

A RESPONSE ELIMINATION MODEL

OF

PAIRED-ASSOCIATE LEARNING

A RESPONSE ELIMINATION MODEL

OF

PAIRED--ASSOCIATE LEARNING

APPLICATION OF A ONE-ELEMENT MODEL
WITH RESPONSE ELIMINATION TO
PAIRED-ASSOCIATE LEARNING DATA

BY

DIANA ELIZABETH FOWLES, B.Sc.

A Thesis

Submitted to the Faculty of Graduate Studies
in Partial Fulfilment of the Requirements
for the Degree
Master of Arts

McMaster University

October 1969

MASTER OF ARTS
(Psychology)

McMASTER UNIVERSITY
Hamilton, Ontario.

TITLE: Application of a one-element model with response
 elimination to paired-associate learning data.

AUTHOR: Diana Elizabeth Fowles, B.Sc. (University of Exeter)

SUPERVISOR: Dr. S. W. Link

NUMBER OF PAGES: vi, 63

SCOPE AND CONTENTS:

This study investigates a response elimination model of paired-associate learning. The structure of the model is identical to that of the one-element model except that the assumption of the latter of a constant probability of guessing before learning is replaced by an assumption that subjects guess from a pool of unassociated responses. It is found that the response elimination model fails to provide an exact description of performance before learning, although it does improve on the one-element model. A three-state model is also investigated and it is found that with four parameters much of the data can be accounted for.

ACKNOWLEDGEMENTS

I wish to express my appreciation and thanks to Dr. Stephen Link for his help and guidance during the development of this thesis.

My thanks are also due to Dr. A. Kristofferson for many constructive comments and to Miss Sharon Cooper for typing the final copy.

Table of Contents

	Page
Introduction	1
Method	6
Results	10
One-element model analysis	12
Response-elimination model analysis	19
Three-state model analysis	22
Discussion and Conclusion	27
References	33
Appendix I	35
Appendix II	37
Appendix III	47
Appendix IV	49

Figures

	Page
1. Representation of events within a cycle	8
2. Proportion of correct responses prior to last error using modification of Vincent's method	21b
3. Learning curve with one-element model and three-state model predictions	25b
4. Distribution of the cycle of last error with three-state model predictions	26b
5. Distribution of k , the number of errors before the first success, with three-state model predictions	26d
6. Distribution of T , the total number of errors, with three-state model predictions	26f
7. Stationarity between the first success and the last error	28b

Tables

		Page
I	Independence of pre-criterion responses	13
II	Vincent quartiles	14
III	Response sequences in blocks of 4 trials	15
IV	Backward stationarity test	17
V	Block sizes and proportion of correct responses in each block in response elimination model analysis	21
VI	Independence of responses between the first success and the last error	29

The one-element conditioning model was developed by Bower (1960, 1961) and represents a special case of more general models of stimulus sampling theory (Estes, 1959). The model has been applied extensively (e.g. Bower, 1962; Suppes and Ginsberg, 1963; Millward, 1964) and while there has been close correspondence between experimental data and values predicted from the model, there have been contradictions in at least one aspect of the data.

Suppes and Ginsberg observed that the one-element model assumption of a constant guessing probability or stationarity of response probability prior to learning implies a binomial distribution of responses prior to the last error. Goodness-of-fit tests of the property of stationarity and of the binomial properties of the sequence of responses prior to the last error have been critical in evaluating the one-element model. For example, Suppes and Ginsberg applied such tests to the data from seven experiments in various areas, including human paired-associate learning, and did not find that the prediction of stationarity was substantiated. Hintzman (1967) demonstrated stationarity when there were two available responses, but found non-stationarity for fourteen.

A strategy which may be adopted when a particular model fails in one or more of its predictions is to retain the basic structure of the model but to modify one or more of its assumptions. The one-element model of paired-associate learning assumes that there are two

learning states, an unconditioned state \bar{C} and a conditioned state C. It is further assumed that a subject guesses a correct response to a stimulus item with a constant probability on each trial as long as that item is in state \bar{C} , and that on any trial the item may become conditioned (i.e. move to state C) with a constant probability c which is known as the learning parameter. The aim of this study is to investigate a model which is based on a modification to the one-element model assumption of a constant probability of a correct guess in state \bar{C} . This model will be referred to as the response-elimination model, and will be applied to data from a paired-associate learning experiment.

The proposed model assumes that the probability of guessing correctly on unlearned items increases as the number of unconditioned responses decreases. Considering the simplest case where there are as many responses as stimuli, it is supposed that once a response has become associated to its proper stimulus then that response is no longer made to other stimuli, and is not included in the 'pool' of responses from which the subject can guess. Thus as more items are learned the subject guesses from a progressively smaller pool. Hence non-stationarity of response probability prior to the last error is expected.

The data to which the response elimination model will be applied will be obtained from an experiment designed to allow each subject to develop what might be called a response pool strategy, where responses made to unlearned items are selected from a pool of as yet unassociated responses.

To avoid confusion a few terminological points need to be clarified. In this study the term "trial" will be used to refer to each exposure to the subject of a stimulus-response pair. This differs from the earlier use of the term to refer to a complete showing of all the items in the paired-associate list, for which the term "cycle" will be used here.

Application of the response elimination model requires consideration of trial-by-trial events since on any trial in any cycle there can be a decrement in the size of the response pool. In this respect data analysis derived from the response elimination model differs markedly from that of the one-element model where, since responses within a cycle are assumed to be independent, it is only necessary to consider the cycle by cycle responses made to each stimulus item. A discussion by Batchelder (1966) of the level of a data analysis is relevant to this difference between the two models. A standard method in paired-associate data analysis is to isolate subject-item protocols, the records of responses made to each item throughout the course of the experiment by a particular subject. Batchelder terms this the paired-associate or 'P'-level of analysis, and it is appropriate for analysis derived from the one-element model. Batchelder points out that other levels of analysis are possible, defined by the organization of the data and the requirements of the model under consideration.

Analysis in terms of the response elimination model requires an estimate of the guessing parameter for each trial of each cycle. A

'P'-level analysis can provide this estimate for the first trial of each cycle, by the use of a matrix whose states are the number of unconditioned items at the beginning of a cycle (Estes, 1959). Consider for example the case of a three item list. At the start of the first cycle all three items are assumed to be in the unlearned state U; at the end of this cycle there may be from zero to three items in state U. The transition matrix P below specifies transition probabilities on the *i*th. cycle.

		# of unconditioned items at end of				
		cycle <i>i</i> .				
# unconditioned items at	start of cycle <i>i</i>	0	1	2	3	
	0	1	0	0	0	=P
	1	<i>c</i>	<i>1-c</i>	0	0	
	2	<i>c</i> ²	<i>2c(1-c)</i>	<i>(1-c)</i> ²	0	
	3	<i>c</i> ³	<i>3c</i> ² <i>(1-c)</i>	<i>3c(1-c)</i> ²	<i>(1-c)</i> ³	

The start vector $S(i)$ for the *i*th. cycle expresses the probabilities associated with there being *j* unconditioned items ($j=0,3$) at the start of cycle *i*. Then $S(0)$ is the initial start vector as follows:-

$$S(0) = (0 \ 0 \ 0 \ 0 \ . \ . \ . \ 0 \ 1)$$

Then $S(1) = P \cdot S(0)$

$$S(2) = P \cdot S(1)$$

.

.

$$S(n) = P \cdot S(n-1)$$

Alternatively,

$$S(n) = P^n \cdot S(0)$$

However events within a cycle are dependent on the order of presentation of the stimuli and cannot be described easily in general terms. Hence an alternative to the 'P' level analysis will be used later in this study to provide an estimate of the guessing parameter on any trial within a cycle.

An alternative application of the strategy of modifying a basic assumption when a model is shown to be inadequate in some way has been to postulate the existence of an intermediate state S between the learned and the unlearned states of the one-element model (states L and U respectively). Suppes and Ginsberg (1963), Kintsch and Morris (1965) and Suppes, Groen and Schlag-Rey (1966) have applied a three-state model to learning data, and a similar model will be investigated in the present study.

METHOD

Subjects

The subjects were 36 male and female summer school students at McMaster University. Each subject was paid \$1.50 for participation in the experiment. Subjects were tested individually and each experimental session lasted approximately one hour. Data from one subject were discarded because of his failure to follow instructions.

Apparatus

The apparatus consisted of a PDP/8I computer and a Teletype. Only the numerical keys of the Teletype keyboard were exposed to the subject, with the exception of keys 0 and 9. A metal shield was attached to the Teletype to restrict the amount of typing area exposed to the subject. The computer was located in a control room adjoining the experimental room.

Both the PDP/8I and a C.D.C. 6400 computer were used in the analyses of the data.

Materials

The stimuli were 14 consonant trigrams, constructed in such a way that each consonant appeared twice only. No consonant appeared in the same position in different trigrams, or was used twice in any one trigram. The trigrams used were DHY, RBM, ZTX, QRV, PCJ, GZB, MWF, LNP, VKS, XSG, FQH, JDW, CYK and TLN. The stimuli were all of less than 21% association value (Underwood and Schultz, 1960).

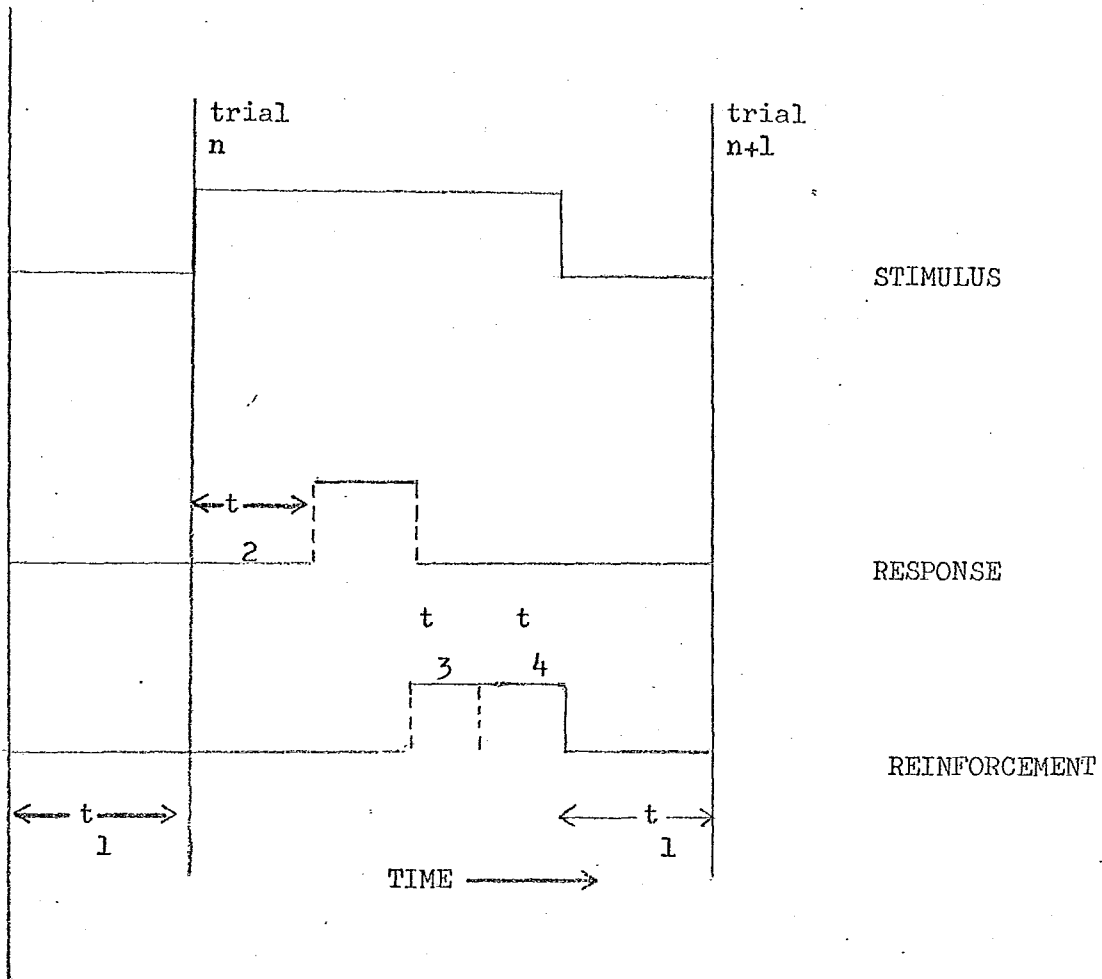
The responses were 14 two-digit numbers in which the digits were always adjacent numerals. There were exactly fourteen responses available to the subjects; these were 12, 23, 34, 45, 56, 67, 78, 21, 32, 43, 54, 65, 76 and 87.

Procedure

The computer was programmed to present to the subject by means of the Teletype a succession of stimulus-response items to be learned by the standard method of anticipation. The stimulus item was typed first. After the subject's two-digit response, or after 10 seconds if no response had been made, the letter C was typed if the response was correct; the letter E if an error. The correct response was then typed and was available for study for 2.3 seconds; after this interval the stimulus-response pair was moved out of sight behind the Teletype shield. The inter-item interval was also 2.3 seconds. Figure 1 is a representation of events within an experimental trial.

Each experimental session consisted of 23 cycles of 14 trials each (i.e. a total of 322 trials) per subject. Each new cycle was introduced by the words "HERE IS THE LIST AGAIN". In each cycle the 14 stimulus-response items were presented in random order. Two randomization tapes were used, each for 18 subjects; the numerical responses were assigned randomly to the stimuli for each set of 18 subjects.

Each subject was seated in front of the Teletype and was read instructions on how to respond in the experiment (see Appendix I for the instructions used). He was requested to respond by pressing any one of



t_1	-inter-item interval of 2.3 seconds
t_2	-response time ($0 < t_2 < 10$) in seconds
t_3	-time of exposure of 'C' or 'E'
t_4	-reinforcement interval of 2.3 seconds

Figure 1. Representation of events within an experimental trial.

the available keys (i.e. numbers 1 - 8) and then immediately to press either of the two adjacent keys (except in the case of keys '1' or '8' where there is only one adjacent key.) The instructions terminated with a few procedural questions. If the subject failed to answer any of these questions or was unclear about any part of the procedure the relevant parts of the instructions were re-read.

The subject was left to work through the 23 cycles without interruption. The experimental record of stimuli and responses was stored on punched paper tape for each subject.

RESULTS

Subject #2 did not follow the instruction to press only adjacent keys and his data were discarded.

Each subject's complete record of responses was first transformed into fourteen subject-item protocols of the form $A_{j,1} A_{j,2} A_{j,3} \dots A_{j,23} A_{j,i}$, where $A_{j,i}$ is 0 or 1 according to whether the response to stimulus j on cycle i was correct or incorrect. A complete listing of the 490 (i.e. 35×14) protocols appears in Appendix II. The criterion for learning for each protocol was taken to be four consecutive successes; and a protocol which met this criterion was labelled criterion protocol. There were 399 criterion protocols in the set of 490 protocols obtained from the 35 subjects.

Basic properties of the data were extracted from the 490 protocols by means of a comprehensive 'P'-level (in Batchelder's terminology) analysis program which was run on the C.D.C. 6400 computer. The scope of this program can be seen from the listing of its table of contents in Appendix III. It includes information about the learning process (e.g. error probability on each cycle; distribution of the cycle of last error; etc.), error and success statistics, and there is a section covering goodness-of-fit tests for the binomial properties of the sequences of pre-criterion responses.

Further analysis in this section will consist of three sections. In the first section the data are analysed in terms of the basic

one-element model, showing that the discrepancy mentioned in the Introduction, i.e. the lack of stationarity prior to the last error, is also a characteristic of the data collected in this experiment. Secondly, an attempt is made to apply the response-elimination model. It will be seen that although this model goes some way toward accounting for pre-criterion responses, it is not altogether satisfactory. In the third section a three-state model is investigated.

I. Analysis in terms of the One-Element model:

The section of the analysis program dealing with goodness-of-fit tests for the binomial properties of the sequences of pre-criterion responses demonstrates that the assumption of a constant guessing probability prior to last error, on the basis of which the binomial properties are predicted, is not valid.

Firstly, the null hypothesis that responses on successive cycles are statistically independent was rejected very decisively. Table I shows the frequencies of transition from success or error on cycle n to success or error on cycle $n+1$. The test for independence of these transition frequencies gave $\chi^2 = 132.05$, with one degree of freedom.

Table II shows the results of applying Vincent's procedure of dividing the responses before last error into quartiles. There is a substantial increase in the probability of a correct response over the successive quartiles. ($\chi^2 = 196.69$, d.f. = 3).

Table III shows the analysis of the data in terms of the distribution of each of the sixteen possible sequences of errors and successes when the pre-criterion responses are looked at in blocks of four cycles. The proportion of each type of sequence differs significantly from those predicted on the basis of the binomial law. ($\chi^2 = 193.32$, d.f.=15).

Suppes and Ginsberg formulate a statistical test of stationarity in terms of the null hypothesis that there is no change in the proportion of correct responses over cycles. The responses to be investigated are divided into t blocks of cycles. Then the appropriate chi-square test is

Table I Independence of responses on successive cycles.

<u>cycle n</u>	<u>cycle n + 1</u>	
	success	error
success	199	411
error	525	3233

Table II Vincent Quartiles.

Quartile	Successes	Errors	Pr(Success)	χ^2
1	67	964	.065	65.831
2	128	903	.124	8.353
3	161	870	.156	0.004
4	291	740	.282	122.499
	647	3477	.157	196.686

Table III Distribution of sequences of responses in 4-trial blocks.

(0 : success 1 : error)

Sequence	Probability		Chi-Square Component
	Observed	Predicted	
0000	.0000	.0004	.376
0001	.0039	.0023	1.166
0010	.0058	.0023	5.691
0011	.0136	.0142	.027
0100	.0107	.0023	31.923
0101	.0116	.0142	.472
0110	.0145	.0142	.010
0111	.0417	.0885	25.477
1000	.0155	.0023	79.468
1001	.0136	.0142	.027
1010	.0165	.0142	.385
1011	.0504	.0885	16.851
1100	.0301	.0142	18.326
1101	.0689	.0885	4.476
1110	.0844	.0885	.194
1111	.6188	.5516	8.455
Totals	1.0000	1.0000	193.324

$$\chi^2 = \sum_{t,i} n(t) \left(\frac{n_i(t)}{n(t)} - \frac{n_i}{N} \right)^2 / \frac{n_i}{N}$$

where $n_i(t)$ is the number of correct ($i=0$) or incorrect ($i=1$) responses in block t ; $n(t)$ is the total number of responses in block t ; and N is the total number of responses summed over all blocks. Forward and backward stationarity chi-square tests are included in the section of goodness-of-fit tests for the binomial properties of the sequences of pre-criterion responses of the analysis program. Forward stationarity examines response probability on cycle j for all those protocols whose cycle of last error is greater than or equal to j . This may introduce a bias toward a high error probability since the last pre-criterion response of each protocol which is considered is always an error. Backward stationarity corrects for this by working backwards from the last error, i.e. response probability is estimated at a distance of j cycles from the last error, where $j \geq 1$, so that the last error itself is not included. Results of the backward stationarity test are shown in Table IV. The second column in the table shows the number of protocols which enter into the estimate of response probability at a distance of j cycles from the last error. The total chi-square from this test is 189.52, with 15 degrees of freedom.

Hence these tests provide evidence against a one-element model with a constant guessing probability prior to the last error since the implication of a binomial distribution of pre-criterion responses is not validated.

Table IV Backward stationarity test.

Cycle j	# of protocols involved	Probability of error	Chi-square
1	470	.689	84.96
2	446	.735	39.68
3	416	.805	4.66
4	388	.835	0.22
5	361	.848	0.04
6	332	.871	1.80
7	305	.869	1.46
8	260	.842	0.00
9	230	.870	1.16
10	215	.930	12.20
11	193	.876	1.49
12	177	.893	3.21
13	155	.897	3.31
14	142	.901	3.58
15	126	.897	2.69
16	118	.890	1.90
17	104	.990	16.96
18	98	.908	3.09
19	91	.945	7.09

Predictions for the mean learning curve were obtained using an estimate of the learning parameter of 0.100. This estimate was obtained from the total number of errors per subject-item statistic. The chi-square on the learning curve predictions was 46.71, which is unsatisfactory with 17 degrees of freedom. (see Figure 3 later)

II. Analysis in terms of the Response-Elimination Model:

To investigate the response-elimination model a different mode of analysis was used. A "P" level analysis (in Batchelder's terminology) was used to identify the cycle of last error, if any, for each subject-item protocol. The subsequent analysis was not on the "P" level, and required no transformation of the primary data. The subjects' complete records of pre-criterion responses were utilized.

Listings were made of the two stimulus presentation orders used in the experiment. The positions of the n trials of last error ($n \leq 14$) were then located exactly; for example, if the cycle of last error for item 12 was identified earlier in the "P" level analysis as being the 6th one, then the particular trial on which item 12 was presented in cycle 6 would be determined by looking at the presentation order.

A trial-by-trial and subject-by-subject analysis then proceeded as follows. For each trial the response made was categorized in one of the following three ways:-

(i) as a "guess", if the response was made before the last error for the presented stimulus (i.e. in cycle k , where $k < j$ is the previously determined cycle of last error for the presented stimulus). 2 sub-categories contained correct and incorrect guesses.

(ii) as a "conditioned response", if it was made after the last error for the presented stimulus.

(iii) as an actual "trial of last error" error (there can of course be no more than 14 responses in this category)

The next step involved taking counts of the number of type (i) responses occurring between two type (iii) responses. For subject y there were X_y block counts of this sort, where X_y is the number of criterion protocols obtained from subject y . A count of the number of correct guesses in each block was also made.

A pooling of individual subjects' data was next obtained. All 'guesses' which all subjects made before the first appearance of a trial of last error were summed and associated with a pool size of 14, since no responses had as yet been eliminated through conditioning. This set of guesses was labelled Block 1; similarly all the guesses made between the first and the second trials of last error were collected together from all subjects and labelled Block 2, and so on. In the same way totals for the sub-category of correct guesses were obtained for each block. (See Table V)

This method of analysis is not unlike Vincent's method of dividing the pre-criterion responses into quartiles as a test of stationarity; this procedure differs in one major respect, which is that since the blocks are defined by the events of the experiment, they are of unequal size.

For each possible response-pool size the proportion of correct responses by guessing prior to the last error was thus found, and compared with the probability of a correct guess predicted by the response-elimination model, which is $1/X$ where X is the associated response pool size. Figure 2 compares the stationarity prediction of the one-element model with the observed data.

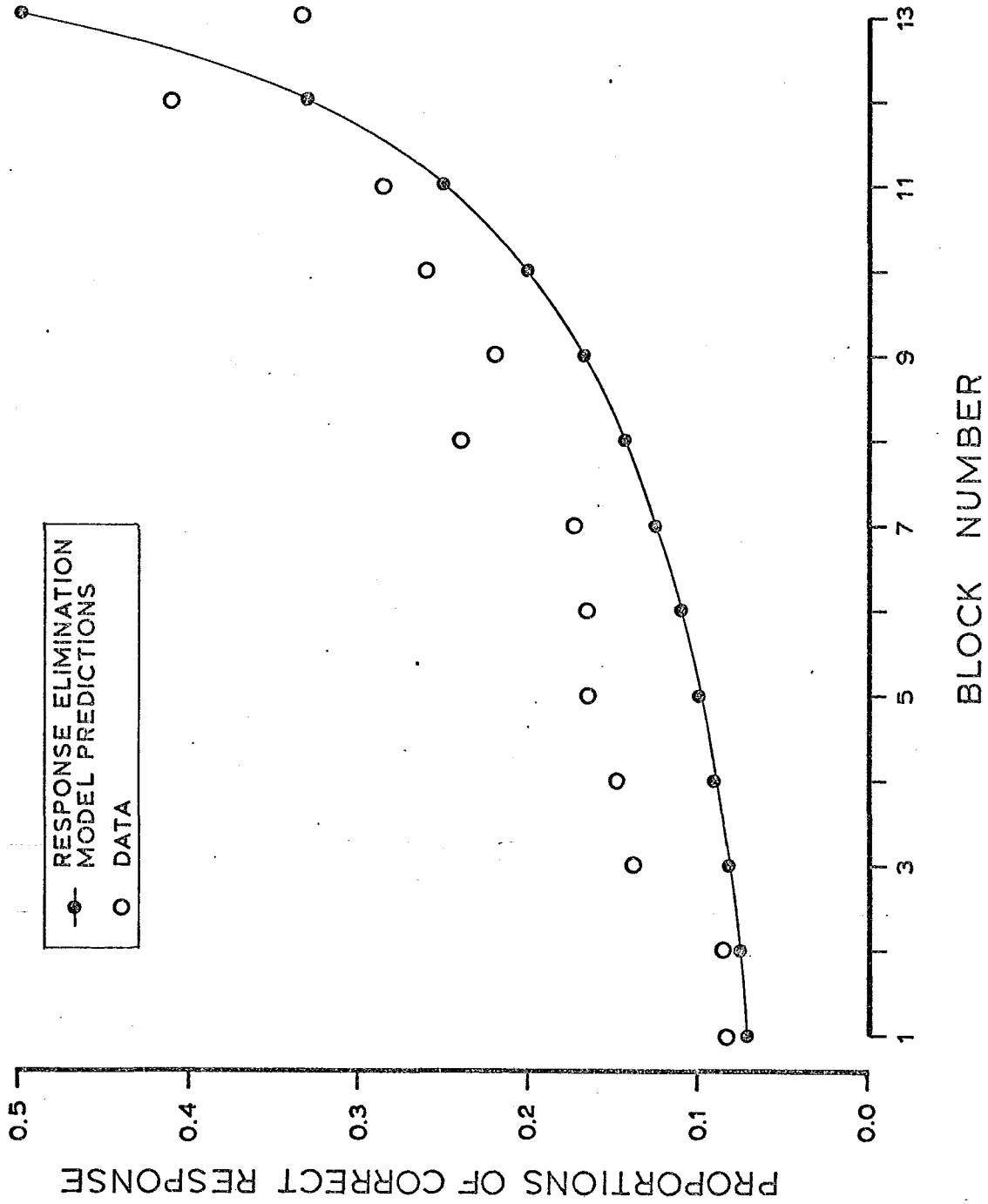
Predictions from the response-elimination model while improving on those of the one-element model do not adequately describe the data ($\chi^2 = 133.75$, d.f = 13,)

Table V Block sizes and proportion of correct guesses in
each block.

Block #	# Items in pool	Total # of responses	# of correct responses	Proportion Correct
1	14	1055	88	.0834
2	13	839	71	.0846
3	12	634	87	.1372
4	11	669	99	.1480
5	10	586	97	.1655
6	9	279	46	.1649
7	8	341	59	.1730
8	7	217	53	.2396
9	6	235	52	.2213
10	5	176	46	.2614
11	4	136	39	.2868
12	3	130	53	.4077
13	2	48	16	.3333
14	1	46	14	.3043

Figure 2

Proportion of correct responses prior to last
error using modification of Vincent's method



III Analysis in terms of a three-state model:

A three-state model is now proposed in an attempt to describe the data more adequately, and a 'P'-level analysis is again appropriate.

The three states as described in the Introduction are a long-term memory state L, an intermediate or short-term stage S which must be passed through in the transition out of an unlearned state U. The moves from state to state are specified by the transition matrix below, together with the response and start vectors.

$$P (L_1, S_1, U_1) = (0, 0, 1)$$

$$\begin{array}{c}
 L_n \\
 S_n \\
 U_n
 \end{array}
 \begin{array}{ccc}
 L_{n+1} & S_{n+1} & U_{n+1} \\
 \left[\begin{array}{ccc}
 1 & 0 & 0 \\
 b & 1-b & 0 \\
 0 & c & 1-c
 \end{array} \right]
 \end{array}
 \begin{array}{c}
 \text{Pr (error/} \\
 \text{row state)} \\
 \left[\begin{array}{c}
 0 \\
 q \\
 r
 \end{array} \right]
 \end{array}$$

Generally the parameter r, representing the probability of an error in the initial state U, is taken to be unity (Theios, 1963; Kintsch and Morris, 1963; Greeno, 1968; and others). Suppes and Ginsberg attempted to define a relationship between parameters q and r in early research on a three-state model (1963). In this study the parameter r is less than unity because subjects were restricted to a finite response set and the probability of a correct response by chance

on the first presentation of any item is not zero, but is taken to be the reciprocal of the number of responses in the response set. Hence r , the error rate in state U , is an observable parameter (in the terminology of Greeno and Steiner, 1964) with an expected value of $(1-1/n)$, where n is the size of the response set.

Derivations from the model

1. Learning curve:-

$$\begin{aligned}
 \Pr(x_n = 1) &= \Pr(U_n) \cdot r + \Pr(S_n) \cdot q \\
 &= (1-c)^{n-1} \cdot r + \sum_{i=1}^{n-1} (1-c)^{i-1} \cdot c \cdot (1-b)^{n-(i+1)} \cdot q \\
 &= (1-c)^{n-1} \cdot r + c \cdot q \cdot (1-b)^{n-2} \cdot \sum_{i=1}^{n-1} \left(\frac{1-c}{1-b} \right)^{i-1} \\
 &= (1-c)^{n-1} \cdot r + \frac{c \cdot q}{c-b} \cdot ((1-c)^{n-1} - (1-b)^{n-1})
 \end{aligned}$$

2. Cycle of last error:-

$$\Pr(L=k) = \Pr(\text{error on cycle } k) \cdot \Pr(\text{no more errors})$$

Define:-

f = Pr (no more errors after a response in state S)

$$= \sum_{j=0}^{\infty} (1-b)^j \cdot (1-q)^j \cdot b$$

$$f = \frac{b}{1-(1-b)(1-q)}$$

g = Pr (no more errors after an error in state U)

$$= \sum_{j=1}^{\infty} (1-c)^{j-1} (1-r)^{j-1} c (1-q) f$$

$$= \frac{c f (1-q)}{1-(1-c)(1-r)}$$

$$\Pr(L=k) = (1-c)^{k-1} r g + \frac{c q f}{c-b} [(1-b)^{k-1} - (1-c)^{k-1}]$$

3. Number of error cycles before the first success.

This statistic is derived by considering the probabilities associated with

- (i) an initial error run of length k in U , where $k > 0$, followed by the first success in either state S or state U .
- (ii) an initial error run of length x in U , where $1 \leq x \leq (k-1)$, followed by an error run of length $(k-x)$ in S ($k > 0$) and the first success in states S or L .

Hence the probability P of there being exactly k errors

before the first success (where $k > 0$) is given by:-

$$P = (1-c)^{k-1} r^k ((1-c)(1-r) + c(1-q)) + c q r [b + (1-b)(1-q)] [(1-b)^{k-1} q^{k-1} - (1-c)^{k-1} r^{k-1}]$$

and when $k=0$:-

$$P = 1-r$$

4. Total number of errors:

The probability of there being k total errors is derived by considering the probabilities associated with a sequence of responses in state S of which $(k-x)$ are errors.

The appropriate expression is as follows:-

$$\sum_{x=0}^k \left[\sum_{m=0}^{\infty} \binom{x-m}{x} (1-c)^{m-x-1} (1-r)^m r^x c \sum_{n=0}^{\infty} \binom{k-x-n}{k-x} (1-b)^{k-x-n-1} (1-q)^n q^{k-x-b} \right]$$

The inner summations do not form a closed expression but can be estimated by means of an iterative computer algorithm.

Estimation of Parameters

A chi-square minimization procedure was used to estimate the three remaining parameters b, c and q.

Firstly, the theoretical expressions were derived for probabilities of occurrence of the sixteen possible four-tuples of responses over both cycles two through five and six through nine (see Appendix III for these expressions). A program was written for the C.D.C. 6400 computer to extract from the data (in the form of subject-item protocols) the number of occurrences of each type of four-tuple in each cycle set, and to evaluate the chi-square on the difference. A wide range of b, c and q values was covered, with each parameter increasing in steps of .005 from initial values of .050 for b and c and of .200 for q. The step size for b and c was decreased to .001 as the search became finer, and those b - c - q combinations which gave relatively low chi-squares were stored. In order to choose final values from the set of values in storage, the learning curve predictions were used in a further minimization procedure. The resulting final parameter values were:-

$$b = .230 \quad c = .114 \quad q = .415$$

$\chi^2 = 32.91$, d.f. = 28, for the four-tuple data;

$\chi^2 = 6.48$, d.f. = 15, for the learning curve data).

Figure 3 plots the mean learning curve, which is the best fitting one by virtue of the parameter selection by chi-square minimization on the learning curve data. Also shown in Figure 3 is the predicted learning curve from the one-element model.

Figure 3

Learning curve with one-element model and
three-state model predictions

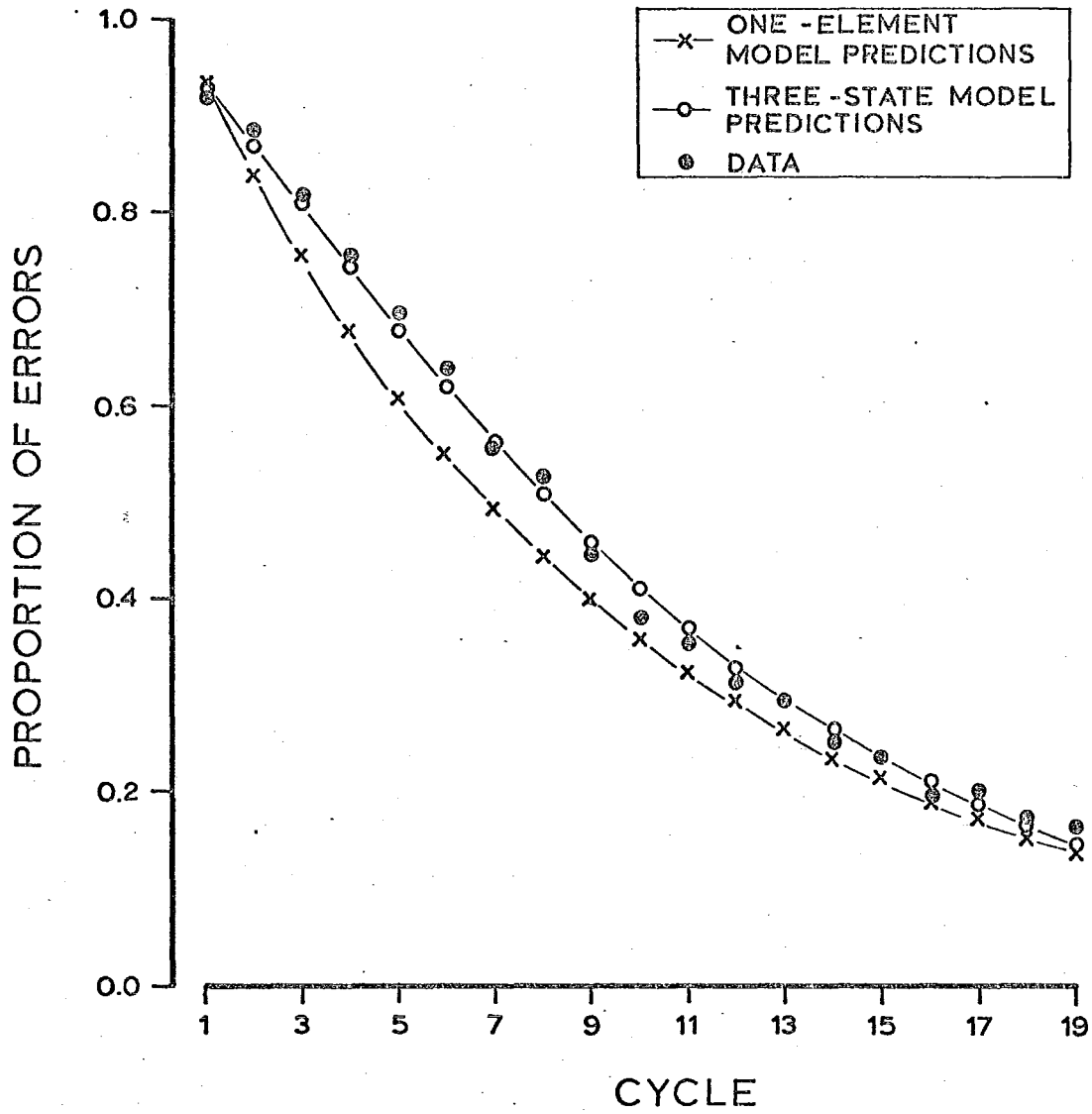


Figure 4 shows that there is reasonable fit of the cycle of last error predictions to the data ($\chi^2 = 39.97$, d.f. = 15, $p < .005$) in view of the irregularity of the data around cycle 8; χ^2 for cycle 8 itself is 9.96.

There is fairly good fit of the predictions for the number of error cycles before the first success ($\chi^2 = 31.09$, d.f. = 15, $.010 > p > .005$) as shown in Figure 5.

Figure 6 compares the predicted and observed probabilities for the total number of errors per subject-item. The predicted distribution is satisfactory; $\chi^2 = 24.40$, d.f. = 15, $.05 < p < .10$.

Figure 4
Distribution of the cycle of last error
with three-state model predictions

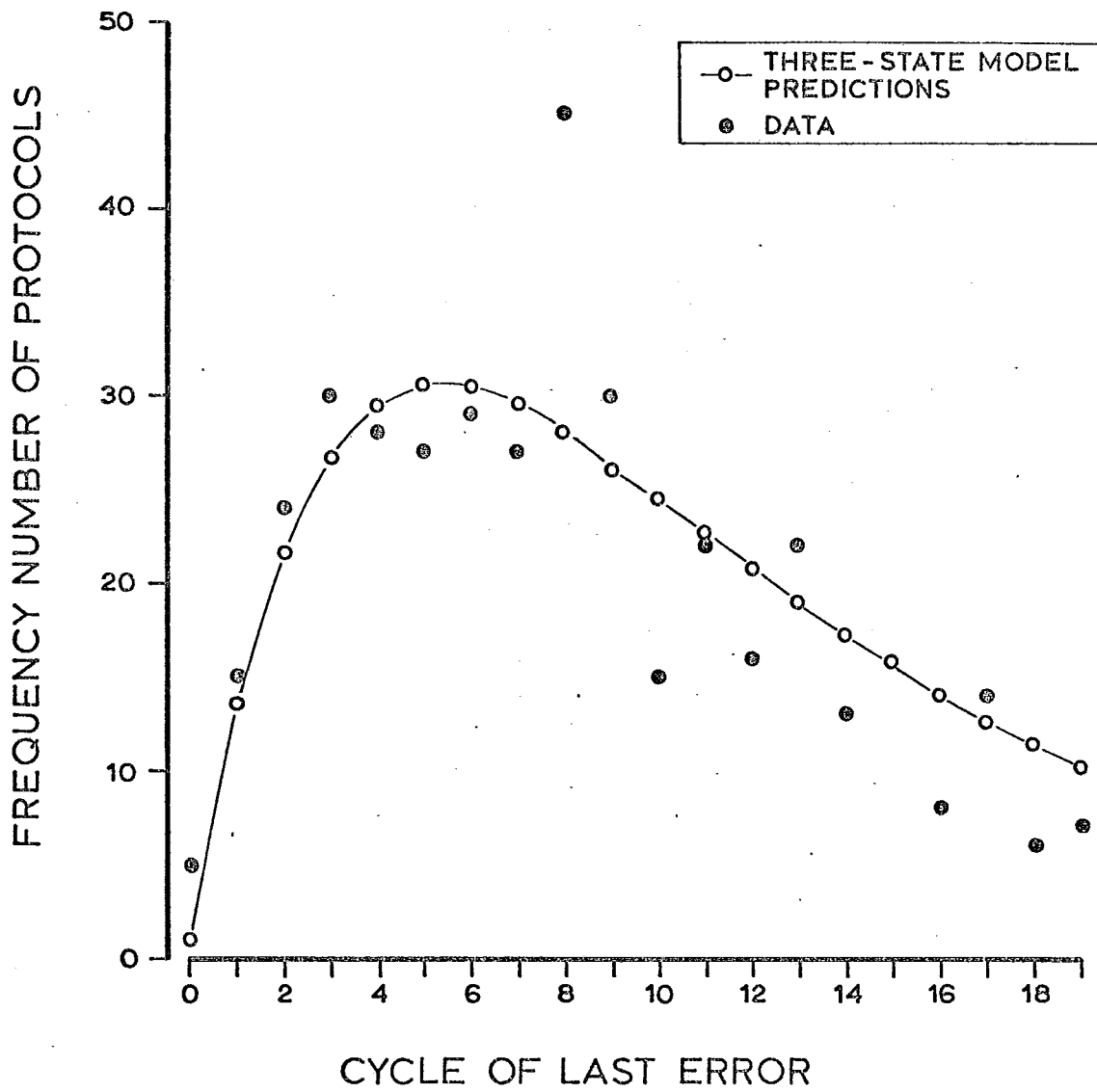


Figure 5

Distribution of k , the number of errors before the first success, with three-state model predictions

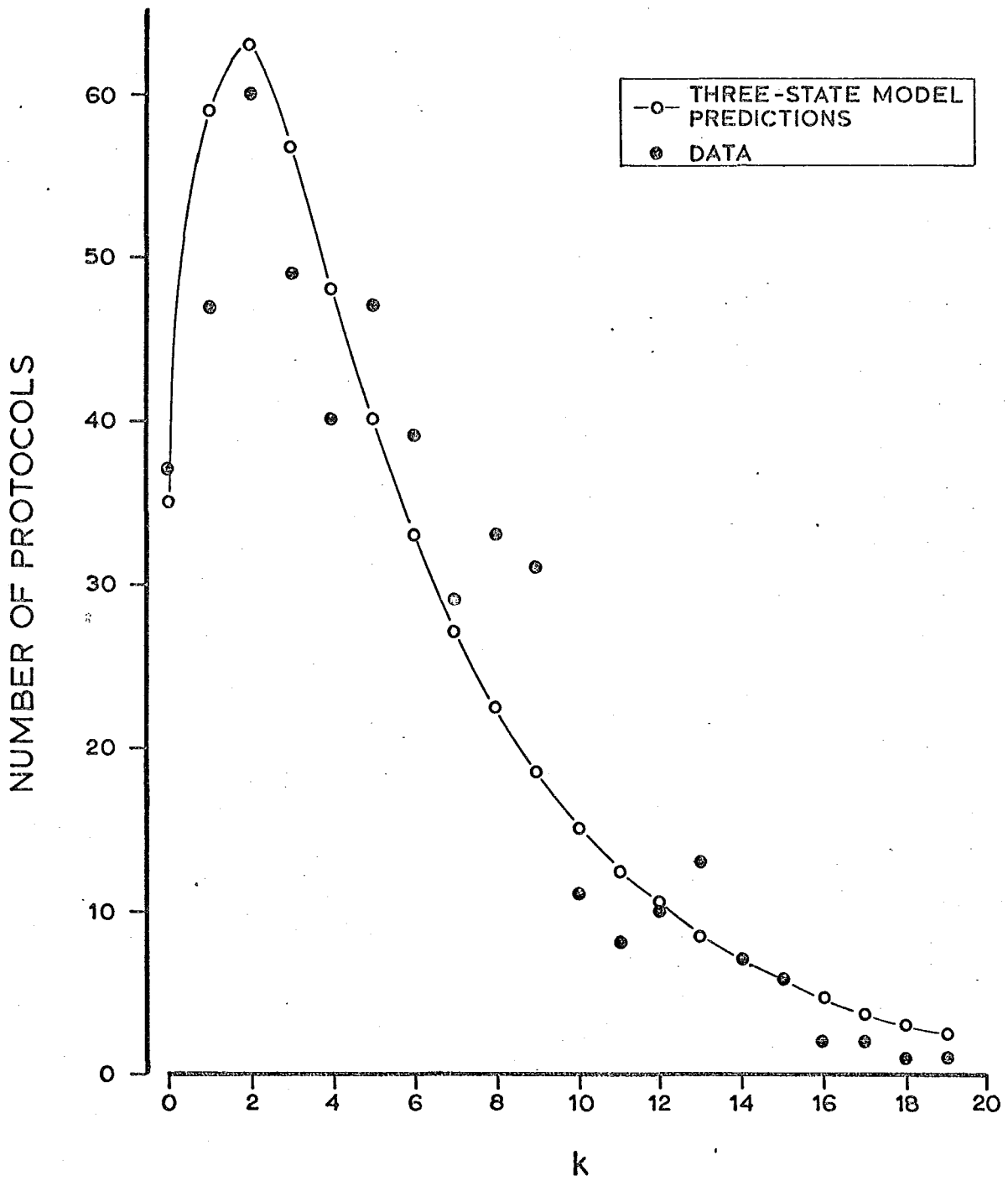
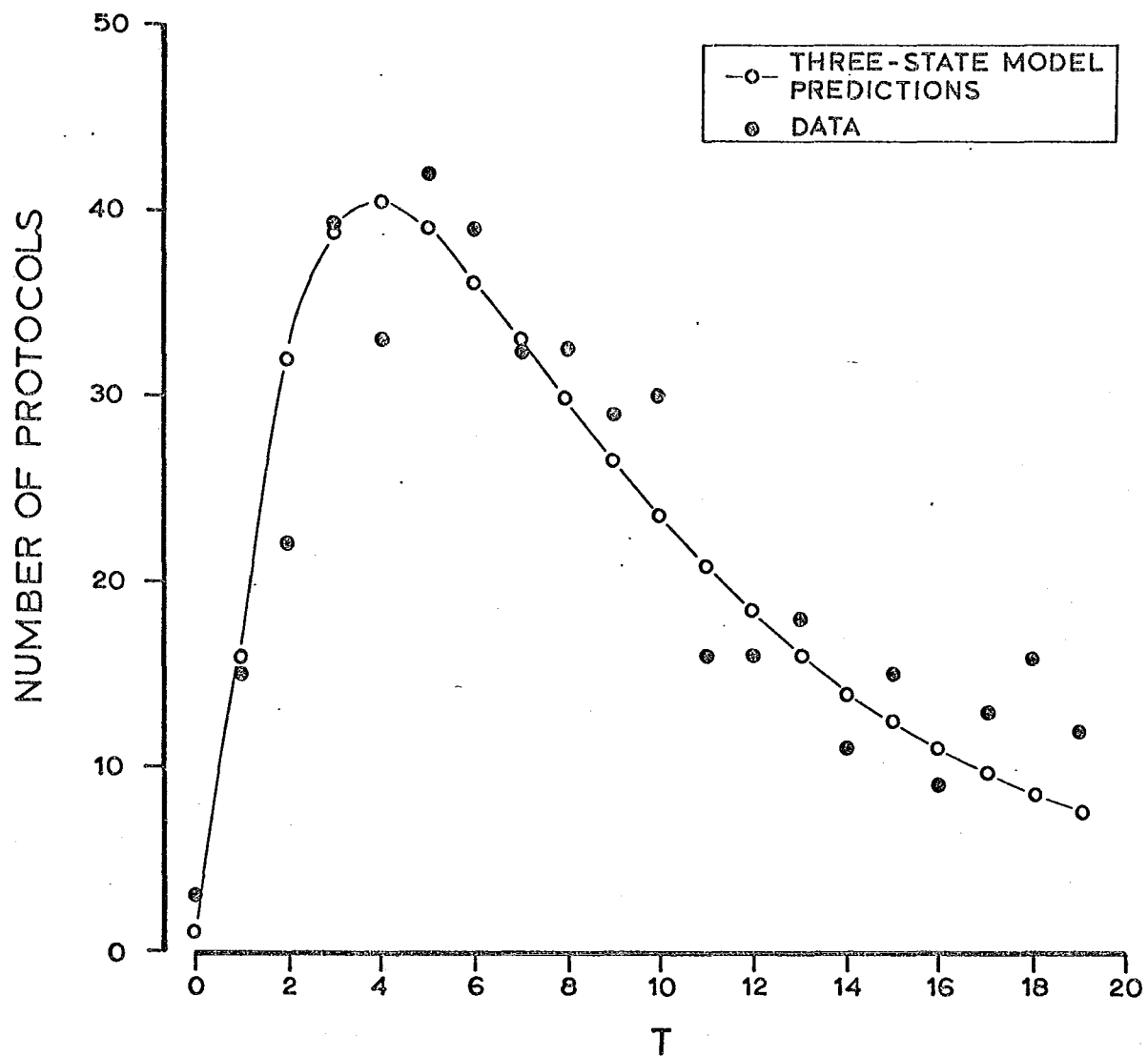


Figure 6

Distribution of T, the total number of errors, with
three-state model predictions



DISCUSSION and CONCLUSION

The response elimination model performed better than the one-element model with respect to pre-criterion responses but still fell short of providing an accurate description of these responses. This of course was the one aspect of the learning data which the model might have handled particularly well since the design of the experiment maximized the chances of a subject developing a response pool strategy, in that the response set was of a finite size, and each cycle was separated from the preceding one. Since the model failed to describe the pre-criterion responses accurately, further analysis was not felt to be worthwhile, and no attempt was made to develop an analytical procedure to isolate the conditioning parameter.

Insofar as the proposed three-state model has been investigated, it appears that with four parameters the data can be accounted for satisfactorily. If the parameter r , the error rate in the unlearned state U , is taken to be unity instead of the factor $(1-1/n)$ of the preceding analysis (where n is the number of response alternatives) a simpler three-parameter three-state model is obtained. In the same way that the one-element model assumption of a constant guessing probability before learning implies that there is a binomial distribution of responses prior to the last error, so the three-state model assumption of a constant guessing probability q in the intermediate state S implies a binomial distribution of state S responses. For the three parameter version the sequence of responses from the first

success through the last error is necessarily a sequence of state S responses, and stationarity of these responses is predicted if the binomial assumption holds. Figure 7 shows that in fact good stationarity was obtained between the first success and the last error ($\chi^2 = 6.62$, d.f. = 12).

A three parameter model analysis was therefore attempted, despite two obvious errors in the data. The first of these lies in the expectation that the probability of a success on the first cycle would be zero, since all items start in state U and all state U responses are zero. The second error is that the intermediate responses between the first success and the last error, as shown in Table VI, were not statistically independent; $\chi^2 = 3.66$, with one degree of freedom. The parameter q is observable; it is the proportion of errors between the first success and the last error. However it was found that no combination of values of the parameters b and c could lead to good learning curve predictions. The choice then was either to introduce a start vector to allow a proportion of the items to start in state S; or to establish the value of ν as something less than unity. Each of these alternatives allows successes to occur on the first cycle; the second was chosen since only one new parameter is introduced and it is a parameter which is directly observable from the error rate on the first cycle. Also it seems unreasonable to assume that any association has occurred prior to the start of the experiment.

The axioms of the one-element model are stated for a single item in the paired-associate learning list, and it is assumed that the learning

Figure 7
Stationarity between the first success
and the last error

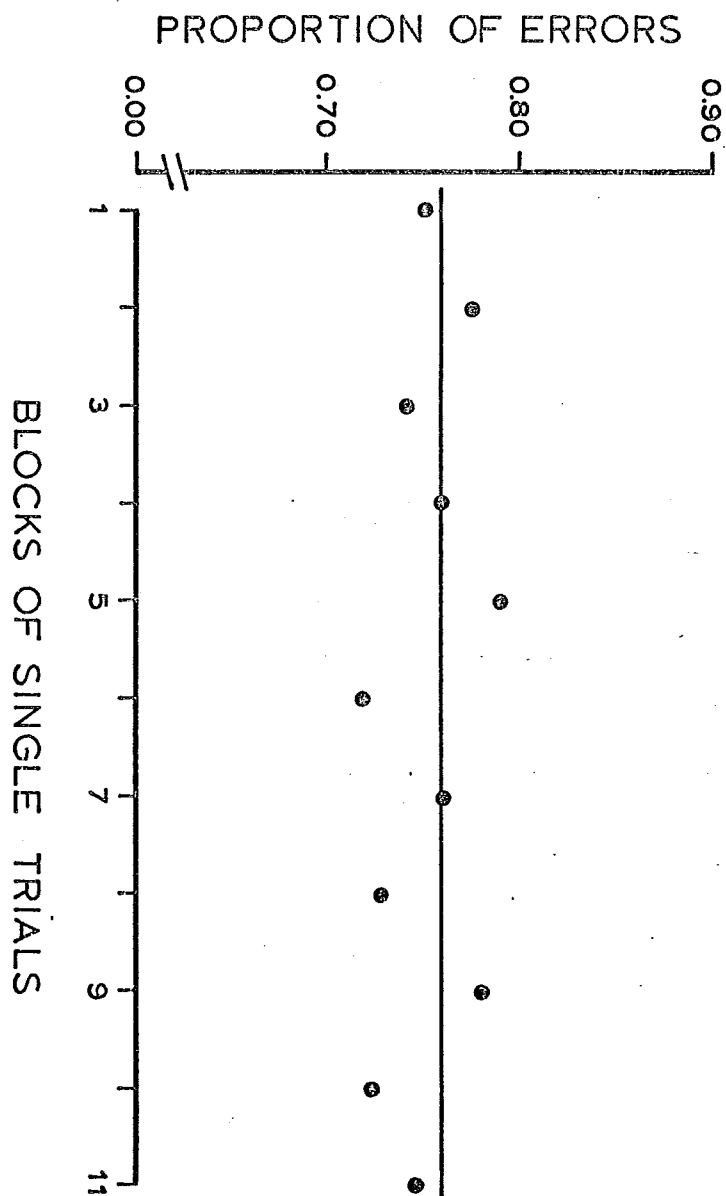


Table VI Independence of responses between the first success and the last error.

<u>cycle n</u>	<u>cycle n + 1</u>	
	success	error
success	140	368
error	149	508

of stimulus-response pairs proceeds independently. However the items in the list can be expected to mutually effect each other, and this was postulated in the response-elimination model; performance on a particular S-R pair was assumed to depend both on its own present state (i.e. learned or unlearned) and also on the present state of the other items in the list (since the guessing probability is assumed to be inversely proportional to the number of unconditioned items at any moment). Since the response-elimination model postulates item interactions in this way it would be better expressed in terms of a set of axioms to describe the events that can happen to the entire list. In this study it was found to be impossible to apply a conventional or 'P'-level analysis and further use of the model had it proved more satisfactory would have required an alternative axiomatization along the lines laid down by Batchelder (1966, Ch. 4).

While the 'P'-level analysis could not be used when the data were analysed in terms of the response-elimination model, it is also true that anything other than a single-item analysis is inappropriate when the three-state model is used. Consequently this study is not able to make direct comparisons of predictions from the two models. In fact the only statistic which might be available for comparison is the pre-criterion responses rate, since the response elimination model was developed no further than this. However there is a major problem associated with this statistic which results from uncertainty as to the exact location of the cycle of transition into the final learned state; it can be the cycle of last error itself or any of the success cycles following the last error.

The analysis in terms of the response-elimination model assumed that the cycle of last error was itself the transition cycle. This cycle marked the point of a unit decrement in the size of the response pool, with the resultant expectation of an increase in the success-by-guessing rate. The error introduced by taking the cycles of last error to be transition cycles is an over-estimation of the pre-criterion success rate because the response pool decrements are effected at the earliest possible moment. However the response pool predictions of the pre-criterion success rate, even with this error working towards an over-estimation, were consistently below the obtained values. The response-elimination model curve in Figure 2 is therefore the best that can be expected from the model and any attempt to allow for the error outlined above would only increase the discrepancy between observed and predicted data points.

In the case of the three-state model the uncertainty about the location of the cycle of transition from state S to state L would also result in an inaccurate count of the pre-criterion success rate, and an attempt to derive predictions of this statistic from the model was not felt to be worthwhile in view of the availability of other statistics which provide more conclusive evidence about the model.

In conclusion, the attempt to apply a two-state model to paired-associate learning data was unsuccessful; Bower's one-element model fails on the prediction of stationarity of pre-criterion responses, as has been previously reported in situations where there were more than

two responses; the response elimination model, with the modification to the assumption of a constant guessing probability prior to learning, was also unable to predict the nature of the pre-criterion responses. The three-state model which was then proposed has been able to describe much of the data. For the time being at least it is considered an acceptable model of the learning process.

REFERENCES

Batchelder, W.H. A mathematical analysis of multi-level verbal learning. Tech. Rep. No.104, Institute for Mathematical Studies in the Social Sciences, Stanford University.

Bower, G.H. Paired associates under two training conditions and different numbers of response alternatives. Amer. Psychologist, 1960, 15, 451

Bower, G.H. Application of a model to paired-associate learning. Psychometrika, 1961, 26, 255-280

Bower, G.H. A model for response and training variables in paired- associate learning. Psychol. Rev., 1962, 69, 34-53

Estes, W.K. Component and pattern models with Markovian interpretations. In R.R. Bush and W.K. Estes (Eds.), Studies in mathematical learning theory. Stanford: Stanford University. Press, 1959, pp 9-52.

Greeno, J.G. and Steiner, T.E. Markovian processes with identifiable states: general considerations and application to all-or-none learning. Psychometrika, 1964, 29, 309-333.

Hintzman, D.L. Some tests of a discrimination net theory: Paired-associate learning as a functional of stimulus similarity and number of responses.

J. verb. Learn. verb. Behav., 1967, 6, 809-816.

Kintsch, W. and Morris, C.J. Application of a Markov model to free recall and recognition. J. exp. Psychol., 1965, 69, 200-206

Millward, R. An all-or-none model for noncorrection routines with elimination of incorrect responses. J. math. Psychol., 1964, 1, 392-404.

Suppes, P. and Ginsberg, Rose. A fundamental property of all-or-none models. Psychol. Rev., 1963, 70, 139-161

Suppes, P., G. Groen and Madeleine Schlag-Rey. A model for response latency in paired-associate learning. J. math. Psychol., 1966, 3, 99-129.

Theios, J. Simple conditioning as two-stage all-or-none learning
Psychol. Rev., 1963, 70, 403-417

Underwood, B.J., and Schultz, R.W. Meaningfulness and verbal learning.
New York: Lippincott, 1960.

APPENDIX

I Instructions to Subjects

This experiment is one of a series in which we are studying learning processes. At the beginning of the experiment a three letter word will be typed by the teletype in front of you. You are to press any one of the keys number 1 - 8 on the teletype keyboard, and then press either of the adjacent keys, except in the case of 1 or an 8 when there is only one available key. For example, if the first key you pressed typed the number 5 then you should next press either the 4 or the 6; but if the first number you pressed was 8 then the second one must be 7. You must try to press both these keys within 10 seconds. As soon as you have done this the letter C or the letter E will be typed. If you have not responded by the end of 10 seconds the letter E is always typed. Each word has a correct two-digit number, which always appears after the letters C or E have been typed. The letter C means that you typed the correct number; the letter E means that you typed the wrong number. Each of the 14 words you will see has its own correct number; no two words have the same one. You will have two seconds to study each word and its correct number together. You will be shown each word several times during the course of the experiment and you will be expected to respond with the right number. If you cannot remember which number goes with a word make your best guess as to what the number should be and press the appropriate keys. Remember that the number which is typed is always the

correct number for that particular word, and is the same as the one you typed only if you were right. You will be shown the list of 14 words and numbers several times, but each time the order of the words will change. Do you have any questions? Just to make sure that you understand the procedure I'm going to ask you a few questions. Firstly, what should you do if you can't remember the correct answer? What does the appearance of an E mean? Could the number 74 be a correct answer? Why not? O.K. Start as soon as the first word is typed. Please keep going until no more words are typed.

II Subject-item protocols

The first section of the paired-associate learning program lists the data in the form of subject-item protocols. The first seven digits under the heading 'ID' serve as identification for each protocol listed. The second and third columns identify the subject by number; the sixth and the seventh columns identify the stimulus to which the sequence of responses in the protocol was given.

The column labelled 'LE' identifies the cycle of last error; i.e. for criterion protocols it contains the number of the cycle of the first error to be followed by four consecutive successes; for non-criterion protocols, which are marked by an asterisk, this column contains the number of the cycle on which the last error was made.

1.1 PROTOCOLS

(AN ASTERISK INDICATES A NON-CRITERION PROTOCOL)

ID	TRIALS	LE	10 /	20 /	30 /	40 /
2012301	23	6	1110010000000000000000			
2012302	23	12	1111111011010000000000			
2012303	23	6	1011010000000000000000			
2012304	23	6	1111110000000000000000			
2012305	23	8	1001100100000000000000			
2012306	23	8	1111111100000000000000			
2012307	23	6	1101110000000000000000			
2012308	23	6	1011110000000000000000			
2012310	23	10	1111111001000000000000			
2012309	23	9	1101000110000000000000			
2012311	23	9	0010011010000000000000			
2012312	23	9	11111010100000000000100			
2012313	23	6	1111110000000000000000			
2012314	23	4	1111000000000000000000			
2032301	23	1	1000000000000000000000			
2032302	23	6	1111010000000000000000			
2032303	23	5	111110000100000000100000			
2032304	23	4	1011000000000000000000			
2032305	23	8	111100010000101000000000			
2032306	23	4	1011000000000000000000			
2032307	23	7	1001001000000000000000			
2032308	23	8	1100100100000000000000			
2032309	23	8	1111101100000000000000			
2032310	23	6	1111110000000000000000			
2032311	23	5	1110100000000000000000			
2032312	23	4	1111000000000000000000			
2032313	23	2	110000000100100100000000			
2032314	23	1	1000000000000000000000			
2042301	23	7	1111111000000000000000			
2042302	23	13	1111011111111000000000			
2042303	23	8	0110011100000000000000			
2042304	23	5	1010100000000000000000			
2042305	23	16	0111110111000101000000			
2042306	23	11	1111101001000000000000			
2042307	23	7	1111111000000000000000			
2042308	23	8	1111111100000000000000			
2042309	23	17	111111111111111001000000			
2042310	23	17	111111111101100010000000			
2042311	23	10	1011111011000000000000			
2042312	23	5	1111100000001000000000			
2042313	23	9	0111111110000000000000			
2042314	23	2	1100000000100000000000			
2052301	23	12	1111110101110000000000			
2052302	23	23	* 11011111110111111101111			
2052303	23	7	1111111000000000000000			
2052304	23	22	* 1111111011111111111110			
2052305	23	2	11000000000000000001000			
2052305	23	12	1011111110110000000000			

2052307	23	12		111110111001000000000000
2052308	23	10		111001010100000000000000
2052309	23	17		111111111111111110000000
2052312	23	23	*	11111111011011101110111
2052311	23	23	*	101111111111111111111111
2052312	23	23	*	111111111111111111111101
2052313	23	15		111110011111111100001000
2052314	23	5		111110000000000000000000
2062301	23	19		011111101111111111110000
2062302	23	4		1111000000000000000010000
2062303	23	19		111111111111111101110000
2062304	23	22	*	111111111101111111110110
2062305	23	23	*	11111111111011111110101
2062306	23	23	*	1011011111111111111110101
2062307	23	11		111111111110000000000000
2062308	23	15		111111111111101000000000
2062309	23	23	*	111111110111111110101111
2062310	23	23	*	111111111111111111111111
2062311	23	23	*	111011111101101111111111
2062312	23	14		111101111110110000000000
2062313	23	11		111111101110000000000000
2062314	23	9		111111011000000000000000
2072301	23	9		111101011000000000000000
2072302	23	21	*	11111111111111111000100
2072303	23	0		000001110100000000001001
2072304	23	15		111111111101001000000000
2072305	23	8		100011110000100011000000
2072306	23	17		111110111111100110000000
2072307	23	10		111111100100000001000000
2072308	23	12		111101111111000010100000
2072309	23	14		111111111111111000000010
2072310	23	23	*	111101111111111111111101
2072311	23	23	*	111111110111111101111111
2072312	23	16		111111111110110100000000
2072313	23	14		111101111100010000000001
2072314	23	1		100000000000000000000000
2082301	23	7		011000100000000000000000
2082302	23	8		011101110000000000000000
2082303	23	8		110001110000000000000000
2082304	23	2		110000000000000000000000
2082305	23	10		111111011100000000000000
2082306	23	7		111111100000000000000000
2082307	23	7		110110100000000000000000
2082308	23	2		110000000000000000000000
2082309	23	9		111111001000010000000100
2082310	23	9		111101111000000000000000
2082311	23	8		011001010000000000000000
2082312	23	7		111110100000000000000000
2082313	23	2		110000000000000000000000
2082314	23	4		110100000000000000000000
2092301	23	13		111011110110100000000000
2092302	23	16		011011000100100100000000
2092303	23	14		111111011101110000000000
2092304	23	13		111110101110100000000000
2092305	23	13		111111111111110000000000
2092306	23	14		111111111111111000000000
2092307	23	10		111111101100000000000000
2092308	23	17		001101011110001010000000
2092309	23	19		111111111100011000100000
2092310	23	17		111111111111101010000000

2092311	23	13		111111101111100000000000
2092312	23	9		111111111000000000000000
2092313	23	5		110010000000000000000000
2092314	23	7		111111100001000000000000
2102301	23	21	*	11111111111111111111100
2102302	23	6		111111000000000001101000
2102303	23	11		111111110110000100000000
2102304	23	18		111111111111111011000000
2102305	23	23	*	11111111101111111111101
2102306	23	23	*	111111111011111111111111
2102307	23	4		111100000000001000000000
2102308	23	16		111111111011000100000000
2102309	23	22	*	11111111111011110110010
2102310	23	23	*	111111111111011111111111
2102311	23	5		11111000010100101001000
2102312	23	23	*	110111101110111111111011
2102313	23	21	*	11011111111111011111100
2102314	23	5		111110000101000000000000
2112301	23	10		01111111110000000001000
2112302	23	19		01111111111111101110000
2112303	23	20	*	10111111111111110111000
2112304	23	12		111111111111000000000000
2112305	23	6		111111000000000100000000
2112306	23	11		111111111010000000000000
2112307	23	8		110110110000000100000000
2112308	23	14		111111111011010000000000
2112309	23	21	*	11111101111110111100100
2112310	23	17		111110001101111110000000
2112311	23	7		01011110000011110001000
2112312	23	15		111111001111011000000000
2112313	23	13		111111111010100000000000
2112314	23	5		111110000000000000000000
2122301	23	21	*	11111011111001100110100
2122302	23	21	*	11111111111111111111100
2122303	23	4		101100000000000000000000
2122304	23	23	*	111111100011111111111111
2122305	23	23	*	111111111111111111111111
2122306	23	23	*	111111101111111111111111
2122307	23	23	*	110111111111111111111011
2122308	23	23	*	111111110001110011111111
2122309	23	14		111111111111010000000000
2122310	23	23	*	111111110111010101111111
2122311	23	23	*	111111111111111111111101
2122312	23	23	*	11111111101111001011001
2122313	23	2		110000000000000000000000
2122314	23	5		111110000000000000000000
2132301	23	11		111111110110000000000000
2132302	23	8		111111110000000000000000
2132303	23	7		111111100000000000000000
2132304	23	7		111100100000000000000000
2132305	23	13		110111111110100000000000
2132306	23	12		111011011011000000000000
2132307	23	5		101110000000000000000000
2132308	23	12		111101110111000001000000
2132309	23	13		11111111111110000000010
2132310	23	15		101111111110111000000000
2132311	23	11		111111111010000000000000
2132312	23	9		111111111000000000000000
2132313	23	12		111111111111000000000000
2132314	23	5		111110000000000000000000

2142301	23	21	*	11011101111010001111100
2142302	23	22	*	11111111111111011110110
2142303	23	21	*	11111111111101111111100
2142304	23	23	*	11011111111111111111111
2142305	23	23	*	11111111111111111111111
2142306	23	23	*	11111111110111111111111
2142307	23	23	*	11111111111111111111111
2142308	23	23	*	11111111111111111111111
2142309	23	12		11111111111100000000000
2142310	23	23	*	11111111110111011111111
2142311	23	23	*	11111111111111011000101
2142312	23	10		1111100110000000001001
2142313	23	15		11101111111101100000000
2142314	23	4		11110000000000000000000
2152301	23	8		11110101000000000000000
2152302	23	12		11111101101000000000000
2152303	23	2		11000000000100000000000
2152304	23	9		11111111100000000000000
2152305	23	11		10011110001000000000000
2152306	23	8		11100101000000000000000
2152307	23	8		11111010000000000000000
2152308	23	3		11100001110000000000000
2152309	23	8		11111001000000000000000
2152310	23	8		11101101000000000000000
2152311	23	14		111000111010111000000001
2152312	23	9		11111111100000010000000
2152313	23	13		10111110101111000000000
2152314	23	8		11111001000000000000000
2162301	23	21	*	11101111111110111001100
2162302	23	23	*	11111111011111111111111
2162303	23	23	*	11111111111101111111111
2162304	23	17		11111101111111111000000
2162305	23	23	*	11111111100111100111111
2162306	23	23	*	11111111111100010101111
2162307	23	11		11001111101000000000000
2162308	23	23	*	11011111111111111101111
2162309	23	23	*	11111111111111111111111
2162310	23	23	*	11111101111111111111101
2162311	23	23	*	11111111111010111111111
2162312	23	23	*	11111100110010111011111
2162313	23	22	*	11011111110110111011110
2162314	23	11		11111111001000000000000
2172301	23	22	*	01111111011111111111110
2172302	23	18		11111111111111100100000
2172303	23	18		11111111111111111100000
2172304	23	9		00111100100000000000000
2172305	23	2		11000010100000000000000
2172306	23	15		01111111111111100001100
2172307	23	14		111111111111110000000001
2172308	23	20	*	11111111111111111111000
2172309	23	15		11111111111110100000100
2172310	23	13		11111111111110000001110
2172311	23	23	*	11111111111111111111111
2172312	23	13		11111111111110000000110
2172313	23	14		11111111011111000000100
2172314	23	13		11111111111110000000000
2182301	23	4		10010000000000000000000
2182302	23	1		10000000000000000000000
2182303	23	3		11100000001000000000000
2182304	23	2		11000000000000000000000

2182305	23	1	100000000000000000000000
2182306	23	3	111000000000000000000000
2182307	23	2	110000000000000000000000
2182308	23	0	000000000000000000000000
2182309	23	6	011111000000000000000000
2182310	23	4	110100000000000000000000
2182311	23	3	111000000000000000000000
2182312	23	2	010000000000000000000000
2182313	23	3	111000000100001000000000
2182314	23	2	110000000000000000000000
2192301	23	13	111110111111100000000000
2192302	23	21	* 11111111001111101000100
2192303	23	23	* 111111011111111010011101
2192304	23	7	111111100000000000000000
2192305	23	13	111111110100100000000000
2192306	23	8	110110010000000000000000
2192307	23	8	111111110000000000000100
2192308	23	9	111111111000000100000000
2192309	23	21	* 11111111111111101101100
2192310	23	21	* 11111111101110001111100
2192311	23	22	* 11111011110100111101010
2192312	23	3	111000000000000000000000
2192313	23	2	110000000000000000000000
2192314	23	3	111000000000000000000000
2202301	23	8	011101010000000000000000
2202302	23	5	111110000000000000000000
2202303	23	5	111110000000000000000000
2202304	23	3	011000000000000000000000
2202305	23	8	111111110000000000000000
2202306	23	10	111001001100000000000000
2202307	23	4	111100000000000000000000
2202308	23	6	111111000000000000000000
2202309	23	3	011000010000000000000000
2202310	23	6	111111000000000000000000
2202311	23	6	111011000000000000000000
2202312	23	5	111110000000000000000000
2202313	23	4	111100000000000000000000
2202314	23	3	111000000000000000000000
2212301	23	10	111011111100000000000000
2212302	23	8	110111110000000000000000
2212303	23	6	111111000000000000000000
2212304	23	3	111000000000000000000000
2212305	23	17	110111111111000110000000
2212306	23	9	111110001000000000000101
2212307	23	5	111110000000000000000000
2212308	23	2	110000101000000000010000
2212309	23	11	111110111110000001000000
2212310	23	13	11111111111010000100001
2212311	23	4	101100001000000001000000
2212312	23	8	111111110000000000000000
2212313	23	11	111111010010000000000000
2212314	23	13	111111111000100000000000
2222301	23	18	110011000100010001000000
2222302	23	1	100000001000010000000000
2222303	23	4	111100000000000000000000
2222304	23	7	111100100000000000000000
2222305	23	19	111111011100011000100000
2222306	23	6	111101000000000000000000
2222307	23	1	100000000000010100000000
2222308	23	4	111100000000000000000000

2222309	23	8	111111110000000000000100
2222310	23	8	1111101000001101000000
2222311	23	17	01111111010010001000000
2222312	23	8	11111111000010000000000
2222313	23	5	11011000000000000000000
2222314	23	4	11010000000000000000000
2232301	23	8	11111111000000000000000
2232302	23	5	11001000000000000000000
2232303	23	11	10010111101000000000000
2232304	23	3	10100000000000000000000
2232305	23	2	11000000000000000000000
2232306	23	7	11011110000000000000000
2232307	23	0	00000000000000000000000
2232308	23	1	10000000000000000000000
2232309	23	1	10000000000000000000000
2232310	23	7	11111100000000000000000
2232311	23	3	11100000000000000000000
2232312	23	11	11111111110000000000000
2232313	23	3	11100000100000000000000
2232314	23	7	11111100000000000000000
2242301	23	8	11111111000000000000000
2242302	23	8	01111101000000000000000
2242303	23	10	11101111110000000000000
2242304	23	8	11101101000000000000000
2242305	23	9	11111111100000000000000
2242306	23	7	11101010000000000000000
2242307	23	1	10000000000000000000000
2242308	23	15	11111011011001000000000
2242309	23	6	11011100000000000000000
2242310	23	5	11111000000000000000000
2242311	23	13	11111111001010000000000
2242312	23	5	11111000000000000000000
2242313	23	2	11000000000000000000000
2242314	23	3	11100000000000000000000
2252301	23	16	11111101111011100000001
2252302	23	14	11111111101101000000000
2252303	23	9	11111000100000000000000
2252304	23	16	11110110101110010000000
2252305	23	11	11111010111000000000000
2252306	23	6	11111100000000000000000
2252307	23	11	11110100111000000000000
2252308	23	10	11100110010000000000000
2252309	23	9	11111111100001000000100
2252310	23	15	10111111101111100000000
2252311	23	22	* 1111111110110001010110
2252312	23	11	11111111110000000000000
2252313	23	3	10100000000000000000000
2252314	23	6	11111000000000000000000
2262301	23	12	11001111010100000000000
2262302	23	17	01111111101011101000000
2262303	23	3	11100000000001000000000
2262304	23	9	11111111100001000000000
2262305	23	8	11111011000000000000000
2262306	23	9	11111111100000000010000
2262307	23	6	11000100000000000000000
2262308	23	3	11100000000000000000000
2262309	23	13	11111111010010000000000
2262310	23	12	11111110001000000000000
2262311	23	11	1111111001000000010000
2262312	23	6	11111100000000000000000

2262313	23	2		11000000000000000000000000000000
2262314	23	8		01101001000000000000000000000000
2272301	23	3		01100000000000000000000000000000
2272302	23	7		11111110000000000000000000000000
2272303	23	3		11100000000000000000000000000000
2272304	23	8		01111101000000000000000000000000
2272305	23	5		11111000000000000000000000000000
2272306	23	6		11111100000000000000000000000000
2272307	23	6		11111100000000000000000000000000
2272308	23	4		11110000000000000000000000000000
2272309	23	8		11110111000000000000000000000000
2272310	23	6		11011100000000000000000000000000
2272311	23	8		11111111000000000000000000000000
2272312	23	2		11000000000000000000000000000000
2272313	23	1		10000000000000000000000000000000
2272314	23	3		11100000000000000000000000000000
2282301	23	17		10101000101110101010000000
2282302	23	21	*	10110111111111111111110100
2282303	23	22	*	11111011111111111111110010
2282304	23	19		11011011111111111111010000
2282305	23	21	*	11111111101000100010100
2282306	23	23	*	11111111111111111111111111
2282307	23	8		1110111100000000000000000000
2282308	23	17		11111111111111111101000000
2282309	23	16		11111111111111111110000000
2282310	23	23	*	111111111011111111000101
2282311	23	19		11011111111000111110000
2282312	23	21	*	11111110111101111011100
2282313	23	7		11111110000000000000000000
2282314	23	0		00000000000000000000000000
2292301	23	21	*	111111111111101000100100
2292302	23	21	*	11111111110111011110100
2292303	23	18		11111111111110111100000
2292304	23	18		111110011111111110100000
2292305	23	8		11111111000000000000000000
2292306	23	8		11011111000000000000000000
2292307	23	15		111111111100111000000000
2292308	23	2		11000000000000000000000000
2292309	23	8		11111111000000000000000000
2292310	23	22	*	11101111101101111110010
2292311	23	17		00111111111111011000000
2292312	23	20	*	111111111111111111111000
2292313	23	7		11111010000000000000000000
2292314	23	6		11111100000000000000000000
2302301	23	3		11100000000000000000000000
2302302	23	7		11111110000000000000000000
2302303	23	6		11111100000000000000000000
2302304	23	3		01100000000000000000000000
2302305	23	3		11100600000000000000000000
2302306	23	8		11111111000000000000000000
2302307	23	7		11110110000000000000000000
2302308	23	4		11110000000000000000000000
2302309	23	8		11111011000000000000000000
2302310	23	12		11111111000100000000000000
2302311	23	5		11111000000000000000000000
2302312	23	7		10010010000000000000000000
2302313	23	8		1110101100000000000010000
2302314	23	4		11110000000000000000000000
2312301	23	22	*	111111111111101111111110
2312302	23	15		111111111001111000000000

2312303	23	7		11111110000011011001100
2312304	23	23	*	11111100111111101111001
2312305	23	22	*	11111101111111110101110
2312306	23	11		11011110011000000000000
2312307	23	9		11101111100000000000000
2312308	23	9		11111101100001100000000
2312309	23	14		11111111010110000000000
2312310	23	23	*	11111111101111101111111
2312311	23	23	*	11111111111111111111011
2312312	23	23	*	11111111111111111111111
2312313	23	7		11101110000000000000000
2312314	23	4		11110000000000000000000
2322301	23	6		11111100000000000000000
2322302	23	9		11111011100000000000000
2322303	23	5		11111000000000000000000
2322304	23	5		11111000000000000000000
2322305	23	9		11111100100000000000000
2322306	23	3		11000000000000000000000
2322307	23	9		111110001000000000000011
2322308	23	4		11110000000000000000000
2322309	23	10		11111011010000000000000
2322310	23	11		11110011101000000000000
2322311	23	5		11111000000000000000000
2322312	23	4		10110000000000001000000
2322313	23	8		11111111000000001000000
2322314	23	4		10110000000000000000000
2332301	23	0		00001001011000000000000
2332302	23	13		11111010110110000000000
2332303	23	9		11111111100000000000000
2332304	23	9		11011111100000000000000
2332305	23	9		11111111100000000000000
2332306	23	7		11111110000000000000000
2332307	23	11		10100011101000000000000
2332308	23	15		11111010111010100000000
2332309	23	10		11110101010000000000000
2332310	23	14		1111111101111000000010
2332311	23	12		11111110100100000000000
2332312	23	12		11111111111100000000000
2332313	23	10		11110100010000000000000
2332314	23	6		11110100000000000000000
2342301	23	9		11111111100000000000000
2342302	23	23	*	11110111111011111110001
2342303	23	23	*	111111111111111110011111
2342304	23	22	*	11111110111001111010110
2342305	23	16		11000101101111110000000
2342306	23	23	*	11111111111111011100011
2342307	23	4		11110000000000000000000
2342308	23	15		11101111010101100000000
2342309	23	9		11010011100000000000000
2342310	23	23	*	11111111100111111111101
2342311	23	23	*	11111111111110010111011
2342312	23	23	*	11111111111111111111111
2342313	23	23	*	11101111100100100011111
2342314	23	2		11000000010000000000000
2352301	23	2		11000000000000000000000
2352302	23	3		11100000000000000000000
2352303	23	5		11101000000000000000000
2352304	23	3		11100000000000000000000
2352305	23	5		11111000000000000000000
2352306	23	3		11100000000000000000000

2352307	23	3		10100000000000000000000000000000
2352308	23	1		10000000000000000000000000000000
2352309	23	2		01000000000000000000000000000000
2352310	23	4		11110000000000000000000000000000
2352311	23	3		11100000000000000000000000000000
2352312	23	2		11000000000000000000000000000000
2352313	23	1		10000000000000000000000000000000
2352314	23	1		10000000000000000000000000000000
2362301	23	13		11111111110010000000000000000000
2362302	23	15		11111111111111110000000000000000
2362303	23	11		11111101011000000000000000000000
2362304	23	13		11111111111111000000000000000000
2362305	23	21	*	111111110111011111100100
2362306	23	21	*	11111111111111111111110100
2362307	23	1		10000000000000000000000000000000
2362308	23	15		11111101111111110000000000000000
2362309	23	4		01110000000100000000000000000000
2362310	23	22	*	11111111101111111111111110
2362311	23	22	*	010111111111111111111111010
2362312	23	13		11111111111110000000000000000000
2362313	23	6		10111100000001000000000000000000
2362314	23	4		11110000000000000000000000000000

 OF THE 490 PROTOCOLS, 91 ARE NON-CRITERION PROTOCOLS

III

TABLE OF CONTENTS OF ANALYSIS PROGRAM

1. PROTOCOLS, LEARNING CURVES, ETC.
 - 1.1 PROTOCOLS
 - 1.2 LEARNING CURVES
 - 1.2.1 All Trials
 - 1.2.2 All Trials (Assume Perfect Learning)
 - 1.2.3 Trials Before The Last Error (Forward)
 - 1.2.4 Trials Before The Last Error (Backward)
 - 1.3 THE DISTRIBUTIONS OF THE NUMBER OF
 - 1.3.1 Errors On All Trials
 - 1.3.2 The Trial Of The Last Error
 - 1.3.3 Successes Before The Last Error
 - 1.3.4 Errors Up Through The Last Error
 - 1.3.5 Alternations Up Through The Last Error
 - 1.4 THE DISTRIBUTIONS OF THE NUMBER OF
 - 1.4.1 Trials
 - 1.4.2 Trials After The Last Error
 - 1.4.3 Successes After The Last Error
 - 1.4.4 Errors After The Last Error
 - 1.5 THE MEAN NUMBER OF
 - 1.5.1 Alternations On Trial K
 - 1.5.2 Errors Following An Error On Trial K
2. ERROR STATISTICS
 - 2.1 THE MEAN NUMBER OF
 - 2.1.1 J-Tuples Of Errors
 - 2.1.2 Error Runs Of Length J
 - 2.2 The Distribution Of the Number Of Errors Between Adjacent Successes
 - 2.3 The Means And The Disributions Of The Number Of Errors Between The K And K+1 Success
 - 2.4 The Means And The Distributions Of the Number Of Errors Between The K And K+1 Success, Indexed Backwards

- 2.5 The Means And The Distributions Of The Length Of The KTH Error Run
- 2.6 The Means And The Distributions Of The Length Of The KTH Error Run, Indexed Backwards
- 2.7 The Means And The Distributions Of the Number Of Errors Before The KTH Success
- 2.8 The Autocorrelation Of Errors K Trials Apart

3. SUCCESS STATISTICS

- 3.1 THE MEAN NUMBER OF
 - 3.1.1 J-Tuples Of Successes
 - 3.1.2 Success Runs Of Length J
- 3.2 The Distribution of The Number Of Successes Between Adjacent Errors
- 3.3 The Means And The Distributions Of The Number Of Successes Between The K And K+1 Error
- 3.4 The Means And The Distributions Of The Number Of Successes Between The K And K+1 Error, Indexed Backwards
- 3.5 The Means And The Distributions Of The Length Of The KTH Success Run
- 3.6 The Means And The Distributions Of The Length Of The KTH Success Run, Indexed Backwards
- 3.7 The Means And The Distributions Of The Number Of Successes Before The KTH Error

4. GOODNESS-OF-FIT TESTS FOR THE BINOMIAL PROPERTIES OF THE SEQUENCE OF RESPONSES PRIOR TO THE LAST ERROR

- 4.1 Vincent Quartiles
- 4.3 The Independence Of Responses On Successive Trials
- 4.4 The Distribution Of Error Frequencies In Disjoint Trial Blocks
- 4.5 Stationarity (Error Frequency By Successive Disjoint Trial Blocks)
 - 4.5.1 Forward
 - 4.5.2 Backward
- 4.6 Stationarity Between The First Success And The Last Error

IV Theoretical Expressions for probabilities of sequences
of responses in 4-cycle blocks.

(i) cycles 2 through 5

The sequences are obtained by reading the sequence number as a 4-bit binary number.

Sequence	Probability
0	$\frac{c}{(1-q)^3} (b+b(1-b)(1-q)+b(1-b)^2(1-q)^2+(1-b)^3) + \frac{(1-c)(1-r)}{(1-c)^2(1-r)^2} (c(1-q)+c(1-q)(b+(1-b)(1-q))+c(1-q)((1-b)^2(1-q)^2+(1-b)(1-q)b+b))$
1	$\frac{cq(1-b)^3(1-q)^3}{(1-c)(1-r)} + \frac{(1-c)(1-r)}{(1-c)^2(1-r)^2} (c(1-b)(1-q)q((1-c)(1-r)+(1-b)(1-q)))$
2	$\frac{cq(1-b)^2(1-q)^2(b+(1-b)(1-q))}{(1-r)} + \frac{(1-c)(1-r)}{(1-c)r(c(1-q)+(1-c)(1-r))+cq(b+(1-b)(1-q))+cq(1-b)(1-q)(b+(1-b)(1-q))}$
3	$\frac{c(1-b)^2(1-q)^2q^2(1-b)}{r(cq+(1-c)r)+c(1-b)q+c(1-q)(1-b)^2q^2} + \frac{(1-c)(1-r)}{(1-c)(1-r)} ((1-c)r(cq+(1-c)r)+c(1-b)q+c(1-q)(1-b)^2q^2)$
4	$\frac{c(1-b)(1-q)q(b+(1-b)(1-q)b+(1-b)^2(1-q)^2)}{(1-r)} + \frac{(1-c)(1-r)}{(1-c)r((1-c)(1-r)+c(1-q))+c(1-q)(b+(1-b)(1-q)+cq(b+(1-b)(1-q)b+(1-b)^2(1-q)^2))}$
5	$\frac{c(1-b)^2(1-q)^2q^2}{(1-c)r} + \frac{(1-c)(1-r)}{(1-c)r((1-c)(1-r)+c(1-q))+c(1-q)(1-b)q+c(1-q)(1-b)^2q^2}$

- 6
$$\underline{c}(1-q)(1-b)^2 q^2 (b+(1-b)(1-q)) + (1-c)(1-r)((1-c)r$$

$$((1-c)r(c(1-q) + (1-c)(1-r)) + cq(b+(1-b)(1-q))) + cq^2$$

$$(1-b)(b+(1-b)(1-q))$$
- 7
$$\underline{c}(1-b)(1-q)(1-b)^2 q^3 + (1-c)(1-r)((1-c)r((1-c)r$$

$$(cq + (1-c)r) + cq^2(1-b)) + cq(1-b)^2 q^2)$$
- 8
$$\underline{c}q(b+(1-b)(1-q)b + b(1-b)^2(1-q)^2 + (1-b)^3(1-q)^3) +$$

$$\underline{(1-c)r((1-c)(1-r)((1-c)(1-r)(c(1-q) + (1-c)(1-r))$$

$$+ c(1-q)(b+(1-b)(1-q)) + c(1-q)(b+(1-b)(1-q)b + (1-b)^2$$

$$(1-q)^2))$$
- 9
$$\underline{c}(1-b)^3(1-q)^2 q^2 + \underline{(1-c)r((1-c)(1-r)((1-c)(1-r)$$

$$(cq + (1-c)r) + c(1-b)(1-q)q) + c(1-b)^2(1-q)^2 q)$$
- 10
$$\underline{c}(1-b)^2(1-q)(b+(1-b)(1-q))q^2 + (1-c)r((1-c)(1-r)$$

$$((1-c)r(c(1-q) + (1-c)(1-r)) + cq(b+(1-b)(1-q) + c(1-b)$$

$$(1-q)q(b+(1-b)(1-q))$$
- 11
$$\underline{c}q^3(1-b)^3(1-q) + \underline{(1-c)r((1-c)(1-r)((1-c)r(cq +$$

$$(1-c)r) + cq^2(1-b)) + c(1-q)(1-b)^2 q^2)$$
- 12
$$\underline{c}(1-b)q^2(b+(1-b)(1-q)b + (1-b)^2(1-q)^2) + \underline{(1-c)r}$$

$$(1-c)r((1-c)(1-r)(c(1-q) + (1-c)(1-r)) + c(1-q)$$

$$(b+(1-b)(1-q))) + cq(b+(1-b)(1-q)b + (1-b)^2(1-q)^2))$$
- 13
$$\underline{c}(1-b)^3 q^3(1-q) \underline{(1-c)r((1-c)r((1-c)(1-r)(cq$$

$$(1-c)r)c(1-b)(1-q)q)c(1-q)(1-b)^2 q^2)$$
- 14
$$\underline{c}(1-b)^2 q^3(b+(1-b)(1-q)) + (1-c)r((1-c)r((1-c)r$$

$$(c(1-q) + (1-c)(1-r)) + cq(b+(1-b)(1-q)) + cq^2(1-b)$$

$$(b+(1-b)(1-q)))$$
- 15
$$\underline{c}(1-b)^3 q^4 + \underline{(1-c)r((1-c)r(cq + (1-c)r) + cq^2(1-b)) +$$

$$c(1-b)^2 q^3)$$

(ii)

cycles 6 through 9

In the above expressions c is replaced by:-

$$c(1-c)^4 + c(1-b)(1-c)^3 + c(1-b)^2(1-c)^2 + c(1-b)(1-c)^3 + c(1-b)^4$$

and (1-c) is replaced by $(1-c)^5$, to allow for the

possible outcomes of the preceding cycles. In

addition, sequence 0 needs an additional expression

to allow for the possibility of starting cycle 5 in

state L:-

$$cb(1-c)^3 + cb(1-c)^2(1+(1-b)) + c(1-c)b(1+(1-b)+(1-b)^2) + cb(1+(1-b)+(1-b)^2+(1-b)^3)$$