will hold for later T 's and so we get another cumulative probability: a conditioned response.

In the described set-up, there is to be expected an effect which is not conditioning, but which depends only on the fact that b_2 's occur **after** b_1 's. Look at the alternative set-up where in each inter-trial interval a **new** input is given:

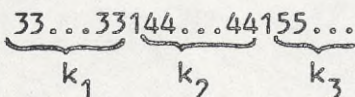


Figure 5. Stimulus sequence in pseudo-conditioning experiment.

Because of the fact that the basic U.R. condition leads to a preponderance of a_1 -reponses to b_1 , and the fact that constant input sequences tend to conserve initial states, there will occur a pseudo-learning effect. The fundamental difference between this process and the above-described one is that in the conditioning set-up, past achievements in the "222..." sequences tend to be conserved for more than one period of time. The problem is that past failures also can be conserved (if, e.g. the automaton goes into an $\{a_2\}$ basin relative to both b_1 and b_2), and at present I cannot offer any strict proof that the random automaton really will perform better in the conditioning context than on the alternative procedure. However, in the absence of a strict proof I have some simulation evidence to offer. In the following table, the results of feeding the R.S.U.R. (i) with the conditioning condition, and (ii) with the alternative condition (broken lines, figures within parenthesis) are presented²⁾. In this first simulation, each single automaton was given its own pair of input sequences. The figures represent the estimated probabilities of state a_1 at the different T_i :s multiplied by n .

Table 5

Results of conditioning and pseudo-conditioning experiments: estimated probabilities of $a(T)=a_1$, multiplied by n . C=conditioning; PC=pseudo-conditioning.

	T=	1	2	3	4	5	6-10 (mean)
n=2	C	1.00	1.13	1.14	1.12	1.12	1.12
N=10.000	PC	1.00	1.13	1.13	1.14	1.13	1.12
$n_1=6 \quad n_2=11$							
n=3	C	0.99	1.17	1.18	1.18	1.18	1.18
N=15.000	PC	0.99	1.13	1.15	1.14	1.14	1.15
$n_1=6 \quad n_2=11$							
n=5	C	0.99	1.18	1.20	1.23	1.23	1.23
N=25.000	PC	1.00	1.13	1.14	1.13	1.16	1.13
$n_1=12 \quad n_2=23$							
n=10	C	1.01	1.18	1.22	1.24	1.27	1.26
N=50.000	PC	0.99	1.09	1.10	1.09	1.09	1.09
$n_1=12 \quad n_2=23$							

As can be seen from this Diagram, for $n \geq 3$ there is a clear positive difference, which grows with n , between the two processes. There is also a tendency towards decreasing steepness of the learning curve for larger n .

Another simulation was performed in the same way as in the case of habituation; i.e., 100 collections of N automata were constructed, and all automata in a collection were given the same sequence of stimuli. Since, according to the model, there is supposed to exist a mechanism which extracts the most common response, it was calculated for each collection whether a_1 was more common than other responses at the end of b_2 -sequences. A corresponding calculation was done for the pseudoconditioning condition. In addition, the proportion of collections which, at the different points of time, performed better under "conditioning" than under "pseudo-conditioning" was calculated. The results are summarized in the following tables.

Table 6

Percentage of **conditioned** collections with single most common response = a_1

T=	1	2	3	4	5	6-10	(mean)
n=2	46	77	73	73	74	70.8	(N=800)
n=3	31	73	75	78	79	74.8	(N=1200)
n=5	20	68	73	76	74	79.0	(N=2000)
n=10	7	65	76	69	73	72.8	(N=4000)

$\left. \begin{array}{l} n_1=6 \\ n_2=17 \end{array} \right\}$
 $\left. \begin{array}{l} n_1=11 \\ n_2=22 \end{array} \right\}$

Table 7

Percentage of **pseudo-conditioned** collections with single most common response = a_1

T=	1	2	3	4	5	6-10 (mean)
n=2	56	72	77	77	76	73.8
n=3	36	81	75	84	78	73.2
n=5	26	70	70	70	69	73.2
n=10	9	53	58	48	61	55.4

Table 8

Percentage of collections with higher a_1 -frequency under conditioning than under pseudo-conditioning

T=	1	2	3	4	5	6-10 (mean)
n=2	48	42	55	45.5	45	48.2
n=3	57.5	57	68.5	67	66	66.1
n=5	43.5	72.5	78.5	76	80	80.8
n=10	42.5	72	78	79	90	85.5

It can again be seen that with larger n , the performance under conditioning becomes distinctly better than under pseudo-conditioning. Altogether it seems worthwhile to investigate further the possibilities of associative learning in random systems.

I have profited much from helpful criticism by Bo Berntsson, Björn Haglund, Peter Jagers, Peter Lundberg and Olof Östensson. Peter Lundberg has also made it possible to realize the more complex simulation experiments by putting computer time at my disposal at the Department of Oceanography. The simulations were run on a TRS-80 personal computer or a HP-8926 desktop computer. Details are supplied on request. Authors present address: Dept. of Philosophy, Avenyen 10-21, S-431 36 Göteborg, Sweden.

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