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SOME APPLICATIONS OF MULTIDIMENSIONAL SCALING TO SOCIAL SCIENCE PROBLEMS

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Volney J. Stefflre

SCHOOL OF SOCIAL SCIENCES UNIVERSITY OF CALIFORNIA IRVINE, CALIFORNIA

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

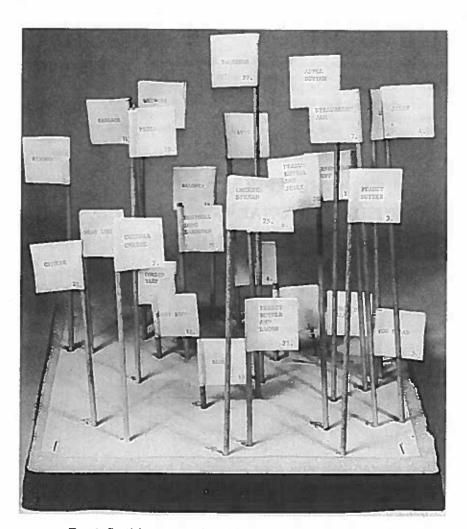


Fig. 1. Spatial representation of judged similarity of sandwiches.

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

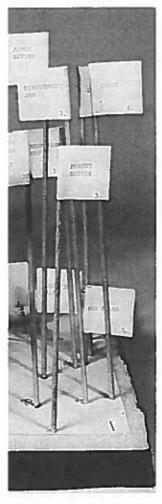
COORDINATI

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

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

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arity of sandwiches.

ne this basis. These indis are then subjected to a sentation in which the recorresponds to the rank

est to social scientists in r possible ways to analyze

TABLE 1 COORDINATE VALUES FOR SANDWICH DATA

		Dimensions		
No.	X	Y	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.

- 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 Steffire, 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 inde developed: Item-by-use tution patterns.

ITEMS WITH THE SAME

Table 2 shows item-by show the stages in the reto distributional similar matrix rearranged into o

Table 2 is the data m of medicine and each col The informant substitu (kind of medicine) when of the sentence thus for to a zero). For example was judged unacceptal column 2, is blank.

Table 3 shows the r row to every other row same patterns of ones. belief-frames allow the ceptable statements. If then the similarity bet

(where r' is the column Table 4 shows the rerows similar to each ot

Table 5 shows the column to every other the belief-frames that zeros and ones for the i and j is as follows:

Table 6 shows the that columns similar t al's culture, the individual e way he behaves toward item.

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dividual sees as similar to one may try to determine cular culture. Figure 1 and similarity data on different espondents are asked which ormalized, and transformed scaling (Kruskal, 1964a,b). ill samples of respondents lents are assigned numbers dealing with a sample of 50, r the 25 odd-numbered and t five sets of similarity data he correlations between the , were .75, .60, .85, .80, and . (e.g., see Gulliksen, 1950, ty of the data for the total

are similar for an individual g forms of aggregated data grns. These can be taken as rity which various pairs of alture studied.

the last few years on market se of the availability of large: in this area and because of natural experiments through sumer products. In this con-Steffire, 1965), patterns of and competition, i.e., objects each other in a single choice 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 *i*th 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

The children have colds Hot and cold flashes Taken a chill Tonsils are inflamed Feel nauseated In the summer Down and out Can't breathe Swollen glands Earache

6 4 28 4 14 11 37 13 15 24

								1	ИE	DIC	IN	ES	AN	р 1	VH	EN	т	T	AK	eЛ	Гне	M
	•	Bad taste in your mouth	Stuffy nose	Headache	Minor muscular aches	Tightness in your chest	The children have a fever	Can't breathe	In the winter	Sore throat	Hangover	Post-nasal drip	Cough	Indigestion	Feel weak	After you've been ill	During the flu season	Broken leg	The children are sick	Neuritis, neuralgia	Runny nose	Back ache
MEDICINES	ROW/COL	1	2	3	4	5	4	7	A	9	10.	11	12	13	14	15	16	17	1*	19	20	21
Bufferin Sucreta Vichs inhaler F & F Cough drops Hot Iemonade Drietan medicated room vaporiter Listerine throat loxenges Vichs cough drops Chloraseptic loxenges Vichs cough drops A hot toddy Mentholatum Seeing the doctor Costac Adulton cough syrup Privine nasal spray Privine nasal spray Krez A, P, A, pain relisever Vicks formula 44 cough disce Contac nasal mise Bromo selites! Hot togen disce Contac nasal mise Bromo selites! Hot tog Spectrocia-T-troches Coricidin cold tablet Vicks vapo-rul Fruit pluc Uritan nasal decongestant capasile An ice paci Aspirit Cough syrup Vitamin Ear dropp Alba selites Naso-de: Squibb analgesic tablet Vichs throat loxenge Heosynephrine nasal spray Privine nose drop Tetrasets antibacterial analgesi Neosynephrine nasal spray Cepacol throat loxenge Fromitar cough loxenge Fomitar compoun Calling the doctor Calling	2 3 3 4 5 5 6 7 8 9 9 111 12 13 6 1 14 1 15 1 17 18 1 17 18 1 17 18 1 17 18 1 17 18 1 17 18 1 17 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 1 18 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 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 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 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 1 1 1	######################################		1 1 1 1 1 1 1	11111111111111111111111111111111111111	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 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 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 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 1 1 1 1 1 1 1

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TABLE Row-Row Similarity Matrix of Medicines

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1 1	1,80	. 34	*50	.43	.41	.11	.44			.14	. 11	.14	. 58	.33	-20	- 34	.06	-34	. 34	*50	:00	.44	- 34	. 30	
2		1.00	1,00	. 17	.10	:::	,14	-37	+48	. 20	44.	-24	.86	-42	- 84	.36	.00	. 55	:	117	.00	-12	.97	41	-11
- 1	.20	. 61	1.17	1.00	. 69	.47	41		.41		***	:43	.43	:11	-17	. 72	. 199	. 43	. 34	.40	-10	. 84	. 52	-92	-67
- 1	4.7	.43	. 98	. 19		- 19	. 92	.11	.43	.11		.77	. 70	.64	.75	.30	-17	- 33	+ 94	- 11	.00	-12	1.00	1.00	-42
ě.	.30	-11		47	.57	3.00	1.00		44	.58	.74	.46	. 37	+40	-17	447	.09	.11	.73	-17	. 00	.92	,97	497	.15
	1.41	. 84	-110	1.00	. 33	.47	10,		.43	.53	.50	+43	. 13	.11	:17	. 46	.10	337	.78	-10	.00	, 44	. 96	.96	.92
	133	.81	.48		-49	. 43	- 96		133	.11	:::	.30	142	.57	. 51	.03	.24	.49	.48	-31	-12	. 74	. 10	.30	.10
10	.90	-19	- 18		- 11	:43	. 10	-53	.34	.33	1.70	.22.	. 11	.59	.67	. 33	-43	.48	.44	-47	.00	.48	44	.64	. 10
- 11	439	- 31	.74		157	.27	. 64	.43	.44	.18	. 21	1.05	134	+14	-13	.15	-10	. 34	. 43	. 87	.00	.46	-37	.37	.49
- 13	111	-14			. 11	179	. 17	.41	.30	.42	:4	.24	1.00	1.00	.12		.27	.27	.71	. 30	.00	.28	-48	-48	.48
14	1	.11	.48	.13	.11	+44	.48	:13	:10	. 11	.41	.11	. 62		1.00	.24	.00	.33		1,00	-11	.11		.17	.72
13	.70	+20		-17	-17	.75	.17	444	.40	441	. 33	+38	. 15	-39		1.00	-30	.10	.33	.24					.84
16	147	-16			+03			.17	.10	.24	.43	.28	- 10	-37	.00		1.00		4.0			. 9 5	- 35	. 19	- 34
17	1:31	.54			49.0	. 11	. 11	+53	.47		.48	. 31	. 30	.27	.21	.13			1.00	- 21	.00	. 10	- 79		-10
15	179	- 61	. 10	-96	. 39	.99	11	-80	.18	.11	- 1	313	. 11		1.00	. 24	400	-25	.21	1.00	1.00				.22
20	#PP	+21			- 40	-60	11,00	.00	.00	.12		.08	. 98	.00	, ne	-11	.00	, 80	.10						111
- 24	-11	.00			-10	-11		. 22	-46		.41	+45	. 44	+26	-11	.71		. 33	. 71	- 11	.00	441	1.04	1,86	-10
23	100	-91			. 12	+41	1,90	.97	. 90	-59	. 34	***	31	.48	-11				.79	- 417	.00		1.00	[-96	-54
12	1 :55	- 445		. 97	-17	-+1		. 97	198	.50	1		.45	.46				.36	+50						1.00
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98	1 1							41	441	+11	1	1 15								3 .1		4 4			
47	13				6 47		4 .5	244							1	0 .6	7	9 .5	1 4	1 4	8 4	0 .1			
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50	- 9	7									1.31	1 .4	4 .2	• .7											
51	1.0		50 .									+1	1 .1		1 .1	1 -1	7 .0	,	• "			-			
58	- 2		*** **			100																			
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TABLE
REARRANGED ROW-ROW SIMILARITY MATRIX OF

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						42	30	24	11	15	,-	. 1		11	24	1•	31	19	44	37	44	23	•	4	1
FD4 /404	21	34	1.3	44	el		_		<u> </u>			_		-	- 44	.00	-80	.00	.00	-00	.00	.00	.00	.00	.90
21	1.00	.00		. 60	.00	-20	. 89	. 80	.00	.00	.13	.08	. 00	.10	-11	.17	+14	.13	-12	+11	-111	-11	-10	-10	+31
34		1.07	-11	-19	-14	.14		-14	.02	47	.07		. 19	.71	.48	,48	- 43	. 43	.40	-36	.17	.17	-17	:41	417
13	1 .01	-11	1.00	1.00	1 - OB	1.00	1.00	1.00	1.00	. 95	+23	+84	. 73	**	. 16	.38	.11	:#	-19	110	117	. 17	-17	-17	-17
41	inc.	-14	1.48	1.00	1.00	1.00	1.00	1.00	1.78	.91	:31	-14	. 75	4.7	. 34	.10	-27	.21	-19	-10	-17	+67	-17	417	:17
40	.80	-14	- 92	1.00	1.60	1.00	1.00	1.80	1.00		. 77	. 94	. 79	.47	. 10	. 3-0	.27	- 21	-17	+10	-17	:17	:17	:17	.17
10	. BR	-114		1.00	1.00	9.400	1.07	1.00	3.07	.99	. 22	.44	. 75	447	- 16	-10	.17	:#1	.19	:11	-17	.17	.17		41.7
20 13	.00	- 14	142	6.69	1.00	1.00	1.00	1.00	1.00	1.20	-71	.11	-73		.10	-11	- 12	. 10	.11	174	.29	-21	-24	. 29	225
33	.07	-61	.47		. 91		94	. 95		1.00	1-28	191	. 61	.72	. 42	. 15	.38	. 50	.27	+84	-25	+33		-14	111
24	.00	-13	. 11		.41	. 49		-46	184	.91	-71	1,00	+ F1	+67	+48	+42	.10	- 16	.33	.40	. 30	.30	.17	.67	.41
1	.00	-112	.74		. 29			. 19	. 11	.87	.*0	421		1.00	171	.61	.34	. 56	.46	.36	. 34	39	440	. 48	+34
15	,ne	-11	.71	- 41	-47	- 41		147	- 67	.73	-31	.42	. 64	-71	1.00	.79	+73	. 70	+64	. 54	. 12	.98	- 17	-17	-12
24	ne	-11			. 36	- 14		- 14	, 10	.33		147	+64	.35	176	8. DO	- 19	+73	+41	-59	.48	. 48	- 22	. 13	,10
14	.00 .00	-67			: 11			-27	188	. 32	**1	-59	. 51	*58	10	.73	1.00	1.00	.91	. 78		. 71	-00	.08	+73
11	1.00	-11	443	- 21	- 21	. 11		-41	-75	.37	-10	.30	. 15	166	-96				1.00	- 80	.89	- 89	- 8 9	-14	. 45
44	-81	+12	. 69					-19	-119	.24		4.8	443	. 14	. 50	.98	.73	. 19		1.00	. 90	1.00	.43		1.00
37	.80	-11	.19					- 117	+17	.24	.75		141	4.94	- 12	+60	.10	.73	.03	. 70	1.06		. 97	. 97	1.00
24 23	.00				+17	.17	-17	-1.0	+17	.75	- 23	- 72	47	.34	. 17	.48	.75	. 00	- 87	.41	. 07	.47	1.00	1.00	-47
17	-89	-11	441	. 17				-17	-11	.24	.74	.17	47	.40	1.7	.55	.79	.00	.89	.43	. 97	. 97		1.00	1.00
4	. 00							-17			.79	.30	= 41	. 34	4.57	+46	- 70	- 73	465	.96	1.00	1.00	.91	. 93	. 96
- 1	.00		. 11					-10	410	.24		***	- 41	-34	. 44	- 14	.73	.74	. #5	.44	1.00	1.00	.97	.97	1.09
- 15	.30		- 41	1.11	+13			-17		-43	.73	.10	:41	.14		.44	.76	. 75	.49	498	1.00	1.90	.41	. 07	1,00
47	.00	+11									. 19	17.9	+31	- 11	2	+33	.60	-67	• 74	.43		.46	-83	.01	. 79
	100							.71	. 11	*50	."0	.77	+ 32	+14		- 14	-51	.33	-11	.11			.67	.47	449
39	1 .11				1 11	1 455	19					.))	- 30	-11	.40	. 10	-43	.43	,54	-48	.19	.39	-97	-57	.11
34	1.17	. 22	. 11										.71	.48		. 27	-48		- 31	- 97		-33	.11	.43	.44
1.0	.00										419	.74	- 22	-22		-13	-24		- 11	.55				134	.50
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ï	Laii			, ,21								.78	. 34										-46	. 44	. 47
16	-11	+25								-31	. *1	136	. 23	-29	. 19	+21	- 13						.44	. 54	44.
10	1:1:							.14	+14															.46	***
50	1 :::				1 43								. 31					, 76	44				- 50	.10	- 11
11	-14	4											. 19	447	. 45	+31								.33	
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10	1:1							- 25				. 50										-51	. 15	. 59	.10
29	+81		F ,4	9 . 2													34	. 37						. 44	. 54
34	+0										111	+73	-21	- 44	+29	1.1								.79	.30
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3 Based on When Used (Indi

26	27	20	29	10	34	34	88	14
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.43	-33	.29	.00	+34	+40	+45	.00	
-48	.13	. 41	.00	.11	- 30	.27	.11	:
.97	-11	.24	.00	:17	.79	. 41	.10	
.45	-44	.00	.00	.33	.50	.23	-11	
-17	-34	.73	.00	.41	- 79	.47	-11	
. 67	-11	-24	.00	.44	. 113	.66	:11	:
. 14	-,58	-24	-27	: 11	. 10	.44	-12	-
.71	:11	. 78	-10	.29	100	-17	-11	
	.11	.10		.10	.36	. 94	*13	•
.44	.20	.07	.00	. 34	-41	.30	.10	
.70		. 35	.00	-119	.71	:10	.00	- 2
-34		.96	.21	. 97	.33	.48	-11	
.41		. ce	+13	- 70	-24	.07	. 33	•
.43	-42	. 112	-10	-10	. 48	.48	-14	
-74	30	130	400	.11	. 45	-13	. 100	- 1
-34	-13	.05	.00	.10	.00	.00	.00	
.00			.12	.40	135	+51	-11	
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4 Medicines Based on Wh

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	117	. 17	.33	:::	-19	1 22	-4
.19	-17	417	.10	:11	119	.37	:
.19	-17	.17	-14	::::	.19	.27	- 4
-19	-17	-17	-29	-21	:13	.27	:1
:14	:11	117	.29	:::	.27	.35	3
-34	.21	.25	.29	.24	. 11	-39	-1
-48	-30	30	-14	+ +27	. 70	- 34	-1
.34	- 34	4 24	- 34	-24	.22	.19	- :1
:50	.43	.92	:51	. 34	. 32	. 346	
:5	-10	19	- 449	.33	. 87	.45	- 4
.74	- 13	.73	. 70	.11	.49	. 14	1
-92	. 99	. 96	-61	. 76	- 172	- 44	
-96	1.00	1.00	.00		- 67		
.91	. 91		. 01	. **		- 91	
493	1.00	1.97	-81	11	- 61		
1.00	- 194	- 70	-61	76	- 14	-64	
. 96	1.00	1,00	-81	17	+84	91	٠.
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TABLE MILARITY MATRIX OF MEDICINES

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.97	.31	.57	.29	.20	.11	.44	+44	.64	.01
.14	,00	.34	+47	.10	.00	-41	. 88	.80	. 48
.36	,00	.17	. 14	. 64	.00	.44	. 18	. 14	+46
.46	.17	.11	-80	.17	. 89	-12	. 97	111	. 59
-77	.84	.43	+39	198	- 14	.12	.41	.41	-47
-34	.17	-11	.94	. 19	.00	.44		1.00	.58
-47		-55	.10	.17	.00	. 52	,97	.97	. 11
.44	+11		.78	iii	. 84	.44	. 96	.96	. 57
- 48	.10		. 66	.11	-12	.74	.10	.10	,10
:41			44	41	.00	.48	. 34	.34	. 10
.14	.24		- 111	-11	.00	-45	144	.44	448
-33	- 11		-47	. 82	.00	. 46	.37	-17	. 49
.79	.21	.27	.73	. 10	.00	.20	+48	:11	,48
.14	. 04	.25	-21	1.00	.00	.35	.37	4.7	.23
1.00	,20	.50		-24	-11	-11	. 89	.01	.63
-10		19	-32	. 00	.00	.45	. 11	. 53	- 14
- ,34	- 31	1,00		.21	.00	.14	.13	.15	.50
.11	- 2			1.00	.04	.35	.17	-17	.11
-24				-04	1.00	.09	, 00	.04	.89
-11				. 39	.89	1.00	.49	449	.52
- 41			.75	.17	.00	.49	1.04	1.00	- 24
,41			. 79	.17	.00	.49	1.00	1.00	.30
- 61			. 10	.22	.87	117	. 50	.58	1,00
- 41		8 .41	.70	. 34	.00	41	-12	- 12	-92
+84		6 .61	. 10		-01	.96	. 54	.23	166
- 21				. 91	.00	.12	,00		.79
-21	1 15		.31	.00	.00	.46	.47		: 17
. 7	1.3	ā -31			. 80	. 33	.74		.12
. 3		3 .45				. 11	41	+47	.44
- 41					.00	-17	+63		.00
- ::				-14	-44	-13	-11	-11	-17
- 11				. 99	.04	.39	-21	+25	.29
			441	27	-13	-34	- 31	119	- 19
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			7 .91						
. 2									- 33
- 42								. 10	. 64
- 1						04	.04	.00	. 14
7				1 1.00	.00	. 31	-1	1 .17	+83
- 11			4 .7	9 -11	00	449	1.0	1.00	- 44
- 17		10 -9	4 .*	1 -19	.44	. 44			. 91
	7 .1	19 .1	4 4				1.0		- 96
	4 .	14 -1		3 -14	-19	1 10			
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TABLE Row-Row Similarity Matrix of

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10		.40						-37			
10	10										.17
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13 13 13 13 13 13 13 13											+17
19								.23			
64								.75			
60 60 60 60 60 60 60 60 60 60 60 60 60 6				-34	. 13	. 48					
71			.98							-47	
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10 100 37 47 47 47 47 47 47 47						.34			491		44
17 17 17 17 18 18 19 17 17 17 18 18 18 18 18			. 73	- 11							. 70
14							.73				. 24
10											. 05
122 2 48			- 11							.91	
10						. 90	1.00	L.00	. 97	.97	
17 17 17 18 18 19 19 19 19 19 19							1.00	1.00	. 97	*41	1.04
17					. 89						
14		.95				. 43			1.00	1.00	1.00
140 . 100 . 121 . 170 . 180 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 . 120 .	. 57						1.00	1.00	- 27		
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18			. 60						-12		.71
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13			- 41			.97	.11	- 33			- 53
19			.24								
10											
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99 23 33 23 23 48 48 48 77 48 68 68 68 19 19 19 19 19 19 19 19 19 19 19 19 19	.43			- 33			*47				-47
190 cft 131 cft 20 cft 27 cft 20 cft 27 cft 20 cft 27 cft								***			47
17 17 17 18 18 19 19 19 19 19 19										.44	.97
197 131 140 139 140 140 140 140 140 140 140 140 140 140	• 34									.30	.93
28											.92
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192 (40 152 150 157 152 150 157 152 150 158 157 155 155 155 155 155 155 155 155 155							. 11	-10			
10					447	-37	- 34	+58			
21 13 11 10 10 10 10 10 10 10 10 13 13 13 13 13 13 13 13 13 13 13 13 13					.44				. 66		. 54
*11 *15 *29 *76 *76 *31 *30 *30 *30 *30 *30 *30 *30 *30 *30 *30				. 10							.10
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3 $$\rm B_{ASED}$ on When Used (Individual Data)

20	27	10	29	20	»L	14	31	34	34	36	97	96	34	40	41	48_	45	44	48	44	G	48	44	10	51	25
						-63	-11	.20	584	458	.49	*10	.47	-20	-20	.46	.00	.10	400	+37	+44	.94	.51	.34	:48	- 14
- 94	-47	:24	-24	- 14	190	.41		.11	.79	.10	. 83	.29	.70	.29	-24	.20	.00	-30	-88	.10	.10	.24		iii	.79	27
-44		94	.00	.31	. 30	.29	.00	.12	-91	.48	.40	.06	433	117	-17	-19	.00	-17	.30	. 29	. 91	- 66	456	.44	.10	. 22
.57	-53	-24	.00	.44	. 79	.44	-11			-57	. 93	:17	.54	-46	-40	.51	.04	140	.53	.64	.12	.78	.63	-71	+71	-31
-43	-68	.43	- 89	:77	.48	.41	:11	-10		114	-43	.75	.30	.79	.75	-24	. 00	- 15	+41	.38	-44	-29	.31	:33	-32	. 19
-54	-31	.75	.00		.70	-47		.11	.71	.99	.99	.17	-47	-17	-17	130	.00	-17	197	.05	3.00	.47	. 56	.44	. 10	. 12
. 41	,13	24	.00	.44	79	+44	-11	-10		.37	- 93	+17	147	:17	:17	.20 31	.00	134		.00	. 94	146	59	+48	+32	170
. 54	.10	.70	.00	-44	.73	.48	-12	:11	. 10	.17	.47	-10	. 43	.31	. 31	.17	.00	-11	.18	.48	. 50	+67	. 13	.29	:41	.50
-48	.14	-34	-27	:43	:5	.17	-111	.10	. 77	.10	- 34	+47	.23	-67	-47	-10	- 00	+47	- 34	- 64	-34	.29	.63	.14	-39	.ni
.17		.19	.21	30	.34	-58	.73	.15	.14	.46	- 40	.13	-41	-11	-13	114	.00	-11	37	.46		.24	-32	.13	-29	-30
.44		.87	.00	. 30	.45	-30	.00	-11	141	.10	- 10	.02	. 32	.30	.30		- 04	-10	.49	.03	.48	.29	-26	-23	-11	. 71
	-11	. 35	.00	.15	.71	-11	-10	-17				1.00		1.00	1.00	. 87	.00	1.00		+17	+17	-10	:11	-11	. 10	
	-13	.74	.25	. 07		- 44	-11	.24	-78	.57	. 48	.74	.49	-34		.30	-90	.74		.10	.07	.94	-19	.2+	.32	.00
.14	-06	.20	+41	-,29	.24	- 87	•13	.60	·M	-12	- 10	-25	67	.29	.23	24	:22	-:5	. 37	.37	. 15	.63	+11	.11	.64	16
-43	-42	+12	+10		•43	-48	.00	:13	:11	.45	.77	:::		. 31	.21	.24	.00	.m	. 19	.91	.75	.33	-119	.11	-34	223
	30	, 10	.00		. 22	-14	.00	-14	.05	.37		1.00	-19	1.00	1.00	.07	.00	1.00		-14		-14	.00		.10	.00
,00		.00	100		.00	.00	.00	.44		*15		-89	.13	. 84	.00	-24	.24		.00	.44		.04	-49	444	.67	. 34
. 43	. 10	.30	-17	.48		-11	-113	-!!		119	. 96	:17		-11	.17	. 10	.00		1.00	.05	1.00		-14	+ 4.7	-21	-23
+34		. 23	.00			:47	-:::	:11	- 11	.11		ii.	449	-17	117	- 10	.00		1.00		1.00		- 10	47	-31	. 75
.51	.54	.24	.14		- 57	-40	.00	. 17	, 14	.39	. 52	.37		-37	-11		- 99	.22				.63	. 10	. 19	. 30	. 25
1,63	.24	.43	-20	. 19	.71	.10	-12	-11	-43	.38		-113	.40	-34	-11	.31		.11					-48	.41	169	442
.29	1.00		-10	. 68		.95	.07	.31		-11		. 91			. 91		- 80	. 95	.25	.21	.29		:74	.21	.21	. 12
-41	.10	1.00		.23			.10	.17	.46	.10		.00	.00	.56	- 00	+ 15	-33	.00						1.07	.94	. 27
.39		.77		1,00		+64		+24	.*1	-37		-12	. 55	-19	-14	.62							142	+31	.10	. 23
.73	. 31	.12			1.90		-15	- 14				.14		:11	-14							+64	- 111	-44	-49	-46
	.43		-21	- 64		1.00	1,00	.24		. 100				,00	.00	.89	. 40	.00					.26	:11	:12	.00
-13						+74		1.00	-13	-22	-11	-14	.12	-14	-14						-11	-19	.24	.21	-71	35
	.10		,04	-23	+32	.20			1.40	? ?	-24			-99	.01		:50				29		44	- 9 F	34.	- 61
	144	- 19		- 87		.42		-11		1.00	1.00	-18	-12	-18	-110	. 31	.00	.14	44	- 84			- 14	.12	-12	. 10
.34	.13		.00			-14			.=5	.27	~ 1.0	1.00	.19	1.00	1.00	.07		1.00	-11				- 70		.11	44
			. 80	11	.97	+54	.00	.12					1.00	12	1.00	.19		1,00		.19			-10	-19	-14	. 21
+34						-14				.27		1.00	-19	1.66	1.00	.07	. 00	1.00	6 7	. 19	467	.84	-18	-14	-10	.31
-34											- 31	.47	.39	. 6T	.07	1,00		.01	- 30	+76			.00	.00	.ca	.58
: 11						.10		.00	- 146	.00				.00	.86		1.00	1,00	.00		117		117	-19	. 14	11.
.31			.00	- 419	.22			+14		-37		1.00		1.00	1.00	.01		11	1.00	- 01	1.00	447	.40	-41	-31	. 75
-11								-11				-17			-19	-21		11	. 41	1.00	. 45	-46	.10	-47	-44	.73
- 444 - 451													-69	-11	.17	- 30			1.00		1.00		. 47		.74	. 27
- 31						. 444	+11	-24	.19					-11					41 34		.34		1.00	-67	+68	. 0 5
-31	44	24	21												- 110						. 41	-97		1.90	-94	- 17
- 31				1.0	31										+14	+41	- 400	10	51					117		1 14 1 CB
-14														-21		.81		• • 21	? 1	. 71	11	.37	***	•••	- 14	****
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4 Medicines Based on When Used (Individual Data)

_	49	47		3.2	30	34	10	12	44	1	14	30	40	10	71	5	227	10	25	14	27	42	29	17	351	43
, 94	.00	.10	100	.00	:11	-12	.00	:00	14	:11	:11	:15	:16	:16	:10	-10 -10	:07	:17	.01 .17	.24	:07	:11	117	.01	.00	.00
:11	. 17	:11	:13	:27	- 12	.30	.34		12	-32 -28	:12	.30	.14	.19	.16	-11	119	' : 62 161	-83	114	:11	:17	.00	-10 -m	.80	.24
:19	-17	+17	120	:::	:12	Ж	.25	41		-20	114	19	-14	117	-14	.48	. 15	-31	:77	:14	:::	.07	.20	.00	.00	.CR
-19	.17	-17	110	:21	:10	127	-25	-13		.70	174	14	-14	:13	-14	.40	. 35	.31	:11	-14	-11	.07	.00	.00	.00	.01
:13			-54	::1	:13	27	.21	:13	.*4	.24	.74	-13	-114	.10	-16	:45	.31	.10	:22	.10	:12	-14	. 80	.00	.00	93.
. 24			:14	.29	:;;	.39	-31	-17		.14	- 29	.29	11	-73	15.	-43	. 38	.30	127	.10	-23	:13	.00	.69	.00	.00
.40		.30	.34	. 27	-33	- 34	.11	:::		. 14	130	:31		. 13	-31	.17	12	-49	-12	:17	-11	:10	20.	:17	-11	.24
- 36	- 134		-11	. 24	-32	.30		:::		14	113	134	10	.19	.30	.11	.10	-51	-12	.13	.30	.11	-20	:35	:14	-09
.54	- 64	448	-11	137	.37	.30	-27			-31	:5	.29	.33	.13	.37	:44	.36	.34	-11	34	- 31		.84	-24	.13	.00
. 14	471		167	-11	-45	-13	.40	:11	.41	.27	. 33	.48	-11	446	.44	-44	44	-48 -47	47	.44	.10	.24	.00	-17	-13	.00
. 91			-83	. 19	. 12	197	. 99	.48			48	.41	448	17	:37	:::	.49	-19	.96	47	.94	. 30	.00	.01	-11	.64
. 94	1.00	1.40	. 89	.79	44.	.99	:11			.41	. 41	.44	.44	,46	111	-11	- 57	.33		.44	-11	-24	.00	-17	iii	.00
. 91	91		.43	-12	. 67	.97	. 13	.43		.43	44	.41	.47	.47	:11	-115	.69		110	47	.34	- 39	.00		iii	.¢8
1.04	₽• I	1.00	.83	.70	.78	+44	.97	44	.44	-45	48	.48	-47	.47	:37	-11	.48	.14	. 10	. 67	. 94	.30	+00		. 11	.00
. 90	1.0	1.00	,00	.75	. 69					-30	36	-34	-36	- 34	:31	.43	-41	. 37	+41	.43	.91	-29	.00	.00	.09	93.
•11		.75	. 70	1.00		.61	+14	-31		-34	49	.37	.137		. 14	-39	.48	-43		. 94	- 41		-17	,00	.00	.50
a Fi	9	1.99	- 50	+61	. 72	1,00	.04	440	.69	-15	. 11		.41	.90		.41	. 45	-,49		. 44	. 44	484	:10	.33		. 46
•51		44	+ 34	-31	-41	+46	+41	1.00		-40	- 16		-10		.94	.12	.69	-88	. 152	.91	.00	+94	:::		- 21	-50
.9	8. 4	4 -44	a34	+34	.47	.93	- 91	.00	449	1.00		.97	494		.90	. 72	-71	-41	-63	- 64	1 464	-50	:24	-21	-11	.00
. 4	4	7 .41	- 4M	-31	-53	497	-34	54	-87	.97	.97	1,00	.97	1.00			-460	- 441	443	- 144	- 461	142	:::	-24	- 111	.00
-4	1.9	T (41	+34	.31	-93	.91	- 91	- 34	-47	.97	. 97	1.00	497	1,00	1.00			+61	.64	- 61	-81	+63	:11	-32	-13	.00
.5		8 -44	441	+31	- 10	-41	-41	191	.43	*49	. 72	.71	.10	.72		1,00	100			. 31	±1H	.19	- 17			466
.1		0 454	1 .31	-94	+41	. 11	41	194			- 63	- 6	+67	. 61	+61	-11	a 74	2.00				,44	-11			
.9	6 +4	F +41	- 41	.44	- 194	+44	-44	.91	**8	+69	. 14	a84	+44	44	.45	401	+91	46		1.0	1.0	-44	.71			
.9				-81	.14	186	- 32	. 41		+40	+94	+61	- +43	+63	+61	91	91	-31				.19	1.00			
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TABLE COLUMN-COLUMN SIMILARITY MATRIX

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ER./COL	1	ŧ.	,	4	8	.11	-19	-42	+47	.09		.03	. 89	+25	.25	.90	.00	-21	.00	-17	:00	-11	:11	-10	.25
1	1,60	1.03	.00		.10	+13	.94	110	115	.00		.27	. 67	.00	111	.24	.00	-13	.71	-70	. 53	.00	.00	. 10	.00
	.11	.87 E	17	1,68	.49	. 141	.31	-23	-79	-31		.74	.24	:11	.10	-19	:11	-13	.30	:21	.24	-10	-11	.20	.37
•	.37	-11	.00	-45 1	-27	1.00	.23	.47	194	. 2.2	.41	-22	: 64	-37	179	141	:11	.17	.00	.84	141	.21	- 32	.10	.14
	1 15	.94	.70	. 27	-96	.23	-21	- 11	.13	.14	.78	.44	. 29	-13	41	.70	.84	.49	. 10	.34	. 17	.00	:11	.91	129
	163	-14	+12	. 24	.19	. 94	-14	.71	.43	1.00		112	139	-13	+67	+43	-11	- 92	-38	.25	. 54	-15	.80	.44	-13
10 21	1:33	-21	173	.72	. 33	.41	.10	.78	443	.30	1.78	1.00	+04	.04	17	-54	.00	. 10	.00	.20	. 22	.00	.29	. 57	-21
12	.61	-27	.00	. 14	:05	-83	-19	-14	. 39	.57	.11	-26	1+00	1.00	.43	.27	.00	.42	.00	+08	.23	.48	. 39	.25	.29
14	1 :::	:11	.00	.18	-11	32	- 10	113	111	+47	.43	.17	-61	-47	1.00	1.00	-117	.76	- 55	. 30	.10	:13		.61	. 20
16	34	-24	12	- 12	-31	:21	. 28	-10	.07	.17	,40	.00	.90	.71		-13	1.00	1.00	-13	. 12	-67	-10	. 10	-69	.70
17	.21	411	.46	. 24	-13	.17	-10	.19	.62	-11	.17	.06	14.	.00	.33	+14		.64	1.90	+27	. 74	-13	.00	-41	.16
14	111	.19	-31	-31	.44	143	.04	.37	110	-24	.44	.22	- 32	.22	41	:10		+67	.10	.34	1,00	1.00	-33	15.	.25
21	1:::	.71	.11	-11	:10	.29	.00	.00	280 211	-34	-00	-13	.04	, 48	.21	:11	.10	460	.00	-86	.31	.00	1.00	119	.25
13	-11	-11	. 30	-19	:::1	. 32	:10	- 14	. 93	:44		113	- 11	-23	.59	-01	.13	.20	.43	.14		+00	.25	-19	1.00
25	1:33		.04	.19	-37	.33	.29	117	-10	+00	.19	.22	. 1010		.13	-74	.00	-13	.00	.31	.84	.12	.48	-91	.27
31	-01	- 1.9	41	:33	-11	. 14	-31	.37	.76	.11	. **	.54	134	.29	+48	.79	-10	-40	. 15	-41	.43	-11	.20	.49	.15
30	1:1	-21	.54	. 10	:19	19	-27	. 10	-51	- 58		-23	-41		. *3	+11	- 21	.04	-30	39	-69	-19			.13
32	1.77	-14	119	.21	-20	- 11	-10	, 14	.91	.46	477	101	- 37			- 49		.48	.79	.41	+48		-12		112
32 35	1:3		.20	-11	-11	. 32	.10	-11	-13	.94		-12	- 29						.00		.21	.06	-11	-14	. 37
36		1.00	.00	-27	.48	.67	. 94	.10		.04	.*1	.27	. 10	+11	-21				.00	.10		.00	.00	.44	.17
36	.00	-14	.94	-60	.25	- 17		.19	. 94	-30	-45	419	. 74	-13	.11	+34	00	.74	. 70					.47	-15
3 f 3 h	1:3		.36	.20	:::	. 97		.89	.48		34.	+90	- 11	-31	-17	-14	.00	+21	.00		- 411				.13
19	1:4	+21	.93	:21	-21	.76	-24		+68	-34	448	-27			. **1	-31	+00	.72	-41		+61	+84	. 31	.41	141
41	1:55		.71	-27	-22	.67	- 14	. 29	.47	-51	. **9	-12						- 400	- 92	,48	64	+24	.31	57	.11
415	- 3	1 -16		110	-31			.47	.33	-61	47	-27	- 61	-31	01					1 431	94	+21	104	.47	. 64
49	.11	+08	.67	-17	-14					+29		7 7	- 44	+11	4.47	71	1 .14	1 441						43	.17
47	13	1 .15	+37	+41	+41	. 11	.30	.81			.10	-21		.61	2 450	3	1 494	- 34	100	61					.21
4-B 4-7	-31	13	.00	-10	-44	-01	-11	-41	- 35					11	1 +1		1 104	- 111	-34	-31	31	1 41			
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92	-3	10	.00	-17	·M	• #		***	***		• • • •														_
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TABLE REARRANGED COLUMN-COLUMN SIMILARITY

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						53	21	11	14		10	27	24	10	46	44	•	30	19	43	49	3	17	34	24_
(m./(m.	11	17	Į4	47	15	-			_		-77	-117	.11	-10	.10	.24	.24	-14	.21	-20	.25		-13	.21	.29
23	1.00	48	-48	.14	.00	-18	.00	.00	.00	.10	+2.7	+37	. 39	.20	-22	.00	- 21	.11	.12	-17	.00	.00	.00	.00	-11
1T	1:18	1.00	1,00	+67	-29	.44	. 10	.48		.10	.77	37	.74	.34	-13		.40	.10	.36	50.	40	.00	.00	:!!	-21
40	134	.00		1.00	- 47	.49	.27	+27	.39	.36	-11	.77	. 37	+20	-11	.11	.21	.11.	.13	.27	.14	.00	.80	.00	-17
25	1:11	.04	-25	,48	. 64	1.78	.47	+47	.79	-17	.~0	.10	47	.18	.44	.22	. 12	.42	-24	-33	. 90	.00	-00	.06	-11
23	.00	. 97	-10	-22	.25	447	1.00	1.06	.47	110	.78	.48	48	.40	,64	111	.12	- 42	:13	:::	.00	.00	. pd	.04	-11
33	100	.93	.75	117	-37	.29	. 67	487 1	.00	122		-11	. 27	:22	.29	.29	-27	427	. 10	.14	118	-17	. 10	.30	.97
	-19	-19	-19	.13	-34	-17	.14	-11	.72	.22	1.00	.53	. 94	.97	. 56	.64	54.	17	.75	177	.57	. 6 3	. 60	.3=	.00
10 27	1:3	-13	.27	.25	.27	. 50	+48	. 40	.15	.11	- **	1.08 .73	. 15	144	-41	.24	. 79	.60	.11	.74	.01	. 16	.45	.55	147
29	111	. 39	+24	. 13	- 35	. 17	, a F	47	. 27	-24	-42	.67	+47	Lion	487	.73	.77	.64	.70	. 14	.47	- 51	. 27	. 92	1.71
10	1:10	.22	. 12	. 42	. 11	. 42	. 44		.29	.14	-76	. 64	. 14	-47	1.00	1.00	.03	.90	. 19	.10	.81	-33	.12	.12	+9.7
84	1.11	. 17	-13	.11	-11	-11	.22	-27	.75	:37	34	+62	.79	.77	.78	.61	1.00	1.00	.99	.44	.60	. 10	,10	.50	444
	1:3		-37	34,	.21	449	7	.48	.74	-27	:41	.17	.17	.10	.98	.90	. 19	. 23	1.00	.07	.87	. 24	-33	.94	+47
30 15	1 .21	-12	.47		:13	:13	.33	. 11	.13	.19		.72	. 74	. 10	* 54	.79	.80	90	-87	1.08	1.00	-11	-12	.52	- 10
41	1 :25		113		-14	+17	.04	. 68	,09	-17	-43	443	.41	44	.67	.03	.50	.10	.30	. 93	.47	1.00	1.00	-54	.11
- 3	100	.67	.09	cc	.00	.00	- 08	400	.00	.17	, ° a	+49	. 45	+64	. 12	. 52	,10	. 50	-11	.92		.30		1.00	. 13
19	1:33		.00		117	.00	.50	- 84	.00	- 40		-11	. 34	. 17	.92	-37	.62	.87	-67	+64	- 50	- 93	.78	-01	1.04
36 21	1 33	.00	11	-21	-53	- 17	-11	- 27	.11	. 57	- 34	.79	. 11	-74	. 8-6	.00	.73	.11	.73			:41	.47	. 55	-41
37	.00				-11	.,,,,	- 31	+31	. 14	.75	147	+67	. 77	-12		-78	104	+84	-61	.61	.68	-4T	+61	. 53	.58
11	, 84	+63	-14	.13	.29	-17		- 79	.17	:17		.97	-42	. 62	. 98	.90	- 56	.50	- 52				. 74	.40	.11
51	1 .01				-14	-13		-13	-10	-21	-44	.13	- 76	-04		.17	141	. 41	.43	+11	. 30	+11	-37	-43	57
A2 11	.01	.01	484	- 19	-10	-11			, II-6.	.24	.10	.35	. 17	.46	3	-43	.43	44	.44				.29	.37	117
32	1 .0				-12		. 17	+12	.09	-37	. 12	.17	. 30	.49			. 14		-48	491	. • 1	-24	- 33	- 40	-41
- 4	1 :		i AH	- 419	-10	-15	+ 29	+20	.16	:27	:::	.10		.63	197	-57	.91	.40	.39				. 43	.48	449
47	1 41								.07	.23		.91	- 44				.11			1 .91	41	-38	.49	.44	.12
31	1:1		.7	3.34	1 -19	- 34			17	:::	.43		. 11	.42	.66	-11	.54	. 99							-10
- 4	1.0							- 427	.14	+18	.13	.54					.43	.73	. 94	- 3	51	+30	. 32	-34	- 34
14 50	1::	1 .11	11	9 .29	-11	.14	-11		-13			.41		441	1 191	-10	.49	.53	- 41	1 491					.99
44	-1	1 .14		2 411 9 42					,00	-34		10					.22			1 .1				-87	*81
12	1::	e -1	7	1 .21	21	+21	1 .21		-12			.21			-81	.23	- 22	*52	+ 24						.24
- 1	1 1								-18	.41		-13										.00	,01	-14	.31
25	1::			4 - 30	11	1 21	n .t:	-11				-11				10	1	- 21	-81	1 • •		00			
34	1 .6	9 .6	9 . 6							-11	100	-94	• 15	61						1	0	04	- 91	F - 455	181
26	1:3			1 .)	1 × 34	1 12	ان و	1 -11	- 414						2	21	+81	21	42	F +1					
7	1.7		4 .1						104	-21	-21	-31	- 41	10	2 . 3			1 .34 1 .31							
20 36	1:5		; ;;							+31	1 151	1 451	- 19	6	8 47	• •••									
-	-1	-														_			_			_		_	_

of Medicine Uses (Individual)

	24	21	84	29	94k	31	11	33
-	-19	6-9	.44	.10	.11	.60	-41	-13
	.97	-14	-33	-21	-28	- 24	20	-11 1 -00
	.00	.43	-29	-14	.58	.10	.11	.10
	419	-11	-53	. 10	.27	.24	344	411
	. 14	-19	-40	.29	47	. 11	443	- 32
	+64	148	- 17	27	-29	.11	-34	-10
	10.	. 27	100	. 14	4.1	. 74	.97	.17
	.10	, 49	. 14	131	+19	. 91	+78	.13
	.04	.99	. 24	. 10	100	. 44	. 14	. 90
	112	3.3	.79	-19	441	.17	.77	.76
	111	-18	. 66	+2.7	. 22	-64	455	-19
	.09	467	. 34	. 61	-64	. 37	.24	+79
	.11	.27	.78	+74	+42	-27	-16	.18
	-13	.13	.49	.77	. 91	-37	-44	:::
	.27	+94	.99	+42	473	-11	.415	. 10
	. 8.1	-27	+10	-15	.71	.44	44	na Pi
	-13	+47	+27	145	,30	. 43	-29	10,
	.41	+6R	449	-41	39	-24	143	.09
	-14		443	-14	269	498	100	.11
	.01	.17	.09	+11	-10	-12	-06	.09
	:11	.40	+26	+47	445	.17		1 .00
	.10	.51	. 40	.49		F - 90	.76	*14
	-11	+27	.10	35	+37	-19	+12	. 23
	1.00	-84	+31	+15	-14	-10	. 17	0
	485	1.00	. 34	. 79	. 77	-11	.47	.70
	. 11	.20	1-78		- 94	.44	. 17	-47
	.19	. 14	.44	1.07	1.00		444	-62
	414	. **	. 94	49	.90	1.00	. 74	. 19
	-13	-73	. 27	117	.40	-74	1-10	112
	.11	4 6 R	.20	. 47	. 42	-19	+13	1.00
		-12	. 11	141	. 24	-14	.44	-11
	97	- 114	+11	+21	.20	.14		- 11
	9.0	. 10		+94	42.	. 44	417	.00
	-13	-11	142	. 79	.77	-31	-34	.21
	. 10		-99	.30	. 51	. 47	+67	. 13
	-13	- 19	- 10	- 27	+24	.01	. 84	, 44
	.10	.00	- 51	- 49	. 94	-67		-11
	.11		+ 19	- 73	.74	-43	.14	.11
	,61		123	+74	90	. 47	447	. 31
	-11		- 1		1.90	. 52	-43	- 11
	.71		. 11		. 90		. 30	. 94
	.84		. 14		. 11	. 12	471	- 24
	- 11							
						+ 90	+20	
			. 46	.21	. 21	-89	149	- 41
	- 10	-41	. 04	.44		- 48	- 73	: 1
	. £1	9 .67	+14		4 3 4	- 21	- 14	
	- 21		19	1 44	- 68	1 124		

6 Matrix of Medicine Uf

37	41	11	11	42	11	32	4
.00	.08	.00	.00	. 22	.00		
.00	+00	.44	.00	.00	. 04		ï
-11	.19	-11	.40	47	.10	-20	i
-40	.31	. 29	.14	.38	+16	+17	
.23	129	.11	.0#	-12	-12	-19	٠
.77	. 21	- 29	-14	-13	.06	:17	•
127	-31	-19	117	-12	. 84	.04	ŀ
.31	. 34	.24	111	iii	.20	.23	
. 55	.58	. 37	.57	- 52	. 30	-15	,
.73	. 78	. 67	.47	493	. 15	-11	•
.79	.13	+41	-58	.30	-16	-17	
. 14	.12	-47	.10	144	.42	. 4.2	ï
.85	.79	. 67	. 10	.11	. 47	-43	i
.44	. 73	- 64	,58	.62	.41	.41	٠
. 27	.75	+84	454	. 24	.41	++6	٠
413	. 23	+61	.57	.72	41	.47	
164	.10	-67	.54	.77	. 34	. 34	Ì
.47	.71	.43	,47	.33	.24	-20	
14	-67	.41	. 74	.10	. 37	+27.	,
40.7	-31	-37	- 61	.48	1	.32	1
.73	.68	.99	. 10	-30	- 37	.22	
1.09	. 90	-76	74	- 61	-37	.29	
.40	1.00	1,00	. 10	59	- 11	.24	
.19	.74	.90	1.00	.99	-11	.79	
. 61	117	-114	. 15	1.00	. 10	. 54	
. 44	. 17	- 11	. 31	- 14	1.00	1.00	
. 35	-54	, 74	. 19	.34	.70	1100	•
1,39	-31	- 39	. 14	.41	.79	. 42	•
.42	. 19	- 111	. 11	. 45	- 0.2	. 47	
.91	.43	- 17	- 17	.44	.77	- 10	
. 91	.43		. 17	-43	-17	14	
.34	-46	.34	.39		- 00		
- 54	491	-41			. 71	. 75	
.44	-49		119		. 78	. **1	
.11		- 04		1 - 14		. 49	
-41	-81	.01	,00	.41	. 99	. 69	
-11	11	- 401	.00	1 11	. 41	10.01	
-21	•11		.01	1 :::	. 71	1.9	
-21						.49	
-10		- 0		01	- 19		
		1.0	9 .00	1 -11	- 48		
- 21	i	1 - 1					
+11	44						
			3 .00				

TABLE -COLUMN SIMILARITY MATRIX

8.7	10	14	20	13	12	21	24	71
. 80	-31	.00	-12	40H	-11	-11	+40	.29
.00	.11	.00	.78	-21	.09	.11	.14	- 32
.04	441	471	. 35	.93	.00	100	. 30	.04
.10	+24	. 36	.21	.57	+15	+19	-33	- 36
-11	-11	.00	. 06	.28	-10	-11	.74	-17
-31	. 11	,10	.44	-68	-29	.32	.11	
.96	-10	.00	.84	.24	.00	.12	.70	.12
.04	+49	. 10	130	. 14	.84	.11	.93	.24
-67	.42	.10	.13	. 34	. 35	.00	.44	-iii
-11	.44	.17	. 40	.17	.00	.84	. 11	+14
:11	-116	-06	.28	-22	.00	.13	+84	.23
.00	. 4.2	. 63	. 32	. 50	.00	. 29	. 17	.79
.33	-40	.00	.00	-22	.40	.10	.35	-23
-11	.76	. 33	+41	+67	-21	-20	.39	- 35
-11	-42	-34	- 70	+30	-13	-27	-81	-10
1.00	.24	-19	.20	-44	-46	. 50	.13	.00
+20	1.60		- 37	.47	-11	. 90	.43	.04
+11	+44	1.00	1.00	-10	.00	. 04	.24	-14
.04	-32	.27	-34	1,00	.79	.33	-37	.12
-44	-18	-13	.00	-28	1.00	. 90	-17	.00
.10	.40	.00	.04	-31	.00	1.00	+19	-25
.13	.44	.43	-24	-92	-12	+19	1.00	-19
.04	.70	-06	-10	-22	.80	.25	+19	1,00
.00	.13	.00	.00	+14	.00	.11	-10	*55
.37	147		- 33	-40	-12	48	491	.77
-10	. 64	. 39	.48	493	.84	- 110	+90	.10
+35		. 03	-41	-74	:!!	41	.49	. 17
-21		50	. 34		:13	.19	1.90	119
+11	.68	-41	-34	-92	.00		.74	112
.06	148	.24	-61	. 11	.00	1.00	-19	
-10	.48	.00	.76	- 21	.00	.11	-14	- 112
.04	.13	.00	.71	-21	.00	-11	+14	-17
-74			.31	.01	-21	.00	.44	-12
.00	.14	. 10	.10	-12	,00	.27	-53	+40
-13	- 67	198	+77	-14	.09	.33	-41	+13
-00	. 22	.00	.89	+13	.00	+67	-07	+13
-22	, 27	. 92	+14	-71	.10	+44	+44	+13
.00	.12	.67	- 48	- 41	.00	.31	-43	.31
.00	-84		-24		.22	.33	-37	.72
+48	.00		+48		. 20	.22	-31	. 11
.00	-11		-11		.25	.00	. 97	- 114
.00					-11	.1.	-78	. (=
-10					-11	. 17	.43	-17
.00					34	-72	- 30	+47
- 111	.11				.00	.21		.81
-04		• 31	+31	- 59				- 113
.04			21			484		-14
. 44		-,100	-81	- 14	+14	-61	+34	-44

TABLE COLUMN-COLUMN SIMILARITY

		30	19	43	45	3	19	36	21
-	.29	-19	.21	.78	.29	.00	+13	-21	-10
à	-71	-21	-12	- 22	.00	.00	-15	.24	494
1	.32	+43	+07	44	+29	.00	.00	.33	.72
à	48	. 94	+94	-48	±48		.00	.12	:::
1	. 81	. 12	. 35	. 22	-11	.00	.00	.00	.53
Ĺ	. 10	448	- 13	.42	.00	.00	.00	.00	.11
\$. 32	-48	+85		.00	. 80	.00	.00	.11
2	.18	- 42	:24		.00	.00	.00	.00	
9	.30	123	. 10	.19	-17	-17	. 38	+40	.37
•	-27	.27	147	44	4.7	-43	.10	.34	414
4	.62	.77	. 73	. 22	.51	-65	. 46	.58	.48
:	. 77	-86	. 117	-14	-61	. 50	. 45	.54	474
1	. ;;	-94	. 74	. 80		.48	+44+	.59	+67
	.74	.96	-61	.19	-47	.93	. 52	-58	*.71
ě	. 61	.90	489	.79	+87	.53	+17	- 52	.97
	.00	. 47	.79	.03	.40	. 90	.10	-97	448
ė	18.	1.00	. 43	.90	- 60	- 50	.98	.50	- 69
.9	-19		1,40	. 89	-47	-10	. 93	-14	T
16	.63	,10		F-88	-81	.93	. 57	.11	+44
13	.68	.40	.07	. 83	1.00	+47	.71	. 24	. 11
13	.50	.10	. 54	. 93	+67	1.00	1.00	.37	.74
1.5	. 10	- 50	. 99	. 92	-47	. 34	. 82	1.00	.41
12	.37	- 20	. 94	444	-10	.13	.19	101	1,00
12	-42	-69	- 67	.64	. 47	-43	.70	447	.72
10	.44	-17	.11	.78	.74	.71	+67	-11	- 63
18	.75	-15	. 61	. 67	- 40	7	443	. 52	. 10
1.5	+64	-34	. 12	.54	-48	-67	- 74	-41	90
56	-54	.19	. 77	-0.7	.73	.33	.38	+40	. 21
17	-67	. 61	.45	. 37	- 30	.24	.37	.43	. 37
43	-43	.40	. 44	-47	+36	*58	.29	-37	,46
33	. 41	447	44	-41	- 34	. 20	.34	. 14	. 17
ši	-94	.94	+8	.91	-43	+14	- 39	-40	.41
12	.11		- 10	-57	. 46	-52	. 39	. 48	449
57	-31	140	.59	+97	-47	. 50	-43	+44	+57
92	- 51	.48	.39	.57	.47	-38	-41	.44	198
99	-54	. 19	. 16	.55	- 190	*33	166	.34	.30
45	+43	+13	+67	+47	- 54	135	. 34	-34	.95
97	-65		-14	+37	.33	. 30	- 34	.47	155
56	.49		.47	+43	-35	.00	. 90	.17	12
22	-42	.22	+17	-11	.00	. 88		407	
14	.07		-31	-14	- :17	.00		-80	.09
1)	+11		.70	:::	-10			-29	. 74
34	-21			:14	. 04				.71
54	-11			.14	.00			-10	11.
-20	-11			-14			.00	.47	.14
-21	-14			-14	486	.00	84		.21
-58	-21				-11	.01	, eM		-24
132	- 64			- 44	-34	.31			.34
144					-48	L ±34	i ∗94	+44	. 94
144	8.4								

5 of Medicine Uses (Individual Data)

					11	12	19	14	39	34	37	30	34	40	41	42	43	44	49	46	47	10	49	90	51	41
- 19 2 9 1 9 1 9 1 9 1 9 1 9 1 9 1 9 1 9	.04 .15 .15 .15 .15 .15 .15 .15 .15 .15 .15	.90 .49 .20 .11 .31	1 0m .86 .47 .17 .21 .21 .56	. 32 . 30 . 77 . 34 . 86 . 40 . 40 . 40 . 40 . 40 . 40 . 40 . 40	.92 .19 .19 .19 .10 .20 .20 .20 .20 .20 .14 .14 .14	28 3 4 4 4 4 4 4 4 4 4 4 4 4 4 4 4 4 4 4	-11 -10 -11 -11 -11 -11 -11 -11 -11 -11	11 mg 12 mg		### ##################################	. 17 . 22 . 23 . 23 . 24 . 29 . 29 . 34 . 34 . 34 . 34 . 34 . 34 . 34 . 34	-11 -00 -20 -21 -70 -70 -70 -70 -70 -70 -70 -70 -70 -70	.10 -12 -12 -12 -12 -12 -13 -14 -15 -15 -15 -15 -15 -15 -15 -15 -15 -15	. 29 . 20 . 20 . 20 . 20 . 20 . 20 . 20	-19 -17 -17 -17 -17 -17 -17 -17 -17 -17 -17	-17 -25 -25 -26 -26 -26 -26 -27 -26 -27 -26 -26 -26 -26 -26 -26 -26 -26 -26 -26	- 23 - 23 - 23 - 23 - 23 - 23 - 23 - 23	-7h	- 10 - 10 - 10 - 10 - 10 - 10 - 10 - 10		- 99 - 27 - 27 - 27 - 28 - 20 - 20 - 20 - 20 - 20 - 20 - 20 - 20	-19 -10 -27 -27 -27 -27 -27 -27 -27 -27 -27 -27	-02 -13 -04 -04 -04 -04 -04 -04 -04 -04 -04 -04	-49 -81 -91 -91 -91 -91 -91 -91 -91 -91 -91 -9		-20 -20 -20 -27 -27 -21 -21 -21 -21 -21 -21 -21 -21 -21 -21
- 11		_46 _63 _61 _61	+50 +79 +87 +87 +87 +87 +87 +87 +87 +87			19 .00 .00 .00 .00 .00 .00 .00 .00 .00 .0	.27 .17 .65 .65 .65 .65 .65 .65 .65 .65 .65 .65	-21 -42 -21 -21 -21 -21 -21 -21 -21 -21 -21 -2	-93 -12 -75 -17 -17 -17 -17 -17 -17 -17 -17 -17 -17	.00 .00 .91 .91 .95 .95 .95 .95 .95 .95 .95	- 0 - 0 - 0 - 0	1 291 291 291 291 291 291 291 291 291 29	.11 1.00 1.00 1.00 1.00 1.00 1.00 1.00	.00 .94 .21 .01 .74 .74 .74 .74 .75 .75 .77	.00 .00 .00 .00 .00 .00 .00 .00 .00 .00	1 .61 1 .29 1 .69 1 .69 1 .69 2 .61 2 .71 6 .71 6 .71 6 .71 6 .71 6 .71 6 .71		1	1 .61 1 .60 1 .61 2 .61 1 .71 1 .61 1 .61 1 .61 1 .61 1 .61 1 .61 1 .61 1 .61		1 .01 1 .01	100 100 100 100 100 100 100 100 100 100	-11 -11 -11 -11 -11 -11 -11 -11 -11 -11	1 191 1	1 .4. 1 .5. 2 .5. 3 .5. 4 .5. 5 .6. 6 .6. 6 .6. 7 .6. 6 .6. 7 .6. 7 .6. 8	2 .29 7 .10 6 .39 6 .39 7 .12 8 .47 8 .31 0 .13 13 .22 10 .20

6 Matrix of Medicine Uses (Individual Data)

17	-1		91	42	11	32		20	4*	11	24	•	14	50	46	12	49	1	4	33	34_	24	7		10	10
.00	.00	.00	.00	+55	.00	.00	.00	.09	:11	:13	:11	:84	:13	.12	:11	:00	.15	:61	:10	90	.00	-00	-95	.01	.77 .77	-17
-11	.00	.00	.00	.00	.08	-16	:12	10	.77	.39	. 25	-11	-27	-19	:17	-22	.11	. 31	-11	.11	:11	31	- 17	35	.14	:11
. 30	.29	-13	-00	.31	:10	-12	+17	.19	.77	:14	. 14	-58	.24	.13	-10	-23	.71	-27	. 12	.37	.32	:::	-10	-19	.19	.29
.40	.29	-11	.00	-12	. 11	:15	:11	-10	: 7	.17	. 19	-13	-27	:14	.24	.15	. 21	-11	.11	-11	-11	-11	-11	113	.09	-31
.27	-31	.29	:14	:13	- 76	+12	-12	.20	31	-14	. 19	-11	-17	.19	-34	-11	.21	:12	:17	:11	-18	-111	-12	111	.09	25.
.31	. 14	.23	:17	.14	.04	-04	123	15.	. * 1	.11	. 73	+24	-10	.17	-17	:12	.10	.11	.41	.37	. 27	.00	.00	.14	.35	-34
- 25	.10	. 27	.37	- 12	. 10	-33	- 12	.39	47	-51	.48	.43	.43	441	.54	- 4 P	.11	.09	-13	.15	-115	.413	-11	27	. 31	.46
.13		.48	-31	. 50	. 16	.37	16	.60	.47	::3	- 49	-91	:::	39	.51	:13	.21	.21	-13	+63	419	-13	-21	:::	. 14	.14
.74		.67	.50	.64		141	.44	.51	.97	145	. 62	.11	.43	.37	-31	:27	-11	-21	.21	.21	-21	+21	-11	-33	. 64	44
.40	.79	. 67	-58	.11	141	.43	47	.11	:47	:11	- 11	-14	+63	.69	-49	-11	10.	-27	15.	.11	-13	-11	.25	125	. 14	-99
.77	. 11	. 64	- 198	74	41	-44	.47	, 54	-31	.40	. 57	.34	117	-54	.47	+17	. 21	-24	.10	-11	-21	-19	-71	117	.47	- 48
.11		. 6 7	-57	.62	- 11	.47	.46	.91	44	.97	.97	-33	.14	.97	.43		,00	-10	-16	.81	.00	.86	*0.4	:13		- 14
461					. 24	- 34	. 10		. 77	. 10	, 30	- 32	132	.30	- 29	.00		.00	.00	.00	.00		-00	-51	.27	-10
.14	1 467	- 61	- 10			.37	.10		.40	.43	. 64	-44	- 36	- 34	.47	+17	.97	.00	.79	-14	-11	.07	: [1	.24	. 14	. 54
. 81	100	. 54	- 14	. 30	-17	-33	.17	. 43		-17		.39	. 50	. 54		.16	. 113	-17	.23	.23		-16	::;	:::		. 10
6.01	1 .90			. 17	. 17	-74	. 33	.30	444	.43	. 4 5	. 14	.31			. 63			.08	.00	.04	.04	.00	.13		
. 11	. 84	1.00	1.00			-74	. 19	. 34	. *3	. 17	. 11	.39	. 39	. 37	- 19	.00			.00	.00			-15	.14	74	. 29
+41	91	- 19	-91	1.00					.*2	.77	. ??	14.	.69	+ 77	. 76	. 71	. 39	.49	.11	.21			.23	. 54	3	+ 0.7
	1 .21	, , 24	- 24	1.54	.71	1.00		-81		.74		.72			. 12		67	448	.42	- 50	-84	447	.10			
. 3					. 19	. *1	.48	1,00		.69	. 80	.74	. 19							-11	- 11	-13	- 11	.30	20	
- 1	ž -31							- 89		1.00	1.70	.43	-01	.03	. 73	.84	61						.10	-15	-24	. 67
	1 .4	1	1 . 13	41	.77	- 14					1.80	8.90			- 44	441	. 51	463	.29	+11	- 11	410	.13	. 29		.49
.5		4	1 43'	1 431	. 61	+49	,16	11					1.00	2 - 84	71		8 454	60	198	. 84	01	+10	.77	-11		
					76	71	.11	1 .71	. 174	13	. 72	- 41	. ,71	11	1 1,00	2 L21	7 .50 3 .70				- 47	-11	.21	-31	-21	419
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 					_		-					•					_				_	-
		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 von've been ill	Going to be ill	
	ROW/COL	2.2	17	14	48	24	52	23	33	39	4	10	27	29	1.6	40	44	6	30	1		-
Bromo seltzer Alka seltzer Contac Vicks Sinex nasal spray Privine nose drops Neosynephrine nose drops Neosynephrine nose drops Contac nasal spray Neosynephrine nose drops Contac nasal mist Privine nasal spray Naso-des Contac nasal mist Privine nasal spray Naso-des Contac nasal mist Privine nasal spray Naso-des Dristan medicated room vaporizer Mentholatum Vicks vapo-ruh Adulton cough syrup Cough syrup Vicks formula 44 cough diacs Romilar cough lozenges Vicks throat lozenges Spectrocla-T-troches Smith Brothers cough drops Vicks cough drops Vicks cough drops Listerine throat lozenges Chioraseptic lozenges Chioraseptic lozenges Cepacol throat lozenges	21 34 41 40 38 20 15 26 11 12 46 37 24 23 6 47 9 45					1					1 1	1					1	1				ž.
Cepacol throat lorenges F & F Losenges Sucreta Salt water garple Tetrazets antibacterial analgesic Squibb analgesic tablets Krex A, P. A. pain relievers Seeing the doctor Calling the doctor Bufferin Anach Aspirin Empirin compound Excedrin A. P. C. Tablets Hot lemonade Hot tea A hot toddy Corieldin cold tablets Vitamias Fruit Juice Warm milk An ice pack Ben-gay Ear drops Murine eye drops	29 17 33 43	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	1 1 1	. 1	L	1 1	1 1	L 1	1	1	1 1 1 1 1	1		111111111111111111111111111111111111111	1 1 1 1 1 1 1 1 1	1 1 1 1 1 1	1	111111111111111111111111111111111111111		
	TOTAL	14	4	4	6 :	5 4	4	5	•	4	2	7 1	ı i	1 1	3 1	•	14 1	- 1	2	. 3	. 3	- •

Girl (boy) friend has a cold
Headache
Neuritis, neuralgia
Bursitis
Backache
Nervous
The children are overtired
Indigestion
Heartburn
You are cold
Doet-need drin 45 3 19 36 21 37 41 13 51 42 1 1 1 1

9 13 14 11 9 10 10 1

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

Wet and tired
The children have a fever
Taken a chill
After you've been ill
Going to be ill Minor muscular aches Hangover Earache Hot and cold flashes The children are sick Fever 4 10 27 29 18 40 44 6 30 15 43

7 11 11 13 16 14 14 15 15 13 14

*	59		
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	
45 3 19 36 21 37 41 13 51 42	2 11 32 6 26 47 31 24	9 16 50 45 12 49 1 5 3	
			1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
10 5 9 13 14 11 9 10 10	12 29 46 45 37 32 28	24 24 24 28 30 22 15 12 15	15 15 14 15 17 21 23 823

								-		_	_					
8		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 funch	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 25 35 10 08 09 44 26 17 45 11 45 11 55 50 19 21	Beer Milk Raisins Jello Canned fruit Leftovers A pickle A bowl of soup Cottage cheese Hard boiled eggs Fresh fruit Apples Candy bars Lec cream Donuts Cherry pie Pastries A piece of cake Cookies Hard candy Cookies Hard candy Coen cola Sausage sticks Cheese flavored popcorn Carmel corn Fiddle-Faddles (like Cracker Jacks) Popcorn	243306803341188817711001001001100110011001100110011	400 1455 2224 11113 100 105 355 2212 200 100	0 29 7 1 16 0 22 5 5 15 28 1 12 7 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1	0 31 11 5 17 3 4 4 6 6 23 30 19 5 2 2 2 13 2 4 4 7 2 2 4 4 3 2 2 2 1	3 6 11 22 20 11 11 0 17 13 13 12 22 23 22 27 22 28 28 23 3 17 17 17 17 17 17 17 17 17 17 17 17 17	2 8 12 3 3 2 1 0 0 5 0 2 2 3 3 4 7 2 2 9 4 4 1 8 2 0 2 6 6 3 1	1869 2218 2334 2334 2300 1001 2071 13	2 18 8 8 3 1 4 5 3 6 6 11 13 22 22 5 11 18 3 6 8 11 5 5 6	8 5 1 7 7 6 0 4 6 3 4 4 4 2 7 5 5 2 2 2 5 6 2 1 2 3 6 4 5 10 7 5	4 3 5 10 12 2 16 11 19 4 2 2 3 3 3 3 6 19 10 5 8 11 5	21 14 23 8 11 8 20 10 9 11 14 3 4 11 6 12 10 9 25 10 9 25 10 10 10 10 10 10 10 10 10 10 10 10 10	8 23 2 12 22 14 11 17 14 10 4 11 15 2 11 19 77 13 44 1	530 223 3114 329 3115 1149 1119 11149 11149 1149 1149 1149	781067776445523188129581114479668	9668550055586611488882118778877
20 15 01 02 03 27 33 59 50 51 52 29 06 30 23 25 40 22 37 41	Nabisco Snacks—chipsters, shapes Fritos Bugles Potato chips Pretzels Nuts Peanuts Meat flavored snacks Daisys Shoe string potatoes Cheese and crackers A meaty snack Cheese Cold cuts—salami, bologna Sandwich A hamburger sandwich Hot dogs Potato chips and sour cream Pizza French fries Beef jerky Peanut butter and jelly	0 1 1 1 1 1 1 0 0 0 0 0 0 1 1 1 1 1 1 1	1 1 1 0 0 3 0 2 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0	1 022000 00402333774455322112217	2 25212222653388474301326	3 22 0 0 2 4 1 3 1 2 3 2 2 1 2 0 0 1 4 1 1 2 0 1 4 1 1 2 0 1 1 1 2 1 1 1 2 1 1 1 1 1 1 1 1	1 2 1 0 0 10 5 0 0 13 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1	4 24 1 3 7 2 2 15 9 20 8 10 11 14 11	9 12 11 10 9 8 13 8 7 5 4 6 10 8 10 7 4 4 4 4 4 4	10 9 13 13 20 11 12 7 7 11 9 18 7 6 6 4 4 15 5 0	15 17 15 17 16 18 18 19 13 11 19 14 23 14 11 4 6 17 7 7	18 19 12 18 10 6 4 21 11 10 22 20 18 23 27 24 14 13 18 18 18 18 19 21 21 21 21 21 21 21 21 21 21 21 21 21	20 17 20 7 22 22 23 23 24 21 10 23 331 27 25 7 7 31 16 10 10 10 10 10 10 10 10 10 10 10 10 10	5 10 6 8 5 2 5 1 21 22 22 24 33 33 34 31 6 25 16 15 30	8 99709010897776313564464454464	8 12 8 9 10 12 9 6 7 7 10 13 10 4 7 10 10 10 10 10 10 10 10 10 10 10 10 10
40 14 13 44 34 36 38 66	sandwich Rolls Tosstems Presweetened breakfast cereal Instant breakfast Sardines Spaghetti-O's Herring Other	1 0 0 4 0 0 0 5	0 0 1 1	24 29 31 31 1 0	26 31 32 31 1 1 4	6 16 14 7 2 1 0	6 9 0 1 0 0 0	22 13 0 11	16 8 1 0 3 0 1	14 2 2 2 8 1 9	7 4 2 20 4 21 14	12 2 2 6 7 5	22 5 0 1 8 7 5	13 8 5 14 17 22 11	7 4 1 4 1 3 2 5	6 2 2 2 3 3 3 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"	40 Whan I'm naronia
22 31 5 20 19 12 33 17 22 24 20 13 11 11 19 12 18 16 4 30 9 7 7	7 20 12 9 5 6 8 7 6 8 23 22 3 10 15 6 12 13 18 22 7 8 10 15 13	7 17 5 11 6 3 9 11 10 4 11 11 12 12 12 14 11 11 12 12 14 17 11 12 12 18 19 19 19 19 19 19 19 19 19 19 19 19 19	1 11 8 12 14 17 13 13 13 8 6 7 13 22 21 27 26 29 4 3 10 10	2 14 5 10 9 17 6 6 8 14 9 4 10 16 29 29 31 31 12 6 6 7	1 16 11 12 25 8 23 15 19 12 28 32 33 7 7 2 15 9 10 10	21 28 9 24 23 26 24 10 22 23 20 22 23 21 21 21 21 21 21 21 21 21 21 21 21 21	1: 1: 1: 1: 1: 1: 1: 1: 1: 1: 1: 1: 1: 1
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8 4 3 6 6 7 9	11 2 0 4 3 2 4 8	12 3 3 4 3 6 10	21 21 10 4 6 9 7	27 24 19 7 7 10 6	23 27 30 21 10 14 5	11 9 7 7 10 6 8 12	1

 $[\]bullet$ Odd-numbered respondents versus even-numbered respondents (split-half reliability .87).

THEM (AGGREGATE DATA)a

6 9 0 1 0 0 0	2 10 00 00 5 00 3 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1	3 2	1 18 20 21 8 33 30 34 4 33 30 27 0 0 1 0 0 1 1 7 7 1 1 1 1 3 3 3 3 3 3 3 3 3 3 3 3	03	03 For a low calorie lunch
3 6 4 22 13 0 11	2 12 11 1 10 11 1 10 13 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1	5	2 18 8 8 8 3 1 4 5 3 6 11 13 2 2 2 2 2 7 15 2 11 18 3 6 8 11 11 18 18 18 18 18 18 18 18 18 18 1	43	43 Coffee break
16 1 0 3 0 1 10 -	10 10 10 10 10 10 10 10 10 10 10 10 10 1	5	8 5 1 7 7 6 0 4 4 6 3 3 4 4 2 7 2 5 5 2 2 2 2 5 6 2 0 1 2 3 6 4 4 5 5 1 0	21	21 For very special occasions
14 2 2 2 8 1 9	17 17 17 17 17 17 17 17 17 17 17 17 17 1	11 15	4 3 5 10 12 2 3 14 2 2 2 3 3 3 3 6 9 10 5 8	13	13 As an appetizer
7 1 4 2 2 2 20 4 21 14	7 10 5 7 18 6 4 10 10 10 10 10 10 10 10 10 10	10 18	21 14 23 8 11 8 20 10 9 11 14 3 4 1 1 2 1 5 1 1 1 2 1 2 1 2 1 1 2 1 2 1 2	40	With cheese
22226759	20 20 20 20 20 20 20 20 20 20 20 20 20 2	18	8 23 12 12 22 14 18 11 17 14 10 4 4 11 5 4 11 11 19 7	15	With soup
22 5 0 1 8 7 5	2 10 10 10 10 10 10 10 10 10 10 10 10 10		5 23 6 21 23 31 14 29 14 10 8 13 12 14 14 10 11 11 11 11	#	14 For a quick lunch
13 8 5 14 17 22 11	0688522511522124423344316525611530	5	7 28 10 6 7 7 6 4 4 5 5 5 8 12 9 8 5 11 14 13 14 14 14 14 14 14 14 14 14 14 14 14 14	22	Three or four times a day
7 4 1 4 1 3 2 5	99 1 1 99 7 6 13 5 8 4 6 4 5 4 6 4 5 4 6 4 5 4 6 4 5 4 6 6 4 5 6 6 6 6		9 16 6 8 8 5 10 6 5 5 8 6 6 6 11 14 11 11 11 11 11 11 11 11 11 11 11	46	46 After a party
622	28909296770136310470455 6222333333	8			

:	24 19 32 12 4 11 11 12 11 11 11 12	30 9 7 7 13 8	22 31 5 5 20 19 12 33 17 22 4 20 13 11 19 12 18 15 4 4 30 9	31	To go with a sandwich
8 1 3 6 6 7 9		14	7 20 12 9 5 6 8 7 6 8 23 100 15 6 12 13 18 10 15 13 15 13 15 15 13	30	When I'm working
1 1 2 0 4 3 2 4 8 1		28 8 7 6 7	7 17 5 11 6 3 9 11 10 4 11 11 23 22 21 16 14 17 11 12 14 28 8 7 6 6 7	47	When I'm shopping
2 2 3 2 3 1 3 4 3 6	1 10 7 9 7 10	3 11 8 10 10 10	1 11 8 12 14 14 7 13 13 13 13 8 6 7 13 20 21 27 26 29 4 3 11 8 10 10 10 10 10 10 10 10 10 10 10 10 10	53	With tea
1 2: 1 2: 0 1: 4 6 9 1: 7 2		1 12 6 6 7 7	2 14 5 10 9 17 6 6 8 8 14 19 4 10 10 29 29 29 31 12 6 6 7	20	With coffee
7 2: 1 2: 2 3: 7 2: 7 1: 7 1: 8 9 1		15 9 10 10 10 12 14	1 16 11 16 12 25 8 23 15 19 12 12 28 27 28 32 37 21 15 9 10 10 10 10 10 10 10 10 10 10 10 10 10	19	With milk
3 11 7 9 0 7 1 7 0 10 4 6 5 1		23 16 7 4 8 8	21 28 9 24 23 26 21 10 19 22 23 22 23 24 11 21 21 21 21 21 21 21 21 21 21 21 21	27	"Raiding the refrigerator"
13		19 11 14 13 14 14	13 14 9 10 10 15 10 7 7 8 16 17 17 11 13 15 16 19 11 11 11 11 11 11 11 11 11 11 11 11	48	When I'm nervous
111 3 3 4 1 9 2 7 12 7 12 5 10 2 1		18 15 15 18 17 16 16	11 12 16 12 9 11 14 13 9 10 16 14 12 22 18 14 12 12 12 12 13 14 11 15 16 16 16 17 17 18 18 18 18 18 18 18 18 18 18 18 18 18	60	Mostly in the afternoon
153 122 1 222 152 2 153 9 144 0 11 16		24 22 17 15 18 19 22	24 24 21 21 21 22 23 22 23 22 24 23 20 24 22 24 22 17 11 11 11 17 20 21 11 11 11 11 11 11 11 11 11 11 11 11	38	When I go camping
23 2 6 3 6 3 10 4 8 9 11 5 12		27 18 18 18 19 20 19	24 117 12 3 16 119 120 120 122 228 119 27 18 18 19	35	When I'm out
3 17 3 7 3 6 3 8 5 7 7 7 7 8 1 8 1 8 1 8 1 8 1 8 1 8 1 8 1 8 1 8 1		27 14 20 13 18 19 20	23 17 17 12 12 11 12 7 14 12 16 30 30 12 27 14 20 18	48	When I'm visiting someone
7 12 7 10 8 8 5 9 7 9 7 9 8 9		29 18 23 25 26 24 21	96 115 12 13 10 10 26 25 27 20 328 23 24 25 25 26 25 26 25 26 26 27 28 28 28 28 28 28 28 28 28 28 28 28 28	36	When I'm babyaitting
2 14 0 13 3 13 9 15 7 19 9 19		22 17 18 16 20 25 19	22 28 15 19 12 19 12 20 20 27 27 17 22 17 18 18 20 20 21 21 21 21 21 21 21 21 21 21 21 21 21	52	Late at night
1 18 3 18 1 10 9 11 22 7 0 4		25 14 14 18 21 13	6 30 21 20 21 16 11 12 21 23 16 20 16 20 19 26 20 19 21 14 14 14 14 14 14 14 14 14 14 14 14 14	90	Almost anytime of the day
3 17 5 10 0 12 1 16 9 13 9 13 4 13 6 1		21 15 15 16 17 13	9 20 20 18 14 15 19 19 22 25 10 17 21 21 21 21 21 21 21 21 21 21 21 21 21	42	To kill my appetite
7 22 3 18 2 17 3 28 3 16 2 14 2 14 4 1		19 18 16 18 15 20	10 127 18 20 225 19 227 227 227 229 222 229 229 18 18 18 18	17	When I'm in a Rush
223 233 3 16 3 18 3 18 5 21 9 11		21 19 18 22 23 20	19 25 20 21 21 24 20 20 20 20 21 25 22 24 21 21 21 21 21 21 21 21 21 21 21 21 21	20	In cool weather
28 3 22 3 20 3 24 1 17 5 23 6 1		28 24 22 21 25 26	31 325 221 21 227 220 222 225 225 225 225 225 225 227 228 229 229 229 229 229 229 229 229 229	54	For men
28 25 25 26 27 11 14 21 28 20		20 27 25 22 26 27 27	326 225 229 230 328 229 328 229 229 220 227 227 227 227 227 227 227 227 227	39	For adults
26 3 26 3 27 21 7 21 5 2 0 1		28 30 28 29 30 30	29 230 27 28 22 21 22 26 26 27 28 29 22 24 26 28 28 29 20 20 20 20 20 20 20 20 20 20 20 20 20	28	Without tea
22 3 19 24 7 22 5 13 5 13 5 14 4 1		21 21 20 24 20 23	310 220 317 222 211 23 24 223 234 224 225 233 231 210 224 225 233 234 242 252 243 253 264 274 274 274 274 274 274 274 274 274 27	23	On warm days
2 28 2 26 5 27 2 29 2 4 3 22 5 21 1 14		26 24 22 23 27 27	20 229 26 31 227 27 28 30 29 21 27 27 29 29 29 26 26 27 27 27 27 27 27 27 27 27 27 27 27 27	91	For women
1					

		_	_	_	_	_	_	_	_	_	_								
5'	For kids	After school	In between meals	Watching T.V.			AB	In the evenings	Little get togethers	At parties	Ę	Wish a go	With a coar	2 While drinking beer	1 To go along with a drink	44 At a bar	45 With cocktails	With	
	12	34	29	10	2	3 9	18	24	26	37	: Z	· ·	> —	02	11	4			_
48 Beer 25 Milk 35 Raisins 10 Jello 80 Canned fruit 09 Leftovers 24 A pickle 05 A bowl of soup 07 Cottage cheese 26 Hard boiled eggs 47 Fresh fruit 40 Apples 26 Candy bars 17 Ice cream 49 Donuts 45 Cherry Pie 31 Pastries 18 A piece of cake 04 Cookies 42 Hard candy 11 Coca cola 55 Sausage sticks 55 Cheese flavored popcorn 09 Carmel corn 19 Fiddle-Faddles (like Cracker Jacks) 10 Popcorn 54 Nabisco snacks 15 Bugles 01 Potato chips 02 Pretzels 03 Nuts 27 Peanuts 33 Meat flavored snacks 59 Daisys 50 Shoe string potatoes 51 Cheese and crackers 52 A meaty snack		2322223333312225 2322223333312225 2322225 2322225 2322225 2322225 2322225 2322225 2322225 2322225 2322225 2322225 2322225 2322225 2322225 2322225 2322225 2322225 2322225 2322225 2322225 2322225 2322225 2322225 2322225 2322225 232225 2322225 232225 232225 232225 232225 232225 232225 232225 232225 232225 232225 232225 232225 232225 232225 232225 232225 232225 232225 232225 232225 232225 232225 232225 232225 232225 232225 232225 232225 232225 232225 232225 232225 232225 232225 232225 232225 232225 232225 232225 232225 232225 232225 232225 232225 232225 232225 232225 232225 23225 23225 23225 23225 23225 23225 23225 23225 23225 23225 23225 23225 23225 23225 23225 23225 23225 23225 23225 23225 23225 23225 23225 23225 23225 23225 23225 23225 23225 23225 23225 23225 23225 23225 23225 23225 23225 23225 23225 23225 23225 23225 23225 23225 23225 23225 23225 23225 23225 23225 23225 23225 23225 23225 23225 23225 23225 23225 23225 23225 23225 23225 23225 23225 23225 23225 23225 23225 23225 23225 23225 23225 23225 23225 23225 23225 23225 23225 23225 23225 23225 23225 23225 23225 23225 23225 23225 23225 23225 23225 23225 23225 23225 23225 23225 23225 23225 23225 23225 23225 23225 23225 23225 23225 23225 23225 23225 23225 23225 23225 23225 23225 23225 23225 23225 23225 23225 23225 23225 23225 23225 23225 23225 23225 23225 23225 23225 23225 23225 23225 23225 23225 23225 23225 23225 23225 23225 23225 23225 2325 2325 2325 2325 2325 2325 2325 2325 2325 2325 2325 2325 2325 2325 2325 2325 2325 2325 2325 2325 2325 2325 2325 2325 2325 2325 2325 2325 2325 2325 2325 2325 2325 2325 2325 2325 2325 2325 2325 2325 2325 2325 2325 2325 2325 2325 2325 2325 2325 2325 2325 2325 2325 2325 2325 2325 2325 2325 2325 2325 2325 2325 2325 2325 2325 2325 2325 2325 2325 2325 2325 2325 2325 2325 2325 2325 2325 2325 2325 2325 2325 2325 2325 2325 2325 2325 2325 2325 2325 2325 2325 2325 2325 2325 2325 2325 2325 2325 2325 2325 2325 2525 2525 2525 2525 2525 2525 2525 2525 2525 2525 2525 2525 2525 2525 2525 2525 2525 2525 2525 2525 2525 2525 2525 2525 2525 2525	12 13 3 3 2 2 2 2 2 2 3 3 3 3 2 2 2 2 2	221111 1333 221111 1333 2212227 75 98977 222 22222222222222222222222222222	1 3 2 2 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3	7 7 1 7 26	258 221 224 226 227 228 227 228 228 228 228 228 228 228	33 33 33 33 33 33 33 33 33 33 33 33 33	31 2 2 3 3 2 2 3 3 2 2 3 3 4 3 3 5 5 5 5 5 5 5 5 5 5 5 5 5 5 5	10 10 10 10 10 10 10 10 10 10 10 10 10 1	33 33 3 8 1 1 2 2 2 3 3 3 4 4 5 5 6 6 6 6 6 6 6 6 6 6 6 6 6 6 6 6	6 1 1 1 8 8 8 4 9 16 10 10 12 12	02254421148479666131128818923322258 927 331222822233222332222332223322233222332	3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3	11 1 2 2 2 2 2 2 3 3 3 3 3 3 3 3 3 3 3 3	12014431422236643224757227120 997 3291	221222354470	5	3
29 Cold cuts—salami, bologna 06 Sandwich 30 A hamburger sandwich		22 28 30 34	21 28 19 18	19 15 9 14	28 20 15	25 25	; 2 ; 2 ; 2	9	22 22 18	24 22 22	26 19 15	18 9 11	3	3 1	29 25 24 22	26 23 16 28	14 9 7 15	8 5 3 22	5 5 25
23 . Hot dogs 25 Potato chips and sour cream 40 Pissa		16 27 29	19 17 14	22 15	26 27	2: 2:	9 2	4 86 21	26 30 21 20	28 27 15	31 27 16 12	26 19 23 21	3	8 0 9	28 19	26 16 19	11 8 8	9 3 8	7 8 8
22 French fries 37 Beef jerky 41 Peanut butter and jelly andwich	.	11 31 20	14 23 18	15 17 21	25	5 2	0 i	24 28 21	12 25	12 9 19	18	1	1 2	12	22 7 5 3	11 13 11	2 2 1	3	0 2 1
40 Rolls 14 Toastems 13 Presweetened breakiss	:	30 33	20 14	11 11	14	4 2	4 :	20 14	8 0	8	1 2	5 1	5	5	0	5	1	ī 1	0
cereal Instant breakfast Sardines Spaghetti-O's Herring Other		15 11 26 6 11	7 10 9 6	1	i 4 3	9 1 9 1 0 1	24 12 13 10 15	13 16 14 15 15	13 13 16 14	11	1	4 1 8	2 5 1	0 14 16 9 17	18 2 11 15	16 10 15	1	12	6 1 5

Table 7 shows the originate clusters (that are base calculations described aboreach other and columns wh

Table 8 is similar to Tab gate data matrix in which a belief-frame about when

If we split the arbitrar for a given aggregate data numbered half, the split-1. 91, .85, .93, and .88. Fol Gulliksen, 1950, Ch. 6), t from these item-by-use me Stefflre, Reich, and McClalations for this type of a spondents with a 50 × 5 was .70; with a 25 × 25 Schizophrenics or respondinterindividual correlation

ITEMS MARKED X BY TE FEARED, ETC.)

Figure 2 shows a phys (N = 200) from a correlation mat odd-numbered responder numbered respondents.

PATTERNS OF SUBSTITU (WHERE AVAILABLE)

With this type of dathe shifts in the individe to the next (Buzzell, 1 variations of switching

We have found it use $(N \approx 50)$ and aggregations. The data relations

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 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. Steffire, 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 \times by the Same Individuals (\times = 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

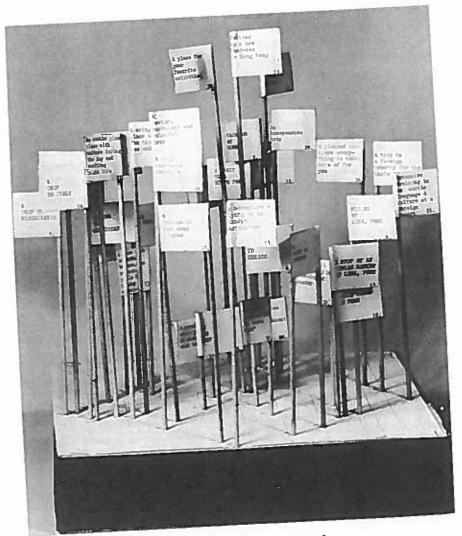


Fig. 2. Spatial representation of trip preferences.

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 and switching of cigarettes (rank tion $\rho = .74$).

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

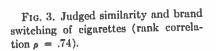
Judged similarity in the scale patterns of routine

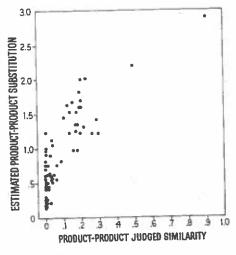
Fig. 4. Relation of prod tution and product sim toilet soap (rank correlation



preferences.

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

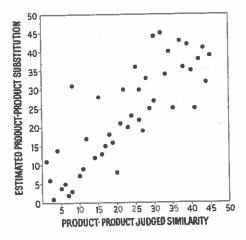




are treated as more substitutable and competitive if they (a) are seen as appropriate for the same uses, and (b) are liked by the same individuals. The Brown, Cardozo, Cunningham, Salmon, and Sultan report (1968, pp. 439 ff., 461–463) contains a description of one of our other early projects and presents in detail some of our data on judged similarity and brandbrand 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 Xs see this new item as similar to other things because of the way they encode it (describe it to themselves).
- (2) Descriptions. The Xs 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 yanapakuqqringokuna to measured by (a) a role by b and then (c) by comparing to of a correlation matrix base roles according to how muc improvement in the quality

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



Fig. 5. Spatial representation model of the correlation matrix

of complex patterns added cross-culturally different sectors of Corps volunteers; and stated above that the routine behavior holds to correlation was .45,

troduced into a culture, the behavior toward alture as similar to the t of our understanding rities mentioned above ations.

relevant to differentiate ag the question of why milar and different and pattern of similarity to tion as having two sep-

to other things because es).

describe it to themselves) et of physical characterin such and such a way,

ticular item fits where it ular pattern of behavior, introduced into a culture arity structure and thereor a description that will esired to perform.

es of some aspects of the ng to prediction. We sur-'eace Corp workers might *jkuna* is a reciprocal work help each other, and the cClaran, 1971)] and then y measuring the similarity of yanapakuqqringokuna 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 yanapakuqqringokuna to voluntarios del cuerpo de paz were as follows: (a) it was second most similar in expected

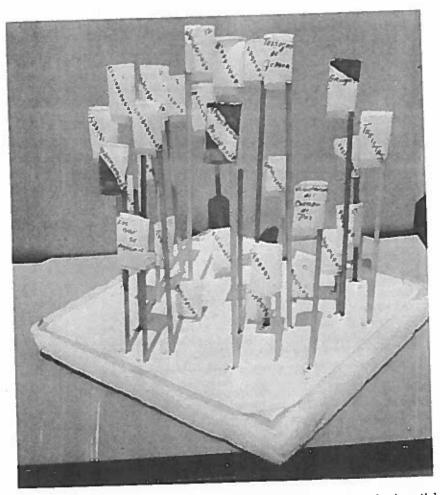


Fig. 5. Spatial representation of Peace Corps versus other types of people: A spatial model of the correlation matrix.

TABLE 9

RANKING OF PEACE CORPS VOLUNTEERS WITH OTHER TYPES OF PEOPLE

1	Testigos de Jehova	Jehova's Witnesses
-	Gringos	Gringos
3	Soldados	Draftees
	Yanapakuqgringokuna	Gringos who mutually help
	Turistas	Tourists
6	Guardias	Policemen
•	Padres	Priests
8	Ingenieros	Engineers
_	Los que ayudan	Those who help
	Q'arkuna	Young men city slickers
11	Maestros	Teachers
	Yanapakuqkuna	Those who help each other
13	Abogados	Lawyers
14		Students
15	Adinerados	Wealthy people
16	Enfermeras	Nurses
17		Landowners
18	•	Merchants
19		Doctors
20		Army 'graduates'
21		Village representatives
22		Pensants
23	_ •	Thieves
24	Parteras	Midwives
25	Indigenas	Indians
26		Creoles, natives
27	Watuqkuna	Diviners
28	Mestizos	Mestizos
29	Obreros	Laborers
30		Female plaza vendors
L	east 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 yanapai positions like voluntarios del c "built" some people seen by yanapakuqqringokuna they wo this description.

PEACE (

	D	imension	
No.	X	Y	Z
1	1.05	5.98	9.4
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	14
27	13.78	17.73	14
28	1.47	15.34	14
29	20.48	8.16	1
30	5.53	0.41	1:
31	8.80	17.14	

THER TYPES OF PEOPLE

Witnesses

ho mutually help

1

no help en city slickers

10 help each other

people

iers its

raduates' epresentatives

3

69

natives

9

~ *a

plaza vendors

e by behavior matrix, (b) it red in the judged similarity slation of the 31 roles ranked in Cuzco. Table 9 shows the voluntarios del cuerpo de paz. atial model of the correlation the model.)

he components concatenated

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 yanapakuqqringokuna they would position and perform approximately like this description.

TABLE 10
PEACE CORPS DATA COORDINATES

	E	imension			
No.	X	Y	\overline{z}	Peo	ople
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	Guardina	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	Peace Corps
14	7.44	0.01		de paz	
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		Army 'graduates'
21	19.41	16.17	11.22	Parteras	Midwives
22	15.44	10.82	12.81	Q'arkuna	Young men city slicke
23	3.51	2.13	10.66	Indigenas	Indians
24	4.21	15.70	12.55	Personerokuna	Village representative
25	10.70	6.74	1.34	and the second s	Gringos who mutually help
26	16.70	15.60	14.48	Estudiantes	Studente
27	13.78	17.73	14.82		Landowners
28	1.47	15.34	14.77		Female plaza vendora
29	20.48	8.16	10.79	_	Teachers
30	5.53	0.41	12.29		Creoles, natives
31	8.80	17.14	2.27	•	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

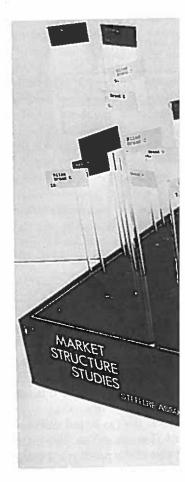


Fig. 6. Spatial representation of characteristics.

representation of the pattern in the national sample. Braeach other are those liked by

What happened in this restion was found that performs was built that (i) was seen to (ii) was liked in the large-scal it was built to match.

The client then decided to

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

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

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

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

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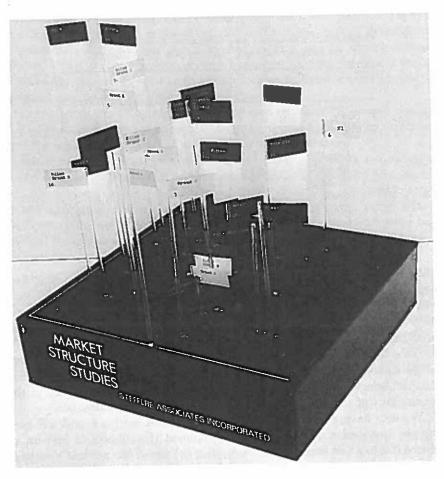


Fig. 6. Spatial representation of preference patterns for brands of coffee and coffee characteristics.

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:		90.05
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. 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 $\pm 30\%$ 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 match them, on the other, ca spatial models both in repre which features lead items to Though most work of this k marketing, the general proces political campaigns, etc. (e.g.

In the work described abo a Euclidean metric space as r and the aggregate patterns of

While the assumption of a useful in some respects, in problem in representing agg ments aggregated across in patterns of behavior or choichavior) by a metric space ha and preferences.

The present author is includistance measure for psycholobe violated fairly frequently. ures which force this assurranging from .5 to 1 (J. Boye

This violation occurs in descriptions) reside in two c

Fig. 7. Comparison of perform of product descriptions and new ucts in Market for five differeducts.

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, (Steffire, ms.,b) describes some problems in applied research of this type.

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
ř.	5.
1	9.6
	4.1
	3.

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

offee, we have done three others o evolve advertising, packaging, tion whose performance in the manufacturer desired.

which we (a) found out how ment (four cases) or just intro-(b) tested the product's descrip-) obtained data on the product's narket in which we had tested ions of the performance for the performance in the market. In e within ±30% of the volume

show one use to which the fit patterns of routine behavior, lescriptions and the things that

Iarvard Business School Case M266, 9. Pp. 439-466. My manuscript, New Ipplied Social Science, (Steffire, ms.,b) 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

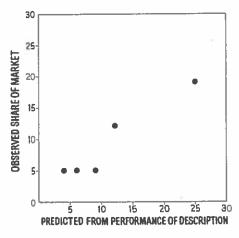
and the aggregate patterns of similarity in behavior.

While the assumption of a metric space² 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.



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) $A_DB + B_DC \ge A_DC$ (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 : item placement.

As soon as coordinates question "What does up n things that are high." Anot both light in weight and "There are no dimensions, may mean something very your understanding of how go where you expect." Alt by analysis but by experim

A second assumption of the author nervous is that just which people like a t Several joint models (Carr 1970; Coombs, 1964; Do been suggested in which it also where each individual

While our own work in t as pessimistic about the p about using the spatial coc for constructing new object two new items which are or behavioral similarity many

An example may illustrate between position and predifferent people and two similarity, the two dog pic If we look at preference deby the same individuals. In not so good, their absoluthan their similarity in location is that judged similarity of tems better than the levels of preference. We similarity correlated with a which it correlated with cr

A number of examples c of view from one which c (a) level of and (b) patt ets of complex natural stimuli ensionality enough to approxi-

words with multiple meanings, and with heavy in another. This orther examination shows that in language can range from its sounding the same, such as the same word (e.g., various nen are men" or slight shifts in och as "the atomic submarine of pairs of appearances of the usion. Light in the context dark to be defined semantically as the its other use, it contrasts with atures.

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to a common space in a metric the complexity of the space to s 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 meansends 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

more often than the correct we take confusions as a meas A_DB and B_DA symmetry freq similarity and confusions. As often judged as similar to a data often indicate similar $(A_DB + B_DC \ge A_DC)$ and i point let it suffice to say that a red Cadillac) and B is similar to a cadillac and an orange of Schwartz might suggest.

This is not to suggest that collection and data analysis suggest that while such man or theoretical purposes their

The present author's own which we deal—the individu mind or collective representa is discrete, and combinator looking more like a dictiona space (Stefflre, Reich, and Mand relations and each elements to which it externative type of developmer Tyler, 1969; Minsky, 1968; I

The basic structure is the Norman, & Cartwright, 1965 usually spatial representation aggregate free judged similar the elements on the description a collective representation.

I am inclined to believe
(a) to calculate from it the s
with more flexibility and gen

In summary, then, it has methods have a real utility ir in the similarity of behavior ful descriptive tool for study aggregates and are of some if features put new items where

Some problems in the use

but that the level of preferirtly by G, a general level of oints in space represent (a), (b) occupying a particular

we have found metric space rities in aggregate-aggregate ve not yet found an algorithm

netric space assumptions may all data, similarities can shift features into salience so that ime represent a metric space ime they represent a different nite antithetical to the whole ree response judged similarity ag individuals; pattern of bedata across individuals and

xibility in sequential behavior te workers who did early work te mind have shifted to means son & Carroll, 1965; Abelson, & Tannenbaum, 1968; Miller, ly, 1955).

structure, the spatial represenit. However, as saliency among figuration appropriate for one ement in the space takes on a es a chalice). In working with a function of context poses a ms A and B are more similar elicit more similar patterns of ngle crucial behavior or context (e.g., legal cases).

ontexts shifting salient features, ts—seem quite unspatial. Even and look at them in terms of ill problems. $A_DA = 0$ suggests out consider confusions in recognrect stimulus may be selected

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 (Steffire, 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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