SOME APPLICATIONS OF MULTIDIMENSIONAL SCALING TO SOCIAL SCIENCE PROBLEMS

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This chapter deals with three interrelated topics: (a) applications of multidimensional scaling to social science problems, (b) problems in applications of multidimensional scaling, and (c) problems in application of multidimensional scaling to social science problems.

Multidimensional scaling refers here to the analysis of judged similarity data (individual or aggregate) by techniques that attempt to represent these data by a spatial configuration. Respondents' judgments of similarity or dissimilarity between pairs of items can be obtained by (a) having each respondent rate or rank all pairs of items by degree of intrapair similarity, (b) having each respondent rate or rank some pairs and aggregating these individual data into an overall set which yields a rating or ranking of all pairs, or (c) having the respondents sort items into groups on the basis of similarity and aggregating these data into an overall similarity measure for the group. The respondent is not told on what basis to judge similarity, for

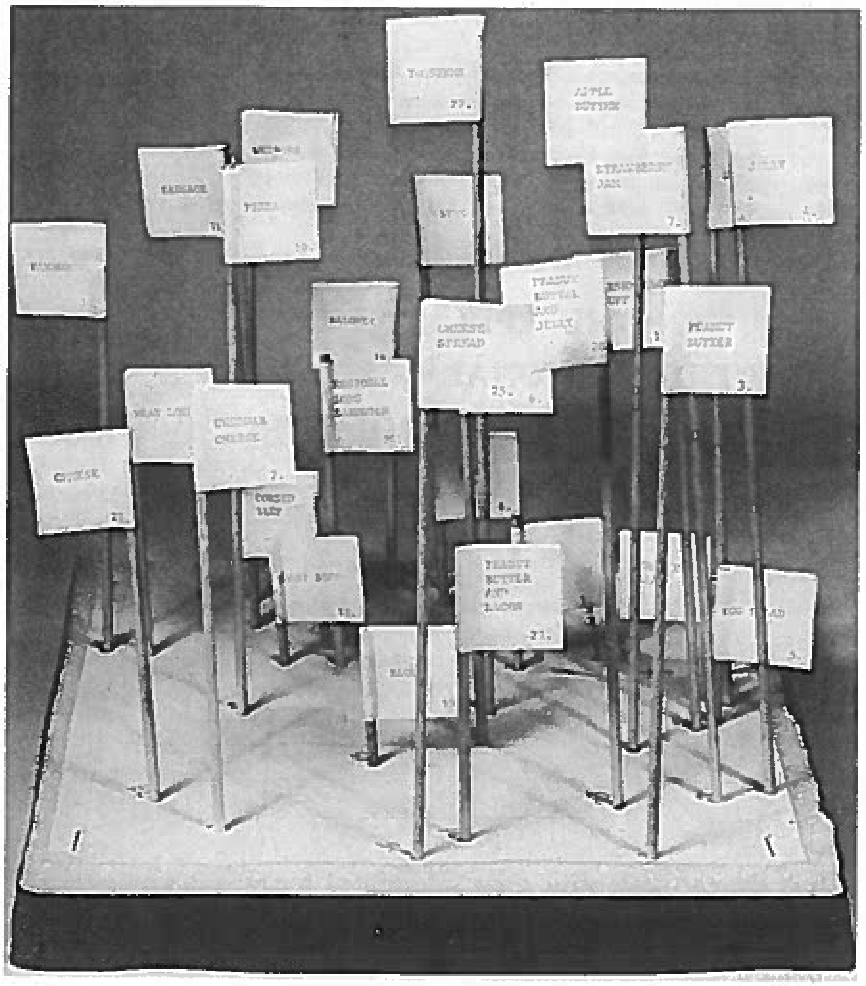


Fig. 1. Spatial representation of judged similarity of sandwiches.

the judgments are elicited in order to determine this basis. These individual or aggregate data on judged similarities are then subjected to a kind of analysis which uses a metric space representation in which the reverse rank ordering of distances between items corresponds to the rank ordering of similarities.

There are many other kinds of data of interest to social scientists in addition to similarity data as well as many other possible ways to analyze

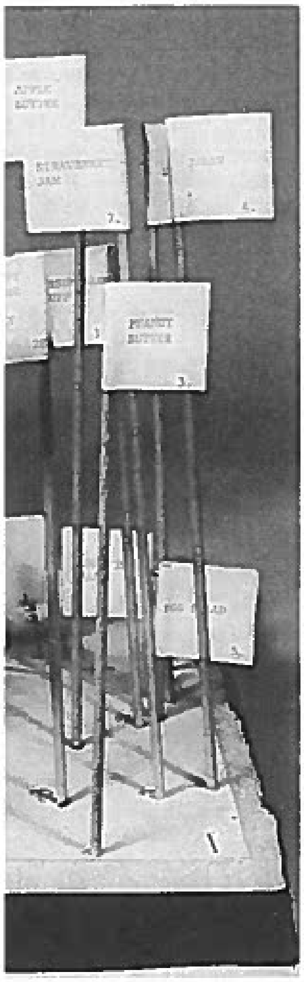
COORDINAT

	Dim
No.	*X*
1	13.21
2	1.85
3	0
4	4.30
5	9.33
6	18.42
7	3.94
8	7.38
9	16.57
10	9.93
11	10.97
12	13.53
13	6.29
14	14.30
15	18.75
16	14.56
17	8.96
18	10.52
19	20.04
20	19.99
21	1.18
22	15.75
23	3.88
24	13.52
25	0.06
26	7.99
27	9.92
28	3.44

similarity data beside mult
ations will be given to other
scaling analysis and also to s
data which may increase th
forms of behavior.

For over ten years most
has been spent pursuing the

1. An individual will beh
to him.



arity of sandwiches.

ne this basis. These indi-
s are then subjected to a
sentation in which the re-
s corresponds to the rank

est to social scientists in
r possible ways to analyze

TABLE 1

COORDINATE VALUES FOR SANDWICH DATA

No.	Dimensions X	Dimensions Y	Dimensions Z	Sandwich
1	13.21	7.38	2.25	Chicken
2	1.85	16.10	10.54	Cheddar cheese
3	0	4.25	14.05	Peanut butter
4	4.30	0.70	17.66	Jelly
5	9.33	1.71	2.52	Egg salad
6	18.42	9.55	3.17	Ham
7	3.94	2.27	17.78	Strawberry Jam
8	7.38	4.45	18.42	Apple butter
9	16.57	15.58	14.89	Weiners
10	9.93	15.76	15.41	Pizza
11	10.97	1.76	2.41	Tuna fish salad
12	13.53	14.65	1.61	Roast Beef
13	6.29	11.97	1.56	Bacon
14	14.30	18.98	6.73	Meat Loaf
15	18.75	15.81	13.16	Sausage
16	14.56	20.31	11.62	Hamburger
17	8.96	2.27	12.73	Marshmallow fluff
18	10.52	1.23	15.83	Honey
19	20.04	11.25	7.79	Baloney
20	19.99	9.60	11.78	Spam
21	1.18	9.37	6.12	Peanut butter and bacon
22	15.75	13.36	3.00	Corned beef
23	3.88	18.02	8.67	Cheese
24	13.52	12.80	7.78	Regional long sandwich
25	0.06	10.87	13.75	Cheese spread
26	7.99	8.69	10.86	Hamburger and cheese
27	9.92	8.47	19.10	Toastems
28	3.44	5.01	13.77	Peanut butter and jelly

similarity data beside multidimensional scaling analysis. Here considerations will be given to other kinds of data well suited to multidimensional scaling analysis and also to some alternative modes of analysis of similarity data which may increase the usefulness of these data for predicting other forms of behavior.

For over ten years most of the author's research and intellectual effort has been spent pursuing the implications of several banal propositions:

1. An individual will behave similarly toward things which seem similar to him.

2. If a new item is introduced into an individual's culture, the individual will behave toward it in a manner similar to the way he behaves toward familiar items that he sees as similar to the new item.

3. The close relationship between what is psychologically similar for the individual and which things are behaved towards similarly by that individual holds across individuals and across cultures despite the wide variation between individuals and cultures as to which objects are seen as similar and in how the objects or situations are behaved towards (Stefflre, 1965, 1968, ms., a).

One way of trying to determine what an individual sees as similar to what is to ask him. By aggregating these data, one may try to determine what is similar to what for members of a particular culture. Figure 1 and Table 1 provide an example of aggregate judged similarity data on different kinds of sandwiches. For this type of study, 50 respondents are asked which is similar to what. Their data are aggregated, normalized, and transformed into a physical model using multidimensional scaling (Kruskal, 1964a,b). This kind of data stabilizes with fairly small samples of respondents ($N = 30$–60). To test reliabilities, the respondents are assigned numbers arbitrarily and divided into two groups. When dealing with a sample of 50, item–item similarity is calculated separately for the 25 odd-numbered and the 25 even-numbered respondents. For the last five sets of similarity data we collected, the split-half reliabilities, i.e., the correlations between the even-numbered and the odd-numbered groups, were .75, .60, .85, .80, and .77. Following the Spearman–Brown formula (e.g., see Gulliksen, 1950, Ch. 6), these figures suggest that the reliability of the data for the total groups ranged from .75 to .92.

Another way to try to learn which things are similar for an individual is to observe his behavior. Several interesting forms of aggregated data can be obtained from routine behavior patterns. These can be taken as indexes of the amount of behavioral similarity which various pairs of items elicit from members of the particular culture studied.

We have done a fair amount of work over the last few years on market research and new product development because of the availability of large scale data on patterns of individual behavior in this area and because of the opportunity for conducting large scale natural experiments through the development and introduction of new consumer products. In this context, as in many marketlike situations (see Stefflre, 1965), patterns of similarity can underly patterns of substitution and competition, i.e., objects substitute for each other or compete with each other in a single choice situation to the extent that they are seen as similar.

Several types of indexes for product–product substitution have been developed: Item-by-use matrices, patterns of preference data, and substitution patterns.

Items with the Same Uses

Table 2 shows item-by-use data for one individual. Tables 3 through 7 show the stages in the rearrangement of this matrix into clumps according to distributional similarity. Table 8 shows a 34-person aggregate data matrix rearranged into clumps according to distributional similarity.

Table 2 is the data matrix for an individual in which each row is a kind of medicine and each column is a belief-frame about when to use medicines. The informant substituted each medicine into each frame, "You take (*kind of medicine*) when you (*condition of use*)," and indicated acceptability of the sentence thus formed by a *1*, unacceptability by a blank (equivalent to a zero). For example, "You take *Bufferin* when *you have a stuffy nose*" was judged unacceptable by the informant and so the position row 1, column 2, is blank.

Table 3 shows the results of the calculation of the similarity of each row to every other row in terms of the extent to which they exhibit the same patterns of ones. This procedure measures the extent to which two belief-frames allow the same form to be placed in them resulting in acceptable statements. If r_i is the row vector of 0's and 1's from the ith row, then the similarity between rows i and j is as follows:

$$s_{ij} = \frac{r_i r_j' + r_j r_i'}{r_i r_i' + r_j r_j'}$$

(where r' is the column vector obtained by transposing the row vector r).

Table 4 shows the row–row similarity of Table 3 rearranged so that the rows similar to each other are placed near each other.

Table 5 shows the results of the calculation of the similarity of each column to every other column in terms of the distributional similarity of the belief-frames that label the columns. If c_i is the column vector of zeros and ones for the ith column, then the similarity between columns i and j is as follows:

$$s_{ij} = \frac{c_i' c_j + c_j' c_i}{c_i' c_i + c_j' c_j}$$

Table 6 shows the column–column similarity of Table 5 rearranged so that columns similar to each other are near each other.

TABLE 2

MEDICINES AND WHEN TO TAKE THEM (DATA FOR ONE INDIVIDUAL

MEDICINES	ROW/COL	Bad taste in your mouth 1	Stuffy nose 2	Headache 3	Minor muscular aches 4	Tightness in your chest 5	The children have a fever 6	Can't breathe 7	In the winter 8	Sore throat 9	Hangover 10	Post-nasal drip 11	Cough 12	Indigestion 13	Feel weak 14	After you've been ill 15	During the flu season 16	Broken leg 17	The children are sick 18	Neuritis, neuralgia 19	Runny nose 20	Back ache 21
Bufferin	1			1			1		1	1	1			1		1	1		1	1	1	1
Sucrets	2	1							1	1			1									
Vicks inhaler	3		1					1	1			1					1				1	
F & F Cough drops	4	1				1			1	1		1	1				1					
Hot lemonade	5	1	1			1	1	1	1	1		1	1			1	1		1		1	
Dristan medicated room vaporizer	6		1			1		1	1			1	1								1	
Listerine throat lozenges	7	1							1	1		1	1				1					
Vicks cough drops	8	1				1			1	1		1	1				1					
Chloraseptic lozenges	9								1	1		1	1				1					
A hot toddy	10		1		1	1		1	1	1	1	1	1			1	1					1
Mentholatum	11		1		1	1		1	1				1								1	1
Seeing the doctor	12														1	1	1	1	1			1
Contac	13		1			1		1	1								1				1	
Adulton cough syrup	14					1			1			1	1								1	
Privine nasal spray	15		1					1	1												1	
Anacin	16			1			1	1	1	1	1	1		1		1	1		1	1	1	1
Ben-gay	17				1	1												1		1		1
Krex A.P.A. pain relievers	18				1				1	1		1							1	1		1
Vicks formula 44 cough discs	19					1			1			1	1									
Contac nasal mist	20		1					1	1												1	
Bromo seltzer	21													1								
Hot tea	22	1	1		1	1	1	1	1	1		1	1	1	1	1	1		1		1	1
Smith Brothers cough drops	23	1							1	1		1	1				1					
Spectrocin-T-troches	24	1							1	1		1	1				1					
Coricidin cold tablets	25					1	1		1	1		1				1	1				1	
Vicks vapo-rub	26				1	1	1	1	1			1	1								1	
Fruit juice	27	1					1		1	1	1				1	1	1		1			
Dristan nasal decongestant capsules	28		1					1	1												1	
An ice pack	29						1				1							1				1
Aspirin	30			1			1		1	1	1	1		1		1	1		1	1	1	1
Cough syrup	31					1			1			1	1									
Vitamins	32						1		1		1				1	1	1		1			
Ear drops	33																					
Alka seltzer	34										1			1								
Naso-dex	35		1					1	1										1		1	
Squibb analgesic tablets	36								1	1		1								1		
Vicks throat lozenges	37	1							1	1		1	1				1					
Neosynephrine nose drops	38		1					1	1												1	
Tetrazets antibacterial analgesic	39								1	1		1							1			
Neosynephrine nasal spray	40		1					1	1												1	
Privine nose drops	41		1					1	1												1	
Warm milk	42						1		1					1			1		1			
Murine eyedrops	43																					
Vicks sinex nasal spray	44		1					1	1												1	
Cepacol throat lozenges	45	1							1	1		1	1				1					
Romilar cough lozenges	46					1			1			1	1									
F & F Lozenges	47	1							1	1		1	1				1					
Empirin compound	48			1	1		1		1	1	1	1		1		1	1		1	1		1
Calling the doctor	49						1		1	1			1				1	1	1			1
Excedrin	50			1			1		1	1	1	1		1		1	1		1	1	1	1
A.P.C. Tablets	51						1		1	1		1		1		1	1		1	1		1
Salt water gargle	52								1	1	1	1	1									
	TOTAL	12	15	5	7	15	15	17	45	26	11	29	22	10	4	13	26	4	16	9	21	14

MEDICINES	ROW/COL	In the summer 22	Feel nauseated 23	Tonsils are inflamed 24	Down and out 25	Can't breathe 26	Earache 27	The children have colds 28	Hot and cold flashes 29	Taken a chill 30	Swollen glands 31
Bufferin	1			1			1	1	1	1	1
Sucrets	2			1				1			1
Vicks inhaler	3					1		1			
F & F Cough drops	4			1				1			1
Hot lemonade	5			1	1	1		1	1	1	1
Dristan medicated room vaporizer	6					1		1			
Listerine throat lozenges	7			1				1			1
Vicks cough drops	8			1				1			1
Chloraseptic lozenges	9			1				1			1
A hot toddy	10			1	1		1		1	1	1
Mentholatum	11					1		1			
Seeing the doctor	12		1	1			1	1	1	1	1
Contac	13					1		1			
Adulton cough syrup	14										
Privine nasal spray	15					1					
Anacin	16			1			1	1	1	1	1
Ben-gay	17	1									
Krex A.P.A. pain relievers	18			1				1			1
Vicks formula 44 cough discs	19							1			
Contac nasal mist	20					1					
Bromo seltzer	21				1						
Hot tea	22		1	1	1	1	1	1	1	1	1
Smith Brothers cough drops	23			1				1			1
Spectrocin-T-troches	24			1				1			1
Coricidin cold tablets	25							1	1	1	
Vicks vapo-rub	26							1			
Fruit juice	27	1		1				1		1	1
Dristan nasal decongestant capsules	28					1		1			
An ice pack	29	1							1		
Aspirin	30			1			1	1	1	1	1
Cough syrup	31							1			
Vitamins	32	1		1				1		1	1
Ear drops	33	1					1				
Alka seltzer	34										
Naso-dex	35					1		1			
Squibb analgesic tablets	36			1				1			1
Vicks throat lozenges	37			1				1			1
Neosynephrine nose drops	38					1					
Tetrazets antibacterial analgesic	39			1				1			1
Neosynephrine nasal spray	40					1					
Privine nose drops	41					1					
Warm milk	42		1					1	1	1	
Murine eyedrops	43	1									
Vicks sinex nasal spray	44					1					
Cepacol throat lozenges	45			1				1			1
Romilar cough lozenges	46			1				1			1
F & F Lozenges	47			1				1			1
Empirin compound	48			1			1	1	1	1	1
Calling the doctor	49		1	1			1	1	1	1	1
Excedrin	50			1			1	1	1	1	1
A.P.C. Tablets	51			1			1	1		1	1
Salt water gargle	52			1							1
	TOTAL	6	4	28	4	14	11	37	13	15	28

TABLE 2

…es and When to Take Them (Data for One Individual)

Column	Heading	Column total
10	[illegible]	11
11	Post-nasal drip	29
12	Cough	22
13	Indigestion	10
14	Feel weak	4
15	After you've been ill	13
16	During the flu season	24
17	Broken leg	4
18	The children are sick	16
19	Neuritis, neuralgia	9
20	Runny nose	21
21	Back ache	14
22	In the summer	6
23	Feel nauseated	4
24	Tonsils are inflamed	28
25	Down and out	4
26	Can't breathe	14
27	Earache	11
28	The children have colds	37
29	Hot and cold flashes	13
30	Taken a chill	15
31	Swollen glands	28
32	Cold	46
33	Stomach ache	4
34	Stuffy head	15
35	Sinus trouble	15
36	Bursitis	13
37	Nervous	11
38	Hay fever	23
39	Upset stomach	2
40	Fever	14
41	The children are overtired	7
42	You are cold	12
43	Going to be ill	14
44	Wet and tired	14
45	Girl (boy) friend has a cold	10
46	Asthma	30
47	Laryngitis	32
48	Overtired	5
49	Sore mouth	15
50	The children are cranky	28
51	Heart burn	10
52	Feel a little dizzy	5
TOTAL		823

Row	TOTAL
1	31
2	11
3	12
4	15
5	36
6	15
7	14
8	15
9	13
10	10
11	15
12	22
13	13
14	7
15	4
16	33
17	8
18	15
19	10
20	9
21	4
22	43
23	14
24	14
25	18
26	13
27	23
28	10
29	7
30	33
31	9
32	20
33	4
34	5
35	10
36	13
37	13
38	9
39	12
40	9
41	8
42	19
43	3
44	9
45	14
46	12
47	14
48	33
49	24
50	33
51	29
52	10
Total	823

TABLE

Row–Row Similarity Matrix of Medicines

Row/Row	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]

TABLE

Rearranged Row–Row Similarity Matrix of

[illegible]

TABLE

...milarity Matrix of Medicines

16	17	18	19	20	21	22	23	24	25
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]

TABLE

Row–Row Similarity Matrix of

[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]

3

Based on When Used (Individual Data)

26	27	28	29	30	31	32	33	34	35	36	37	38	39	40	41	42	43	44	45	46	47	48	49	50	51	52
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]

4

Medicines Based on When Used (Individual Data)

[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]

TABLE 5

COLUMN–COLUMN SIMILARITY MATRIX OF MEDICINE USES (INDIVI…

TABLE 6

REARRANGED COLUMN–COLUMN SIMILARITY MATRIX OF MEDICINE U…

TABLE 5

-Column Similarity Matrix of Medicine Uses (Individual Data)

TABLE 6

Column–Column Similarity Matrix of Medicine Uses (Individual Data)

TABLE 7

REARRANGEMENT OF ORIGINAL DATA MATRIX (MEDICINES AND MEDICINE USE FRAMES) ON BASIS OF F

	ROW/COL	In the summer	Broken leg	Feel weak	Over-tired	Down and out	Feel a little dizzy	Feel nauseated	Stomach ache	Upset stomach	Minor muscular aches	Hangover	Earache	Hot and cold flashes	The children are sick	Fever	Wet and tired	The children have a fever	Taken a chill	After you've been ill	Going to be ill
		22	17	14	48	25	52	23	33	39	4	10	27	29	18	40	44	6	30	15	43
Bromo seltzer	21					1															
Alka seltzer	34											1									1
Contac	13																				
Vicks Sinex nasal spray	44																				
Privine nose drops	41																				
Neosynephrine nasal spray	40																				
Neosynephrine nose drops	38																				
Contac nasal mist	20																				
Privine nasal spray	15																				
Naso-dex	35																				
Dristan nasal decongestant capsules	28																				
Vicks inhaler	3																				
Dristan medicated room vaporizer	6																1				
Mentholatum	11										1										
Vicks vapo-rub	26										1							1			
Adulton cough syrup	14																				
Cough syrup	31																				
Vicks formula 44 cough discs	19																				
Romilar cough lozenges	46																				
Vicks throat lozenges	37																				
Spectrocin-T-troches	24																				
Smith Brothers cough drops	23																				
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F & F cough drops	4																				
Listerine throat lozenges	7																				
Chloraseptic lozenges	9																				
Cepacol throat lozenges	45																				
F & F Lozenges	47																				
Sucrets	2																				
Salt water gargle	52											1									
Tetrazets antibacterial analgesic	39														1	1					
Squibb analgesic tablets	36														1						
Krex A. P. A. pain relievers	18										1				1						
Seeing the doctor	12		1	1			1	1	1				1	1	1	1			1	1	1
Calling the doctor	49		1				1	1	1				1	1	1	1		1	1		1
Bufferin	1											1	1	1	1	1	1	1	1	1	1
Anacin	16											1	1	1	1	1	1	1	1	1	1
Aspirin	30											1	1	1	1	1	1	1	1	1	1
Empirin compound	48										1	1	1	1	1	1	1	1	1	1	1
Excedrin	50											1	1	1	1	1	1	1	1	1	1
A. P. C. Tablets	51												1		1	1	1	1	1	1	1
Hot lemonade	5				1	1	1							1	1	1	1	1	1	1	1
Hot tea	22			1	1	1	1	1	1	1	1		1	1	1	1	1	1	1	1	1
A hot toddy	10				1	1					1	1	1	1		1	1		1	1	
Coricidin cold tablets	25													1			1	1	1	1	1
Vitamins	32	1		1	1							1			1		1	1	1	1	1
Fruit juice	27	1		1	1							1			1	1	1	1	1	1	1
Warm milk	42							1	1	1				1	1	1	1	1	1		
An ice pack	29	1	1									1		1				1			
Ben-gay	17	1	1								1										
Ear drops	33	1					1						1								
Murine eye drops	43	1																			
	TOTAL	6	4	4	5	4	5	4	4	2	7	11	11	13	16	14	14	15	15	13	14

	ROW/COL	Girl (boy) friend has a cold	Headache	Neuritis, neuralgia	Bursitis	Backache	Nervous	The children are overtired	Indigestion	Heartburn	You are cold
		45	3	19	36	21	37	41	13	51	42
Bromo seltzer	21								1	1	1
Alka seltzer	34								1	1	
Contac	13										
Vicks Sinex nasal spray	44										
Privine nose drops	41										
Neosynephrine nasal spray	40										
Neosynephrine nose drops	38										
Contac nasal mist	20										
Privine nasal spray	15										
Naso-dex	35										
Dristan nasal decongestant capsules	28										
Vicks inhaler	3										
Dristan medicated room vaporizer	6										
Mentholatum	11				1	1					
Vicks vapo-rub	26				1						
Adulton cough syrup	14										
Cough syrup	31										
Vicks formula 44 cough discs	19										
Romilar cough lozenges	46										
Vicks throat lozenges	37										
Spectrocin-T-troches	24										
Smith Brothers cough drops	23										
Vicks cough drops	8										
F & F cough drops	4										
Listerine throat lozenges	7										
Chloraseptic lozenges	9										
Cepacol throat lozenges	45										
F & F Lozenges	47										
Sucrets	2										
Salt water gargle	52										
Tetrazets antibacterial analgesic	39										1
Squibb analgesic tablets	36			1	1					1	
Krex A. P. A. pain relievers	18			1	1	1	1				
Seeing the doctor	12					1					
Calling the doctor	49					1					
Bufferin	1	1	1	1	1	1	1	1	1	1	
Anacin	16	1	1	1	1	1	1	1	1	1	
Aspirin	30	1	1	1	1	1	1	1	1	1	1
Empirin compound	48	1	1	1	1	1	1	1	1	1	1
Excedrin	50	1	1	1	1	1	1	1	1	1	1
A. P. C. Tablets	51	1		1	1	1	1	1	1	1	1
Hot lemonade	5	1					1	1			1
Hot tea	22					1	1	1	1		
A hot toddy	10				1	1	1				1
Coricidin cold tablets	25	1									1
Vitamins	32	1									1
Fruit juice	27	1									1
Warm milk	42						1	1	1	1	1
An ice pack	29				1	1					
Ben-gay	17			1	1	1					
Ear drops	33										
Murine eye drops	43										
	TOTAL	10	5	9	13	14	11	9	10	10	1

Use Frames) on Basis of Row–Row, Column–Column Similarity

Girl (boy) friend has a cold	Headache	Neuritis, neuralgia	Bursitis	Backache	Nervous	The children are overtired	Indigestion	Heartburn	You are cold	Post-nasal drip	You have a cold	In the winter	The children have a cold	Laryngitis	Swollen glands	Tonsils are inflamed	Sore throat	During the flu season	The children are cranky	Asthma	Cough	Sore mouth	Bad taste in your mouth	Tightness in your chest	Sinus trouble	Stuffy head	Can't breathe	Stuffy nose	Can't breathe	Runny nose	Hay fever	
45	3	19	36	21	37	41	13	51	42	11	32	8	28	47	31	24	9	16	50	45	12	47	1	5	35	34	26	2	7	20	38	TOTAL
							1	1	1																							4
							1	1			1																					5
											1	1	1	1				1						1	1	1	1	1	1	1	1	13
											1	1													1	1	1	1	1	1	1	9
											1	1													1	1	1	1	1	1	1	9
											1	1													1	1	1	1	1	1	1	9
											1	1													1	1	1	1	1	1	1	9
											1	1													1	1	1	1	1	1	1	9
											1	1													1	1	1	1	1	1	1	9
											1	1	1												1	1	1	1	1	1	1	10
											1	1	1												1	1	1	1	1	1	1	10
										1	1	1	1					1							1	1	1	1	1	1	1	12
										1	1	1	1							1	1			1	1	1	1	1	1	1	1	15
			1	1							1	1	1							1	1			1	1	1	1	1	1	1		15
			1							1	1	1	1						1	1	1			1					1	1		13
										1	1	1								1	1			1						1		7
										1	1	1	1	1					1	1	1			1								9
										1	1	1	1	1					1	1	1	1		1								10
										1	1	1	1	1	1	1			1	1	1	1		1								12
										1	1	1	1	1	1	1	1	1	1	1	1		1									13
										1	1	1	1	1	1	1	1	1	1	1	1	1	1									14
										1	1	1	1	1	1	1	1	1	1	1	1	1	1									14
										1	1	1	1	1	1	1	1	1	1	1	1	1	1	1								15
										1	1	1	1	1	1	1	1	1	1	1	1	1	1	1								15
										1	1	1	1	1	1	1	1	1	1	1	1	1	1									14
										1	1	1	1	1	1	1	1	1	1	1	1	1										13
										1	1	1	1	1	1	1	1	1	1	1	1	1	1									14
										1	1	1	1	1	1	1	1	1	1	1	1	1	1									14
											1	1	1	1	1	1	1		1		1	1	1									11
										1	1	1		1	1	1	1				1	1										10
									1	1	1	1	1	1	1	1	1		1													12
		1	1					1		1	1	1	1	1	1	1	1														1	13
		1	1	1	1					1	1	1	1	1	1	1	1														1	15
				1							1		1	1	1	1		1		1		1									1	22
				1							1	1	1	1	1	1	1	1	1	1	1										1	24
1	1	1	1	1	1	1	1	1			1	1	1	1	1	1	1	1	1	1										1	1	31
1	1	1	1	1	1	1	1	1		1	1	1	1	1	1	1	1	1	1	1									1	1	1	33
1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1										1	1	33
1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1											1	33
1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1										1	1	33
1		1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1											1	29
1					1	1			1	1	1	1	1	1	1	1	1	1	1	1	1		1	1	1	1	1	1	1	1	1	36
				1	1	1	1			1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	43
			1	1	1				1	1	1	1		1	1	1	1	1	1	1	1	1		1	1	1		1	1			30
1									1	1	1	1	1	1			1	1	1					1						1		18
1									1		1	1	1	1	1	1		1	1													20
1									1		1	1	1	1	1	1	1	1	1				1									23
					1	1	1	1	1			1	1					1	1	1												19
			1	1																												7
		1	1	1																1				1								8
																				1												4
																																1
10	5	9	13	14	11	9	10	10	12	29	46	45	37	32	28	28	26	26	28	30	22	15	12	15	15	15	14	15	17	21	23	823

TABLE 8

SNACKS AND WHEN TO CONSUME THEM (AGGREGATE DATA)[a]

		33 Anytime I was thirsty	32 With pie	18 For breakfast	12 In the morning	41 When I want something sweet	08 For dessert	03 For a low calorie lunch	43 Coffee break	21 For very special occasions	13 As an appetizer	40 With cheese	15 With soup	14 For a quick lunch	25 Three or four times a day	46 After a party
48	Beer	24	4	0	0	3	2	1	2	8	4	21	8	5	7	9
25	Milk	33	30	29	31	6	8	18	18	5	3	14	23	23	28	16
35	Raisins	0	1	7	11	11	12	16	8	1	5	2	2	6	10	6
10	Jello	6	4	1	5	22	33	29	8	7	10	3	12	21	6	8
08	Canned fruit	8	5	16	17	21	32	21	3	6	12	8	12	23	7	5
09	Leftovers	0	2	0	3	0	1	8	1	0	3	11	22	31	7	10
24	A pickle	3	2	2	4	1	0	23	4	4	14	8	14	14	6	6
05	A bowl of soup	4	4	2	4	1	0	30	5	6	22	20	18	34	4	5
07	Cottage cheese	1	1	5	6	1	5	34	3	3	16	10	11	29	5	5
12	Hard boiled eggs	1	1	15	23	0	0	33	6	4	11	9	17	31	5	8
47	Fresh fruit	8	1	28	30	17	32	30	11	14	19	11	14	25	23	6
40	Apples	8	3	11	19	13	25	27	13	2	4	14	10	20	18	6
26	Candy bars	1	1	2	5	31	23	0	22	7	2	3	4	14	8	11
17	Ice cream	7	30	0	2	26	34	1	12	25	3	4	5	10	12	14
49	Donuts	1	0	28	32	23	27	0	27	5	3	1	4	8	9	8
45	Cherry pie	1	10	0	9	27	32	0	15	22	2	6	11	13	5	8
31	Pastries	0	5	15	21	27	29	1	22	25	3	3	6	12	8	8
18	A piece of cake	1	3	12	8	29	34	0	20	26	3	6	11	14	11	12
04	Cookies	0	5	7	13	28	31	4	25	20	3	1	5	9	14	11
42	Hard candy	2	2	1	2	28	18	2	11	12	3	2	2	1	13	8
11	Coca cola	10	12	1	4	23	2	0	18	13	6	15	11	11	14	17
50	Sausage sticks	0	2	10	7	3	0	7	3	6	10	10	19	20	7	8
55	Cheese flavored popcorn	0	0	1	2	3	2	1	6	4	10	9	7	4	9	8
09	Carmel corn	1	1	2	4	17	6	1	8	5	5	2	1	1	6	7
19	Fiddle-Faddles (like Cracker Jacks)	0	0	1	3	17	6	3	11	10	8	5	3	4	8	7
21	Popcorn	1	1	0	2	4	3	2	5	7	11	10	4	1	6	8
54	Nabisco Snacks—chipsters, shapes	0	1	1	2	3	1	4	9	5	15	18	18	5	8	8
20	Fritos	1	1	0	2	2	2	2	12	10	17	19	20	10	9	12
15	Bugles	0	1	2	5	2	1	4	11	9	15	12	17	6	9	8
01	Potato chips	1	0	0	2	0	0	1	10	13	17	18	20	8	7	9
02	Pretzels	1	0	0	1	0	0	3	9	13	16	10	7	5	6	10
03	Nuts	1	3	0	2	2	10	1	8	20	18	6	2	2	9	9
27	Peanuts	0	0	0	2	4	5	3	13	11	18	4	2	5	10	12
33	Meat flavored snacks	0	2	4	2	1	0	7	8	12	19	21	22	21	8	9
59	Daisys	0	0	0	6	3	3	2	7	7	13	11	13	5	9	6
50	Shoe string potatoes	0	1	2	5	1	1	2	5	7	11	10	23	12	7	7
51	Cheese and crackers	0	0	3	3	2	6	15	4	11	19	22	24	21	7	7
52	A meaty snack	0	0	3	3	3	0	9	6	9	14	20	21	22	6	10
16	Cheese	1	19	7	8	2	13	20	10	18	23	18	16	24	13	13
29	Cold cuts—salami, bologna	1	2	4	4	1	1	18	8	7	14	23	23	32	5	6
06	Sandwich	0	5	5	7	2	1	15	10	6	11	27	31	33	6	13
30	A hamburger sandwich	1	5	3	4	2	1	8	7	6	4	24	27	34	4	10
23	Hot dogs	1	2	2	3	1	0	10	4	4	6	14	25	31	6	4
25	Potato chips and sour cream	1	0	1	0	1	1	1	0	15	17	13	7	6	4	7
40	Pizza	0	0	1	1	2	1	1	4	4	7	18	13	25	5	10
22	French fries	0	0	2	3	0	1	1	4	3	4	6	16	16	4	4
37	Beef jerky	0	2	1	2	0	1	14	4	5	11	8	10	15	6	5
41	Peanut butter and jelly sandwich	3	1	7	6	14	2	1	4	0	4	2	18	30	4	5
40	Rolls	1	0	24	26	6	6	3	16	14	7	12	22	13	7	6
14	Toastems	0	1	29	31	16	9	6	8	2	4	2	5	8	4	2
13	Presweetened breakfast cereal	0	0	31	32	14	0	4	1	2	2	2	0	5	1	2
44	Instant breakfast	4	0	31	31	7	1	22	0	2	2	2	1	14	4	2
34	Sardines	0	0	1	1	2	0	13	3	8	20	6	8	17	1	3
36	Spaghetti-O's	0	1	0	1	1	0	0	0	1	4	7	7	22	3	3
38	Herring	0	1	3	4	0	0	11	1	9	21	5	5	11	2	3
66	Other	5	4	9	11	9	10	13	10	7	14	9	13	12	5	13

		31 To go with a sandwich	30 When I'm working	47 When I'm shopping	53 With tea	20 With coffee	51 With milk	52 "Raiding the refrigerator"
48	Beer	22	7	7	1	2	1	21
25	Milk	31	20	17	11	14	16	28
35	Raisins	5	12	5	8	5	11	9
10	Jello	20	9	11	12	10	16	24
08	Canned fruit	19	5	6	14	9	12	23
09	Leftovers	12	6	3	14	17	25	26
24	A pickle	31	8	9	7	6	8	24
05	A bowl of soup	33	7	11	13	6	23	10
07	Cottage cheese	17	6	10	13	8	15	19
12	Hard boiled eggs	22	8	4	13	14	19	22
47	Fresh fruit	24	23	11	8	9	12	23
40	Apples	20	22	11	6	4	13	20
26	Candy bars	13	23	23	7	10	19	12
17	Ice cream	14	10	22	13	16	12	28
49	Donuts	11	15	16	20	29	28	14
45	Cherry pie	19	6	14	21	29	27	21
31	Pastries	12	12	17	27	29	28	18
18	A piece of cake	18	13	11	26	31	32	21
04	Cookies	15	18	12	29	31	33	12
42	Hard candy	4	20	14	4	5	7	5
11	Coca cola	30	27	28	3	1	2	23
50	Sausage sticks	9	8	8	11	12	15	16
55	Cheese flavored popcorn	7	10	7	8	6	9	7
09	Carmel corn	7	15	6	10	6	10	4
19	Fiddle-Faddles (like Cracker Jacks)	13	13	7	10	7	10	8
21	Popcorn	8	14	10	7	7	12	8
54	Nabisco Snacks—chipsters, shapes	14	11	9	11	9	14	10
20	Fritos	24	16	14	9	9	13	11
15	Bugles	19	11	7	11	8	13	9
01	Potato chips	32	17	7	4	3	9	8
02	Pretzels	12	14	10	6	4	10	9
03	Nuts	6	13	9	7	5	7	9
27	Peanuts	4	20	15	6	5	8	8
33	Meat flavored snacks	9	12	9	10	13	19	17
59	Daisys	15	10	8	11	6	10	4
50	Shoe string potatoes	23	10	7	12	6	12	11
51	Cheese and crackers	11	11	7	16	12	17	15
52	A meaty snack	11	9	9	14	11	20	20
16	Cheese	25	10	12	15	11	16	19
29	Cold cuts—salami, bologna	13	7	9	18	19	24	30
06	Sandwich	15	13	20	24	30	29	24
30	A hamburger sandwich	11	11	22	16	27	27	15
23	Hot dogs	6	7	18	15	20	21	16
25	Potato chips and sour cream	14	3	6	11	7	7	13
40	Pizza	3	5	14	13	12	14	10
22	French fries	25	6	14	10	11	13	8
37	Beef jerky	8	10	7	9	13	11	11
41	Peanut butter and jelly sandwich	12	7	7	16	17	25	15
40	Rolls	8	11	12	21	27	23	11
14	Toastems	4	2	3	21	24	27	9
13	Presweetened breakfast cereal	3	0	3	10	19	30	7
44	Instant breakfast	6	4	3	4	7	21	7
34	Sardines	6	3	4	6	7	10	10
36	Spaghetti-O's	7	2	3	9	10	14	6
38	Herring	9	4	6	7	6	5	8
66	Other	11	8	10	12	9	16	12

[a] Odd-numbered respondents versus even-numbered respondents (split-half reliability .87).

TABLE 8

NACKS AND WHEN TO CONSUME THEM (AGGREGATE DATA)[a]

	03 For a low calorie lunch	43 Coffee break	21 For very special occasions	13 As an appetizer	40 With cheese	15 With soup	14 For a quick lunch	25 Three or four times a day	46 After a party
[illegible]	1	2	8	4	21	8	5	7	9
[illegible]	18	18	5	3	14	23	23	28	16
[illegible]	16	8	1	5	2	2	6	10	6
[illegible]	20	8	7	10	3	12	21	6	8
[illegible]	21	3	6	12	8	12	23	7	5
[illegible]	8	1	0	3	11	22	31	7	10
[illegible]	23	4	4	14	8	14	14	6	6
[illegible]	30	5	6	22	20	18	34	4	5
[illegible]	34	3	3	16	10	11	29	5	5
[illegible]	33	6	4	11	9	17	31	5	8
[illegible]	30	11	14	19	11	14	25	23	6
[illegible]	27	13	2	4	14	10	20	18	6
[illegible]	0	22	7	2	3	4	14	8	11
[illegible]	1	12	25	3	4	5	10	12	14
[illegible]	0	27	5	3	1	4	8	9	8
[illegible]	0	15	22	2	6	11	13	5	8
[illegible]	1	22	25	3	3	6	12	8	8
[illegible]	0	20	26	3	6	11	14	11	12
[illegible]	4	25	20	3	1	5	9	14	11
[illegible]	2	11	12	3	2	2	1	13	8
[illegible]	0	18	13	6	15	11	11	14	17
[illegible]	7	3	6	19	10	19	20	7	8
[illegible]	1	6	4	10	9	7	4	9	8
[illegible]	1	8	5	5	2	1	1	6	7
[illegible]	3	11	10	8	5	3	4	8	7
3	2	5	7	11	10	4	1	6	8
1	4	9	5	15	18	18	5	8	8
2	2	12	10	17	10	20	10	9	12
1	4	11	9	15	12	17	6	9	8
0	1	10	13	17	18	20	8	7	9
0	3	9	13	16	10	7	5	6	10
0	1	8	20	18	6	2	2	9	9
5	3	13	11	18	4	2	5	10	12
0	7	8	12	19	21	22	21	8	9
3	2	7	7	13	11	13	5	9	6
1	2	5	7	11	10	23	12	7	7
6	15	4	11	19	22	24	21	7	7
0	9	6	9	14	20	21	22	6	10
13	20	10	18	23	18	16	24	13	13
1	18	8	7	14	23	23	32	5	6
1	15	10	6	11	27	31	33	6	13
1	8	7	6	4	24	27	34	4	10
0	10	4	4	6	14	25	31	6	4
1	1	0	15	17	13	7	6	4	7
1	1	4	4	7	18	13	25	5	10
1	1	4	3	4	6	16	16	4	4
1	14	4	5	11	8	10	15	6	5
2	1	4	0	4	2	18	30	4	5
6	3	16	14	7	12	22	13	7	6
9	6	8	2	4	2	5	8	4	2
0	4	1	2	2	2	0	5	1	2
1	22	0	2	2	2	1	14	4	2
0	13	3	8	20	6	8	17	1	3
0	0	0	1	4	7	7	22	3	3
0	11	1	9	21	5	5	11	2	3
10	13	10	7	14	9	13	12	5	13

31 To go with a sandwich	30 When I'm working	47 When I'm shopping	53 With tea	20 With coffee	51 With milk	52 "Raiding the refrigerator"	49 When I'm nervous	09 Mostly in the afternoon	38 When I go camping	35 When I'm out	48 When I'm visiting someone	36 When I'm babysitting	22 Late at night	06 Almost anytime of the day	42 To kill my appetite	17 When I'm in a Rush	50 In cool weather	54 For men	39 For adults	28 Without tea	23 On warm days	16 For women
22	7	7	1	2	1	21	13	11	24	24	23	9	22	6	9	10	19	31	32	29	31	20
31	20	17	11	14	16	28	14	12	24	21	17	26	28	30	20	27	25	25	26	30	30	29
5	12	5	8	5	11	9	9	16	21	11	9	15	15	21	20	18	20	22	25	29	20	26
20	9	11	12	10	16	24	10	12	9	17	17	15	18	20	18	20	21	21	29	27	31	31
19	5	6	14	9	12	23	10	9	21	12	12	12	12	21	14	25	21	24	29	28	27	28
12	6	3	14	17	25	26	15	11	14	3	8	9	19	16	15	24	24	27	29	27	22	27
31	8	9	7	6	8	24	10	14	23	16	12	13	12	11	14	19	20	29	30	31	25	27
33	7	11	13	6	23	10	7	13	20	19	11	9	12	12	17	25	30	29	30	25	11	28
17	6	10	13	8	15	19	7	9	9	13	12	10	9	15	19	19	20	22	28	26	23	30
22	8	4	13	14	19	22	8	10	24	10	7	10	13	21	19	20	20	26	28	26	24	29
24	23	11	8	9	12	23	16	16	28	20	14	26	23	32	25	27	20	25	29	28	30	31
20	22	11	6	4	13	20	17	14	30	15	12	25	20	31	25	25	19	26	30	27	30	31
13	23	23	7	10	19	12	17	20	20	22	16	27	20	23	25	27	25	25	28	30	23	27
14	10	22	13	16	12	28	17	21	9	31	30	30	26	18	19	19	18	29	28	28	34	27
11	15	16	20	29	28	14	12	8	18	21	19	18	19	20	17	25	26	25	29	29	23	29
19	6	14	21	29	27	21	11	14	11	21	22	19	22	16	17	18	23	26	29	25	24	28
12	12	17	27	20	28	18	13	12	11	22	28	20	20	20	21	20	24	25	30	23	22	29
18	13	11	26	31	32	21	15	17	17	28	30	30	27	19	21	22	24	28	28	24	25	29
15	18	12	29	31	33	12	12	22	30	18	30	28	25	26	20	22	25	24	26	26	23	26
4	20	14	4	5	7	5	16	14	20	19	17	25	17	10	18	19	20	22	26	28	23	26
30	27	28	3	1	2	23	19	18	24	27	27	29	22	25	21	22	24	29	20	26	33	28
9	8	8	11	12	15	16	11	15	22	18	14	18	17	14	15	19	21	28	27	28	21	26
7	10	7	8	6	0	7	14	15	17	18	20	23	18	14	15	18	19	24	25	30	21	24
7	15	6	10	6	10	4	13	18	15	18	13	25	16	18	16	16	18	22	22	28	20	22
13	13	7	10	7	10	8	14	17	18	19	18	26	20	21	17	18	22	21	26	29	24	23
8	14	10	7	7	12	8	14	16	19	20	19	24	25	13	13	15	23	25	27	30	20	27
14	11	9	11	9	14	10	13	16	22	19	20	21	19	15	10	20	20	26	27	30	23	27
24	16	14	9	9	13	11	15	19	26	21	23	29	21	22	19	23	23	28	31	32	23	26
19	11	7	11	8	13	9	12	21	18	18	21	28	20	17	16	19	22	29	30	30	23	25
32	17	7	4	3	9	8	15	15	27	22	26	29	25	19	19	20	23	28	29	29	21	27
12	14	10	6	4	10	9	16	15	23	20	23	26	24	18	15	18	23	28	29	28	24	26
6	13	9	7	5	7	9	16	15	24	22	24	27	21	18	19	16	24	29	30	30	23	26
4	20	15	6	5	8	8	17	15	24	19	24	27	20	21	21	21	23	29	30	31	21	27
9	12	9	10	13	19	17	12	15	19	17	19	16	22	18	21	20	22	29	30	27	22	27
15	10	8	11	6	10	4	12	15	20	15	19	24	16	18	15	17	20	23	28	27	24	28
23	10	7	12	6	12	11	13	11	23	15	16	19	16	15	15	21	21	27	28	29	23	26
11	11	7	16	12	17	15	16	15	22	18	17	23	23	15	23	22	22	27	31	29	26	28
11	9	9	14	11	20	20	15	17	20	17	17	19	21	17	20	23	21	30	29	28	24	28
25	10	12	15	11	16	19	15	14	25	20	23	21	21	22	23	23	20	30	29	27	23	30
13	7	9	18	19	24	30	14	14	28	15	16	18	19	15	20	26	22	29	31	27	26	27
15	13	20	24	30	29	24	14	17	29	25	19	23	23	18	10	32	26	30	29	29	28	27
11	11	22	16	27	27	15	9	13	25	23	15	13	15	17	15	18	25	30	32	28	25	26
6	7	18	15	20	21	16	8	14	29	24	17	12	12	13	14	22	26	30	27	28	25	27
14	3	6	11	7	7	13	12	14	10	18	24	17	17	10	18	12	20	28	28	31	23	29
3	5	14	13	12	14	10	11	16	8	24	15	18	20	14	16	16	23	26	27	28	19	26
25	6	14	10	11	13	8	11	13	16	21	14	13	13	9	16	12	22	29	29	27	21	26
8	10	7	9	13	11	11	11	15	23	12	9	12	12	12	17	17	20	25	27	27	22	20
12	7	7	16	17	25	15	11	14	22	5	11	14	17	18	19	27	22	18	18	28	23	24
8	11	12	21	27	23	11	13	11	15	23	17	12	14	18	17	22	22	28	28	26	22	28
4	2	3	21	24	27	9	5	3	12	6	7	10	13	15	10	18	23	22	25	26	19	26
3	0	3	10	19	30	7	5	1	22	3	6	8	11	10	12	17	16	20	23	29	25	27
6	4	3	4	7	21	7	9	2	15	6	5	9	9	11	16	25	18	20	26	27	22	29
6	3	4	6	7	10	10	7	12	13	10	7	9	12	9	13	16	18	24	27	25	19	24
7	2	3	9	10	14	6	7	9	14	5	7	7	7	9	12	15	21	17	19	25	13	22
9	4	6	7	6	5	8	5	10	9	11	8	9	0	4	12	9	15	24	25	25	15	21
11	8	10	12	9	16	12	12	11	16	13	14	18	14	16	14	15	16	16	20	14	11	14

ndents (split-half reliability .87).

TABLE 8 (Continued)

	10 For kids	34 After school	29 In between meals	01 Watching T.V.	05 Just by itself	19 As a snack	24 In the evenings	26 Little get togethers	37 At parties	04 To nibble on	07 With a coke	02 While drinking beer	11 To go along with a drink	44 At a bar	45 With cocktails	27 With dips
48 Beer	2	10	25	31	26	17	29	28	29	8	0	26	5	26	7	12
25 Milk	33	28	27	26	27	25	30	23	16	6	0	1	2	3	2	8
35 Raisins	29	25	26	24	31	28	15	12	13	31	12	2	6	1	2	2
10 Jello	31	22	21	20	27	21	25	16	16	11	5	1	3	2	2	2
08 Canned fruit	25	20	20	13	27	24	20	10	10	8	4	1	3	0	0	0
09 Leftovers	18	20	17	16	21	22	21	8	4	18	24	16	14	1	2	5
24 A pickle	24	20	21	14	17	26	20	20	20	25	11	9	8	4	3	7
05 A bowl of soup	28	14	7	12	26	12	16	7	7	4	14	1	6	3	2	0
07 Cottage cheese	18	10	14	8	14	19	14	14	10	9	8	0	3	1	2	5
12 Hard boiled eggs	22	15	18	17	19	21	17	14	11	16	14	15	12	7	4	4
47 Fresh fruit	29	29	30	31	32	33	28	20	19	30	7	0	2	1	1	5
40 Apples	30	31	31	31	33	32	26	15	14	30	9	0	2	0	1	2
26 Candy bars	33	29	29	28	32	32	25	20	16	29	16	2	6	5	4	1
17 Ice cream	34	32	26	30	33	28	31	30	26	12	16	0	6	2	2	1
49 Donuts	30	23	25	25	26	27	19	19	19	19	13	3	14	2	1	3
45 Cherry Pie	26	24	22	25	25	27	29	23	21	12	11	2	13	1	1	1
31 Pastries	26	23	25	26	27	28	26	27	30	22	12	3	12	2	2	2
18 A piece of cake	29	28	25	29	28	29	30	33	30	23	18	3	14	2	2	2
04 Cookies	33	32	32	31	31	32	29	29	26	31	18	4	17	2	1	3
42 Hard candy	27	30	28	29	30	26	24	21	26	27	9	1	5	3	3	1
11 Coca cola	30	31	29	32	32	23	27	31	29	10	23	0	7	15	8	17
50 Sausage sticks	13	19	22	21	22	23	23	22	22	21	23	24	22	14	14	15
55 Cheese flavored popcorn	28	25	26	31	25	29	24	26	24	30	27	27	27	14	12	12
09 Carmel corn	31	27	27	30	31	28	23	20	23	31	25	14	21	7	3	2
19 Fiddle-Faddles (like Cracker Jacks)	32	27	27	30	28	31	28	28	25	34	28	18	20	10	9	12
21 Popcorn	33	25	27	34	28	30	31	25	27	34	29	27	29	18	13	9
54 Nabisco snacks—chipsters, shapes	25	23	25	30	26	28	28	29	30	30	27	28	27	20	19	27
20 Fritos	30	31	29	34	29	31	31	31	29	34	31	31	32	21	21	20
15 Bugles	30	27	28	30	25	31	25	26	28	32	31	28	29	16	14	25
01 Potato chips	31	30	29	33	24	31	32	33	34	34	32	32	31	27	21	34
02 Pretzels	27	28	27	33	28	31	33	32	34	33	31	33	31	29	22	19
03 Nuts	25	27	29	33	29	30	33	34	33	34	28	31	31	30	28	7
27 Peanuts	31	29	29	33	31	32	28	30	32	34	29	32	27	24	21	10
33 Meat flavored snacks	20	21	25	28	24	30	25	28	28	29	28	23	24	17	17	15
59 Daisys	25	24	23	23	22	24	26	30	27	27	28	22	26	10	13	22
50 Shoe string potatoes	26	22	20	21	23	26	24	20	21	24	29	27	25	13	11	15
51 Cheese and crackers	20	27	27	30	27	30	29	29	29	30	27	28	28	18	21	20
52 A meaty snack	20	22	24	29	25	29	28	25	28	26	30	29	28	13	16	14
16 Cheese	22	23	26	26	25	31	26	30	28	28	22	27	20	18	19	16
29 Cold cuts—salami, bologna	22	21	19	19	19	25	21	28	26	19	28	27	22	8	12	13
06 Sandwich	28	28	15	28	25	24	22	24	26	18	32	29	26	14	8	5
30 A hamburger sandwich	30	19	9	20	25	21	22	22	19	9	33	25	23	9	5	5
23 Hot dogs	34	18	14	15	21	19	18	22	15	11	31	24	16	7	3	5
25 Potato chips and sour cream	16	19	22	26	19	24	26	28	31	26	28	22	28	15	22	25
40 Pizza	27	17	15	27	25	26	30	27	27	19	30	28	26	11	9	7
22 French fries	29	14	15	16	22	21	21	15	16	23	29	19	16	8	3	8
37 Beef jerky	11	14	17	16	20	24	20	12	12	21	19	22	19	8	8	8
41 Peanut butter and jelly sandwich	31	23	21	25	20	28	12	9	8	11	22	7	11	2	3	0
40 Rolls	20	18	18	15	20	21	25	19	18	15	12	5	13	2	3	2
14 Toastems	30	20	11	14	24	20	8	8	5	20	12	3	11	1	1	1
13 Presweetened breakfast cereal	33	14	11	11	21	14	0	0	5	15	5	0	5	1	1	0
44 Instant breakfast	15	7	5	12	24	13	6	2	6	2	0	1	2	1	1	1
34 Sardines	11	10	11	9	12	16	13	12	14	12	14	18	16	7	9	6
36 Spaghetti-O's	26	9	4	7	13	14	13	4	6	5	16	2	10	1	1	1
38 Herring	6	6	13	9	10	15	16	11	14	11	9	11	15	4	12	5
66 Other	11	14	17	10	15	15	14	13	15	11	17	15	13	10	11	12

Table 7 shows the original data matrix for one individual rearranged into clusters (that are based on the separate row–row and column–column calculations described above) such that both rows which are similar to each other and columns which are similar to each other are near each other.

Table 8 is similar to Table 7 but displays group data. It shows an aggregate data matrix in which each row is a kind of snack and each column is a belief-frame about when to eat snacks.

If we split the arbitrarily numbered respondents who form the group for a given aggregate data matrix into an even-numbered half and an odd-numbered half, the split-half reliabilities for our last five studies are .77, .91, .85, .93, and .88. Following the Spearman–Brown formula (e.g., see Gulliksen, 1950, Ch. 6), these figures suggest that reliability of the data from these item-by-use matrices ranged from .83 to .97 for the total groups. Stefflre, Reich, and McClaran (1971) presented some interindividual correlations for this type of data in a number of languages. For normal respondents with a 50 × 50 matrix, a typical interindividual correlation was .70; with a 25 × 25 matrix, the median of 423 correlations was .59. Schizophrenics or respondents under the influence of drugs exhibited lower interindividual correlations.

Items Marked × by the Same Individuals (× = Liked, Respected, Feared, Etc.)

Figure 2 shows a physical model of trips *liked* by the same individuals ($N = 200$) from a correlation matrix based on preference data. The reliability of correlation matrices of this size and type run around .75 if the odd-numbered respondents' matrix is correlated with that for the even-numbered respondents.

Patterns of Substitution from Panel Purchase Data (Where Available)

With this type of data, we can see the patterns of brand-switching or the shifts in the individual family purchase bundles from one time period to the next (Buzzell, 1964, pp. 217 ff. reviews briefly some of the early variations of switching models from Markov to Casbah).

We have found it useful to work with aggregate judged similarity data ($N \approx 50$) and aggregate data ($N = 200$–$10{,}000$) on substitution among items. The data relating judged similarity to item–item substitution is

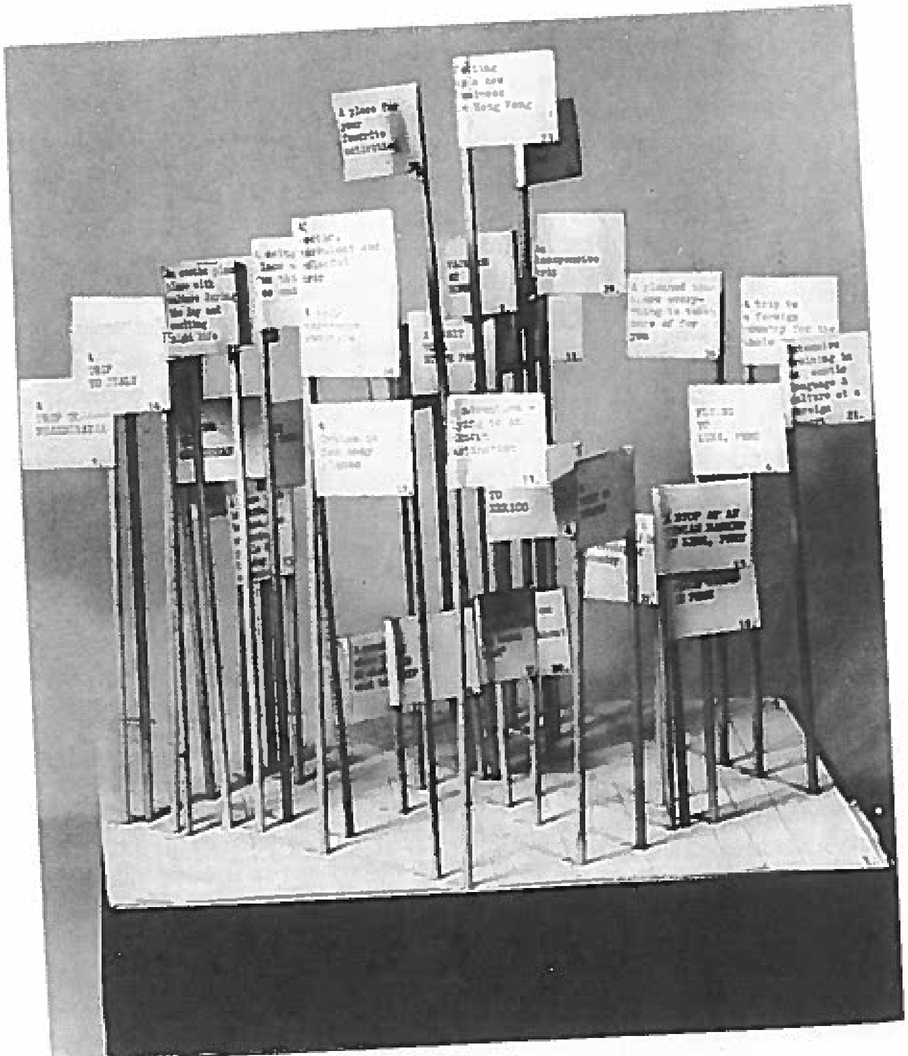


FIG. 2. Spatial representation of trip preferences.

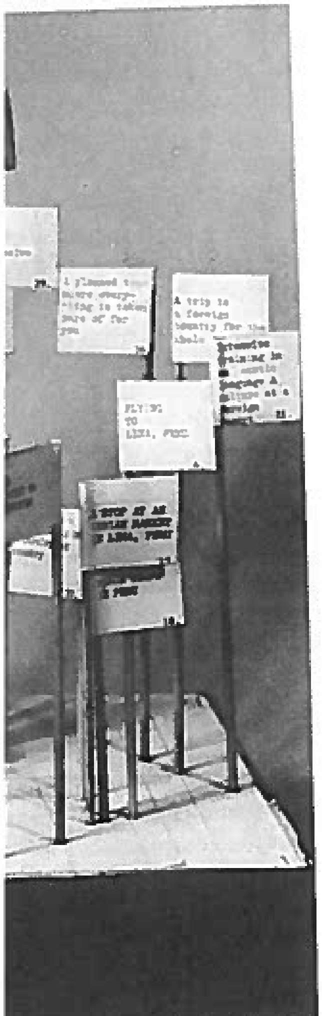
fairly consistent. Figure 3 shows some 1961 data on judged similarity and brand switching ($N \approx 3000$) for 12 brands of cigarettes and Figure 4 shows data on judged similarity and substitution for toilet soap. The substitution index for toilet soap was obtained by combining product–product similarity-in-use rankings from data like those in Figure 2 with product–product preference correlations like those in Figure 3. Products

FIG. 3. Judged similarity an
switching of cigarettes (rank
tion ρ = .74).

are treated as more subst
appropriate for the same
The Brown, Cardozo, Cu
439 ff., 461–463) contain
and presents in detail so
brand substitution in th
panel-purchase diaries fo
tition were available.

Judged similarity in t
scale patterns of routine

FIG. 4. Relation of prod
tution and product sim
toilet soap (rank correlation



ɔ preferences.

.ta on judged similarity and
of cigarettes and Figure 4
tution for toilet soap. The
.ed by combining product–
like those in Figure 2 with
those in Figure 3. Products

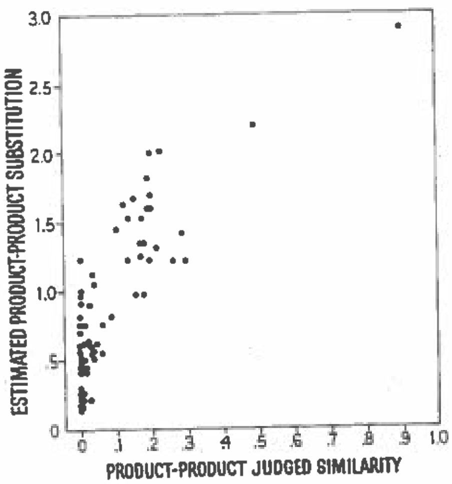


FIG. 3. Judged similarity and brand switching of cigarettes (rank correlation $\rho = .74$).

are treated as more substitutable and competitive if they (a) are seen as appropriate for the same uses, and (b) are liked by the same individuals. The Brown, Cardozo, Cunningham, Salmon, and Sultan report (1968, pp. 439 ff., 461–463) contains a description of one of our other early projects and presents in detail some of our data on judged similarity and brand–brand substitution in the coffee market. For this project, several years panel-purchase diaries for estimating patterns of substitution and competition were available.

Judged similarity in the above examples is a useful indicator of larger scale patterns of routine behavior in a culture and a spatial representation

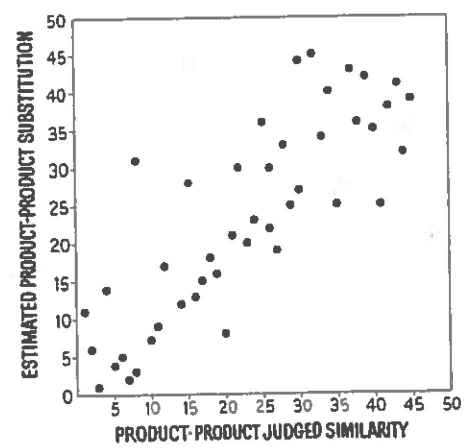


FIG. 4. Relation of product substitution and product similarity for toilet soap (rank correlation $\rho = .82$).

of judged similarity data offers a succinct summary of complex patterns of behavioral similarity. In this manner, we have studied cross-culturally perception of and behavior towards approximately 20 different sectors of the world of objects, ranging from coffee to Peace Corps volunteers; and we have found in support of the first proposition stated above that the relation between judged similarity and similarity in routine behavior holds in varying degrees in all these sectors. The lowest correlation was .45, the highest was .85, and the median, .70.

The second proposition states that a new item introduced into a culture will be behaved towards in a manner similar to the behavior toward familiar items that are seen by members of the culture as similar to the new item. It provides us with an experimental test of our understanding of the features that underly the descriptive regularities mentioned above and it is also useful for a variety of practical applications.

In order to discuss the propositions further, it is relevant to differentiate *items* and *descriptions*. My own bias in approaching the question of why an individual in a culture sees certain things as similar and different and why he sees a new thing as exhibiting a particular pattern of similarity to familiar things is to view the answer to this question as having two separable levels.

(1) *Items.* The *X*s see this new item as similar to other things because of the way they encode it (describe it to themselves).

(2) *Descriptions.* The *X*s encode this new thing (describe it to themselves) in a particular manner because it has a certain set of physical characteristics and configurations over time, was presented in such and such a way, etc.

On one level, then, the inquiry into why a particular item fits where it does in a similarity structure and elicits a particular pattern of behavior, or the attempt to design a new item which when introduced into a culture will be located in a particular position in the similarity structure and therefore will elicit certain behavior, is the search for a description that will perform as the item has been observed to or is desired to perform.

Figure 5 and Tables 9 and 10 show examples of some aspects of the search for a description which performs according to prediction. We surmised that in Quechua (an Indian language), Peace Corp workers might be described as *yanapakuggringokuna* [*yanapakugkuna* is a reciprocal work group, that is, people who work together to help each other, and the meaning of *gringo* is obvious (Stefflre and McClaran, 1971)] and then tested the fit of this description for Cuzqueños by measuring the similarity

of *yanapakuggringokuna* to
measured by (a) a role by b
and then (c) by comparing t
of a correlation matrix base
roles according to how mu
improvement in the quality

The results of the comp
del cuerpo de paz were as fol

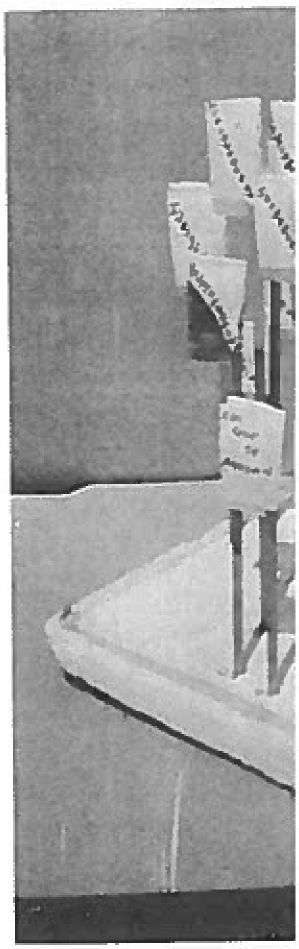


FIG. 5. Spatial representatio
model of the correlation matri

y of complex patterns
tudied cross-culturally
20 different sectors of
Corps volunteers; and
stated above that the
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rticular item fits where it
ular pattern of behavior,
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arity structure and there-
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ng to prediction. We sur-
Peace Corp workers might
qkuna is a reciprocal work
help each other, and the
cClaran, 1971)] and then
y measuring the similarity

of *yanapakuqgringokuna* to *voluntarios del cuerpo de paz*. Similarity was measured by (a) a role by behavior matrix, (b) a judged similarity matrix, and then (c) by comparing the location of these roles in the physical model of a correlation matrix based on having 500 Cuzqueños rank a group of 31 roles according to how much they thought each role was contributing to improvement in the quality of life in Cuzco.

The results of the comparison of *yanapakuqgringokuna* to *voluntarios del cuerpo de paz* were as follows: (a) it was second most similar in expected

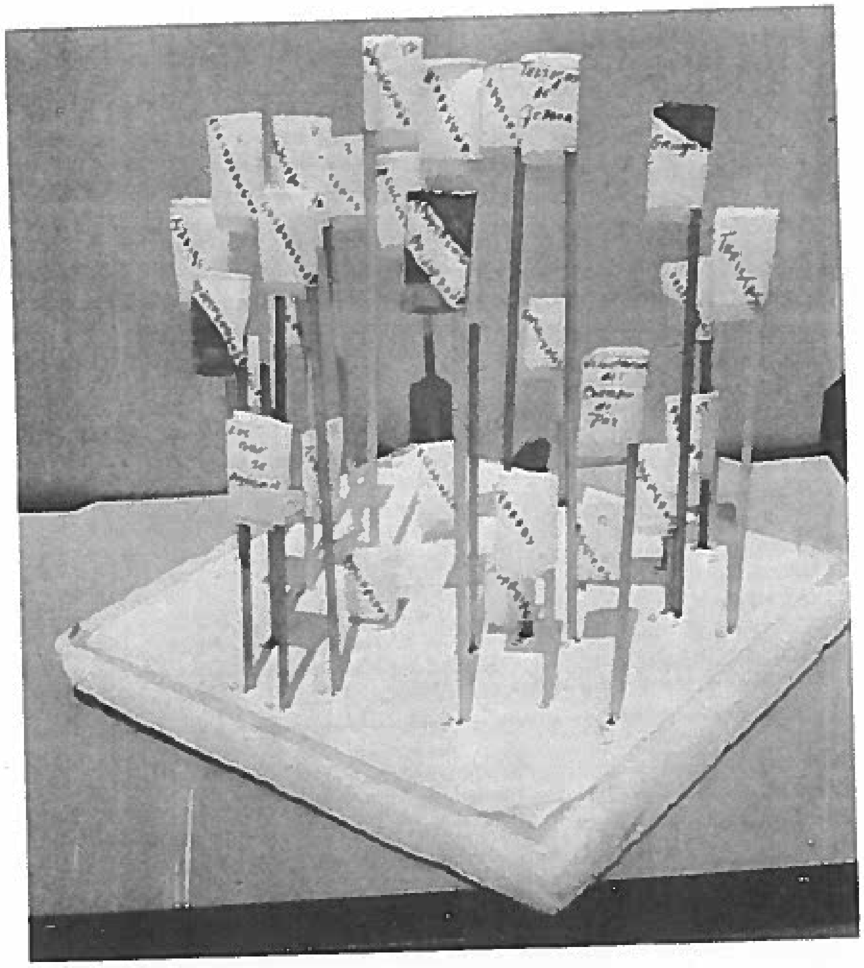

Fig. 5. Spatial representation of Peace Corps versus other types of people: A spatial model of the correlation matrix.

TABLE 9

Ranking of Peace Corps Volunteers with Other Types of People

Most similar to peace corps volunteers		
1	Testigos de Jehova	Jehova's Witnesses
2	Gringos	Gringos
3	Soldados	Draftees
4	*Yanapakuggringokuna*	*Gringos who mutually help*
5	Turistas	Tourists
6	Guardias	Policemen
7	Padres	Priests
8	Ingenieros	Engineers
9	Los que ayudan	Those who help
10	Q'arkuna	Young men city slickers
11	Maestros	Teachers
12	Yanapakuqkuna	Those who help each other
13	Abogados	Lawyers
14	Estudiantes	Students
15	Adinerados	Wealthy people
16	Enfermeras	Nurses
17	Hacendados	Landowners
18	Comerciantes	Merchants
19	Médicos	Doctors
20	Licenciadukuna	Army 'graduates'
21	Personerokuna	Village representatives
22	Campesinos	Peasants
23	Ladrones	Thieves
24	Parteras	Midwives
25	Indígenas	Indians
26	Cholos	Creoles, natives
27	Watuqkuna	Diviners
28	Mestizos	Mestizos
29	Obreros	Laborers
30	Placeras	Female plaza vendors
Least similar to peace corps volunteers		

behavior of the 53 roles compared in the role by behavior matrix, (b) it was the most similar of the 27 roles compared in the judged similarity work, and (c) it had the fourth highest correlation of the 31 roles ranked in terms of contributing improvement to life in Cuzco. Table 9 shows the ranking of the roles by their correlation with *voluntarios del cuerpo de paz.* and Figure 5 shows their positioning in a spatial model of the correlation matrix. (Table 10 shows the coordinates for the model.)

From these results we can surmise that the components concatenated

by infixing *gringo* in *yanapa*
positions like *voluntarios del c*
"built" some people seen by
yanapakuggringokuna they w
this description.

PEACE (

No.	Dimension X	Y	Z
1	1.05	5.98	9.
2	19.22	15.67	6.
3	10.35	2.97	13.
4	13.45	2.13	10.
5	8.99	5.68	18.
6	13.87	4.81	3.
7	0	6.53	9.
8	9.10	8.84	20.
9	3.61	16.46	13.
10	12.94	7.01	1.
11	13.73	10.74	20.
12	11.42	20.54	13.
13	.47	12.20	9
14	4.22	6.84	
15	8.74	14.49	2
16	11.50	7.63	19
17	17.49	18.10	10
18	6.97	15.79	4
19	18.96	2.93	9
20	10.57	5.40	1
21	19.41	16.17	11
22	15.44	10.82	12
23	3.51	2.13	10
24	4.21	15.70	12
25	10.70	6.74	1
26	16.70	15.60	1
27	13.78	17.73	1
28	1.47	15.34	1
29	20.48	8.16	1
30	5.53	0.41	1
31	8.80	17.14	

by infixing *gringo* in *yanapakuqkuna* make a combination that roughly positions like *voluntarios del cuerpo de paz.* We can also surmise that if we "built" some people seen by our respondents as matching the description *yanapakuqgringokuna* they would position and perform approximately like this description.

TABLE 10

Peace Corps Data Coordinates

No.	Dimension X	Y	Z	People	
1	1.05	5.98	9.42	Turistas	Tourists
2	19.22	15.67	6.68	Médicos	Doctors
3	10.35	2.97	13.16	Ingenieros	Engineers
4	13.45	2.13	10.93	Testigos de Jehova	Jehova's Witnesses
5	8.99	5.68	18.36	Obreros	Laborers
6	13.87	4.81	3.50	Guardias	Policeman
7	0	6.53	9.45	Campesinos	Peasants
8	9.10	8.84	20.51	Ladrones	Thieves
9	3.61	16.46	13.86	Comerciantes	Merchants
10	12.94	7.01	1.07	Soldados	Draftees
11	13.73	10.74	20.01	Watuqkuna	Diviners
12	11.42	20.54	13.66	Adinerados	Wealthy people
13	.47	12.20	9.58	Gringos	Gringos
14	4.22	6.84	.23	Voluntarios del cuerpo de paz	Peace Corps
15	8.74	14.49	2.32	Yanapakuqkuna	Those who help each other
16	11.50	7.63	19.25	Abogados	Lawyers
17	17.49	18.10	10.30	Enfermeras	Nurses
18	6.97	15.79	4.63	Mestizos	Mestizos
19	18.96	2.93	9.92	Padres	Priests
20	10.57	5.40	1.86	Licenciadukuna	Army 'graduates'
21	19.41	16.17	11.22	Parteras	Midwives
22	15.44	10.82	12.81	Q'arkuna	Young men city slickers
23	3.51	2.13	10.66	Indígenas	Indians
24	4.21	15.70	12.55	Personerokuna	Village representatives
25	10.70	6.74	1.34	Yanapakuqgringokuna	Gringos who mutually help
26	16.70	15.60	14.48	Estudiantes	Students
27	13.78	17.73	14.82	Hacendados	Landowners
28	1.47	15.34	14.77	Placeras	Female plaza vendors
29	20.48	8.16	10.79	Maestros	Teachers
30	5.53	0.41	12.29	Cholos	Creoles, natives
31	8.80	17.14	2.27	Los que ayudan	Those who help

TABLE 11

COMPARISON OF (1) RATING OF PRODUCT (A NEW COFFEE) ON DESCRIPTIVE SCALE, AND (2) CORRELATION OF PREFERENCE FOR THE PRODUCT WITH PREFERENCE FOR DESCRIPTION

Coffee	(1) Ratings ($N = 100$)	(2) Preference correlations ($N = 600$)
(1) Light	64.00	(2) +.071
(2) Clean	61.00	(3) +.062
(3) Friendly clean	60.50	(4) +.052
(4) Friendly	57.66	(1) +.088
(5) Mild	57.66	(5) +.049
(6) Bright flavorful	56.16	(7) −.025
(7) Lively	52.66	(6) +.011
(8) Strong	46.66	(8) −.049

$\rho = .80 (p < .05)$.

If, however, we wish to move to a more basic level of analysis, our problem becomes one of actually creating the thing that matches the description and therefore elicits the behavior desired.

One example of this problem of translating descriptions into things can be found in some early work we did several years ago on coffee. The manufacturer wished to add another brand of coffee to increase his corporate share of the market in a region where it was low and, particularly, to do so at the expense of two major competitors. We found a description—or rather a set of descriptions—of a coffee which should serve this purpose, and then we were faced with the problem of building a coffee (by varying bean selection and roasting processes) to fit these descriptions.

The process used to evolve such a coffee was rather complicated but can be summarized as systematically testing the fit of varied stimuli against description and preference until one combination has been selected that fits the description better than any competitive product. The column entitled "Ratings" in Table 11 shows the fit of the product to a set of eight descriptions.

The preference correlations column in Table 11 shows the correlation between preference for this product and preference for each of these descriptions in a 600-person national sample. Figure 6 shows a spatial

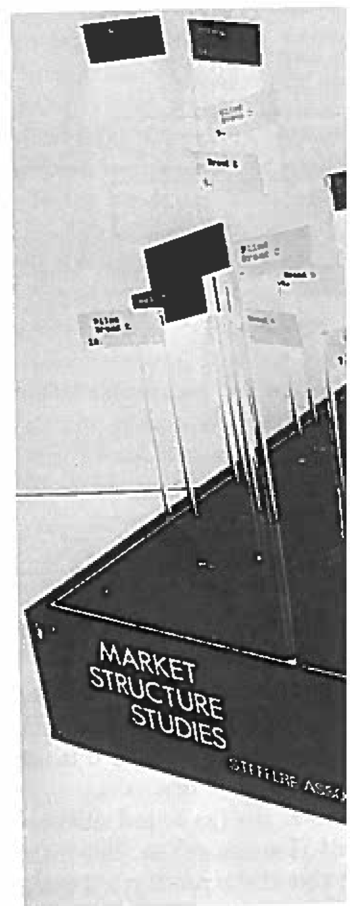

FIG. 6. Spatial representation o
characteristics.

representation of the patter
in the national sample. Bra
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What happened in this res
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(ii) was liked in the large-scal
it was built to match.
The client then decided to

…UCT (A NEW COFFEE) ON
…TION OF PREFERENCE FOR
…E FOR DESCRIPTION

…ngs …0)	(2) Preference correlations (N = 600)
	(2) +.071
	(3) +.062
	(4) +.052
	(1) +.088
	(5) +.049
	(7) −.025
	(6) +.011
	(8) −.049

…ore basic level of analysis, our …ng the thing that matches the …ior desired.

…ting descriptions into things can …l years ago on coffee. The manu… coffee to increase his corporate … was low and, particularly, to do …ors. We found a description—or …which should serve this purpose, … of building a coffee (by varying … fit these descriptions.

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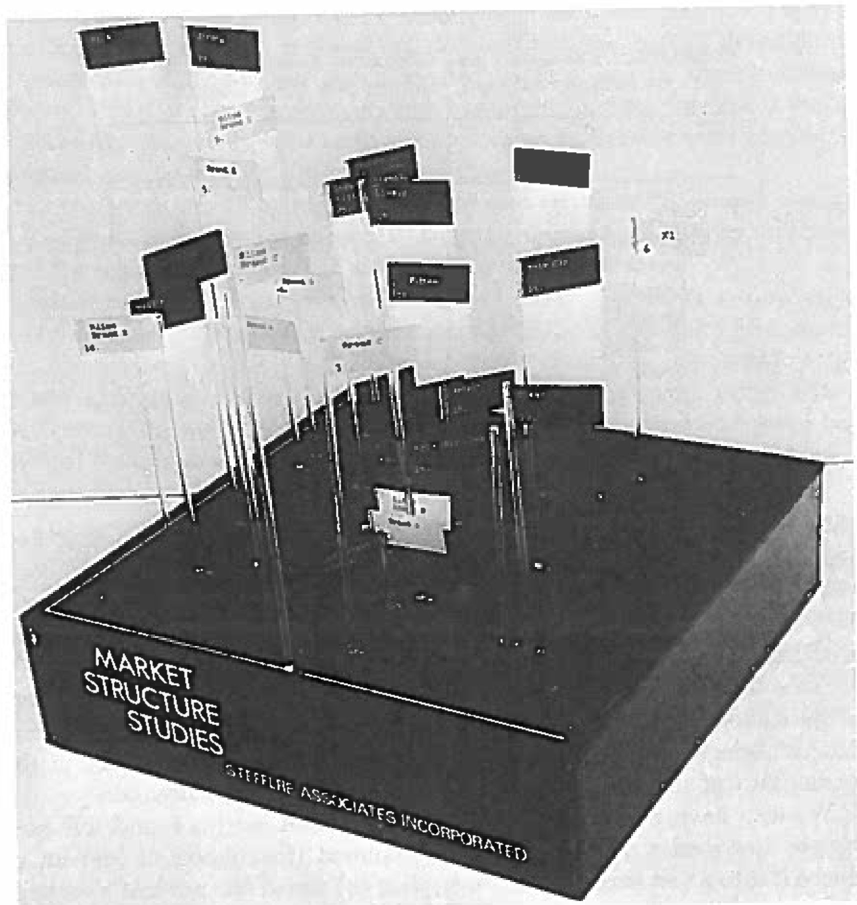

FIG. 6. Spatial representation of preference patterns for brands of coffee and coffee characteristics.

representation of the patterns of preference for this new blend of coffee in the national sample. Brands of coffee and coffee characteristics near each other are those liked by the same people.

What happened in this research was quite straightforward (a) a description was found that performed as the manufacturer desired, (b) a product was built that (i) was seen by consumers as matching the description and (ii) was liked in the large-scale test by the people who liked the descriptions it was built to match.

The client then decided to put the product in another part of the country

TABLE 12

Comparison Predicted and Obtained Percentage (Share) of Market in Test Market for New Coffee

	Predicted %	Obtained %
1 Share	4.	5.1
2 Business from:		
brand M	38.	36.35
brand W	11.	2.3
brand C	8.	10.5
brand B	5.5	5.
brand A	5.5	9.6
brand L	4.	4.1
brand N	4.	3.

than had been its original target.[1] We tested its description in that new region and gave the client our guess as to its performance. Table 12 compares this prediction with what in fact happened during the product's first 38 weeks in test market (combining panel data adjusted for warehouse withdrawals with a telephone survey).

Since the first project of building a new coffee, we have done three others of the same type. At present we also work to evolve advertising, packaging, etc., all selected to fit a particular description whose performance in the earlier part of the research has been as the manufacturer desired.

We also have five experimental cases in which we (a) found out how people described a product under development (four cases) or just introduced it into a test market (one case), then (b) tested the product's description in a 1500-person sample, and finally (c) obtained data on the product's performance in the regional or national market in which we had tested its description. Figure 7 shows the predictions of the performance for the five different products and their actual performance in the market. In four of the five cases, the predictions were within ±30% of the volume obtained by the product.

The aim of this digression has been to show one use to which the fit between judged similarity and large scale patterns of routine behavior, on the one hand, and the performance of descriptions and the things that

[1] This project was written by our client as a Harvard Business School Case M266, 1967 and reprinted in Brown *et al.*, 1968 as Ch. 19, Pp. 439–466. My manuscript, *New Products and New Enterprises: An Experiment in Applied Social Science*, (Stefflre, ms.,b) describes some problems in applied research of this type.

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While the assumption of a
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and preferences.
The present author is inc
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be violated fairly frequently.
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ranging from .5 to 1 (J. Boy
This violation occurs in
descriptions) reside in two c

Fig. 7. Comparison of perfor
of product descriptions and new
ucts in Market for five di
products.

[2] A metric space is commonly
(a) $A_D A = 0$ if and only if $A = A$
(the triangle inequality).

:D PERCENTAGE (SHARE)
FOR NEW COFFEE

d %	Obtained %
	5.1
	36.35
	2.3
	10.5
	5.
	9.6
	4.1
	3.

ted its description in that new its performance. Table 12 com- ıappened during the product's nel data adjusted for warehouse

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match them, on the other, can be put; and to show the heuristic value of spatial models both in representing these structures and in determining which features lead items to be located as they are in the structures. Though most work of this kind that has been done to date has been in marketing, the general processes are applicable to development problems, political campaigns, etc. (e.g., Mauser, this volume).

In the work described above, the modes of representation used assume a Euclidean metric space as representing the aggregate similarity structure and the aggregate patterns of similarity in behavior.

While the assumption of a metric space[2] underlying these structures is useful in some respects, in other respects it is misleading. The major problem in representing aggregate–aggregate data (i.e., similarity judgments aggregated across individuals and across responses, using either patterns of behavior or choice measures as surrogates for patterns of behavior) by a metric space has to do with the relationship between features and preferences.

The present author is inclined to believe that in using an appropriate distance measure for psychological similarity, the triangle inequality would be violated fairly frequently. It is of course possible to use distance measures which force this assumption never to be violated, e.g., numbers ranging from .5 to 1 (J. Boyd, personal communication).

This violation occurs in two ways (a) some items (things or verbal descriptions) reside in two disjoint spaces simultaneously, and (b) three-

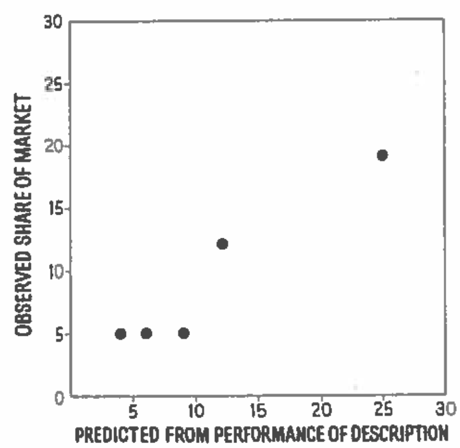

FIG. 7. Comparison of performance of product descriptions and new products in Market for five different products.

[2] A metric space is commonly defined as one in which three assumptions are met (a) $A_DA = 0$ if and only if $A = A$, (b) $A_DB = B_DA$ (symmetry), (c) $A_DB + B_DC \geq A_DC$ (the triangle inequality).

dimensional representations of disparate sets of complex natural stimuli force a common space and understate dimensionality enough to approximate (a) above.

A simple example of (a) above is found in words with multiple meanings, e.g., *light* contrasts with *dark* in one sense and with *heavy* in another. This example may seem irrelevant; however, further examination shows that it is indeed pertinent. Multiple meanings in language can range from homonyms (e.g., different, unrelated words sounding the same, such as *board* and *bored*) to multiple meanings of the same word (e.g., various senses of the same word such as "not all *men* are *men*" or slight shifts in meaning of a word in a new context such as "the atomic *submarine* Nautilus"). The degree of interrelatedness of pairs of appearances of the same form is essentially a continuous dimension. *Light* in the context dark contrasts with one set of terms *dark* and can be defined semantically as the intersection of one set of features, while in its other use, it contrasts with and is defined in terms of another set of features.

The form itself when presented, for example, as a free association stimulus, is responded to out of context in both ways by respondents; and thus as an object in a similarity structure, it resides jointly in two spaces. Its contrasts *dark* and *heavy* each reside in one of these spaces. A synonym for *light* in one space would be *well illuminated* and in the other *not weighty* and clearly these two phrases are not synonymous.

A physical object may exhibit the same kind of multiple meaning. As a *bowl* an object fits in one space, as a *chalice* the same object fits in another.

The argument here is not just that individuals differ in the frame of reference they impute to the same object, but that the same individual will differ in the space treated as relevant to a particular object from context to context and that individual differences may only reflect differing salience in contexts.

The examples chosen here are extreme and confusion could only be avoided in such cases by subscripts—$light_1$, $light_2$, or $thing_B$, $thing_C$—but the phenomenon is continuous and ubiquitous. A and B may be similar for one reason, B and C similar for another, and A and C share nothing. I think of this as the "you can't get there from here" phenomenon in which the triangle inequality appears to be violated (e.g., James, 1890, p. 578). *Bright* is similar to *light*, and *not weighty* is similar to *light*, but *bright* and *not weighty* share *little*.

By attempting to jam the similarities into a common space in a metric space analysis and, further, by reducing the complexity of the space to a workable number of dimensions, problems appear in the heuristic value of the spatial representation as a help in determining the features underlying item placement.

As soon as coordinates are specified and a physical model built, the question "What does up mean?" emerges. One answer is "Up means the things that are high." Another is "Up is a synesthetic dimension including both light in weight and bright in illumination." Or, one we prefer is "There are no dimensions, just labeled regions—up on one end of the space may mean something very different from up on the other—and to test your understanding of how to go where, build new things and see if they go where you expect." Alternative interpretations are not to be resolved by analysis but by experimentation.

A second assumption of the current work on metric space which makes the author nervous is that location uniquely determines preference—not just which people like a thing more, but also how many people like it. Several joint models (Carroll, this volume; Carroll & Chang, 1964, 1967, 1970; Coombs, 1964; Doehlert, 1968; Doehlert & Hoerl, 1967) have been suggested in which it is inferred not only where items are located, but also where each individual's ideal point resides in the space.

While our own work in this area has been quite crude, we are at present as pessimistic about the prospects of an algorithm of this type as we are about using the spatial coordinates of a metric representation as a formula for constructing new objects. What we have found fairly frequently is that two new items which are quite near each other in free judged similarity or behavioral similarity may be differentially preferred.

An example may illustrate the possibility of the lack of correspondence between position and preference. If we present twelve pictures, ten of different people and two prints of the same dog photo to be judged on similarity, the two dog pictures will probably turn out to be quite similar. If we look at preference data both pictures will probably tend to be liked by the same individuals. If one is a good print, however, and the other not so good, their absolute levels of preference may differ rather more than their similarity in location would indicate. Another way to say this is that judged similarity may predict correlations between the preferences for items better than the cross-products of the items preferences or their levels of preference. We have analyzed several cases in which judged similarity correlated with items correlations in preferences .64, .45, and in which it correlated with cross-products .002 and .06.

A number of examples of this kind have caused me to change my point of view from one which considers location as uniquely determining both (a) level of and (b) pattern of preference to one which considers that location determines the pattern of preference, but that the level of preference is determined partly by location and partly by G, a general level of preference evaluation. Items rather than points in space represent (a) nodules with a specified level of preference, (b) occupying a particular position in the space.

Let it suffice in this context to say that we have found metric space models useful heuristics in describing regularities in aggregate–aggregate data and in positioning new items, but we have not yet found an algorithm for doing the latter that is satisfactory.

For other kinds of data we suspect the metric space assumptions may prove even more troublesome. In individual data, similarities can shift radically as various contexts call different features into salience so that individual similarity data at one point in time represent a metric space (Shepard, 1964), while at another point in time they represent a different metric space. This kind of change seems quite antithetical to the whole notion of spatial representation. Aggregate free response judged similarity data aggregate these contexts by aggregating individuals; pattern of behavior data or choice data aggregate these data across individuals and contexts.

Due to the perverse and/or delightful flexibility in sequential behavior on the part of human beings, several first-rate workers who did early work on similarity and spatial representation of the mind have shifted to means–ends process models (Abelson, 1954; Abelson & Carroll, 1965; Abelson, Aronson, McGuire, Newcomb, Rosenberg & Tannenbaum, 1968; Miller, Galanter and Pribram, 1960; Miller & Nicely, 1955).

In addition to assuming stability of the structure, the spatial representation assumes that an element is an element. However, as saliency among dimensions shifts, i.e., as the spatial configuration appropriate for one context flows into that for another, an element in the space takes on a new set of properties (e.g., a *bowl* becomes a *chalice*). In working with aggregate data, the change in similarity as a function of context poses a problem. Consider the following case: Items A and B are more similar than items A and C and hence generally elicit more similar patterns of behavior, yet there may go undetected a single crucial behavior or context in which A and C may prove more similar (e.g., legal cases).

These properties of the mind—shifting contexts shifting salient features, and shifting features transforming elements—seem quite unspatial. Even if we freeze the data at one point in time and look at them in terms of the metric space assumptions, there are still problems. $A_DA = 0$ suggests that there is nothing closer to A than A, but consider confusions in recognition experiments in which a single incorrect stimulus may be selected

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more often than the correct stimulus. Such a situation suggests that if we take confusions as a measure of distance, $A_DA' < A_DA$ and $A_DA \neq 0$. A_DB and B_DA symmetry frequently seems to be violated in data on judged similarity and confusions. An imperfect example of an X may be more often judged as similar to a prototypic X than vice versa. Confusions data often indicate similar asymmetries. The triangle inequality ($A_DB + B_DC \geq A_DC$) and its problems were considered above. At this point let it suffice to say that though A is similar to B (a red apple and a red Cadillac) and B is similar to C (a red apple and an orange), A and C (a red Cadillac and an orange) may be more dissimilar than a strict reading of Schwartz might suggest.

This is not to suggest that by appropriate manipulations of our data collection and data analysis we cannot force a metric space, but only to suggest that while such manipulation may be useful for specific practical or theoretical purposes their utility is limited and provisional.

The present author's own notion of the reality of the phenomenon with which we deal—the individual mind and its aggregated analog, the group mind or collective representations (Durkheim, 1915)—is that its structure is discrete, and combinatorial rather than continuous and geometric, looking more like a dictionary, thesaurus, and a grammar than a three-space (Stefflre, Reich, and McClaran, 1971). It is composed of elements and relations and each element can be represented as a description list of the elements to which it exhibits specified classes of relations. (This alternative type of development can be seen in the works of Goodman, 1951; Tyler, 1969; Minsky, 1968; Hartmanis & Stearns, 1966.)

The basic structure is that of a multigraph (Berge, 1962; Harary, Norman, & Cartwright, 1965; Ore, 1963), though the data we deal with are usually spatial representations of the similarity structure obtained in aggregate free judged similarity; e.g., frozen slices of individual data with the elements on the description list at a particular salience aggregated into a collective representation.

I am inclined to believe that a multigraph description will allow us (a) to calculate from it the spatial configuration, and (b) offer us a model with more flexibility and generality than a spatial approach.

In summary, then, it has been suggested that multidimensional scaling methods have a real utility in describing patterns of similarity and patterns in the similarity of behavior elicited by things or events. They are a powerful descriptive tool for studying regularities in the patterns of behavior of aggregates and are of some help, if used heuristically, in determining *what* features put new items *where* in structures of this kind.

Some problems in the use of these methods stem from the shifting nature of psychological salience in an individual through time and the fact that many crucial behaviors one may wish to predict can hinge on the presence or absence of particular features rather than overall similarity.

A spatial configuration, while not a very good model for the structure of the individual or group mind or of the society, does provide a useful device for working on special problems.

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