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A GRAPH THEORY APPROACH TO COMPARING CONSUMER INFORMATION PROCESSING MODELS*

JAMES R. BETTMAN

University of California, Los Angeles

This study argues the need for, and then develops, some graph theoretic approaches for comparing complex information processing models of individual decisions. Two similarity coefficients are proposed, and a coefficient based on path and reachability structure is shown to be preferable. Some properties of this coefficient are outlined, as well as a computational method. The coefficient is applied to actual information processing models of consumer choice and stock selection. The results of this application are interpreted for insights into process structure, stability of decision processes over time, and possibilities of developing process-oriented typologies. Finally, problems and prospects for this type of approach are assessed.

Introduction

Recently, information processing models of individual decision making have been proposed in many fields [7], [10], [12], [14], [15]. In particular, several information processing models of consumer choice have been developed [1], [2], [4], [5], [9], [13]. Interpreting these models has been somewhat difficult, as they have normally been merely presented in all their complexity, with no attempt at internal analysis of their properties. This is certainly understandable, as most of these models, particularly those of consumer choice, are complex discrimination net models, and analysis techniques are not at all obvious or straightforward.

A problem with information processing models that is accentuated by this lack of analytical methods is that these information processing models of individuals tend to be very idiosyncratic. Different individual's models can be rather dissimilar (e.g., see [2]). However, one would like to use particular information processing models as data points for inductive reasoning about the structure of a general information processing model. Thus, it would be very useful to have some methods for analyzing and comparing information processing models.

Accordingly, the purpose of this study is to develop tools for comparing information processing models as to their similarity. The tools will be applied to several actual information processing models of consumer choice, making comparisons between models for different individuals or different situations to see what insights can be developed.

A fruitful approach to analyzing certain information processing models has been to look at the models as graphs[1] and attempt to use the framework of graph theory to develop the desired analytical tools [3]. Hence, this study first considers a brief introduction to the terminology and simple results of graph theory which are used; develops methods for comparing models; applies one of these methods to a series of actual consumer information processing models; discusses use of the comparative procedure, extensions, and problems with the procedure.

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[1] Many information processing models have the form of decision nets, which can be easily represented as graphs. The nodes represent tests on stimuli, and the arcs depict the flow of processing. For examples, see Figure 2.

Graph Theoretic Terminology[2]

A graph consists of a set N of nodes, and a set $A \subset N \times N$ of arcs. If $i, j \in N$, then the pair (i, j) is a directed arc if it denotes an arc specifically directed from node i to node j. In the following, we will consider graphs with only directed arcs, or directed graphs. A path from node n_1 to node n_m is a collection of distinct nodes $n_1, n_2, \cdots, n_m$, together with the arcs $(n_1, n_2), (n_2, n_3), \cdots, (n_{m-1}, n_m)$ in the following order: $n_1, (n_1, n_2), n_2, (n_2, n_3), \cdots, n_{m-1}, (n_{m-1}, n_m)$ [6, p. 31]. If there is a path from node i to node j, node j is said to be reachable from node i [6, p. 32]. Finally, the distance from node i to node j, denoted by d_{ij}, is the number of arcs in the path with the minimum number of arcs that connects node i to node j.

Matrix methods are very useful in graph theoretic problems. The following matrices will be useful for any given graph:

(i) The adjacency matrix A

$a_{ij} = 1$ if $\exists$ an arc directed from node i to node j,

$a_{ij} = 0$ otherwise (in particular $a_{ii} = 0$ for all i).

(ii) The nth reachability matrix R_n

$r_{ij}^n = 1$ if $\exists$ a path from node i to node j of length n or less,

$r_{ij}^n = 0$ otherwise.

(iii) The reachability matrix R

$r_{ij} = 1$ if $\exists$ a path from node i to node j regardless of length (in particular $r_{ii} = 1$ for all i),

$r_{ij} = 0$ otherwise.

(iv) The distance matrix D

$d_{ij} =$ distance between node i and node j.

Finally, we will need the following simple results:

(1) If λ is the minimum value of n such that $R_n = R_{n+1}$, then $R_\lambda = R$ [6, p. 122].

(2) If $D = [d_{ij}]$ is the directed distance matrix for a graph, then every diagonal entry $d_{ii} = 0$; $d_{ij} = \infty$ if $r_{ij} = 0$; and otherwise d_{ij} is the smallest power n to which A must be raised so that $a_{ij}^n > 0$ [6, p. 135].

Methods for Comparing Information Processing Models

The overall goal in developing tools for measuring the similarity between pairs of complex information processing models is to give an investigator a basis for developing process-oriented typologies if he has models of several individuals. From these typologies, more general models may result. In this section we consider two such comparative tools.

A Path Structure Coefficient

One basis for comparing information processing models would be to examine the order and sequence of particular nodes in the decision process. Since the nodes in a discrimination net represent cues, or stimuli, two models would represent similar processes if their nodes were ordered in roughly the same fashion and if these nodes were processed in roughly the same sequence. Accordingly, one way of defining similarity is with respect to path and reachability structure. If for a given node i there is a path to another node j of length n or less in a graph G_1, then if such a path from i to j also exists in graph G_2 this should add to the similarity coefficient between the two

[2] Much of the ensuing is taken from [6].

graphs. With this brief rationale,[3] we will now define a path structure similarity coefficient.

Consider two graphs representing decision processes, G_1 and G_2. Let N_1 and N_2 be the node sets of G_1 and G_2 respectively. The accept and reject actions of the decision process are not included in the node set for that process. For example, in Figure 1, the node set for each graph would be $\{1, 2, 3, 4\}$. The nodes are labeled because we must be able to retain the identity of the various cues to be able to make meaningful comparisons. Since G_1 and G_2 will not necessarily use the same set of cues, we define the sets $S = \{i: i \in N_1 \cap N_2\}; I_1 = \{i: i \in N_1, i \notin S\}; I_2 = \{i: i \in N_2, i \notin S\}$. Thus S is the set of cues used by both decision processes, and I_1 and I_2 represent the idiosyncratic cues used by G_1 and G_2 respectively. Finally, if $\nu(X)$ is the number of elements in a set X, let $t = \nu(S) + \nu(I_1) + \nu(I_2)$, the number of distinct cues used by both processes.

Now we define the binary descriptors p_{ij1}^n and p_{ij2}^n for graphs G_1 and G_2 respectively. Recall that $R_n(G)$ is the nth reachability matrix for a graph G. Then, for i, $j = 1, 2, \cdots, t$, and $k = 1, 2$:

$$p_{ijk}^n = r_{ij}^n(G_k) \quad \text{if} \quad i, j \in N_k,$$

$$p_{ijk}^n = 0 \quad \text{if} \quad i \quad \text{or} \quad j \notin N_k.$$

Thus, p_{ijk}^n just describes the reachability structure for nodes in the same process. However, if node i or node j is not used in process k, the p_{ijk}^n term is zero.

Let l_1 be the value of λ mentioned in Result 1 above for G_1, and let l_2 be defined similarly for G_2. Then define $l = \max(l_1, l_2)$. Now define a path structure similarity coefficient $S_p(G_1, G_2)$ as follows:

$$(1) \qquad S_p(G_1, G_2) = \frac{\sum_{n=0}^{l} \sum_{i=1}^{t} \sum_{j=1}^{t} p_{ij1}^n p_{ij2}^n}{\sum_{n=0}^{l} \sum_{i=1}^{t} \sum_{j=1}^{t} (p_{ij1}^n + p_{ij2}^n - p_{ij1}^n p_{ij2}^n)}.$$

This coefficient is thus based on the following ideas: if both graphs have node i reaching node j in a path of length n or less, this increases the numerator and hence similarity. If only one graph has such a path, only the denominator is increased. Likewise, if a node is used by only one of the graphs (i.e., i is not an element of S), it can increase only the denominator and hence detract from similarity. Finally, note that for nodes $i \in N_k$, p_{iik}^n is 1 for all n, since node i reaches itself, but for nodes $i \notin N_k$, p_{iik}^n is 0 for all n by our convention. This is done because it was felt that nodes not appearing in both graphs should not add similarity increasing terms to the numerator for $i = j$. This coefficient is admittedly somewhat arbitrary. However, it does attempt to deal with the problem of comparing path structures and the order and sequencing of nodes. The coefficient is somewhat similar to one derived independently by Jackson for use in numerical taxonomy [8].

The following properties of S_p can be shown:

P1. If G_1 and G_2 are identical graphs, $S_p = 1$. If $\nu(S) = 0$, $S_p = 0$.

P2

$$S_p \leqq \{\nu(S) + l\nu(S)^2\}/\{t + l\nu(S)^2 + l(\nu(I_1) + \nu(I_2))\},$$

$$S_p \geqq (l + 1)\nu(S)/\{t + l(t^2 - 2\nu(I_1)\nu(I_2))\}.$$

Sketch of Proof of P2. First consider the upper bound. Because of the terms for

[3] It is not the purpose of this paper to present an extended discussion of this rationale. However, other bases for a coefficient could be developed. Coefficients based on the adjacency matrix itself could be considered, for example. It was decided that the present coefficient, although somewhat arbitrary, was less arbitrary than the alternatives.

$i = j$ we have at least $(1 + l)\nu(S)$ in the numerator and $(1 + l)t$ in the denominator. The best we can do from that point is to add ones to both the numerator and denominator simultaneously, *without* adding any ones only to the denominator. This yields an S_p of the form $\{(1 + l)\nu(S) + a_1\}/\{(1 + l)t + a_1\}$. It is clear we wish to make a_1 as large as possible. But we can only add terms to the numerator from S. Since we have already counted the terms from S where $i = j$, we can only add at most $\nu(S)^2 - \nu(S)$ terms from S for $n > 0$. Even this is not attainable. Adding $\nu(S)^2 - \nu(S)$ ones would mean all possible terms would be one for both graphs for $n < l$, and this would contradict the meaning of l, and hence be inadmissible. However, adding $\nu(S)^2 - \nu(S)$ ones will only serve to overstate the upper bound, not change the sense of inequality.[4] Thus, we would get

$$S_p \leqq \{(1 + l)\nu(S) + l\nu(S)^2 - l\nu(S)\}/\{(1 + l)t + l\nu(S)^2 - l\nu(S)\},$$

or

$$S_p \leqq \{\nu(S) + l\nu(S)^2\}/\{t + l\nu(S)^2 + l(\nu(I_1) + \nu(I_2))\}.$$

For the lower bound, since $p^n_{iik} = 1, \forall\, i \in S, n = 0, 1, \cdots, l$, the numerator must be $\geqq (l + 1)\nu(S)$. To make the denominator as large as possible, we would like to make all terms one. However, i, j pairs of the form $i \in I_1, j \in I_2$, and $j \in I_1, i \in I_2$ are zero for $k = 1$ and $k = 2$. The number of such pairs is $2\nu(I_1)\nu(I_2)$. Hence we have for $n = 0$ t ones, since $p^0_{ijk} = 0$ for $i \neq j$, and for $n = 1, \cdots, l$, at most $t^2 - 2\nu(I_1)\nu(I_2)$ ones in the denominator. Thus we must have

$$S_p \geqq (l + 1)\nu(S)/\{t + l(t^2 - 2\nu(I_1)\nu(I_2))\}.$$

If the two graphs have all their nodes in common, $\nu(S) = t$, and $\nu(I_1) = \nu(I_2) = 0$. We then obtain $(l + 1)/(lt + 1) \leqq S_p \leqq 1$.

A simple computational scheme for S_p can be motivated as follows. Suppose the distance between nodes $i, j \in S$ is given by d^1_{ij} and d^2_{ij} for G_1 and G_2 respectively. Then i reaches j in a path of length d^1_{ij} in G_1 and in a path of d^2_{ij} in G_2. Therefore, for $n \geqq \min\,[d^1_{ij}, d^2_{ij}]$, there will be a one in the denominator. For $n \geqq \max\,[d^1_{ij}, d^2_{ij}]$ there will be a one in the numerator of S_p. Since l is the maximum value of n, we can thus determine for each pair i, j how many ones will be in the numerator and denominator. If $d^k_{ij} = \infty$ for either graph, then there will be no ones in the numerator, but possibly ones in the denominator. Let us now briefly outline a procedure for computing S_p using these ideas. This procedure is exact for S_p as defined by Equation (1).

Step 1. For G_1 and G_2 compute the distance matrices D_1 and D_2 for the node sets N_1 and N_2 respectively, using powers of the adjacency matrix as mentioned earlier in Result 2.

Step 2. Form the matrices δ_{ijk}, $i, j = 1, \cdots, t; k = 1, 2$ by using the following conventions:

$$\delta_{ijk} = d^k_{ij} \quad \text{if} \quad i, j \in N_k,$$

$$\delta_{ijk} = \infty \quad \text{if} \quad i, j \notin N_k.$$

Step 3. Form the sums

$$\text{Num} = \textstyle\sum_{i=1}^{t} \sum_{j=1}^{t} \{l + 1 - \max\,(\delta_{ij1}, \delta_{ij2})\},$$

[4] Note that the expression below will always be a strict inequality unless $l = 1$ or $\nu(S) = 1$ due to this overstatement.

N No
Y Yes
A Accept
R Reject

FIGURE 1. Example graphs

TABLE 1
Calculations for Example

Undirected Distance Matrix for Both Graphs	δ_{ij1}	δ_{ij2}
$\begin{array}{c} \\ 1 \\ 2 \\ 3 \\ 4 \end{array}\begin{array}{c} \begin{array}{cccc} 1 & 2 & 3 & 4 \end{array} \\ \begin{bmatrix} 0 & 1 & 2 & 3 \\ 1 & 0 & 1 & 2 \\ 2 & 1 & 0 & 1 \\ 3 & 2 & 1 & 0 \end{bmatrix} \end{array}$	$\begin{array}{c} \\ 1 \\ 2 \\ 3 \\ 4 \end{array}\begin{array}{c} \begin{array}{cccc} 1 & 2 & 3 & 4 \end{array} \\ \begin{bmatrix} 0 & 1 & 2 & 3 \\ \infty & 0 & 1 & 2 \\ \infty & \infty & 0 & 1 \\ \infty & \infty & \infty & 0 \end{bmatrix} \end{array}$	$\begin{array}{c} \\ 1 \\ 2 \\ 3 \\ 4 \end{array}\begin{array}{c} \begin{array}{cccc} 1 & 2 & 3 & 4 \end{array} \\ \begin{bmatrix} 0 & \infty & \infty & \infty \\ 1 & 0 & \infty & \infty \\ 2 & 1 & 0 & \infty \\ 3 & 2 & 1 & 0 \end{bmatrix} \end{array}$
$S_u = 1$	$l = 3$	

$\text{Num} = 4 + 4 + 4 + 4 = 16$

$\text{Den} = 4 + 3 + 2 + 1 + 3 + 4 + 3 + 2 + 2 + 3 + 4 + 3 + 1 + 2 + 3 + 4 = 44$

$S_p = 16/44 = 0.364$

$\text{Lower Bound} = 4.(3 \cdot 4 + 1) = 4/13 = 0.308$

where if δ_{ij1} or $\delta_{ij2} = \infty$, $l + 1 - \max\ (\delta_{ij1}, \delta_{ij2}) = 0$.

$$\text{Den} = \sum_{i=1}^{t} \sum_{j=1}^{t} \{l + 1 - \min\ (\delta_{ij1}, \delta_{ij2})\},$$

where if $\delta_{ij1} = \delta_{ij2} = \infty$, $l + 1 - \min\ (\delta_{ij1}, \delta_{ij2}) = 0$.

Step 4. $S_p = \text{Num/Den}$.

An Undirected Distance Coefficient

A second possible method would be the following: suppose that process similarity might be measured by how far apart cues are in one process compared to how far apart they are in a second process. To determine how far apart the cues are, however, we might use an undirected distance rather than a directed distance. An undirected distance is simply the distance between nodes obtained when arc directions are eliminated. The reason for using undirected distance is that if neither i reaches j nor j reaches i, the directed distances d_{ij} and d_{ji} are ∞. However, the undirected distance between i and j is only ∞ if i and j are in disconnected subgraphs.

Let $U^k = [u_{ij}^k]$ be the matrix of undirected distances for graph G_k. Also, we assume that graphs G_1 and G_2 have the same node set, i.e., $N_1 = N_2 = S$. Then an undirected distance coefficient S_u could be defined as follows: Let

$$\mu_1 = \{u^1_{21}, u^1_{31}, u^1_{32}, \cdots, u^1_{t,t-1}\}$$
$$\mu_2 = \{u^2_{21}, u^2_{31}, u^2_{32}, \cdots, u^2_{t,\,t-1}\},$$

where $t = \nu(S)$. Thus these vectors are the lower triangular portions of the undirected distance matrices. Now if $r(x, y)$ is the product moment correlation coefficient between x and y, define S_u by

$$S_u = r(\mu_1, \mu_2). \tag{2}$$

This is similar to the ideas in [16].

Let us examine this coefficient on a hypothetical example. Consider G_1 and G_2 as shown in Figure 1. The calculations are shown in Table 1. Although the order of the cues is totally reversed, since the u_{ij} are identical for both graphs, $S_u = 1$. If we calculate S_p, we obtain $S_p = 0.364$. We see that this is fairly close to the lower bound for S_p in this situation. Thus, the undirected distance coefficient does not mirror ordering properties of the process and S_p does. Is this reasonable?

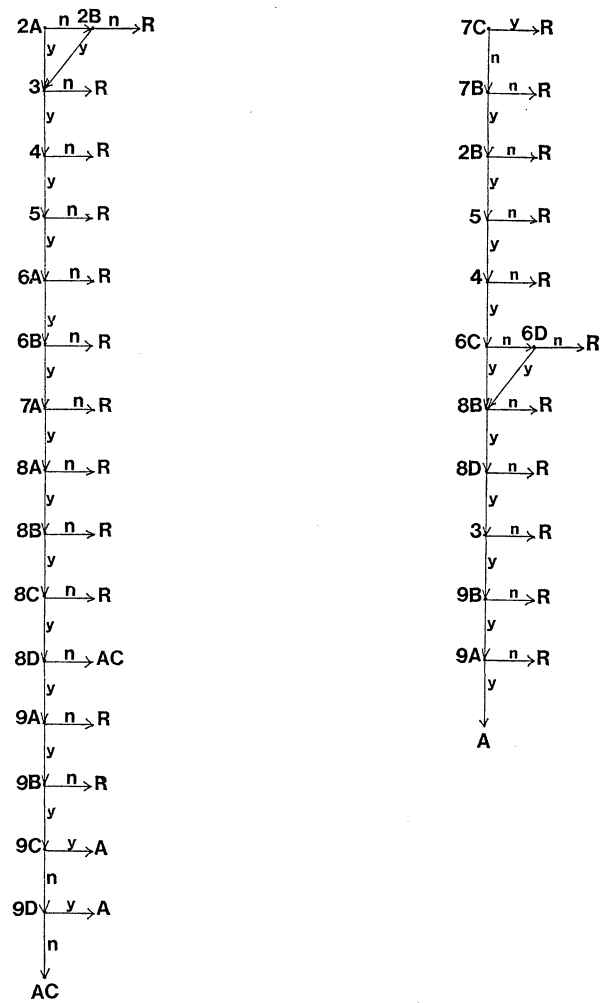
Graphs of the type shown in Figure 1 represent conjunctive satisficing decision processes. Only if all cues are satisfactory is an accept decision made. Given acceptable levels for each cue, *all* conjunctive satisficing processes using the same cue set have the same output. However, one of the basic tenets of information processing models is an interest in depicting the process structure. Hence, it would seem that the conjunctive satisficing models should have different similarity coefficients depending upon cue order, including the case of reversed cue order. Therefore, the coefficient based on path structure, since it explicitly takes into account the order of cues and also whether or not cues are on the same branches of a graph, is preferable. Also, the path coefficient has an advantage in being applicable when processes do not use the same cues, as will generally be the case. In the empirical results we will therefore concentrate on the path coefficient, S_p.

Empirical Results

In this section the path coefficient is applied to several sets of information processing models of buying behavior. First the coefficient will be applied to models developed by Alexis, Haines, and Simon and by Clarkson [1], [4], [5]. Second, models developed by Russ will be analyzed [13].

The Alexis, Haines, and Simon Models

Alexis, Haines, and Simon developed models of two consumers' shopping rules for raincoats [5] and of two consumers' shopping rules for women's clothing [1]. These models are given in Figures 2 and 3 respectively. A first analysis was run to see whether cues used by both the individuals modeled had similar path structure relations when the cues idiosyncratic to each individual were ignored. For example, for the raincoat decision, both Subjects A and C used cues 2B, 3, 4, 5, 8B, 8D, 9A, and 9B. The second analysis collapsed nodes such as 8A, 8B, 8C, and 8D in the raincoat models into one node, 8, having to do with proper fit. The processes resulting from this node collapsing were then compared (for example, the order of nodes in the collapsed raincoat process for subject C is 7, 2, 5, 4, 6, 8, 3, 9). Finally, the entire processes, with all nodes included, were compared. The results are shown in Table 2. We will now interpret these results.



Subject A Subject C

FIGURE 2. Raincoat shopping decision models: Alexis, Haines and Simon. (Adapted from Haines, G., "Information and Consumer Behavior," Working Paper, University of Rochester, College of Business Administration, July 1969, pp. 7–1.)

KEY TO FIGURE 2

A	Accept
R	Reject
AC	Accept Conditionally
n	No
y	Yes

2. Is it desired brand:
   (A) London Fog?
   (B) Misty Harbor?
3. Is it lined?
4. Is my size available?
5. Is it within the desired price range?
6. Style:
   (A) Does it not have "football" shoulders?
   (B) Is it A-line or straight?

Since it is unclear how one should interpret S_p in absolute terms, we will make relative comparisons in our analysis. Note that for both of the Alexis, Haines, and Simon models the commonly used cues are used in much the same manner in both the raincoat and shopping models. Also, in both cases, the entire process similarities are low, mainly because different cues are used. Comparing the results for the collapsed processes with those for the entire processes yields interesting insights. For the raincoat decision, these results imply that much of the dissimilarity in process may be due to details in the general cue categories, but that the general structure of the processes is reasonably similar for the two individuals. That is, details in color or style preferences vary, but the general cues of color and style are used similarly. For the clothing decision, this is much less true. The raincoat models seem to be more similar than the two clothing decision models. It is the above type of micro-analysis of information processing model structure that the path coefficient makes possible. Such quantitative analysis must be undertaken if full insight into decision process structure is desired.

The Clarkson Model

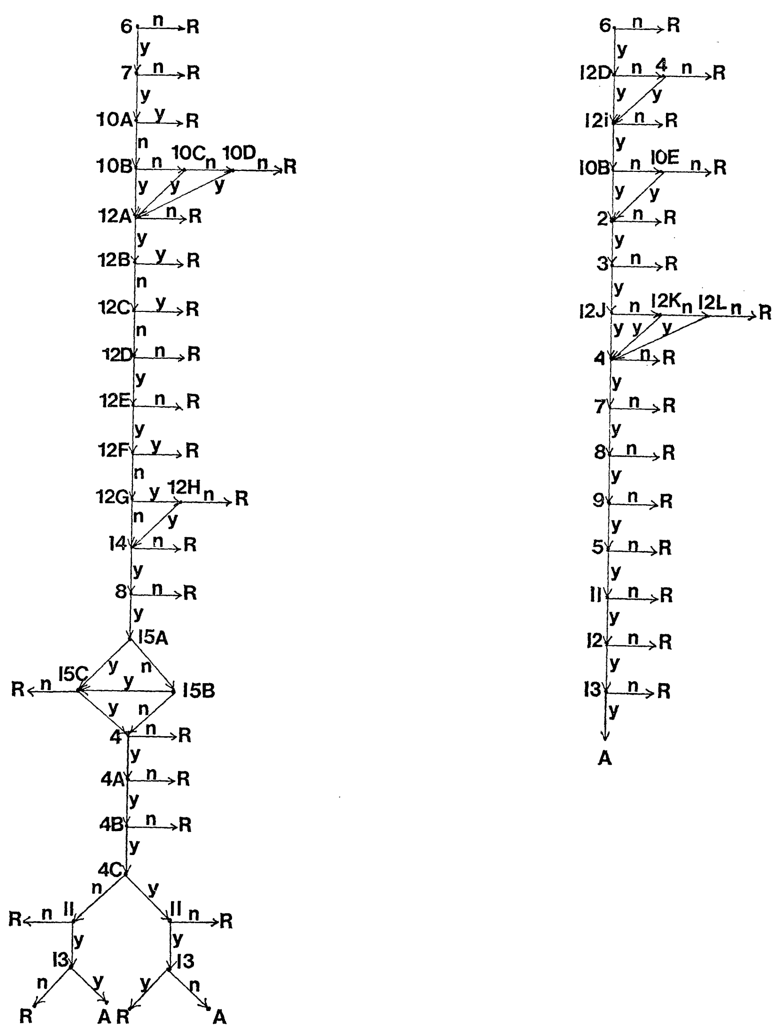
Clarkson built a model of stock selection by a trust investment officer [4]. Separate discrimination net models were built for yield portfolios and for growth portfolios. These models are given in Figures 4 and 5. These models were compared in the following manner. Since each model had two branches, one negative and one positive regarding a stock, and since cues could be used in both branches, cues were labeled to denote branch location. Thus there were two cues T_6 used for the yield model analysis: T_6^N and T_6^P for the negative and positive branches. The corresponding cues for the growth model were T_3^N and T_3^P. The reason for labeling was so that comparisons for cues used by both models would be well defined for these multiple cue occurrences. In the entire process comparison, because of the size of the model, only the negative branches were compared. The results are given in Table 2.

These results are most interesting. The cues used by both models are used extremely similarly. The entire process similiarity is low because of different cues being used.

These results show how insights into information processing model structure that are not obvious from mere presentation of the models can be obtained by using the path structure coefficient. The real value of this approach is in setting up a *formal framework* for analyzing the models, rather than relying on casual inspection. The insights gained would probably never be sought without such a formal technique.

(C) Turndown dollar?
(D) Mandarin collar?

7. Color:
   (A) Is it dark blue, black, or beige?
   (B) Is it blue or peacock (blue with some green in it)?
   (C) Is it orange?
8. Fit:
   (A) Is it not tight under arms and without pull across back?
   (B) Are sleeves right length?
   (C) Does it fit correctly without the lining?
   (D) Is the length correct?
9. Practicality:
   (A) Is it easy to care for?
   (B) Can it be worn with most of my clothes?
   (C) Is a less expensive lining unavailable?
   (D) Is the more expensive lining worth the difference?



Subject A Subject B

FIGURE 3. Women's clothing shopping decision models: Alexis, Haines and Simon. (Adapted from Alexis, M. Haines, G. and Simon, L., "Consumer Information Processing: The Case of Women's Clothing," American Marketing Association Proceedings, *Marketing and the New Science of Planning*, Series 28, 1968, pp. 201–204.)

KEY TO FIGURE 3

A	Accept
R	Reject
n	No
y	Yes

2. Do I need this type of item?

3. Do I have this type of item, color included, already in my wardrobe?

4. Is the item practical—in style, in fabric—i.e., will it be comfortable to wear and easy to care for?

(A) Is it a dress I could not make?

(B) Is it well made?

(C) Can I wear it in many situations?

5. Is the item on sale?

TABLE 2

Results for Alexis, Haines, Simon and Clarkson Models

	Alexis, Haines, Simon Raincoat Decision	Alexis, Haines, Simon Clothing Dceision	Clarkson
Same Nodes	0.554	0.537	0.828
Collapsed Process	0.473	0.210	—
Entire Process	0.150	0.060	0.158
Lower Bound for Entire Process	0.024	0.010	0.024
Upper Bound for Entire Process	0.834	0.711	0.715

Russ' Models

The models analyzed above were only for single pairs of individuals, modeled at one point in time. Russ developed models for twenty subjects in an experimental choice situation for small durable goods (frying pans, electric coffeemakers, irons, portable radios, and table and clock radios) [13]. The models were also developed for the same individuals at two points in time. Thus, the Russ data provide an opportunity to look at two further types of questions: stability of process over time for the same individuals and comparing several different subjects. These results are given in Tables 3 and 4.

The stability results have to be interpreted with some caution, because the set of alternatives available differed somewhat between experimental sessions. In spite of this difference, the coefficients remain reasonably high. However, the models are fairly simple models, so there can be no firm conclusion drawn about choice process invari-

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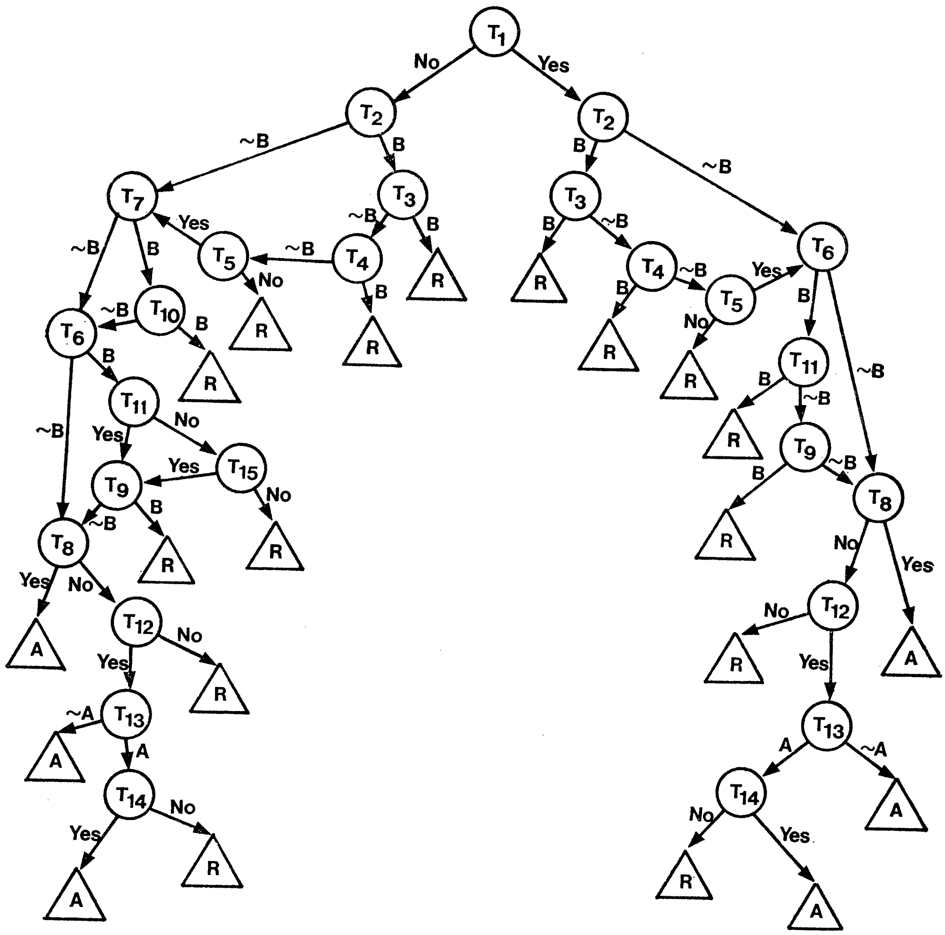
6. Is my size available?
7. Is the item within the price range I can afford?
8. Does the item fit in hips, thighs, rear, and at the waist?
9. Does the item fit at the neckline, shoulders, and bustline?
10. Color
    (A) Is it black?
    (B) Is it yellow or blue?
    (C) Is it red with white flowers?
    (D) Are the colors not too bright?
    (E) Green, cranberry, or butterscotch print?
11. Is the item worth the price?
12. Do I like the item in general?
    (A) Does it have large, rounded, glossy buttons?
    (B) Does it have short cap sleeves?
    (C) Is it a shirtwaist, or does it accent the waist?
    (D) Does it have long sleeves?
    (E) Is it youthful and/or innocent and demure?
    (F) Is the skirt straight?
    (G) Is the skirt pleated?
    (H) Is it not polka dot or clashing patterns?
    (I) Round or roll (Cowl) collar?
    (J) Cotton or synthetic mixture?
    (K) Cotton pique?
    (L) Arnel knit?
13. Do I like it better than other dresses considered?
14. Is it a known and favored brand?
15. Length
    (A) Is it too long?
    (B) Is it too short?
    (C) Can the length be easily adjusted?

Yield portfolios
discrimination net



Dictionary
Yield portfolios
discrimination net

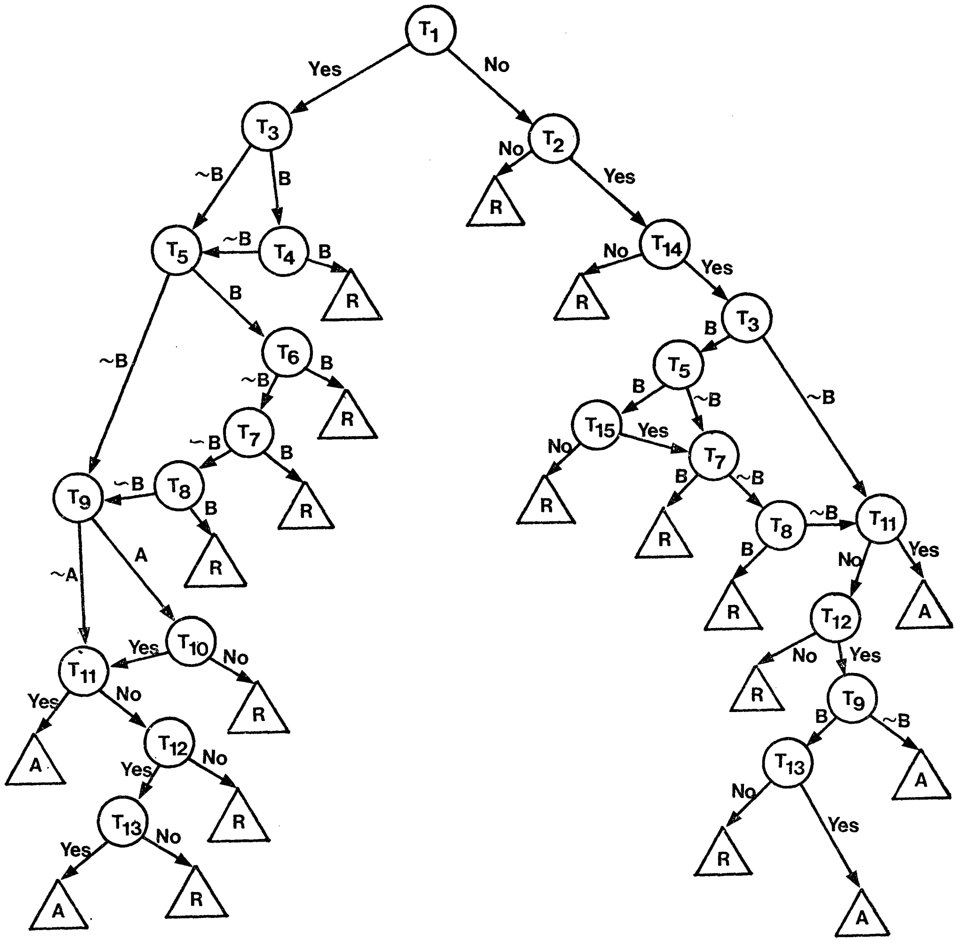
T_1—Defensive characteristics
T_2—Dividend yield ≧4%
T_3—Dividend yield ≧3.5%
T_4—Mean yield (past)
T_5—Have we selected a stock with ≧4%
T_6—Mean growth in earnings per share
T_7—Stability of earnings

B—"Below"
~B—"Not below"
A—"Above"
~A—"Not above"

T_8—Is forecasted dividend >0
T_9—Mean growth in working capital
T_{10}—Stability of dividend
T_{11}—Are forecasted earnings >0
T_{12}—Is forecasted dividend = 0
T_{13}—(*y*) on Relative Value List
T_{14}—Is price >10% below high
T_{15}—Is industry depressed-marked "hold"
△A—Accept
△R—Reject

FIGURE 4. Clarkson's yield portfolio stock selection model. (Clarkson, G., *Portfolio Selection: A Simulation of Trust Investment*, Prentice-Hall, 1962, p. 110.)

Growth portfolios
discrimination net



Dictionary
Growth portfolios
discrimination net

T_1—Mean growth in price $\geqq 20\%$

T_2—Mean growth in price $\geqq 10\%$

T_3—Mean growth in earnings per share

T_4—Mean growth in sales

T_5—Forecasted growth in earnings (1 yr)

T_6—Forecasted growth in sales (1 yr)

T_7—Mean growth in cash flow per share

T_8—Mean growth in profit margin

T_9—(y) on Relative Value List

T_{10}—is $P/E^* < \left(\frac{\bar{P}}{E}\right)$ by 10%

T_{11}—Is forecasted dividend >0

T_{12}—Is forcasted dividend $= 0$

T_{13}—Is price $>10\%$ below high

T_{14}—Is dividend yield $\geqq 2\%$

T_{15}—Is industry depressed marked "hold"

B—"Below" A—"Above" A—Accept

$\sim B$—"Not below" $\sim A$—"Not Above" R—Reject

FIGURE 5. Clarkson's growth portfolio stock selection model. (Clarkson, G., *Portfolio Selection: A Simulation of Trust Investment*, Prentice-Hall, 1962, p. 111.)

TABLE 3

Stability Results for Russ' Models

	S_p
Frying Pans	0.300
Electric Coffeemakers	0.600
Irons	0.469
Portable Radios	0.557
Table and Clock Radios	0.421
Mean S_p over all subjects	0.466

TABLE 4

Russ' Models: Across-Subject Comparisions: S_p Values

Electric Frying Pan

	1	2	3	7	8	11	13	17
1	1	1	0.33	0	0.071	0.108	0	0.395
2		1	0.33	0	0.071	0.108	0	0.395
3			1	0	0.2	0.108	0	0.429
7				1	0.133	0	0	0
8					1	0.108	0	0.2
11						1	0.25	0.108
13							1	0
17								1

Mean $S_v = 0.155$

Table and Clock Radios

	1	6	8	9	10	11	12	15	19
1	1	0.12	0.33	0.12	0.12	0.087	0.12	0.091	0.22
6		1	0.12	0.33	0.33	0.087	0.4	0.091	0.087
8			1	0.12	0.4	0.087	0.33	0.091	0.087
9				1	0.33	0.22	0.12	0.241	0.087
10					1	0.087	0.33	0.091	0.087
11						1	0.087	0.906	0.224
12							1	0.091	0.087
15								1	0.216
19									1

Mean $S_p = 0.189$

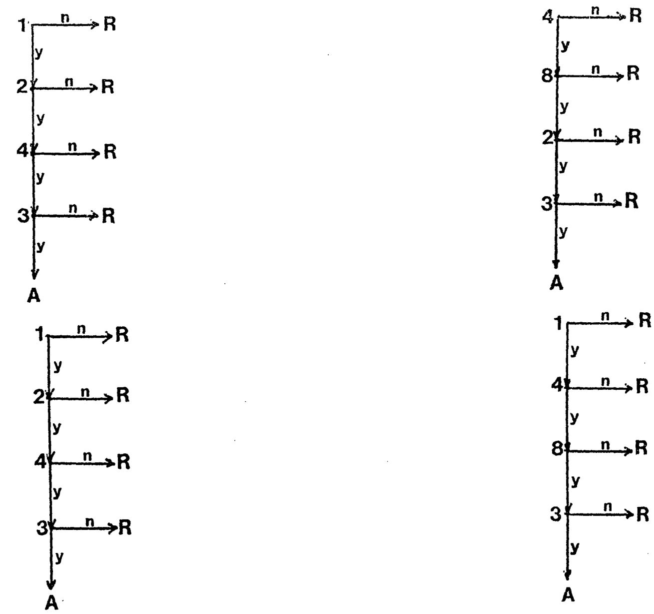
ance. The present method offers an intriguing research tool in this area, however. If subjects are modeled over time using the same alternative sets, S_p can be computed. Then the subjects could be given different alternative sets, and changes in S_p due to variations in alternative sets could be studied. This change in process due to changed alternative set structure has not been investigated to date, although it appears to be a fertile research area.

All twenty of Russ' subjects did not participate in the same small durables decisions. At most nine subjects were modeled for any durable. For those subjects who were modeled for the same durable, pairwise S_p coefficients were computed for the second choice session. Table 4 shows typical results, for electric frying pans and table and clock radios. The average across-subject coefficients for these matrices are small compared to the average same subject, across time coefficients, as would be expected.

Building Consumer Decision Process Typologies

One of the original purposes of developing a path structure coefficient was to aid in building process-oriented typologies. The results developed for the Russ models show both the problem and prosects. The matrix of inter-individual similarity coefficients can be used as inputs to a cluster analysis to define groups. As shown in Table 4 there are great idiosyncracies in process. Thus the resulting clusters are not tremendously homogeneous. However, some reasonable results appear for electric frying pans. Subjects 1, 2, 3, and 17 have somewhat similar processes. Their processes are shown in Figure 6. Hopefully, the approach of computing similarity coefficients and clustering could yield generalizable results for larger samples of consumers. The ultimate goal is to discover systematic individual differences and infer more general information processing models from the idiosyncratic individual models used as data points.

The methodology proposed in this study is certainly only a start in this area, and



Subject 1   Subject 3
Subject 2   Subject 17

FIGURE 6. Russ' electric frying pan decision models.

KEY TO FIGURE 6

A Accept
R Reject
n No
y Yes

1. Is size satisfactory?
2. Does it have a Cook Guide?
3. Cheapest satisfactory alternative?
4. Does it have teflon?
8. Is style satisfactory?

there are many problems to be solved. One major problem is that one must have models of many individuals to cluster. However, building information processing models is a very tedious and time-consuming process. Some methods for formalizing inference from protocols have been proposed [11], but as yet no real breakthroughs have occurred. A second problem is that coefficients based on graphs of different sizes may not be strictly comparable. Adjustments based on lower bounds of the coefficients and other possible techniques must be investigated.[5] Third, for large graphs (e.g., those found in [2]), the computation becomes time consuming. Finally many other types of similarity measures could be tried. The measure proposed in this paper deals mostly with order and sequence. One might wish to consider complexity, pure structure of the net, or many other possible measures.

[5] One possible technique would be to define the set of all distinct cues used by the entire group of individuals, and compute all coefficients between pairs of individuals with respect to this set of cues.

Conclusions

The major conclusion of this study is that it is possible to develop analytical techniques for investigating information processing models. Such analysis is necessary to understand and try to systematize to some extent the complexity involved. Without such systematic approaches, progress in information processing model interpretation is apt to be very slow. By defining a path structure coefficient, this study has attempted to show how some insights into process models can be obtained. Also, since the ultimate goal of building idiosyncratic models is to eventually build a general model, steps for approaching this objective were outlined.

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